A Deep Learning Approach for Automatic Cluster Shape Detection

A Thesis

Submitted in partial fulfillment of the requirement for the award of the Degree of

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By

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PREFACE

Clustering, a fundamental technique in the realms of machine learning and data analysis, entails the segmentation of data points into cohesive groups predicated on their intrinsic resemblances. Departing from the rigidity of supervised learning paradigms, clustering operates under the auspices of unsupervised learning, thus obviating the prerequisite for preordained labels during the training phase. Essentially, its principal objective lies in the revelation of latent structures latent within a dataset, orchestrating the amalgamation of data points that exhibit similar traits.

The major objective of this thesis is to develop a novel methodology, which aims to enhance the interpretability and robustness of clustering results by incorporating a shape detection component. To develop that methodology the present work deals with Attention Mechanism, Deep Learning and some other robust algorithms.

This thesis comprises six chapters, each addressing crucial aspects of machine learning, clustering, and feature learning. Chapter 1 provides a comprehensive introduction to machine learning, tracing its historical trajectory and discussing its contemporary significance. It examines the distinctions between artificial intelligence (AI), machine learning (ML), and deep learning (DL), while also exploring their societal impact, future trends, and challenges. Chapter 2 delves into clustering, exploring its essence and taxonomy. It examines various clustering algorithms, including hierarchical, partitioning, density-based, and probabilistic approaches, to elucidate the methodologies used in segregating data into meaningful clusters. Chapter 3 deals with the details of feature extraction process using convolutional neural network. Chapter 4 illustrates the experiment and results of the proposed deep learning based cluster shape detection algorithm along with its comparison with traditional techniques. Chapter 5 synthesizes the findings from the thesis, distilling key conclusions drawn from clustering and feature learning methodologies. Chapter 6 looks to the future, discussing potential avenues for further research and reflecting on the limitations of the current work. Additionally, an Appendix section at the end of the thesis provides step-by-step procedures for executing the codes included in the accompanying CD-ROM.

List of Publications

1. Apurba Nandi, Rupayan Halder, Sayantani Ghosh, Amit Konar, "Cluster Shape Detection Using Dual Attention Induced Convolutional-Clustering Algorithm," *In IEEE 2024 International Conference on Information Technology, Electronics and Intelligent Communication Systems*, Bengaluru, Karnataka, India ,2024 (accepted)

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Chapter 1

Introduction

1.1 Machine Learning

Machine Learning (ML) [1] is like teaching a computer to learn from examples, just like how we learn from experiences. It's a fascinating field where computers can automatically learn and improve without being explicitly programmed. Imagine if you could show a computer lots of pictures of cats and dogs and tell it which is which, and then it learns to recognize them on its own. That's what ML does—it enables computers to understand patterns in data and make predictions or decisions based on that understanding. ML is everywhere around us, quietly working behind the scenes in things like recommendation systems [1] (think of Netflix suggesting movies you might like), voice assistants (like Siri or Alexa understanding what you say), and even in self-driving cars, where they learn to navigate roads safely.

In this introduction to ML, we'll break down the basics so anyone can understand. We'll start with the two main types of learning [2]: supervised and unsupervised. Supervised learning is like having a teacher guide the computer by giving it labelled examples (like our cat and dog pictures). Unsupervised learning is more like letting the computer explore and find patterns on its own without a teacher.

As we dive deeper, we'll explore advanced techniques such as deep learning [3], which is inspired by how our brain works and is used for tasks like image and speech recognition. Then there's reinforcement learning, where computers learn through trial and error, just like how we learn to ride a bike by falling and getting back up.

But it's not all technical stuff. We'll also look at real-life examples to see how ML is changing the world around us. For instance, in healthcare, ML helps doctors diagnose diseases earlier by analysing medical images like X-rays and MRIs. In finance, it's used to detect fraudulent transactions, saving companies billions of dollars. And in agriculture, ML guides farmers on when to plant and harvest crops, increasing yields and reducing waste.

However, it's not all that easy. ML comes with its own set of challenges, especially when it comes to ethics and fairness. Imagine if a loan application system unfairly denied loans to certain

groups of people because of biased algorithms. That's why it's crucial to build ML systems that are fair and unbiased, and that respect privacy and security.

So whether you're just starting to explore ML or you're already knee-deep in algorithms, this introduction aims to be your friendly guide. Together, we'll unravel the mysteries of machine learning and see how it's shaping the world we live in. So, let's embark on this journey and discover the endless possibilities of teaching computers to learn on their own.

1.2 Difference Between AI vs ML vs DL

Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL) are terms often used interchangeably, but they represent distinct concepts with unique characteristics and applications. Understanding the differences between them is crucial for grasping their roles in modern technology.

Artificial Intelligence (AI) is the broad field of computer science dedicated to creating intelligent machines that can perform tasks requiring human-like intelligence. These activities encompass problem-solving, decision-making, comprehension of language, and perception. AI aims to develop systems that can reason, learn from experience, adapt to new situations, and interact with humans in natural ways. In essence, AI seeks to mimic human cognitive abilities using machines.

Machine Learning (ML) is a branch of Artificial Intelligence (AI) that concentrates on empowering computers to enhance their performance by learning from data, rather than relying solely on explicit programming instructions. ML algorithms allow computers to identify patterns in data, make predictions, and take actions based on those patterns. The key idea behind ML is to provide algorithms with large amounts of data and let them learn from it to make decisions or predictions without human intervention. ML algorithms can be broadly categorized into supervised learning, unsupervised learning, and reinforcement learning, depending on the type of data and feedback they receive during training.

Deep Learning (DL) [4] is a specialized subset of ML that uses artificial neural networks with multiple layers to learn complex patterns in data. Inspired by the structure and function of the human brain, DL algorithms simulate the behaviour of interconnected neurons to process and interpret

information. Deep learning has gained prominence due to its ability to automatically discover intricate patterns in large datasets, leading to breakthroughs in areas such as image and speech recognition, natural language processing, and autonomous driving.

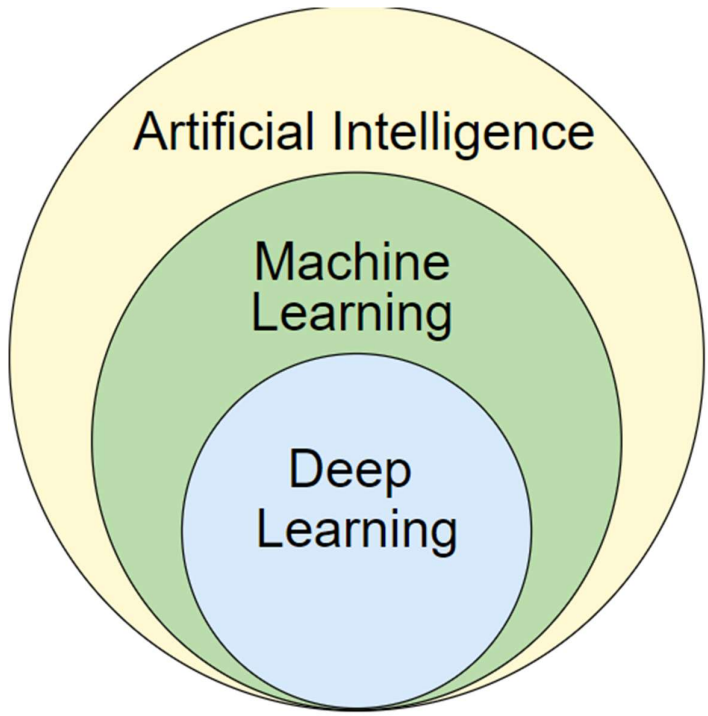


Figure 1.1. AI vs ML vs DL

To better understand the differences between AI, ML, and DL, let's delve deeper into each concept:

- **Artificial Intelligence (AI)**

AI is the overarching field encompassing all efforts to create intelligent machines. It aims to develop systems capable of reasoning, learning, understanding natural language, and interacting with humans in a human-like manner. AI systems may employ various techniques, including rule-based systems, expert systems, symbolic reasoning, and statistical methods. Applications of AI range from virtual assistants (like Siri and Alexa) and recommendation systems (like those used by Netflix and Amazon) to autonomous vehicles and healthcare diagnostics.

- **Machine Learning (ML)**

ML is a subset of AI concerned with enabling computers to learn from data and improve their performance over time. ML algorithms analyse large datasets to identify patterns and relationships, which are then used to make predictions or decisions. Supervised learning involves training ML models on labelled data, where the correct answers are provided during training. Unsupervised learning involves training ML models on unlabelled data, allowing them to discover hidden patterns and structures independently. Reinforcement learning involves training ML models to interact with an environment and learn optimal behaviour through trial and error. Applications of ML include image and speech recognition, predictive analytics, fraud detection, and personalized recommendations.

- **Deep Learning (DL)**

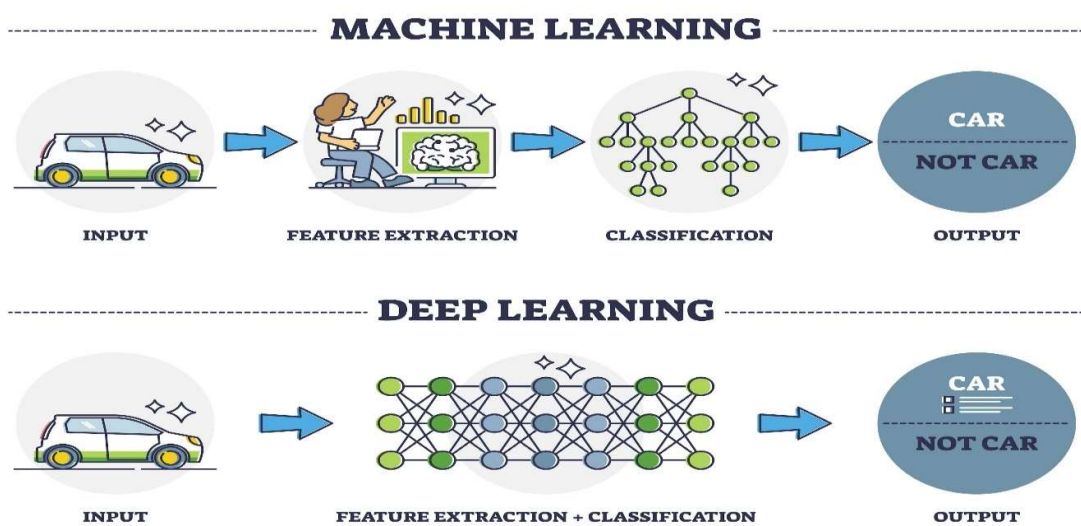


Figure 1.2. Machine Learning & Deep Learning

DL is a subset of ML that employs artificial neural networks with multiple layers (hence the term "deep") to learn complex representations of data. DL algorithms automatically extract features from raw data and hierarchically learn patterns at different levels of abstraction. Convolutional Neural Networks (CNNs) are widely used in DL for tasks such as image recognition, while Recurrent Neural Networks (RNNs) excel in sequential data processing tasks like natural language processing. DL has

achieved remarkable success in various fields, including computer vision, speech recognition, natural language understanding, and autonomous driving. While AI, ML, and DL are distinct concepts, they are interconnected and often used in conjunction to solve complex problems. AI serves as the overarching goal, while ML provides the techniques and algorithms to achieve that goal, and DL represents a powerful subset of ML that excels in learning complex patterns from data. Together, these technologies drive innovation and fuel advancements in numerous industries, shaping the future of technology and society.

To understand the differences between AI, ML, and DL, let's use an analogy, Imagine you're trying to build a robot that can recognize fruits.

- **AI**

Building the robot itself is like AI—it's the big picture goal of making a smart machine. You want the robot to be able to recognize all kinds of fruits, not just apples or oranges, and to be able to pick them up, sort them, and maybe even make juice out of them.

- **ML**

Now, teaching the robot to recognize fruits is where ML comes in. You could use ML algorithms to train the robot on different fruits—showing it lots of examples of apples, oranges, bananas, and so on. The robot learns from these examples and gets better at recognizing fruits over time. It's like giving the robot a crash course in fruit recognition.

- **DL**

Deep learning is like a specific technique you might use to teach the robot. Instead of just showing it pictures of fruits and hoping it figures things out, you could use deep learning algorithms, which are inspired by how our brains work. These algorithms would create layers of artificial neurons that can analyse the features of the fruits—like their shape, colour, and texture—and learn to distinguish between them. It's like teaching the robot to recognize fruits by breaking down their characteristics into smaller, more manageable pieces.

1.3 History

The history of machine learning [5] is like tracing the footsteps of how computers learned to think on their own. It all began in the 1950s when Arthur Samuel created a program that could play checkers and calculate the chances of winning for each player. This was a significant step because it showed that computers could learn and improve their performance over time.

But the roots of machine learning go even further back, rooted in the human quest to understand how our brains work. In 1949, a psychologist named Donald Hebb proposed a theory about how neurons in our brains interact with each other to form connections. This idea laid the groundwork for how artificial intelligence (AI) and machine learning algorithms function, using artificial neurons to process and communicate data.

Other researchers, like Walter Pitts and Warren McCulloch, also contributed to the development of early mathematical models of neural networks. These models aimed to mimic the way humans think, paving the way for modern machine learning technologies.

By the early 1960s, experiments with "learning machines" were underway. Raytheon Company developed a machine called Cybertron, which used punched tape memory to analyse various signals, such as sonar and speech patterns. It was trained by a human operator to recognize patterns and correct its mistakes—a primitive form of what we now call reinforcement learning.

Books like Nilsson's "Learning Machines" in the 1960s and Duda and Hart's work on pattern recognition in the 1970s reflected growing interest in machine learning and pattern classification. In 1981, there was a breakthrough in using teaching strategies to train artificial neural networks to recognize characters from a computer terminal.

Tom M. Mitchell later provided a formal definition of machine learning algorithms, stating that a computer program learns from experience if its performance improves over time based on tasks and measurements. This definition shifted the focus from whether machines can think like humans to whether they can perform tasks as effectively as humans—a key concept in modern machine learning.

Today, machine learning serves two main purposes: classification and prediction. Classification involves sorting data into categories based on models that have been developed, like using computer vision to classify cancerous moles. Prediction, on the other hand, involves forecasting future outcomes based on these models, such as predicting stock market trends.

Machine learning has come a long way since its inception, with advancements in algorithms, computing power, and data availability driving its growth. It's used in various fields, from healthcare and finance to entertainment and transportation, revolutionizing how we tackle problems and make decisions. But with great power comes great responsibility. As machine learning becomes more prevalent in our lives, we must address ethical concerns, such as bias and privacy, to ensure that AI systems are fair and accountable.

The history of machine learning is a journey of curiosity, innovation, and discovery. From humble beginnings to cutting-edge technologies, it continues to shape the way we interact with computers and the world around us, promising a future where machines can learn, adapt, and improve alongside us.

1.4 Approaches – Types of Learning

Machine learning is like teaching computers to learn and improve from experience, just like we do. But within this vast field, there are different approaches, each tailored to the type of feedback available to the learning system. Let's explore these approaches in simpler terms.

1.4.1 Supervised Learning

Imagine you're teaching a child with examples and answers. That's what supervised learning is like for computers. Here, the computer is shown example inputs along with their correct answers, given by a "teacher." The goal is for the computer to learn a general rule or pattern that connects inputs to outputs. For example, if you were teaching a computer to recognize animals in pictures, you'd show it lots of pictures of animals with labels indicating which animal is in each picture. Supervised learning algorithms then analyse these examples to understand patterns and relationships. They use this information to create a mathematical model that helps them predict the correct output when given new

inputs. Think of it as teaching a computer to recognize handwriting by showing it examples of letters and numbers with their correct labels. There are two basic types of Supervised Learning techniques , 1) Classification & 2) Regression .

Here are examples of some supervised learning algorithms:

- **Linear Regression**

Linear regression is one of the simplest and most commonly used supervised learning algorithms for regression tasks. It's used to predict a continuous outcome variable (dependent variable) based on one or more input features (independent variables) that have a linear relationship with the outcome. For example, linear regression can be used to predict house prices based on features like the number of bedrooms, square footage, and location.

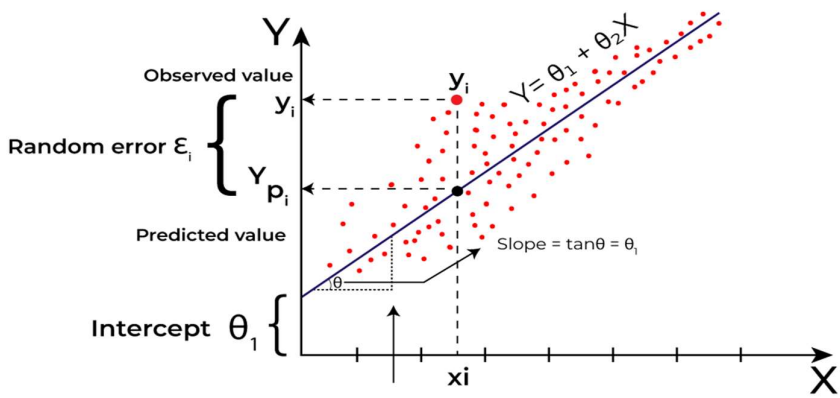


Figure 1.3. Linear Regression

- **Logistic Regression**

Despite its name, logistic regression is a classification algorithm used to predict the probability of an observation belonging to a particular class. It's widely used in binary classification tasks where the outcome variable has two possible outcomes (e.g., true/false, yes/no, 0/1). For instance, logistic

regression can be used to predict whether an email is spam or not based on features like the presence of certain keywords and email sender.

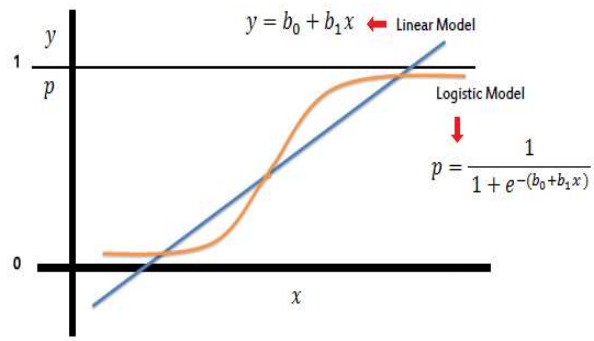


Figure 1.4. Logistic Regression

- ## Decision Trees

Decision tree is a supervised learning algorithm that can be used for both classification and regression tasks. They partition the feature space into segments by asking a series of questions based on feature values, ultimately leading to a prediction or decision at the leaf nodes. Decision trees are intuitive and easy to interpret, making them useful for tasks where understanding the reasoning behind predictions is important, such as medical diagnosis.

- ## Random Forest

Random forest is an ensemble learning method that constructs multiple decision trees during training and combines their predictions through voting or averaging. It improves upon the performance of individual decision trees by reducing overfitting and increasing robustness. Random forest is commonly used in classification and regression tasks across various domains, including finance, healthcare, and marketing.

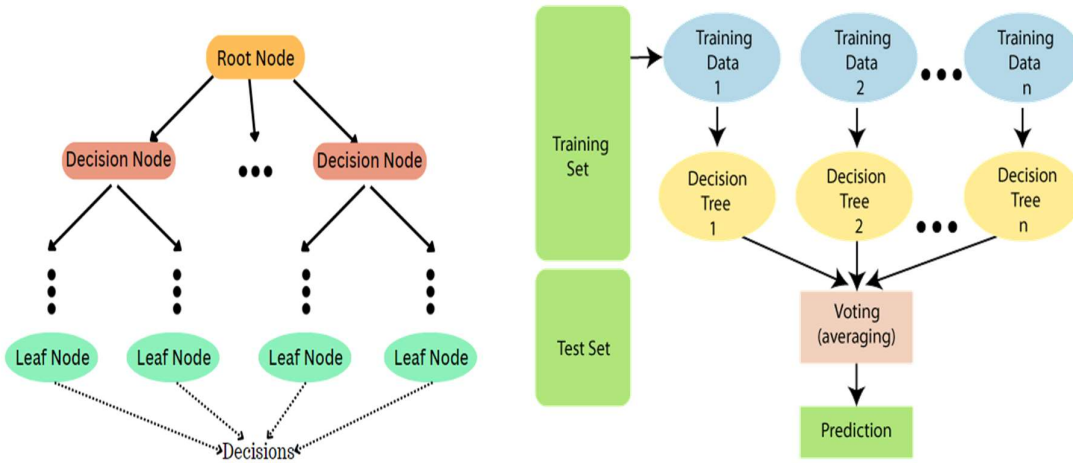


Figure 1.5. Decision Tree & Random Forest

- **Support Vector Machines (SVM)**

Support vector machines are powerful supervised learning algorithms used for both classification and regression tasks. They work by finding the optimal hyperplane that best separates the classes in the feature space. SVMs can handle high-dimensional data and are effective in cases where the data is not linearly separable by transforming it into a higher-dimensional space using kernel functions.

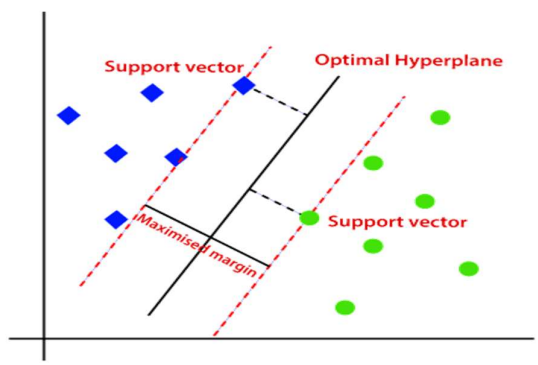


Figure 1.6. Support Vector Machine

- **K-Nearest Neighbours (KNN)**

K-nearest neighbours is a simple yet effective supervised learning algorithm used for classification and regression tasks. It makes predictions by identifying the k nearest neighbours of a new data point in the feature space and taking a majority vote (for classification) or averaging (for regression) their labels or values. KNN is non-parametric and lazy-learning, meaning it does not make assumptions about the underlying data distribution and does not require training a model.

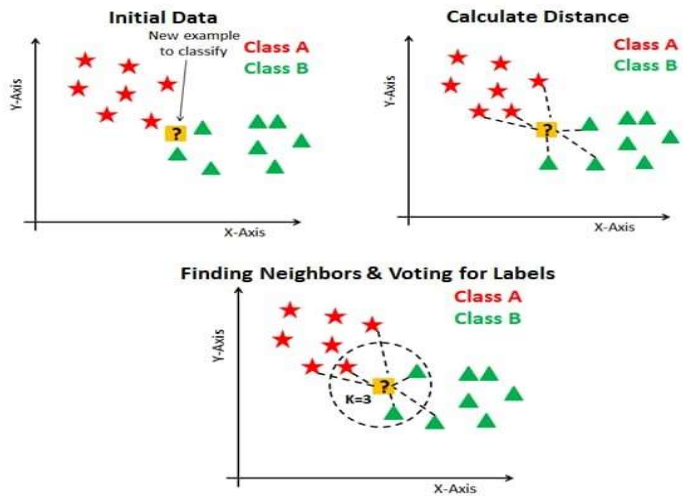


Figure 1.7. K-Nearest Neighbour

- **Naive Bayes**

Naive Bayes is a simple yet powerful algorithm in the realm of machine learning, particularly in the field of probabilistic classification. Its simplicity belies its effectiveness, making it a popular choice for various tasks, including spam filtering, sentiment analysis, and document categorization. At its core, Naive Bayes relies on Bayes' theorem, which provides a way to calculate conditional probabilities given prior knowledge. The "naive" assumption in Naive Bayes stems from the simplifying assumption that features are conditionally independent, meaning that the presence of one feature does not affect the presence of another. While this assumption may not hold true in all real-world scenarios, Naive Bayes often performs remarkably well in practice. One of the key strengths of Naive Bayes lies in its efficiency and scalability, as it requires only a small amount of training data to

estimate parameters and make predictions. Additionally, it can handle high-dimensional data effectively, making it suitable for tasks with a large number of features. Despite its simplicity, Naive Bayes can achieve impressive results, particularly in situations where the independence assumption holds reasonably well. Its ability to provide probabilistic predictions also lends itself well to applications where understanding the uncertainty of predictions is important.

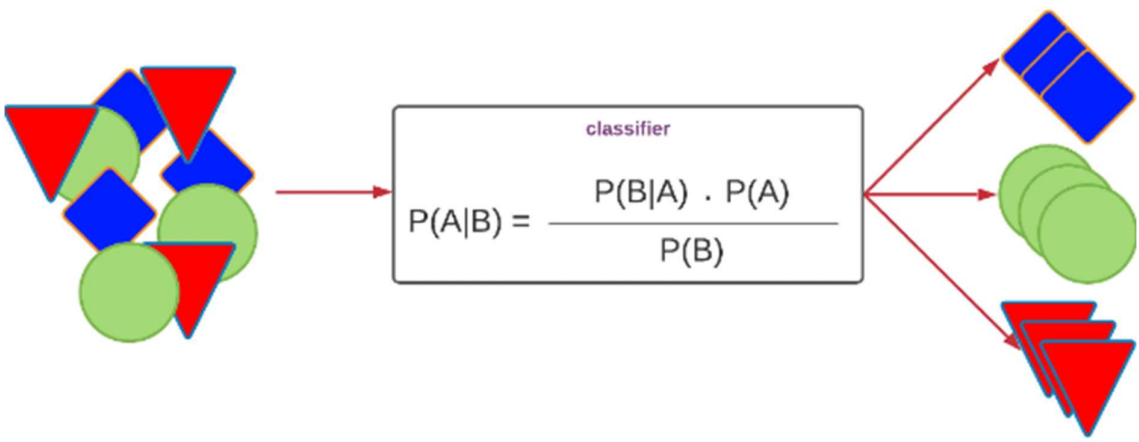


Figure 1.8. Naïve- Bayes

1.4.2 Unsupervised Learning

Now, imagine the computer has to find its own patterns in a pile of data without any guidance. That's unsupervised learning. Here, the computer is given a bunch of data but no labels or answers. Instead of being told what to look for, the computer has to figure it out on its own. It looks for similarities or common features in the data and groups them accordingly. For instance, if you gave the computer a bunch of pictures without telling it what's in each picture, it might group similar pictures together based on shared features. Unsupervised learning is like finding hidden patterns in data without anyone telling you what to look for. There are also 2 types of Unsupervised learning techniques ,1) Clustering & 2) Association.

1.4.2.1 Clustering

Clustering algorithms aim to group similar data points together based on their inherent characteristics or features, without any prior knowledge of labels or categories. The primary goal of clustering is to uncover patterns or structures within the data that may not be immediately apparent. In clustering, data points are partitioned into clusters such that points within the same cluster are more similar to each other compared to points in different clusters. This process helps in understanding the natural groupings present in the data. Common clustering algorithms include K-means, which partitions data into K clusters based on centroids, hierarchical clustering, which creates a tree-like structure of nested clusters, and DBSCAN, which groups together densely packed data points.

1.4.2.2 Association

Association techniques focus on discovering relationships and associations between variables or items within a dataset. These techniques are particularly useful in transactional data analysis, market basket analysis, and recommendation systems. Association algorithms identify sets of items, known as item sets, that frequently co-occur in transactions. They also quantify the strength of these associations using metrics such as support and confidence. Apriori and FP-growth are popular association algorithms used to extract frequent item sets from transactional data. Apriori generates candidate item sets using a breadth-first search approach, while FP-growth constructs a compact data structure called a frequent pattern tree to efficiently mine frequent item sets.

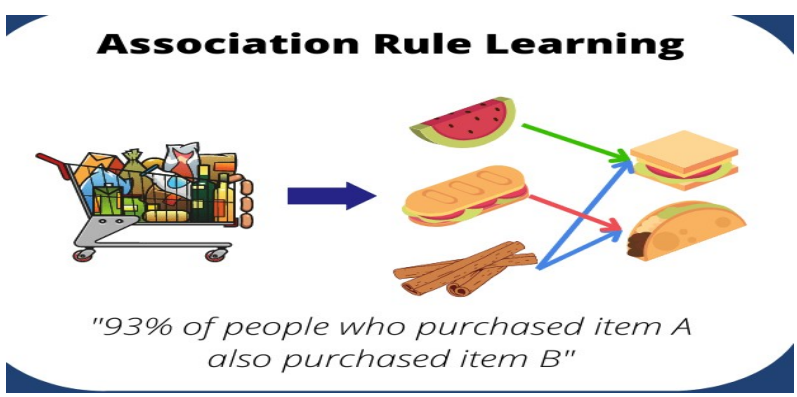


Figure 1.9. Learning Association

Here are examples of some clustering algorithms:

- **K-Means Clustering**

K-means clustering is one of the most widely used clustering algorithms. It partitions the dataset into k clusters by iteratively assigning data points to the nearest centroid and updating the centroids based on the mean of the points assigned to each cluster. K-means is simple, efficient, and effective for datasets with a large number of samples.

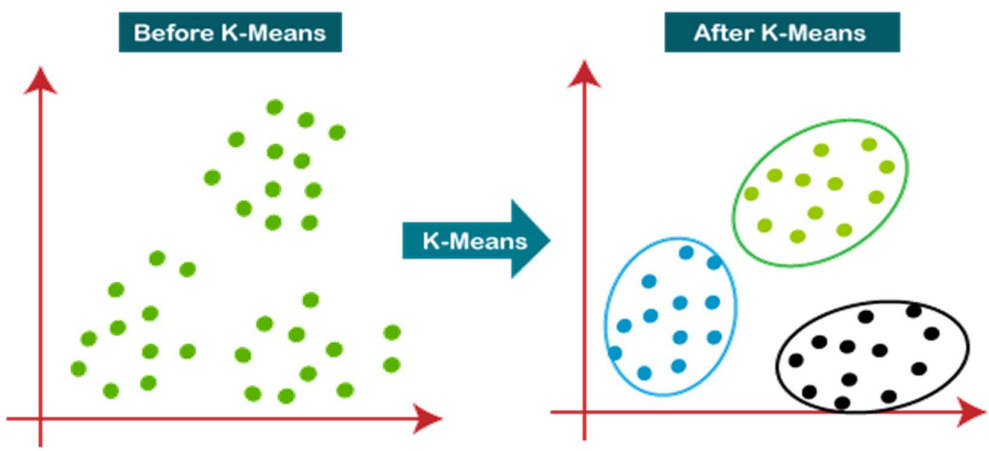


Figure 1.10. K-Means Clustering

- **C-Means (FCM) clustering**

Fuzzy C-means (FCM) clustering assigns data points to clusters with varying degrees of membership, allowing for softer cluster assignments. It initializes centroids, computes membership values for each data point, updates centroids based on weighted averages, and iterates until convergence. FCM's flexibility in handling overlapping clusters and providing probabilistic assignments makes it valuable in scenarios with ambiguous boundaries. However, its performance may depend on the choice of the fuzzifier parameter (m) and require careful tuning.

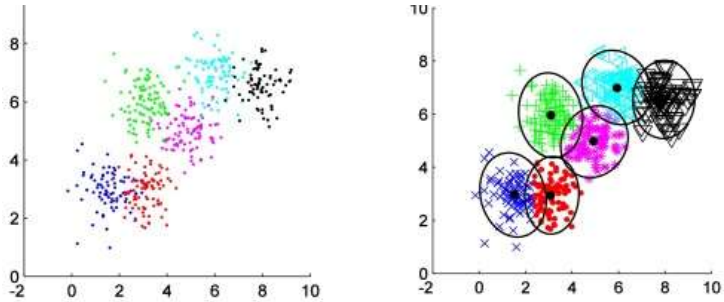


Figure 1.11. C-Means Clustering

- **DBSCAN (Density-Based Spatial Clustering of Applications with Noise)**

DBSCAN is an algorithm for clustering that identifies clusters by grouping nearby data points together based on their density. It defines clusters as areas of high density separated by areas of low density and is capable of discovering clusters of arbitrary shape. DBSCAN is robust to outliers and does not require specifying the number of clusters in advance.

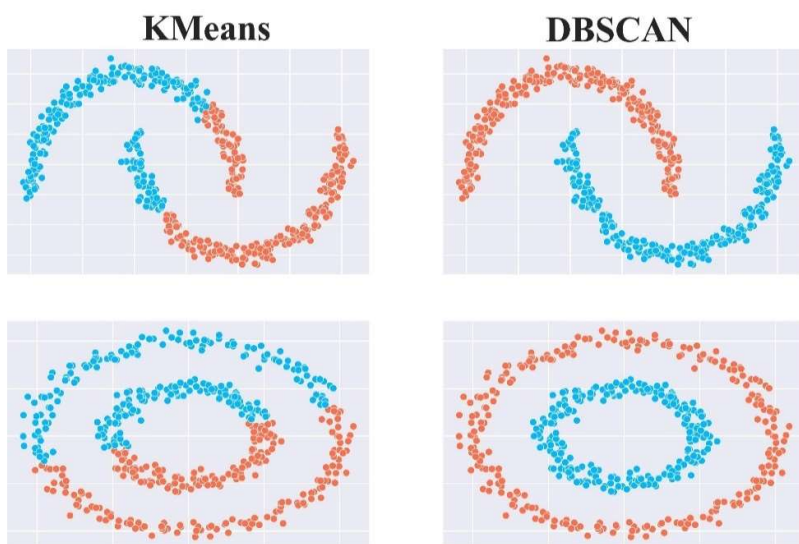


Figure 1.12. Difference Between K-means and DBSCAN clustering

1.4.3 Reinforcement Learning

Lastly, think of reinforcement learning as learning through trial and error in a game. Here, the computer interacts with an environment and receives feedback based on its actions. The feedback comes in the form of rewards or penalties, kind of like points in a game. The computer's goal is to figure out which actions lead to the most rewards and avoid actions that lead to penalties. For example, if you were teaching a computer to play a video game, you'd reward it for making good moves and penalize it for making bad ones. Reinforcement learning is like teaching a computer to navigate a maze by rewarding it for finding the right path and punishing it for taking wrong turns. A type of Reinforcement Learning in Q – Learning.

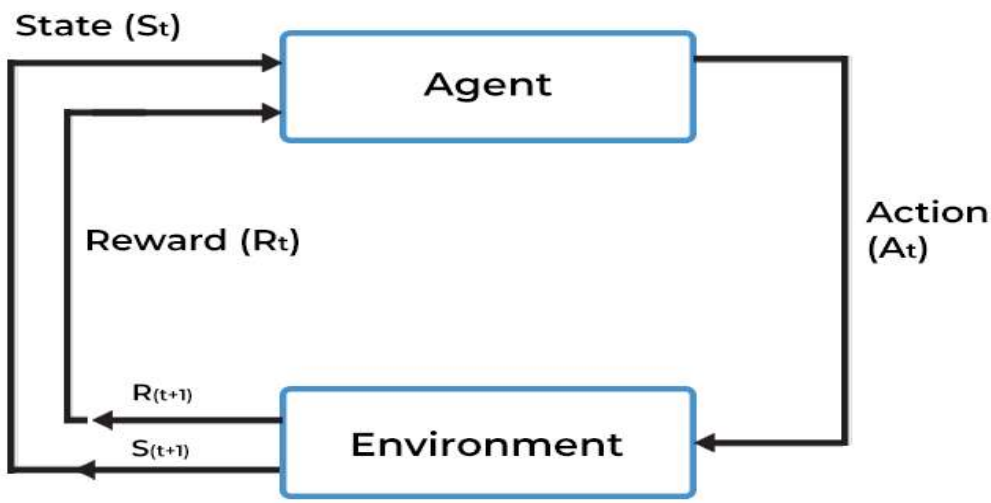


Figure 1.13: Reinforcement Learning

Now, let's delve deeper into each approach:

- **Supervised Learning**

Supervised learning is all about learning from examples with clear answers. It's like being taught by a teacher who shows you how to do things step by step. In supervised learning, the computer learns from labelled examples, where each example consists of inputs and their corresponding correct outputs. By analysing these examples, the computer builds a mathematical model that allows it to make

predictions or decisions when given new inputs. Classification and regression are common types of supervised learning tasks. For example, you could use supervised learning to predict whether an email is spam or not based on its content.

- **Unsupervised Learning**

Unsupervised learning is about discovering patterns and structures in data without any guidance. It's like exploring a new place without a map—you have to find your own way around. In unsupervised learning, the computer is given a bunch of data without any labels or answers. Its job is to find similarities or common features in the data and group them together. Clustering and dimensionality reduction are tough tasks in the field of unsupervised learning. For instance, you could use unsupervised learning to group customers based on their purchasing behaviour to understand their preferences better.

- **Reinforcement Learning**

Reinforcement learning is like learning through experience and feedback. It's like playing a game where you get points for making good moves and lose points for making bad ones. In reinforcement learning, the computer interacts with an environment and learns to maximize cumulative rewards over time. It tries different actions and learns from the feedback it receives. Reinforcement learning is often used in scenarios where there is no pre-existing dataset or clear instructions, such as teaching a computer to play chess or drive a car.

Each of these approaches has its strengths and weaknesses, and the choice of approach depends on the problem at hand. Supervised learning is effective when you have labelled data and want precise predictions or classifications. Unsupervised learning is useful when you want to discover hidden patterns or structures in data without explicit guidance. Reinforcement learning is suitable for dynamic environments where the computer needs to learn from experience and adapt its behaviour over time.

Moreover, these approaches are not always used in isolation. Hybrid approaches, such as semi-supervised learning, combine elements of supervised and unsupervised techniques to leverage the

benefits of both. Semi-supervised learning is like having some answers but not all, so you use them together with unsupervised learning to learn more efficiently.

Machine learning offers a variety of approaches, each tailored to different learning paradigms and problem domains. By understanding these approaches, we can better harness the power of machine learning to solve complex problems and make intelligent decisions in various fields, from healthcare and finance to robotics and autonomous systems.

1.5 Deep Learning

Deep Learning have been a labour of love for researchers over many years, striving to capture the remarkable abilities of the human brain in computational form. Initially, they were like young children, struggling to make sense of the vast complexity of real-world data and learning from it. But with time, dedication, and countless trials, they evolved into something truly ground breaking: deep learning. This transformation marked a turning point in the world of machine learning, opening doors to possibilities we could only dream of before.

1.5.1 Deep Learning Revolution

Deep learning emerged as a breakthrough in machine learning, leveraging ANNs with multiple layers to unlock unprecedented performance gains. This paradigm shift, enabled by advancements in computational power and algorithmic innovations, propelled ANNs into the realm of deep neural networks (DNNs). DNNs boast hierarchical architectures capable of automatically learning intricate patterns and representations from raw data, thereby surmounting the limitations that hindered traditional ANNs.

The architecture of deep neural networks is characterized by its depth, comprising multiple layers of interconnected neurons that progressively extract hierarchical features from input data. These layers include the input layer, which receives raw data, hidden layers responsible for feature extraction and representation learning, and the output layer, which produces final predictions. Each neuron in the network performs computations on the input data using weighted connections and activation functions, collectively enabling complex information processing and decision-making.

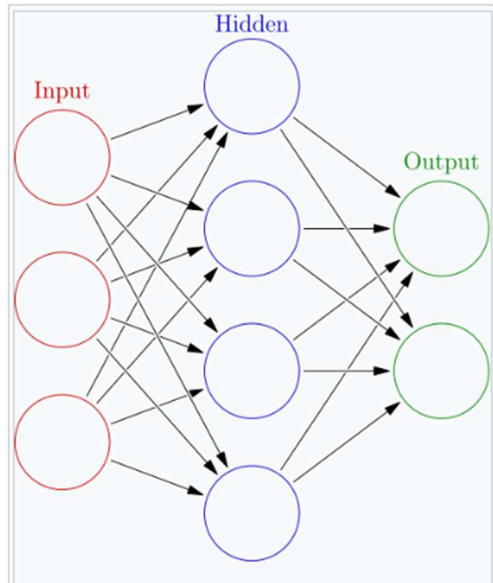


Figure 1.14. An artificial neural network is an interconnected group of nodes, akin to the vast network of neurons in a brain. Here, each circular node represents an artificial neuron and an arrow represents a connection from the output of one artificial neuron to the input of another.

An Artificial Neural Network (ANN) is a model composed of interconnected units or nodes known as "artificial neurons," which are loosely inspired by the neurons found in biological brains. Each connection between neurons, similar to synapses in the brain, can transmit information, or a "signal," from one artificial neuron to another. Upon receiving a signal, an artificial neuron processes it and may then signal other connected neurons. In typical ANN setups, the signal transmitted between artificial neurons is represented by a real number, and each neuron's output is determined by a non-linear function applied to the sum of its inputs. These connections between neurons are referred to as "edges," and both neurons and edges usually possess weights that adjust as the network learns. These weights regulate the strength of the signal transmitted through a connection, potentially affecting whether the signal is transmitted based on a neuron's threshold. Artificial neurons are typically organized into layers, each of which may perform distinct transformations on their inputs. Signals propagate through the network from the initial layer (the input layer) to the final layer (the output layer), possibly traversing through the layers multiple times.

1.5.2 Training Deep Neural Networks

Training deep neural networks is a multi-stage process that hinges on the principles of forward propagation and backpropagation. During forward propagation, input data propagates through the network, undergoing successive transformations through the layers to generate predictions. Backpropagation, the cornerstone of deep learning, facilitates learning by iteratively adjusting the weights of the network based on the discrepancy between predicted and actual outputs. This optimization process fine-tunes the network parameters, gradually enhancing its performance and predictive accuracy.

1.5.3 Applications of Deep Learning

The aim of the ANN approach was to mimic the problem-solving capabilities of the human brain. However, focus gradually shifted towards task-specific performance, resulting in departures from biological principles. Artificial neural networks have been used on a variety of tasks, including computer-vision, speech-recognition, machine-translation, playing board and video games and medical diagnosis. The transformative impact of deep learning reverberates across diverse domains, ranging from computer vision and natural language processing to healthcare and finance. In computer vision, Convolutional Neural Networks (CNNs) have revolutionized tasks such as image classification, object detection, and image segmentation, achieving human-level or superhuman performance in many benchmarks. In natural language processing, Recurrent Neural Networks (RNNs) and their variants, such as Long Short-Term Memory (LSTM) networks, excel in tasks like machine translation, sentiment analysis, and speech recognition, enabling breakthroughs in human-computer interaction and language understanding.

1.6 Other Types---- Sparse Dictionary Learning

Sparse dictionary learning [6] , also known as sparse coding or SDL, is a technique used in representation learning to find a concise representation of input data. It aims to express data as a linear combination of basic elements, known as atoms, which are part of a dictionary. These atoms need not be orthogonal and can form an over-complete spanning set. This property allows for higher-dimensional signals to be represented in a space where the dimensionality of the signals observed may

be lower. This setup leads to seemingly redundant atoms, enabling multiple representations of the same signal while enhancing sparsity and flexibility in representation.

One significant application of sparse dictionary learning lies in compressed sensing or signal recovery. Compressed sensing allows for the reconstruction of high-dimensional signals from a small number of linear measurements, given that the signal is sparse or nearly sparse. To achieve this, it's crucial to obtain a sparse representation of the signal, such as through the wavelet transform or directional gradient of a rasterized matrix. Once the signal is transformed into a sparse space, various recovery algorithms like basis pursuit, CoSaMP, or fast non-iterative algorithms can be employed to reconstruct the original signal.

A fundamental principle of dictionary learning is that the dictionary should be learned from the input data itself. Sparse dictionary learning methods emerged because traditional signal processing often aims to represent input data using the fewest components possible. Previously, predefined dictionaries like Fourier or wavelet transforms were commonly used. However, in some cases, learning a dictionary tailored to fit the input data can significantly enhance sparsity. This has wide-ranging applications in data decomposition, compression, and analysis, and has been applied in image denoising and classification, as well as video and audio processing.

The concept of sparsity and overcomplete dictionaries finds extensive use in image compression, fusion, and inpainting. By representing images with sparse dictionaries, redundant information can be minimized, leading to more efficient compression algorithms. Moreover, sparse dictionaries enable the fusion of multiple images while preserving essential features and details. Inpainting, which involves filling in missing parts of an image, benefits from the ability of sparse dictionaries to capture the underlying structure and texture of the image, resulting in more accurate reconstructions.

We have a dataset $X=[x_1,...,x_K]$, where each $x_i \in R^d$, and we seek to find a dictionary $D \in R^{d \times n}$: $D=[d_1,...,d_n]$ and a representation $R=[r_1,...,r_K]$, where $r_i \in R_n$, such that both the Frobenius norm $\|X-DR\|_F^2$ is minimized, and the representations r_i are sparse. This problem is formulated as the optimization problem:

$$argmin_{D\in C, r_i \in R^n} \sum_{i=1}^{K} \| x_i - Dr_i \|_2^2 + \lambda \| r_i \|_0 \quad (1.1)$$

$$where\ C \equiv \{ D \in R^{d\times n} : \| d_i \|_2 \leq 1\ \forall_i = 1, \ldots, n \}, \lambda > 0$$

Here, C constrains D such that the Euclidean norm of each atom d_i is less than or equal to 1, and λ>0 controls the trade-off between sparsity and error minimization.

However, this problem is non-convex due to the $\ell 0$-"norm", making it NP-hard to solve. In some cases, the $\ell 1$-norm ensures sparsity, transforming the problem into a convex optimization problem when either D or R is fixed, but it remains non-convex when both are optimized jointly.

The dictionary D can be "undercomplete" if $n<d$ or "overcomplete" if $n>d$, with the latter being typical for sparse dictionary learning. Undercomplete dictionaries represent situations where the input data lies in a lower-dimensional space, akin to dimensionality reduction techniques like principal component analysis. Overcomplete dictionaries allow for more flexible representations, as they do not require atoms to be orthogonal.

Algorithms for solving this problem typically alternate between updating D and R iteratively. One such method is the Method of Optimal Directions (MOD), which minimizes the Frobenius norm subject to a constraint on the sparsity of the representations. MOD alternates between obtaining sparse coding using methods like matching pursuit and updating the dictionary using the Moore-Penrose pseudoinverse. However, computing the pseudoinverse in high-dimensional cases can be computationally expensive.

Sparse dictionary learning has applications in signal processing, image processing, and data compression, where efficient representation of data is crucial. Despite its computational challenges, it remains a powerful tool for extracting essential features from high-dimensional datasets while minimizing redundancy.

1.7 Artificial Intelligence in Various Fields

Artificial Intelligence (AI) is at the forefront of the digital revolution, fundamentally transforming how computers process information and make decisions. At its core lies a symbiotic relationship with data—a transformative force propelling industries forward, reshaping societies, and

pushing the boundaries of what's possible. In this exploration of the scope of machine learning, we delve into the intricate dance between algorithms and data, illuminating the profound significance of data within the expansive landscape of artificial intelligence.

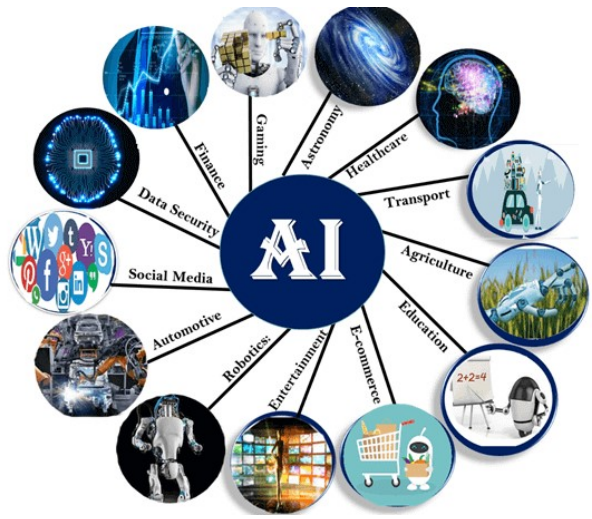


Figure 1.15. Scope of the Work with AI

At the heart of machine learning lies data—the lifeblood fuelling algorithms and shaping their behaviour. Data comes in myriad forms—structured and unstructured, text, images, audio, and more—each holding invaluable insights waiting to be unlocked. The abundance of data generated daily, coupled with advances in storage and computing infrastructure, has paved the way for unprecedented opportunities in leveraging machine learning to extract actionable intelligence, drive informed decision-making, and unlock transformative capabilities across industries.

1.7.1 Agriculture

The scope of work in agriculture involves harnessing machine learning (ML) and data-driven approaches to address key challenges and opportunities in farming. The objectives include enhancing crop yield and quality through predictive models based on factors like soil quality, weather patterns, and crop genetics, as well as managing pests and diseases with early detection and timely interventions. Precision agriculture techniques are employed to optimize resource utilization, such as water, fertilizers, and pesticides, while climate-smart farming practices are developed to adapt to changing

environmental conditions. Methodologies encompass data collection from diverse sources, model development using ML algorithms, validation, and calibration to local conditions, and deployment of decision support tools for farmers.

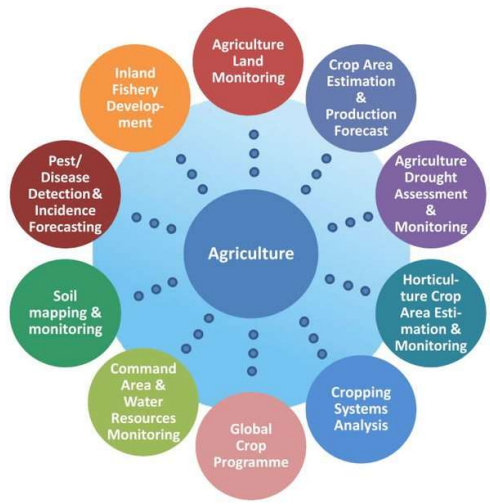


Figure 1.16. Scope of the Work in Agriculture

Deliverables include trained ML models, user-friendly interfaces or mobile apps, comprehensive documentation, and capacity building for stakeholders. The timeline spans data collection and preprocessing, model development and training, validation and calibration, deployment and integration, with ongoing monitoring and evaluation. Resources required include data sources like satellite imagery and weather data, expertise from data scientists, agronomists, and software developers, as well as computing infrastructure and mobile devices for field implementation. Ultimately, the aim is to empower farmers with actionable insights, optimize resource allocation, and enhance productivity while ensuring sustainability and resilience in agriculture.

1.7.2 Predictive Analytics

The scope of work in predictive analysis encompasses several key components aimed at leveraging data to forecast future trends and outcomes. From anticipating customer behaviour to predicting stock market fluctuations and identifying equipment maintenance needs, predictive analytics empowers organizations to gain a competitive edge by making data-driven decisions and mitigating risks. Initially, the objectives involve defining the problem statement and desired outcomes, identifying relevant data sources, and selecting appropriate predictive modelling techniques. Data

preprocessing is crucial, involving cleaning, normalization, and feature engineering to ensure data quality and relevance.

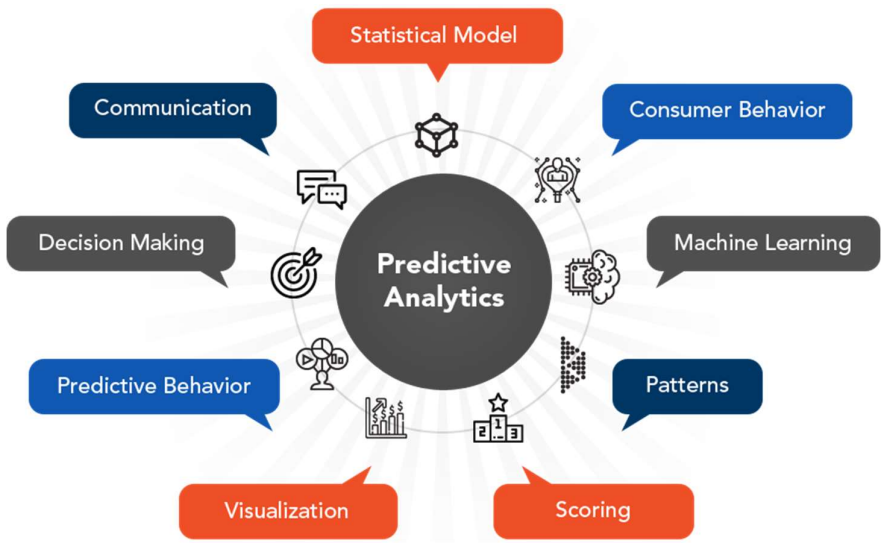


Figure 1.17. Scope of the Work in Predictive Analytics

The next phase entails model development, where various algorithms such as regression, decision trees, or neural networks are applied to train predictive models using historical data. Model evaluation is then conducted to assess performance and refine model parameters through techniques like cross-validation or holdout validation. Once the predictive model is validated, it is deployed into production systems or integrated into decision-making processes, often through user-friendly interfaces or automated systems. Continuous monitoring and refinement are essential to ensure the predictive model remains accurate and relevant over time. Throughout the process, documentation of methodologies, findings, and model performance is maintained to facilitate transparency and reproducibility. The timeline typically includes phases for data collection and preprocessing, model development and training, model evaluation and refinement, deployment, and ongoing monitoring and maintenance. Resources required may include data scientists, domain experts, computing infrastructure, relevant datasets, and software tools for model development and deployment. Overall, the scope of work in predictive analysis aims to harness the power of data to make informed decisions, anticipate future trends, and drive value across various domains and industries.

1.7.3 Natural Language Processing (NLP)

Natural language processing (NLP) enables computers to understand, interpret, and generate human language, bridging the gap between machines and humans. NLP powers a myriad of applications, including chatbots for customer service, language translation, sentiment analysis for social media monitoring, and speech recognition for virtual assistants. By harnessing the power of NLP, organizations can enhance communication, streamline processes, and deliver more personalized experiences to users.

1.7.4 Computer Vision

Computer vision is another transformative application of machine learning, enabling computers to interpret and understand visual information from images and videos. From facial recognition and image classification to object detection and scene understanding, computer vision algorithms have diverse applications across industries, including surveillance, autonomous vehicles, medical imaging, and augmented reality. By imbuing machines with the ability to "see" and interpret their surroundings, computer vision opens up a world of possibilities for automation, safety, and innovation.

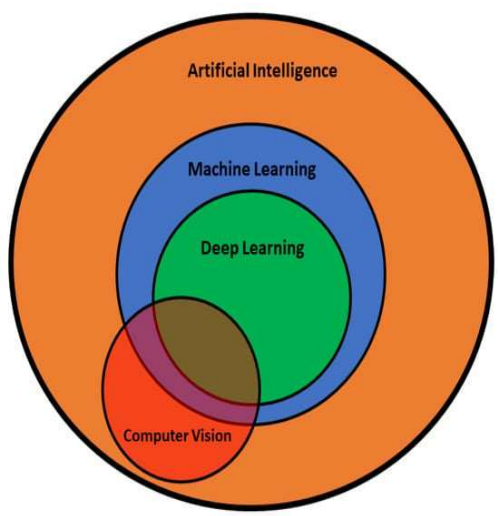


Figure 1.18. Computer Vision

1.7.5 Recommendation Systems

Machine learning-driven recommendation systems have revolutionized how businesses deliver personalized content and product recommendations to users. From streaming platforms like Netflix and music services like Spotify to e-commerce giants like Amazon, recommendation systems leverage user data and behavioural patterns to suggest relevant content, products, and services, enhancing user engagement, satisfaction, and retention.

1.7.6 Fraud Detection

In detecting and preventing fraudulent activities, offering a wide scope of applications across various sectors. From financial institutions to e-commerce platforms and government agencies, the implementation of machine learning-powered fraud detection systems is paramount. These systems analyse vast volumes of transactional data in real-time, flagging anomalous patterns and suspicious behaviours indicative of fraud. In finance, machine learning is utilized for credit card fraud detection, identity theft prevention, and anti-money laundering efforts, safeguarding financial institutions, businesses, and consumers against financial losses and reputational damage. Similarly, in cybersecurity, machine learning is deployed to detect and mitigate cyber threats, including malware, phishing attacks, and data breaches, protecting sensitive information and infrastructure. The scope of work extends to diverse industries and sectors where fraud detection and cybersecurity are critical concerns, underscoring the pervasive impact and importance of machine learning in safeguarding digital ecosystems and financial integrity.

1.7.7 Healthcare

In healthcare, machine learning holds immense promise for improving patient outcomes, accelerating medical research, and optimizing healthcare delivery. From medical image analysis and disease diagnosis to drug discovery and personalized treatment planning, machine learning algorithms leverage vast repositories of patient data to identify patterns, predict disease progression, and tailor interventions to individual patient needs. By harnessing the power of machine learning, healthcare organizations can enhance diagnostic accuracy, optimize resource allocation, and ultimately save lives.

1.7.8 Autonomous Vehicles

Self-driving cars represent the pinnacle of machine learning-powered automation, combining advanced sensors, data fusion techniques, and sophisticated algorithms to navigate complex environments and make split-second decisions in real-time. By integrating machine learning models for perception, decision-making, and control, autonomous vehicles promise to revolutionize transportation, offering safer, more efficient, and more accessible mobility solutions while reshaping urban landscapes and redefining the future of mobility.

1.7.9 Finance

In the realm of finance, machine learning algorithms are transforming how financial institutions manage risk, detect market trends, and optimize investment strategies. From algorithmic trading and portfolio optimization to credit scoring and risk assessment, machine learning empowers financial institutions to extract actionable insights from vast volumes of market data, identify profitable opportunities, and mitigate risks in an increasingly complex and dynamic financial landscape.

1.7.10 Cybersecurity

The proliferation of cyber threats poses a significant challenge to organizations across sectors, underscoring the critical importance of robust cybersecurity measures. Machine learning offers a powerful arsenal of tools and techniques for detecting, analysing, and mitigating cyber threats in real-time. From anomaly detection and behavioural analytics to malware classification and threat intelligence, machine learning-powered cybersecurity solutions help organizations proactively defend against cyber attacks, safeguard sensitive data, and maintain the integrity and availability of digital assets.

1.7.11 Robotics

In the field of robotics, the scope of work utilizing machine learning (ML), artificial intelligence (AI), and deep learning (DL) is expansive, offering transformative opportunities across various applications and industries. The integration of ML, AI, and DL techniques enhances robots'

capabilities to perceive, reason, and act autonomously in dynamic and unstructured environments. Key areas of focus include:

a) Perception and Sensing: ML and DL algorithms enable robots to interpret sensor data from cameras, LIDAR, and other sensors to perceive their surroundings accurately. This includes object recognition, scene understanding, and depth estimation, allowing robots to navigate and interact with their environment effectively.

b) Motion Planning and Control: AI techniques facilitate motion planning and control algorithms, enabling robots to plan optimal paths and trajectories to navigate complex environments safely. Reinforcement learning (RL) algorithms can train robots to learn from experience and adapt their motion control strategies based on real-time feedback.

c) Manipulation and Grasping: ML algorithms enable robots to learn dexterous manipulation skills, including object grasping, picking, and placing. DL techniques, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), can be employed to recognize objects and predict optimal grasping strategies in diverse scenarios.

d) Human-Robot Interaction: AI and ML algorithms enable robots to understand and respond to human gestures, speech, and commands, facilitating natural and intuitive human-robot interaction. This includes the development of chatbots, virtual assistants, and collaborative robots (cobots) designed to work alongside humans in shared workspaces.

e) Autonomous Navigation and Localization: DL algorithms can be utilized for autonomous navigation and localization, allowing robots to localize themselves within a given environment and navigate to predefined locations autonomously. This includes SLAM (Simultaneous Localization and Mapping) techniques and reinforcement learning for learning navigation policies.

f) Task Automation and Optimization: ML and AI techniques enable robots to automate repetitive tasks in industrial settings, such as assembly, packaging, and quality control. DL algorithms

can optimize task performance by learning from large-scale datasets and identifying patterns to improve efficiency and productivity.

g) Healthcare and Assistive Robotics: ML and DL technologies are employed in healthcare and assistive robotics to develop robotic devices that assist individuals with disabilities or perform tasks in healthcare settings. This includes robotic prosthetics, exoskeletons, and robotic companions designed to provide assistance and support to patients and caregivers.

1.8 Societal Impact

As machine learning (ML) becomes more widespread, we need to think about its impact on society. One big concern is ethics. We worry about things like bias in algorithms, which can unfairly favour certain groups of people. We also worry about our privacy—how much of our personal information is being collected and used by ML systems. And we want these systems to be transparent, so we can understand how they make decisions. ML is also changing the job market. Some jobs might disappear because machines can do them better, but new jobs are popping up in fields like data science and AI ethics. We need to make sure people are prepared for these changes by giving them the right skills and training. ML is everywhere now, so it's important for everyone to understand it. We need to teach people about ML so they can understand how it's changing the world and participate in conversations about its impact.

1.9 Future Trends

In the future, we'll see some exciting developments in ML. One trend is explainable AI, which means making AI systems easier to understand. This is important so people can trust AI and know why it's making certain decisions. Another trend is federated learning, which is a way of training AI models without sharing all our data in one place. This helps protect our privacy while still improving AI systems. Lastly, there's quantum machine learning, which combines ML with quantum computing. Quantum computers are super powerful, and they could help us solve really hard problems much faster than we can now. These trends show that ML is always evolving, and it's important to keep up with the latest developments to understand how they'll shape our future.

1.10 Challenges and Opportunities

While the potential of machine learning to drive innovation and transformation is immense, it also presents a host of challenges and ethical considerations. Let's explore these challenges and how we can tackle them in simple terms.

1. **Getting Good Information**

Imagine you're teaching a robot how to recognize different fruits. You show it pictures of apples, oranges, and bananas. But what if some of the pictures are blurry or have weird colors? The robot might get confused and mix up apples with oranges. This is what happens when computers learn from messy or incomplete information, called data. We need to make sure the data we give them is clear and correct, like showing clear pictures of fruits. This process is like cleaning up a messy room before inviting guests over – we need to tidy up the data so computers can learn effectively.

2. **Understanding How Computers Think**

Have you ever engaged in a game of guessing with a friend? You try to guess what they're thinking, but it's like a mystery – you don't know how they came up with their answer. Computers can be like that too. They can give us answers, but sometimes we don't know how they got there. This is because some computer models are very complicated, like big puzzles. We need to make these models simpler so we can understand how they think. It's like asking your friend to explain their guess so you can follow their logic.

3. **Being Fair to Everyone**

Imagine you're playing a game with your friends, but the rules are different for each person. That wouldn't be fair, right? Well, sometimes computers can be unfair too. This happens when they learn from data that only represents one group of people, like always picking the same team for a game. We need to make sure computers treat everyone equally, no matter who they are. It's like making sure everyone gets a fair turn on the playground.

4. **Dealing with Lots of Information**

Think about trying to read a thousand books in one day – it's impossible! Similarly, teaching computers with a lot of data can be overwhelming. Some methods work well with small amounts of data, but they struggle when there's too much. We need to find ways to teach computers efficiently, even when there's a mountain of information to learn from. It's like organizing your toys into boxes so you can find them easily when you need them.

5. **Keeping Secrets Safe**

Imagine you have a special secret, like the recipe for your favourite cookies. You want to keep it safe from others who might try to take it. Computers have secrets too, like personal information or important data. We need to make sure this information stays safe and doesn't fall into the wrong hands. It's like putting a lock on your diary to keep your secrets secure.

But just like how we learn from our mistakes, researchers and engineers are working hard to tackle these challenges and make sure computers become better learners in the future. Here I am trying to work with one of the machine learning algorithm that is Clustering.

1.11 Clustering in Brief

Clustering [7] is a way to group things together based on similarities. Imagine you have a bunch of fruits, and you want to organize them. You might put all the apples together, all the bananas together, and so on. That's what clustering does, but with data. Let's dive deeper into what clustering is, how it works, and why it's useful.

1.11.1. What is Clustering?

Clustering is a type of machine learning technique where we try to find groups in data. These groups, or "clusters," contain data points that are similar to each other in some way.

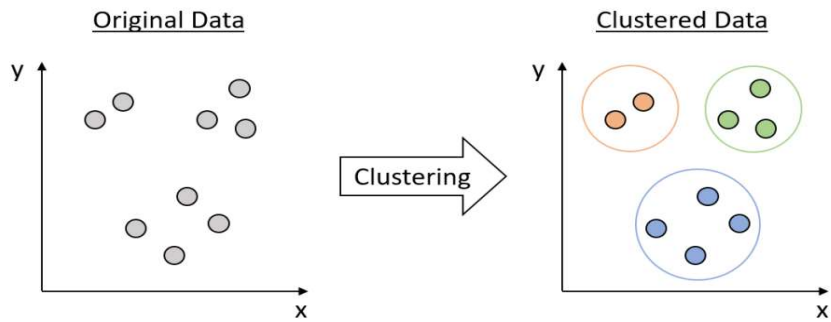


Figure 1.19: Clustering

1.11.2. How Does Clustering Work?

Clustering algorithms work by finding patterns or similarities [8] in data and grouping similar data points together into clusters. Here's a more detailed look at the process:

a) Choosing a Clustering Algorithm

There are various clustering algorithms available, each with its own approach to finding clusters. Some popular algorithms include K-Means, C-Means, Hierarchical Clustering, and DBSCAN. The choice of algorithm depends on factors like the type of data, the desired number of clusters, and the computational resources available.

b) Selecting Features

Before applying a clustering algorithm, it's essential to decide which features or attributes of the data will be used for clustering. These features could be numerical values (such as age or income) or categorical variables (such as product categories or customer segments).

c) Calculating Similarity

Once the features are selected, clustering algorithms measure the similarity or distance between data points. The similarity metric used depends on the nature of the data. For example, in Euclidean

distance, similarity is measured based on the straight-line distance between data points in a multi-dimensional space.

d) Grouping Data Points

After calculating similarities, the clustering algorithm starts grouping data points into clusters. Points that are closer to each other (i.e., have higher similarity) are grouped together in the same cluster. The goal is to maximize the similarity within clusters while minimizing the similarity between clusters.

e) Iterative Process

Clustering is often an iterative process where the algorithm refines the clusters in multiple iterations to improve their quality. The process continues until certain convergence criteria are met, such as the clusters no longer changing significantly between iterations.

f) Evaluating Cluster Quality

Once the clusters are formed, it's essential to evaluate their quality. Common metrics for evaluating cluster quality include silhouette score, Davies-Bouldin index, and within-cluster sum of squares (WCSS). These metrics help assess how well-defined and separated the clusters are.

1.11.3. Types of Clustering Algorithms

There are different algorithms for clustering, but they all aim to achieve the same goal of grouping similar data points together. Some popular clustering algorithms include K-Means, C-Means, Hierarchical Clustering, and DBSCAN. Each algorithm has its strengths and weaknesses, and the choice of which one to use depends on the nature of the data and the specific problem you're trying to solve.

1.11.4. Applications of Clustering

Clustering has a wide range of applications across various fields:

a) Customer Segmentation

Customer segmentation is vital for businesses to understand their diverse customer base and tailor their marketing strategies accordingly. Clustering algorithms help identify groups of customers with similar purchasing behaviours, demographics, or preferences. By segmenting customers, companies can personalize their marketing campaigns, offer targeted promotions, and enhance customer satisfaction. For instance, a retail store might use clustering to identify high-spending customers and design loyalty programs to retain them, while also targeting different segments with specific product recommendations or discounts.

b) Image Segmentation

In image processing, clustering plays a crucial role in segmenting images into meaningful regions or objects. This process involves grouping pixels with similar attributes, such as colour, intensity, or texture, to delineate different objects within an image. Image segmentation is fundamental in various applications, including medical imaging [10] (identifying tumours or organs) [9], satellite image analysis (land cover classification), and computer vision (object recognition and tracking). By segmenting images, algorithms can extract relevant information and facilitate tasks like image understanding, compression, and enhancement.

c) Anomaly Detection

Anomaly detection involves identifying unusual patterns or outliers in data that deviate from normal behaviour. Clustering algorithms can be employed for anomaly detection by grouping data points into clusters representing typical behaviour and flagging instances that fall outside these clusters as anomalies. In cybersecurity, clustering techniques are used to detect suspicious activities in network traffic, such as unauthorized access attempts, malware infections, or unusual data transfers. By detecting anomalies early, organizations can mitigate security threats, prevent potential breaches, and safeguard sensitive data.

d) Recommendation Systems

Recommendation systems leverage clustering to group similar items or users together, enabling personalized recommendations based on user preferences or item similarities. Collaborative filtering, a popular approach in recommendation systems, utilizes clustering to identify clusters of users with similar tastes or behaviour patterns. By analysing past interactions and preferences, recommendation systems can suggest relevant items, products, or content to users, enhancing their browsing experience and increasing engagement. Platforms like e-commerce websites, streaming services, and social media platforms rely on clustering-based recommendation systems to deliver personalized suggestions and drive user satisfaction and retention.

These applications demonstrate the versatility and utility of clustering across diverse domains, from marketing and image processing to cybersecurity and personalized recommendation systems. By harnessing the power of clustering algorithms, organizations can extract valuable insights from data, improve decision-making processes, and deliver tailored solutions to meet the needs of their users or customers.

1.12. Literature Review

In recent years, significant progress has been made in the field of clustering algorithms, offering various methodologies to address different challenges across diverse domains. Bindra et al. [21] conducted a thorough review of clustering algorithms, providing valuable insights into their efficiency, advantages, and drawbacks, thereby aiding in understanding the key characteristics of effective clustering methods. Similarly, Zhao et al. [9] delved into clustering approaches specifically tailored for large datasets in life sciences, shedding light on their underlying assumptions and merits. Their work, organized into three informative sections, outlined the evolution and types of clustering algorithms, offering a comprehensive overview of the field.

Furthermore, Assent et al. [18] explored the impact of high-dimensional spaces on clustering paradigms, uncovering implications crucial for algorithm design and application. Ghosh et al. [11] undertook a detailed analysis of the K-Means and Fuzzy C-Means clustering algorithms, focusing on their efficiency and performance metrics. In parallel, Guerin et al. [12] proposed an innovative multi-view clustering approach integrating convolutional neural network architectures, resulting in significant enhancements in clustering accuracy, particularly in image datasets.

Meanwhile, Selvakumar et al. [10] introduced a pioneering computer-aided method for brain tumour detection and segmentation in MRI images, utilizing clustering algorithms to identify tumour characteristics accurately. Balasubramaniyan et al. [8] presented CLARITY, a novel method for analysing microarray time course experiments, leveraging local shape-based similarity measures for clustering analysis. Yang et al.'s[13] work introduced the k-shape algorithm, revolutionizing the identification of patterns in building energy usage and its subsequent application in forecasting models.

Additionally, Wozniak et al. [14] proposed a detection method combining cluster analysis with convolutional neural networks, showcasing promising results in object recognition tasks. Srivastava et al.'s [16] differential-geometric approach offered valuable tools for hierarchical clustering of imaged objects, constructing probability models, and assessing newly observed shapes, facilitating shape analysis across various applications. Chanchlani et al. [17] explored the fusion of K-means and Fuzzy c-means algorithms with multi-thresholding techniques for brain MRI analysis, offering new perspectives in medical imaging.

Moreover, Zaboli et al. [15] contributed to the field with their innovative skeleton-based method for shape recognition, employing clustering techniques for efficient shape analysis. Finally, Yang et al.'s [13] ClusDet network introduced a ground breaking approach to object clustering and detection in aerial images, significantly improving efficiency and accuracy through a unified framework integrating cluster proposal, scale estimation, and detection networks.

Furthermore, despite the considerable advancements in clustering algorithms across various domains, research focused on specific shape detection using clustering techniques remains relatively limited. This gap in the literature has piqued my interest, prompting me to explore this area further in my thesis. By leveraging clustering methodologies for shape detection, there is a significant opportunity to contribute novel insights and methodologies to the field, addressing existing challenges and expanding the scope of clustering applications.

1.13. Scope of the Work

Historically, while clustering algorithms have been extensively studied and applied across various domains, traditional methods often struggle to accurately identify and characterize clusters with complex or irregular shapes. This limitation has significant implications across multiple fields where precise cluster delineation is paramount, such as urban planning, medical imaging, environmental monitoring, and beyond. Urban Structure Analysis stands out as one domain where improved cluster shape detection holds immense potential. The complex spatial arrangements and distributions of urban elements pose significant challenges for traditional clustering methods. However, by developing advanced algorithms capable of accurately dissecting and categorizing urban fabric, we can empower urban planners and architects to optimize designs and foster sustainable development, thereby addressing pressing urbanization challenges.

Similarly, in the realm of Medical Imaging, the ability to precisely identify and characterize pathological structures is critical for accurate diagnosis and treatment planning. Conventional clustering algorithms often fall short in capturing the nuanced shapes and textures present in medical images, hindering diagnostic accuracy. By innovating in cluster shape detection techniques, we can enhance medical imaging analysis, leading to improved patient outcomes and healthcare decision-making.

Furthermore, applications such as Water Quality Assessment, Environmental Monitoring, and Natural Disaster Response necessitate robust cluster shape detection methodologies to analyse complex spatial patterns and phenomena. By developing algorithms capable of effectively identifying clusters of interest, we can bolster efforts to safeguard public health, conserve natural resources, and enhance disaster preparedness and response.

The potential impact of advancing cluster shape detection extends beyond specific domains, encompassing broader societal benefits such as improved public safety, environmental sustainability, and economic prosperity. By leveraging cutting-edge technologies and interdisciplinary approaches, we can unlock new insights and capabilities in cluster analysis, paving the way for transformative advancements across various fields.

The limited progress and unsatisfactory results in cluster shape detection research have sparked my interest in addressing this challenging problem. The inefficacy of conventional clustering approaches in capturing intricate cluster shapes has underscored the need for innovative solutions. Recognizing this gap, I am drawn to the prospect of advancing the state-of-the-art in cluster shape detection through rigorous research and novel methodologies. By delving into this relatively underexplored area, there lies an opportunity to make meaningful contributions with broad-reaching impacts across diverse domains.

1.13.1 Aim

The aim of this work is to develop a robust framework for cluster shape detection in complex datasets by integrating Convolutional Neural Networks (CNNs) for hierarchical feature extraction, Fuzzy C-Means (FCM) clustering for pattern grouping, and an iterative ellipse fitting algorithm for identifying elliptical clusters.

1.13.2 Objective

We developed an integrated framework for cluster shape detection in complex datasets by combining Convolutional Neural Networks (CNNs) for hierarchical feature extraction, Fuzzy C-Means (FCM) clustering for pattern grouping, and an iterative ellipse fitting algorithm for identifying elliptical clusters. Specifically, the objectives include implementing attention mechanisms to enhance feature representation, applying FCM clustering to partition extracted features into distinct clusters, developing an iterative algorithm for accurate ellipse fitting to clustered data points, evaluating the framework's performance against traditional methods, and validating its efficacy in detecting cluster shapes in both synthetic and real-world datasets.

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Chapter 2

Clustering

2.1 What is Clustering?

Cluster analysis [1], also known as clustering, entails grouping a collection of objects in a manner where items within the same group, referred to as a cluster, exhibit greater similarity to each other than to those in other groups. It serves as a fundamental task in exploratory data analysis and finds extensive utility in diverse fields such as pattern recognition, image analysis, bioinformatics, and machine learning. Clustering encompasses a variety of algorithms and methodologies [2], each differing in their interpretation of what constitutes a cluster and the approach to efficiently identifying them. Notions of clusters may involve tight-knit groups with minimal intra-cluster distances, dense regions within the data space, or adherence to specific statistical distributions, thereby framing clustering as a multi-objective optimization challenge. The selection of an appropriate clustering algorithm and parameter configuration hinges on factors such as the dataset's characteristics, the desired outcome, and the analyst's expertise. Cluster analysis is not a one-size-fits-all solution but rather an iterative process of discovery and refinement, often necessitating adjustments to data preprocessing and model parameters until the desired clustering structure is achieved. Additionally, synonymous terms like automatic classification, numerical taxonomy, and community detection are utilized in related contexts, each emphasizing distinct aspects such as the interpretability of resulting groups or the discriminative power of classification. Originating in anthropology and psychology in the early 20th century, cluster analysis has evolved into a cornerstone of unsupervised learning [3], facilitating the extraction of meaningful patterns and structures from data without explicit guidance, thereby driving advancements in diverse domains through its application in problem-solving and decision-making processes.

2.2 Taxonomy of Clustering Algorithms

There exist many measures and initial conditions which are responsible for numerous categories [6] of clustering algorithms. Hard clustering and soft clustering are two fundamental approaches in the field of clustering analysis, each with distinct characteristics and applications. Also a widely accepted classification frames clustering techniques as: 1) Partitional Clustering, 2) Hierarchical Clustering, 3) Density-Based Clustering [7].

Hard clustering, also known as crisp clustering, involves partitioning data into non-overlapping clusters, where each data point is assigned exclusively to a single cluster. Algorithms such as K-Means [8] and hierarchical clustering are examples of hard clustering techniques. In hard clustering, the assignment of data points to clusters is binary, resulting in clear and distinct boundaries between clusters. This approach is suitable for scenarios where data points inherently belong to distinct groups and there is no ambiguity in their assignments. Hard clustering is often used in applications where data points are expected to have well-defined memberships, such as customer segmentation in marketing or image segmentation in computer vision.

On the other hand, soft clustering, also known as fuzzy clustering, allows for more flexible cluster assignments by assigning membership degrees to data points, indicating the degree of belongingness to each cluster. Soft clustering algorithms, such as Fuzzy C-Means (FCM) and Gaussian Mixture Models (GMM) [9], provide a probabilistic interpretation of cluster assignments, allowing data points to belong to multiple clusters simultaneously with varying degrees of membership. Soft clustering is particularly useful in situations where data points exhibit uncertainty or ambiguity in their cluster affiliations, or when there is overlap between clusters. This approach is commonly employed in tasks such as pattern recognition, where data points may exhibit complex relationships and do not neatly fit into distinct categories.

2.2.1 Partitional Clustering

Partitional clustering is a method where we divide our data into groups without any overlap. Each data point belongs to only one group, and our goal is to minimize the total distance between the points within each group and their group's centre. Imagine we have a bunch of points on a graph, and we want to divide them into clusters, ensuring that each cluster's points are close to each other and far from the points in other clusters.

2.2.2 Hierarchical Clustering

Hierarchical clustering [10] is like building a family tree of our data points. We start with each point as its own cluster and then merge them based on their similarity. We keep doing this until we have one big cluster containing all the points. This creates a tree-like structure called a dendrogram,

which shows how the clusters are related to each other. It's helpful because we don't need to decide in advance how many clusters we want.

2.2.3 Density-Based Clustering

Density-based clustering focuses on finding areas in our data where points are close together, forming dense regions. These regions become our clusters, and points that are not part of any dense region are considered noise. Instead of specifying the number of clusters, we set parameters like the minimum number of points needed to form a cluster and the maximum distance between points in a cluster.

These groupings are based on several factors, and a few algorithms have been created to combine different approaches. In recent times, many new algorithms have been developed to solve problems in various fields. However, no single algorithm can solve all clustering problems. Creating a unified clustering solution is challenging because there are many diverse clustering algorithms available. It's essential to discuss the characteristics that an efficient clustering algorithm should have to solve the problem at hand. Some of these characteristics are listed here:

1. Scalability

Scalability refers to the ability of a clustering algorithm to handle large volumes of data efficiently. As datasets grow in size, it's crucial for clustering algorithms to perform well without consuming excessive memory or taking too long to run. Efficient algorithms should be designed to handle big data sets without sacrificing performance, ensuring that they can scale gracefully to meet the demands of real-world applications. This scalability allows organizations to analyse massive datasets and extract valuable insights without encountering performance bottlenecks or crashing issues.

2. Prior Domain Knowledge

While some clustering algorithms require prior knowledge or assumptions about the data, such as the number of clusters expected, it's often impractical to have this information readily available.

Efficient clustering algorithms should be able to adapt to diverse datasets and perform well even without explicit user input regarding the data's characteristics. By being able to autonomously identify meaningful patterns and structures in the data, these algorithms empower users to explore and analyse data without the need for specialized domain knowledge or manual intervention, enhancing the usability and applicability of clustering techniques across various domains.

3. Discovering Arbitrary Shaped Clusters

Real-world data often exhibits complex and irregular patterns, with clusters taking on diverse shapes and configurations. Traditional clustering algorithms may struggle to identify clusters that deviate from simple geometric shapes, such as spheres or ellipsoids. However, efficient clustering algorithms should be capable of detecting clusters of any shape, including irregular or non-convex shapes like spirals, crescents, or clusters with varying densities. By employing flexible and adaptive clustering techniques, these algorithms can accurately capture the inherent structure of complex datasets, ensuring robust and reliable clustering results across a wide range of scenarios.

4. Similarity or Dissimilarity Measures

The choice of similarity or dissimilarity measures plays a crucial role in clustering algorithms, as it determines how data points are compared and grouped together. These measures quantify the resemblance or dissimilarity between pairs of data points based on various attributes or features. Efficient clustering algorithms should employ appropriate similarity or dissimilarity measures that capture the underlying structure of the data and reflect the desired clustering objectives. By using robust and meaningful similarity measures, clustering algorithms can accurately identify clusters and produce interpretable clustering results that align with the inherent characteristics of the data, facilitating insightful data analysis and knowledge discovery.

TABLE 2.1 : Measures For Finding Similarity

SL. NO.	Popular Similarity Measures For Data Points		
	Measure	**Form**	**Example**
1	Euclidean Distance	$D = (\sum_{i=1}^{d} \parallel x_a - x_b \parallel^{1/2})^2$	K-Means , PAM
2	Minkowski Distance	$D = (\sum_{i=1}^{d} \parallel x_a - x_b \parallel^{n})^{1/n}$	Fuzzy C-Means
3	Cosine Distance	$S_{ij} = cos\ \alpha = \frac{x_i^T x_j}{\parallel x_i \parallel \parallel x_j \parallel}$	K-Means , Many Partitional Algorithms

2.3 Hierarchical Clustering

Hierarchical clustering is like organizing a family reunion, where you start with individual family members and gradually group them into larger family units based on their similarities. Imagine you have a big family with cousins, aunts, uncles, and grandparents, and you want to organize them into smaller groups for different activities.

At the beginning of the reunion, everyone is treated as a separate group. Then, you start looking for pairs of family members who are most alike, such as siblings or cousins who share similar traits or interests. Once you find these pairs, you merge them into bigger groups, creating clusters of related individuals. As the reunion progresses, you continue to identify pairs of clusters that are most similar and merge them together. This process repeats until you've formed one big family group that includes everyone. Along the way, you keep track of the merging process, creating a family tree that shows

how the smaller clusters combine to form larger ones. In hierarchical clustering, the goal is to create a hierarchical structure of nested clusters, similar to branches of a tree. Each branch represents a cluster, and the distance between branches indicates how similar or different the clusters are from each other.

A dendrogram is like a family tree for your data, showing the sequence of merges or splits as the clustering process unfolds. It's like looking at the family reunion from above, seeing how different family members come together to form larger family groups. Overall, hierarchical clustering is a method of organizing data into a hierarchical representation of clusters, similar to how families are organized into smaller and larger groups based on their relationships. It's a way of visualizing the similarities and differences within a dataset and understanding the hierarchical structure of the data.

- Hierarchical clustering has several advantages over other clustering methods

a) Handling of Non-Convex Clusters and Varying Densities

Unlike some clustering methods that assume clusters are spherical or have uniform densities, hierarchical clustering can accommodate clusters of diverse shapes and densities. It is capable of identifying non-convex clusters and clusters of different sizes and densities, providing a more accurate representation of the underlying data structure.

b) Robustness to Missing and Noisy Data

Hierarchical clustering demonstrates robustness in dealing with missing or noisy data, common challenges in real-world datasets. By iteratively merging similar data points and clusters, it can effectively handle data with missing values or outliers, enabling the identification of meaningful patterns even in the presence of incomplete or noisy information.

c) Revealing Hierarchical Structure

Through the construction of a dendrogram—a tree-like diagram that illustrates the merging process—hierarchical clustering unveils the hierarchical structure of the data. This visual representation offers insights into the relationships among the clusters, facilitating a deeper understanding of the hierarchical organization of the dataset.

- Hierarchical clustering has some disadvantage also:

a) Need for Stopping Criterion

One significant drawback of hierarchical clustering is the requirement for a stopping criterion to determine the final number of clusters. Unlike some other clustering methods that automatically determine the optimal number of clusters based on predefined criteria, hierarchical clustering relies on the user to specify when to stop merging clusters. This subjectivity can lead to inconsistent results and may require careful consideration and experimentation to determine an appropriate stopping point.

b) Computational Complexity

Hierarchical clustering can be computationally intensive, especially for large datasets. The algorithm's complexity increases with the number of data points and clusters, resulting in longer processing times and greater memory usage. This can pose challenges for applications with limited computational resources and may necessitate the use of alternative clustering methods for efficiency.

c) Sensitivity to Parameters

The results of hierarchical clustering can be sensitive to various factors, including the initial conditions, linkage criterion, and distance metric used. Different choices in these parameters can lead to different clustering outcomes, affecting the interpretability and reliability of the results. Therefore, hierarchical clustering may require careful parameter tuning and validation to ensure robust and meaningful clustering results.

2.3.1 Types of Hierarchical Clustering

There are two types of hierarchical clustering 1) Agglomerative Clustering 2) Divisive Clustering.

1. Agglomerative Clustering

Initially consider every data point as an individual Cluster and at every step, merge the nearest pairs of the cluster. (It is a bottom-up method). At first, every dataset is considered an individual entity or cluster. At every iteration, the clusters merge with different clusters until one cluster is formed. The algorithm for Agglomerative Hierarchical Clustering is:

i. Calculate the similarity of one cluster with all the other clusters (calculate proximity matrix)
ii. Consider every data point as an individual cluster
iii. Merge the clusters which are highly similar or close to each other.
iv. Recalculate the proximity matrix for each cluster
v. Repeat Steps 3 and 4 until only a single cluster remains.

Let's see the graphical representation of this algorithm using a dendrogram.

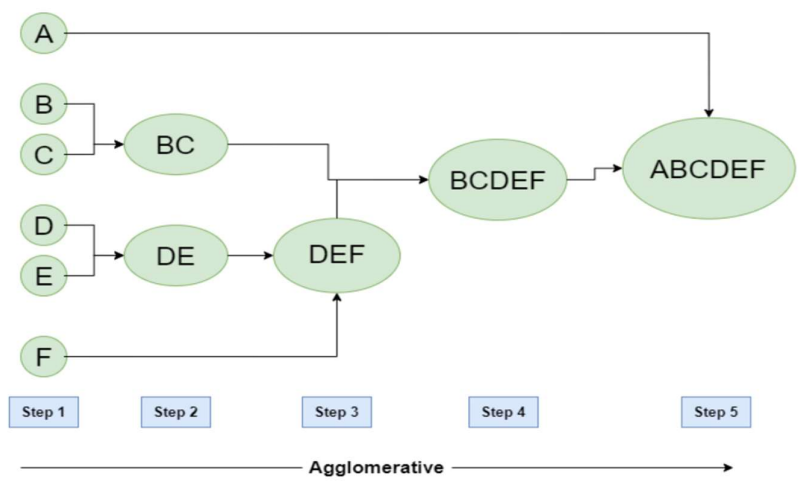


Figure 2.1. Agglomerative Hierarchical Clustering

Step-1: Consider each alphabet as a single cluster and calculate the distance of one cluster from all the other clusters.

Step-2: In the second step comparable clusters are merged together to form a single cluster. Let's say cluster (B) and cluster (C) are very similar to each other therefore we merge them in the second step similarly to cluster (D) and (E) and at last, we get the clusters [(A), (BC), (DE), (F)]

Step-3: We recalculate the proximity according to the algorithm and merge the two nearest clusters([(DE), (F)]) together to form new clusters as [(A), (BC), (DEF)]

Step-4: Repeating the same process; The clusters DEF and BC are comparable and merged together to form a new cluster. We're now left with clusters [(A), (BCDEF)].

Step-5: At last, the two remaining clusters are merged together to form a single cluster [(ABCDEF)].

2. Divisive Clustering

We can say that Divisive Hierarchical clustering is precisely the opposite of Agglomerative Hierarchical clustering. In Divisive Hierarchical clustering, we take into account all of the data points as a single cluster and in every iteration, we separate the data points from the clusters which aren't comparable. In the end, we are left with N clusters.

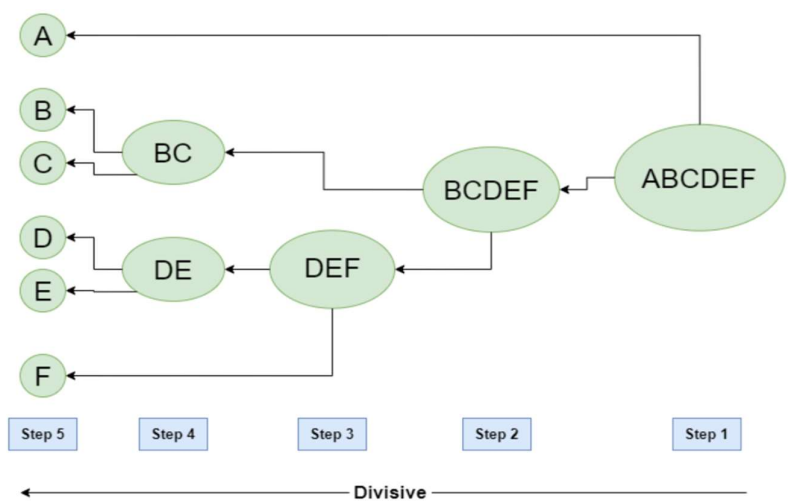


Figure 2.2. Divisive Hierarchical Clustering

2.4 Partitioning Clustering

Clustering methods organize data into groups based on similarities. In partitioning methods like K-Means, C-Means, the analyst specifies the number of clusters (K) desired. The method then divides the dataset into K partitions, with each representing a cluster. Popular partitioning algorithms include K-Means, PAM (K-Medoids), and CLARA. K-Means, for instance, starts by randomly selecting K objects as cluster centers. Each remaining object is assigned to the nearest cluster center. The algorithm iteratively recalculates cluster means based on the assigned objects until convergence, aiming for high intracluster similarity and low intercluster similarity. It's essentially an error minimization process, optimizing the clustering based on squared distances. This iterative process continues until cluster centroids stabilize. This method is efficient for large datasets and well-suited for situations where the number of clusters is known. However, its performance can vary based on the initial selection of cluster centers and the nature of the data. Overall, K-Means offers a straightforward approach to clustering data, widely used across various fields for its simplicity and efficiency.

2.4.1. Advantage of Partitioning Clustering

Partitioning clustering provides a versatile and scalable approach to data analysis, offering advantages such as ease of implementation, flexibility in specifying the number of clusters, and applicability to various data types including numerical, categorical, and mixed data. Algorithms like K-Means iterate through simple steps of centroid initialization, data point assignment, and centroid updating, making them computationally efficient and suitable for large datasets. Moreover, partitioning methods produce clear, non-overlapping clusters, facilitating straightforward interpretation of results. Additionally, iterative refinement enhances clustering accuracy by capturing complex data patterns over multiple iterations. These characteristics make partitioning clustering methods an attractive choice for a wide range of clustering tasks across different domains

2.4.2 Disadvantage of Partitioning Clustering

While partitioning clustering methods like K-Means offer various advantages, they also suffer from several limitations. One major drawback is their sensitivity to the initial selection of centroids,

which can lead to suboptimal clustering results and make the algorithm converge to local minima. Additionally, partitioning algorithms like K-Means require the user to specify the number of clusters beforehand, which can be challenging in real-world scenarios where the optimal number of clusters is unknown. Moreover, these methods assume that clusters are spherical and of similar size, which may not hold true for complex datasets with irregularly shaped or varying density clusters. Furthermore, partitioning algorithms struggle with handling noise and outliers effectively, often leading to distorted cluster boundaries and reduced clustering quality. Overall, while partitioning clustering methods offer simplicity and efficiency, their performance can be significantly impacted by these limitations, necessitating careful consideration and preprocessing steps to mitigate their effects.

2.4.3 K-Means Clustering

K-Means is undeniably one of the most popular partitioning algorithms in the field of data analysis and machine learning. Its origins trace back to several researchers across different periods, including Steinhaus (1965), Ball and Hall (1965), Lloyd (proposed in 1957 and published in 1982), and MacQueen (1967). This algorithm, fundamentally distance-based, divides data into predetermined clusters, with the choice of distance metric often relying on either Euclidean or cosine measures.

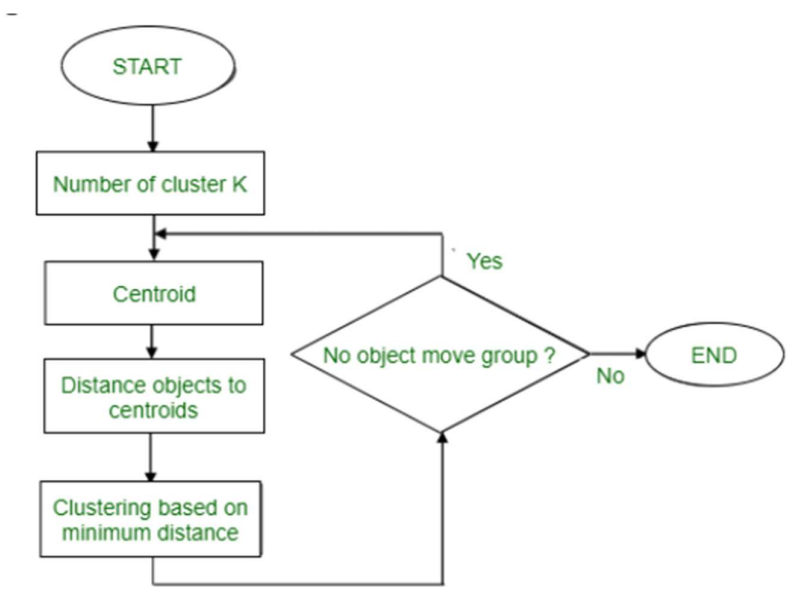


Figure 2.3. Flowchart of K-Means Clustering

The essence of K-Means lies in its iterative process. Initially, a fixed number of cluster centroids (K) are randomly placed in the feature space. Then, each data point is assigned to the closest centroid, forming initial clusters. Subsequently, the centroids are recalculated based on the data points assigned to them. This iterative process continues until convergence, which is typically determined by the squared error reaching a threshold.

The steps of K-Means can be summarized as follows:

I. Initialization: Begin with K initial cluster centroids and the dataset.
II. Assignment: Assign each data point to its nearest centroid, forming clusters.
III. Update Centroids: Recalculate the centroids based on the data points in each cluster.
IV. Iteration: Repeat steps 2 and 3 until convergence is achieved.

Despite its widespread use, K-Means is not without limitations. One notable issue is its sensitivity to noise and outliers in the dataset. Since the algorithm strictly assigns each point to the nearest centroid, outliers or noisy data can distort the resulting clusters. Additionally, K-Means assumes a fixed number of clusters (K) is known beforehand, making it necessary for users to specify this parameter. Moreover, K-Means is not applicable to categorical data due to its reliance on distance measures, which are not meaningful for categorical variables.

Furthermore, K-Means lacks a universal method for determining the optimal number of clusters. As a result, users often need to rely on domain knowledge or trial-and-error to select an appropriate value for K. Additionally, K-Means can produce slightly different results upon each iteration, particularly if initialized with random centroids.

Despite its limitations, K-Means remains a cornerstone in clustering algorithms, owing to its simplicity, efficiency, and scalability. Over the years, numerous variations and enhancements have been developed to address its shortcomings and adapt it to different types of data and applications. As the field of data science & machine learning continues to evolve, K-Means and its variants will likely remain essential tools for clustering and exploratory data analysis.

- **Elbow Method**

The elbow method is a popular technique used to determine the optimal number of clusters (k) in K-means clustering. K-means clustering partitions a dataset into k clusters by iteratively assigning data points to the nearest cluster centroid and updating the centroids based on the mean of the assigned points. However, determining the appropriate value of k is crucial for the effectiveness of the clustering algorithm.

The elbow method aids in identifying the optimal value of k by evaluating the within-cluster sum of squared distances (WCSS) for different values of k. WCSS measures the compactness of the clusters, with lower values indicating tighter clusters. As the number of clusters increases, WCSS tends to decrease since each data point is closer to its cluster centroid. However, adding more clusters may not necessarily lead to a significant improvement in clustering quality, as the decrease in WCSS becomes marginal beyond a certain point.

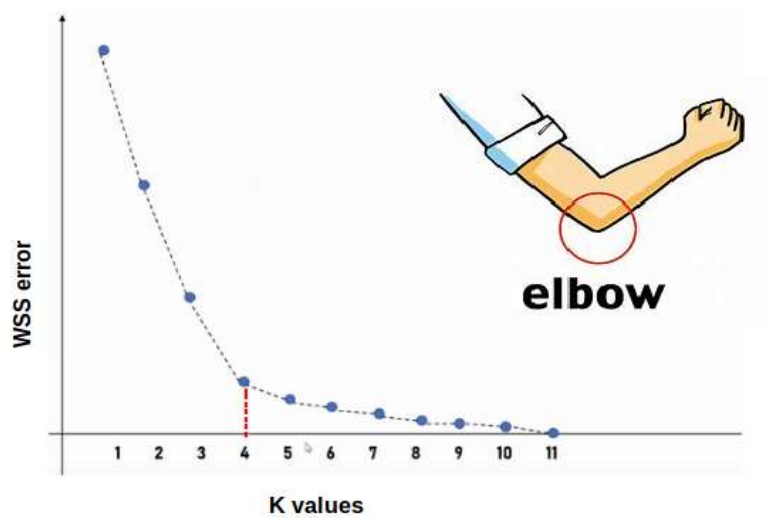


Figure 2.4. Elbow Method for K-Means Clustering

To apply the elbow method, the WCSS is computed for a range of k values, typically starting from 1 to a predefined maximum value. Then, a plot of the number of clusters (k) against the

corresponding WCSS values is generated. The "elbow" point in the plot represents the optimal value of k, where the rate of decrease in WCSS significantly slows down, forming an elbow-like bend in the plot. This bend indicates the point at which adding more clusters does not result in a substantial reduction in WCSS, suggesting that the optimal number of clusters has been reached.

Interpreting the elbow point requires some subjective judgment, as the bend may not always be clearly defined. In some cases, the plot may exhibit a gradual decrease in WCSS without a distinct elbow, making it challenging to determine the optimal value of k. Additionally, the elbow method may not be suitable for all datasets, especially if the clusters are not well-separated or if the data is highly dimensional.

2.4.4 C-Means Clustering

FCM [11], renowned as a soft clustering algorithm, brings about a notable level of flexibility by assigning membership degrees to individual data points. This unique approach allows for a nuanced representation of cluster assignments, thereby accommodating instances where data points exhibit uncertainty regarding their cluster affiliations. Unlike traditional hard clustering methods, FCM iteratively refines both cluster centroids and membership degrees, effectively adapting to the complex structures often present in datasets characterized by overlapping patterns. This adaptability renders FCM particularly well-suited for scenarios where traditional clustering approaches may fall short in capturing the intricacies of the data.

The iterative optimization process inherent in FCM ensures that the resulting clusters accurately reflect the underlying structures within the feature space. By accommodating uncertainty and accounting for varying degrees of association between data points and clusters, FCM contributes to a more faithful and comprehensive representation of the intrinsic patterns present within the dataset.

Now, delving into the technicalities of the Fuzzy C-Means algorithm, let's consider a set of unlabelled patterns denoted by $X=\{x_1, x_2,\ldots,x_N\}$ where each x_i resides in the f-dimensional real vector space R_f .Here, N represents the total number of patterns, and f-denotes the dimensionality of the feature vectors. The core objective of the FCM algorithm revolves around minimizing an objective function, which evaluates the quality of the partitioning that segregates the dataset into C clusters. This

optimization function gauges the within-group sum of squared errors (WGSS) by comparing the distances from each pattern x to the current candidate cluster center W_j with those to other candidate cluster centers. The objective function is designed to achieve an optimal clustering configuration by iteratively adjusting the membership degrees of data points with respect to each cluster. This process facilitates the identification of cluster centers that effectively capture the data's inherent structure while considering the varying degrees of data-point association with the clusters. The objective function is an optimization function that calculates the weighted within-group sum of squared errors (WGSS) as follows:

$$\mathrm{J_m(U,W)} = \sum_{\mathrm{j=1}}^{\mathrm{C}} \sum_{\mathrm{i=1}}^{\mathrm{N}} (\mu_{\mathrm{ij}})^{\mathrm{m}}\, \mathrm{d}_{\mathrm{ij}}^2 \qquad \ldots\ldots\ldots(2.1)$$

In the Fuzzy C-Means (FCM) algorithm, where N represents the number of patterns in dataset X, C signifies the number of clusters, Udenotes the membership function matrix. Each element μ_{ij} of U represents the membership value of the i-th pattern belonging to the j-th cluster. The term dij corresponds to the distance between pattern x_{i} and the j-th cluster center wtj, computed as $||x_i - w_{tj}||$, where $wt\mathrm{j}$ denotes the cluster center of the j-th cluster for the t-th iteration. W represents the cluster center vector, while m serves as the exponent on μ_{ij}, regulating the degree of fuzziness or cluster overlap. The primary objective of the FCM algorithm revolves around minimizing the objective function J_m, subject to constraints on U. These constraints ensure that μ_{ij} values lie within the interval [0,1], and the sum of membership values for each pattern x_{i} across all clusters equals 1. This optimization process seeks to find an optimal clustering configuration by iteratively adjusting membership degrees to capture the inherent structure of the dataset while considering the trade-off between cluster compactness and overlap.

$$\mu_{\mathrm{ij}} \in [0,1], \mathrm{i} = 1,2,\ldots\ldots,\mathrm{N} \text{ and } \mathrm{j} = 1,2,\ldots\ldots,\mathrm{C} \qquad (2.2)$$

$$\sum_{j=1}^{\mathrm{C}} \mu_{\mathrm{ij}} = 1, \mathrm{j} = 1,2,\ldots\ldots,\mathrm{C} \qquad (2.3)$$

$$0 < \sum_{i=1}^{N} \mu_{ij} < N \, , i = 1,2, \dots \dots , N \tag{2.4}$$

Function (2.1) Objective Function describes a constrained optimization problem, which can be converted to an unconstrained optimization problem by using the Lagrange multiplier technique.

$$\mu_{ij}^{(t)} = \frac{1}{\sum_{l=1}^{C} (\frac{d_{ij}}{d_{il}})^{\frac{1}{(m-l)}}} . 1^{(\frac{2}{m-l})} \tag{2.5}$$

$$i = 1,2, \dots \dots , N \; and \; j, l = 1,2, \dots \dots , C$$

$$if \; d_{ij} = 0 \, , then \; \mu_{ij} = 1 \; and \; \mu_{ij} = 0 \; for \; l \neq j \tag{2.6}$$

$$w_j^t = \frac{\sum_{i=1}^{N} (\mu_{ij}^{(t-l)})^{m} x_i}{\sum_{i=1}^{N} (\mu_{ij}^{(t-l)})^{m}}, j = 1,2, \dots \dots , C \tag{2.7}$$

The FCM algorithm starts with a set of initial cluster centers (or arbitrary membership values). Then, it iterates the two updating functions (2.5) and (2.7) at the t-th iteration until the cluster centers are stable or the objective function in (2.2) converges to a local minimum. The complete algorithm consists of the following steps:

- Step 1: Given a fixed number C, initialize the cluster centre matrix W_0 by using a random generator from the dataset. Record the cluster centres, set t=0, m = 2, and decide E, where E is a small positive constant.
- Step 2: Initialize the membership matrix U_0 by using functions (2.2) and (2.3).
- Step 3: Increase t by one. Compute the new cluster centre matrix (candidate) W_t by using (2.4).
- Step 4: Compute the new membership matrix U_t by using function (2.5) and (2.6).
- Step 5: If $||U_t - U_{t-1}|| < E$ then stop, otherwise go to step 3.

2.5. Density Based Algorithm

Density-based clustering focuses on the concept of "neighbourhood", where clusters are identified based on regions of high local density. Rather than proximity between individual objects, the emphasis lies on the density of points within a given neighbourhood. Clusters are perceived as sets of data points scattered throughout the data space, with contiguous regions of low density acting as separators between clusters. Density-based clustering methods, such as Density-Based Spatial Clustering of Applications with Noise (DBSCAN) and Density-Based Clustering (DENCLUE), utilize the notion of local density to identify clusters and detect outliers or noise points. These algorithms excel in discovering clusters of various shapes and sizes, as well as demonstrating robustness against noise. By focusing on density rather than strict proximity, density-based clustering offers an effective approach for uncovering complex structures in datasets with irregular shapes and varying densities.

2.5.1. Advantage and Disadvantage of Density Based Clustering

Density-based methods excel in discovering clusters with arbitrary shapes and exhibit robustness against noise, surpassing hierarchical or partitional methods in this aspect. Unlike traditional methods, density-based algorithms such as DBSCAN and DENCLUE don't necessitate predefined specifications for the number of clusters, offering flexibility in cluster identification. However, while these methods are adept at handling complex data structures and noise, their efficiency tends to decrease as the dimensionality of the data increases. Although DENCLUE demonstrates some improvement in dealing with high-dimensional data, it still falls short of being fully effective in such scenarios. Despite this limitation, density-based methods remain valuable tools for clustering tasks, particularly in datasets where traditional methods struggle to identify clusters with irregular shapes or significant noise.

2.5.2 DBSCAN

The Density-Based Spatial Clustering of Applications with Noise (DBSCAN) algorithm, proposed by Martin Ester, Hans-Peter Kriegel, Jorg Sander, and Xiaowei Xu in 1996, stands out as one of the most popular density-based clustering methods. Unlike traditional clustering algorithms that

rely on predetermined cluster numbers, DBSCAN identifies clusters based on the density of points in their neighbourhoods. The algorithm requires two parameters: ε (epsilon) and MinPts. ε defines the radius of the neighbourhood around each point, while MinPts specifies the minimum number of points required to form a dense region. DBSCAN operates through the following steps:

- **Initialization:** An unvisited random point is chosen as the initial point to start the clustering process.

- **Neighbourhood Determination:** Using the parameter ε, the algorithm determines the neighbourhood of the initial point in the data space.

- **Cluster Formation:** If there are a sufficient number of points within the neighbourhood, the initial point is labelled as visited, indicating that it belongs to a cluster. If the point is deemed to be a core object (i.e., it has at least MinPts points within its ε-neighbourhood), a cluster is formed around it. Points within the ε-neighbourhood of the core object are also considered part of the same cluster. The process continues recursively, expanding the cluster until all reachable points are visited.

- **Noise Identification:** Points that are not visited during the clustering process are labelled as noise or outliers, as they do not belong to any cluster.

- **Cluster Discovery:** The algorithm repeats steps 1-4 for all unvisited points until all clusters and noise are identified.

DBSCAN is known for its robustness against noise and its ability to detect clusters of arbitrary shapes, making it particularly useful in real-world scenarios where data may exhibit complex structures. However, the algorithm can encounter challenges when applied to high-dimensional datasets, as the concept of distance becomes less meaningful in higher dimensions. Additionally, DBSCAN's performance can be sensitive to the choice of MinPts parameter, which may need to be carefully tuned based on the characteristics of the dataset.

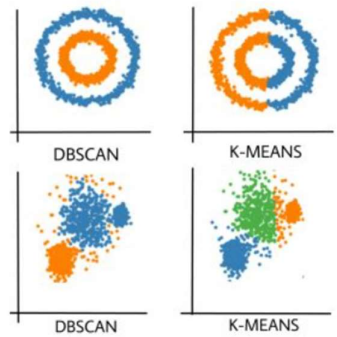


Figure 2.5. Difference Between DBSCAN And K – Means Clustering

Despite these limitations, DBSCAN outperforms traditional clustering algorithms like K-Means in terms of handling datasets with varying shapes and densities. Its ability to identify clusters based on local density rather than distance metrics allows it to capture clusters with irregular shapes and densities effectively. Overall, DBSCAN remains a powerful tool in the clustering toolkit, offering a flexible and robust approach to clustering in diverse datasets.

2.6. Probabilistic Clustering

There is another type of Clustering Techniques, Probabilistic clustering is a clustering approach that models the uncertainty inherent in the assignment of data points to clusters using probabilistic methods. Unlike traditional clustering algorithms that produce hard assignments of data points to clusters, probabilistic clustering assigns probabilities to each data point indicating its likelihood of belonging to different clusters. This probabilistic representation allows for a more flexible and nuanced understanding of cluster assignments, particularly in situations where data points may exhibit ambiguity or overlap between clusters.

One of the most common probabilistic clustering techniques is Gaussian Mixture Models (GMM), which represents clusters as probability distributions, typically Gaussian distributions, in the feature space. GMM assumes that the data points are generated from a mixture of several Gaussian distributions, each representing a cluster. The parameters of these Gaussian distributions, including mean and covariance, are estimated using an iterative optimization algorithm such as Expectation-

Maximization (EM). By modelling the data distribution as a mixture of Gaussians, GMM can capture complex data patterns and identify clusters with varying shapes and densities.

Probabilistic clustering techniques offer several advantages over traditional clustering methods. Firstly, they provide a more probabilistic interpretation of cluster assignments, allowing for uncertainty to be quantified and accounted for in the analysis. This is particularly useful in scenarios where data points may belong to multiple clusters simultaneously or when there is uncertainty in the clustering process. Additionally, probabilistic clustering methods are more robust to noise and outliers in the data, as they can incorporate these uncertainties into the clustering model.

2.7. Evaluation of Clustering Algorithm

Internal evaluation measures play a crucial role in assessing the quality of clustering algorithms by analysing the similarity within clusters and dissimilarity between clusters, directly based on the clustered data itself. However, it's essential to recognize their limitations and understand that high scores on internal measures do not necessarily translate to effective information retrieval applications.

The Davies–Bouldin index [15], one of several internal evaluation measures, quantifies cluster quality by considering both intra-cluster similarity and inter-cluster dissimilarity. It calculates the average distance of elements within clusters to their centroid and compares it with the distance between cluster centroids. A lower Davies–Bouldin index indicates better clustering performance, as it signifies tighter clusters and greater separation between them. The Davies–Bouldin index (DB index) is calculated using the following formula:

$$DB = \frac{1}{n} \sum_{i=1}^{n} max_{j \neq i} \left(\frac{\sigma_i + \sigma_j}{d(c_i, c_j)} \right) \quad (2.8)$$

Where, n is the number of clusters, c_i is the centroid of cluster i_i, σ_i is the average distance of all elements in cluster i_i to centroid c_i, d (c_i, c_j) is the distance between centroids c_i and c_j.

Another widely used metric, the Dunn index, focuses on identifying dense and well-separated clusters. It computes the ratio between the minimal inter-cluster distance and the maximal intra-cluster distance. A higher Dunn index indicates superior clustering quality, as it suggests clusters are both

compact and well-separated. For each cluster partition, the Dunn index can be calculated by the following formula:

$$D = \frac{min_{1\leq i<j\leq n}\, d(i,j)}{max_{1\leq k\leq n}\, d'(k)} \tag{2.9}$$

where d (i,j) represents the distance between clusters i and j, and d '(k) measures the intra-cluster distance of cluster k.

Additionally, the silhouette coefficient [15] offers a nuanced perspective by contrasting the average distance of objects within clusters with the average distance to objects in other clusters. Objects with a high silhouette value are deemed well-clustered, while those with a low value may be considered outliers. This coefficient serves as a valuable tool, particularly in conjunction with k-means clustering, aiding in determining the optimal number of clusters for a given dataset.

While these internal evaluation measures provide valuable insights into the performance of clustering algorithms, it's important to interpret their results cautiously. The validity of these measures depends on the underlying assumption that the data exhibits a particular structure, which may not always hold true. Moreover, certain algorithms may be better suited to specific types of data or cluster shapes, and evaluation criteria should be chosen accordingly to ensure fair assessment.

In summary, internal evaluation measures offer valuable guidance in comparing and selecting clustering algorithms based on their performance on the given dataset. By considering factors such as intra-cluster cohesion and inter-cluster separation, these metrics provide a quantitative means of assessing clustering quality and informing algorithmic decisions. However, it's essential to complement internal evaluation with external validation methods and domain knowledge to ensure robust and meaningful clustering results.

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Chapter 3

Feature Extraction

3.1 Introduction

Imagine you have a big box of puzzle pieces, but there's no picture on the box to show you what the puzzle should look like when it's finished. You start by picking up pieces one by one, trying to figure out how they fit together. Feature Extraction is a bit like this, but with data instead of puzzle pieces. In simple terms, feature extraction [1] is about finding the important patterns and relationships within data. It helps us make sense of the information we have, much like putting together a puzzle helps us see the bigger picture.

Let's break it down a bit further. When we talk about data, we're referring to all sorts of information—numbers, words, images, and more. But this data isn't always organized in a way that makes it easy to understand. Feature extraction steps in to help us organize and make sense of this data by identifying the most relevant aspects, or features, within it.

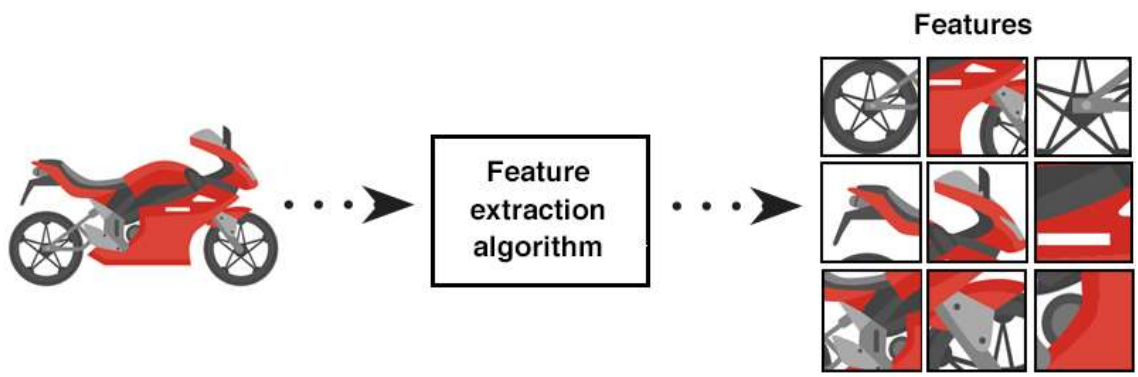


Figure 3.1. Feature Extraction

For example, if we're looking at a collection of images, feature extraction might help us identify common shapes, colours, or textures that are important for distinguishing one image from another. In other words, it helps us find the pieces of the puzzle that matter most. Now, you might be wondering how feature extraction actually works. Well, there are different techniques and algorithms that can be used, but they all have the same goal: to extract meaningful features from the raw data.

One common approach is called deep learning [2], which uses artificial neural networks to learn complex patterns directly from the data. These networks are inspired by the way our brains

process information, with layers of interconnected nodes that gradually build up a deeper understanding of the data.

Another approach is called dimensionality reduction [3], which aims to simplify the data by reducing the number of features while preserving as much relevant information as possible. It's like condensing the puzzle pieces into a smaller, more manageable set without losing the overall picture.

In conclusion, feature extraction is like a superpower that helps us unlock the hidden patterns and insights within data. Whether we're analysing images, text, or any other type of information, feature extraction allows us to see the underlying structure and make better decisions. Just like putting together a puzzle, it can be a challenging process that requires patience and creativity. But the rewards are worth it, as feature extraction enables us to uncover new discoveries, solve complex problems, and ultimately, understand the world around us in a deeper way.

3.2 Convolutional Neural Network

Convolutional Neural Networks (CNNs) [5], also known as ConvNets, represent a special type of deep learning architecture primarily used for processing spatial data like images. While they gained widespread attention after the remarkable performance of AlexNet in 2012, the roots of CNNs trace back to the foundational work of Hubel and Wiesel in 1959. Their discovery about the receptive fields of cells in the animal visual cortex inspired Kunihiko Fukushima to propose the neocognitron in 1980, considered the precursor to modern CNNs.

3.2.1 Foundation of Convolutional Neural Network

The early 1990s saw the development of LeNet-5 by LeCun et al. [6], a pioneering CNN model used for recognizing handwritten digits. Despite its promise, CNNs faced limitations due to scarce training data, algorithmic constraints, and computational power. However, recent advancements in large labelled datasets, innovative algorithms, and powerful GPU machines have propelled CNNs into the forefront of computer vision and natural language processing. A traditional CNN architecture consists of convolutional and pooling layers followed by fully connected (FC) layers and an output layer. The convolutional layer, the cornerstone of a CNN, aims to learn feature representations of the

input data. It comprises learnable convolution kernels or filters used to compute different feature maps. Each unit of a feature map is connected to a receptive field in the previous layer, and new feature maps are generated by convolving the input with kernels and applying element-wise non-linear activation functions. This convolutional layer's parameter sharing property reduces model complexity. Pooling or subsampling layers down sample the convolutional output by taking small regions as input and producing a single output, thereby reducing the number of parameters and making the network translation invariant. Different pooling techniques like max pooling, min pooling, or average pooling can be employed. The final part of a CNN typically includes one or more FC layers, which take input from the last convolutional or pooling layer and generate the final output.

In the realm of image classification, a CNN can be conceptualized as comprising two main parts: feature extraction and classification. Convolution and pooling layers perform feature extraction by detecting various features such as edges, shapes, or textures at different levels. The subsequent FC layers act as a classifier, assigning probabilities to input images belonging to different classes, such as identifying whether an image contains a dog.

Beyond the architectural design, the efficacy of CNNs depends on various factors like activation functions, normalization methods, loss functions, regularization techniques, optimization algorithms, and processing speed. CNNs have found wide-ranging applications in image classification, object detection, segmentation, human pose estimation, text detection, visual saliency detection, action recognition, scene labelling, visual question answering, speech processing, and natural language understanding.

In 1959, neurophysiologists David Hubel and Torsten Wiesel conducted groundbreaking experiments that shed light on the organization of neurons in the cat's brain. Their seminal paper, "Receptive fields of single neurons in cats striate cortex" [16], revealed that these neurons are structured in layers. Through their research, Hubel and Wiesel observed that these layers possess the remarkable ability to recognize visual patterns. Their findings suggested that neurons first extract local features before combining them to form higher-level representations. This discovery laid the groundwork for what would later become a core principle of Deep Learning. Building upon the insights of Hubel and Wiesel, Kunihiko Fukushima proposed the Neocognitron in 1980. This self-organizing Neural Network consisted of multiple layers capable of hierarchically recognizing visual patterns

through. The Neocognitron marked the first theoretical model of CNNs. Further advancements in CNN architecture came in 1989 with the development of LeNet-5 by LeCun et al. LeNet-5 represented a significant improvement over the Neocognitron. It successfully recognized patterns in the MNIST handwritten digits dataset. Utilizing the error back-propagation algorithm, LeNet-5 demonstrated the capability to directly recognize visual patterns from raw input images without the need for separate feature engineering mechanisms.

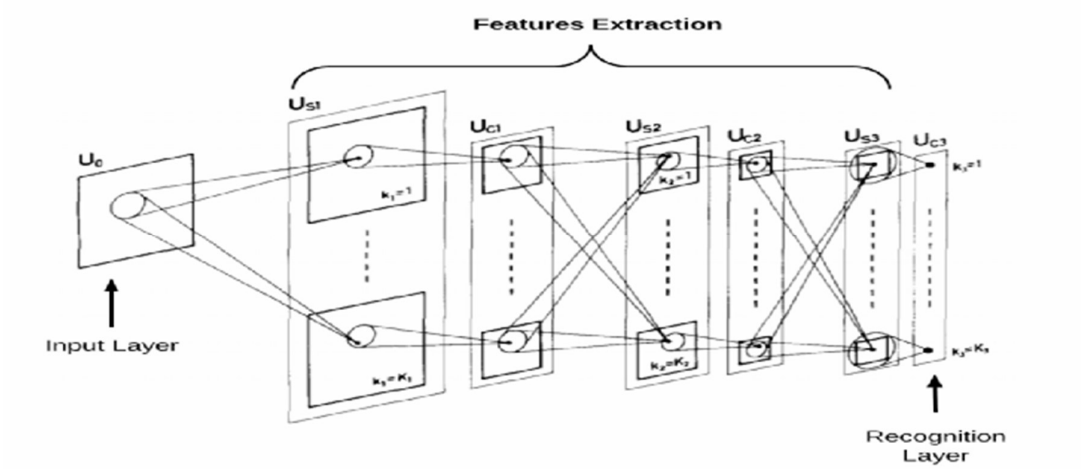


Figure 3.2. Schematic diagram illustrating the interconnections between layers in the neocognitron, Kunihiko Fukushima

Despite these early breakthroughs, CNNs faced limitations, including a scarcity of large training datasets, stagnation in algorithmic innovation, and insufficient computational power. However, the advent of the Big Data era brought about significant advancements. With the availability of large labelled datasets, innovative algorithms, and powerful GPU machines, CNNs experienced a resurgence. In 2012, Krizhevsky and his team introduced AlexNet, a CNN that achieved remarkable accuracy in the ImageNet Large Scale Visual Recognition Challenge (ILSVRC). The success of AlexNet marked a turning point, leading to the development of numerous CNN models and their widespread application across various fields, including computer vision and natural language processing.

The journey of CNNs, from the foundational work of Hubel and Wiesel to the breakthroughs of modern architectures like AlexNet, underscores the transformative power of research and technological innovation. As CNNs continue to evolve, fuelled by advances in data, algorithms, and computing resources, they promise to revolutionize our understanding of artificial intelligence and its applications in solving complex real-world problems.

3.2.2 Biological Inspiration of Convolutional Neural Network

Biological inspiration has profoundly influenced the development of convolutional neural networks (CNNs), particularly in understanding the mechanisms underlying visual processing and cognition [18] . One significant avenue of exploration involves correlating the response of later layers in CNNs with the memorability of images, mirroring the involvement of higher cortical regions in memory encoding. Additionally, the incorporation of attractor networks based on semantic features simulates cortical activity during semantic tasks, reflecting the intricate interplay between visual and semantic processing observed in the brain. Leveraging principles of visual attention, CNNs integrate attentional mechanisms, especially in later layers, to selectively enhance processing of relevant information, akin to the modulatory effects of attention observed in the brain. Moreover, by replicating behavioural and neural effects of perceptual learning, CNNs demonstrate improved discrimination and processing of visual stimuli, mirroring the experience-dependent changes in neuronal connectivity observed in biological systems. Integrating biological details such as local recurrence, feedback connections, foveation, and saccading enhances CNNs' ability to emulate the functional organization and processing strategies observed in the visual system, contributing to more biologically plausible models of visual perception and cognition. Despite these advancements, addressing limitations such as weight sharing assumptions, violations of Dale's law, and reliance on backpropagation for training remains crucial for further aligning CNNs with the biological principles underlying visual processing. Ultimately, the convergence of artificial neural networks and biological insights offers promising avenues for advancing our understanding of visual cognition and creating more effective models of human-like perception.

3.2.3 Concepts of Convolutional Neural Network

Convolutional Neural Network (CNN), also called ConvNet [7], is a type of Artificial Neural Network (ANN), which has deep feed-forward architecture and has amazing generalizing ability as compared to other networks with FC layers, it can learn highly abstracted features of objects especially spatial data and can indentify them more efficiently. A deep CNN model consists of a finite set of processing layers that can learn various features of input data (e.g. image) with multiple level of abstraction. The initiatory layers learn and extract the high level features (with lower abstraction), and the deeper layers learns and ex tracts the low level features (with higher abstraction). The basic conceptual model of CNN was shown in Figure 3.3, different types of layers described in subsequent sections.

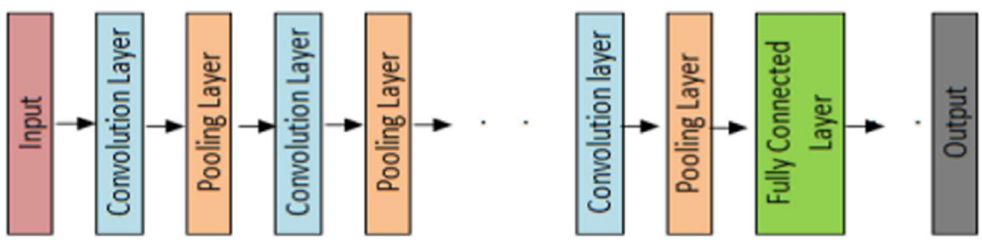


Figure 3.3. Conceptual Model of CNN

Now description of different components or basic building blocks of CNN briefly as follows.

3.2.3.1 Network Layers

A Convolutional Neural Network (CNN) comprises several essential building blocks, known as layers [8], each playing a unique role in the network's architecture. In this subsection, we will provide a concise description of some of these crucial components.

3.2.3.2 Convolutional Layers

The convolutional layer is arguably the most critical component of any CNN architecture. It consists of a set of convolutional kernels, also referred to as filters. These kernels are convolved with

the input image, which is typically represented as an N-dimensional matrix, to produce an output feature map.

3.2.3.3 Understanding Kernels

A kernel [9] can be conceptualized as a grid of discrete numerical values, where each value represents the weight assigned to that specific position within the grid. At the beginning of the training process for a CNN model, these kernel weights are initialized with random numbers (though various initialization approaches exist). As the model undergoes training epochs, these weights are adjusted through the process of backpropagation, enabling the kernel to learn and extract meaningful features from the input data. In Figure 3.4, we illustrate a 2D filter, highlighting its grid-like structure and the weights assigned to each position within the kernel.

3.2.3.4 Convolution Operation

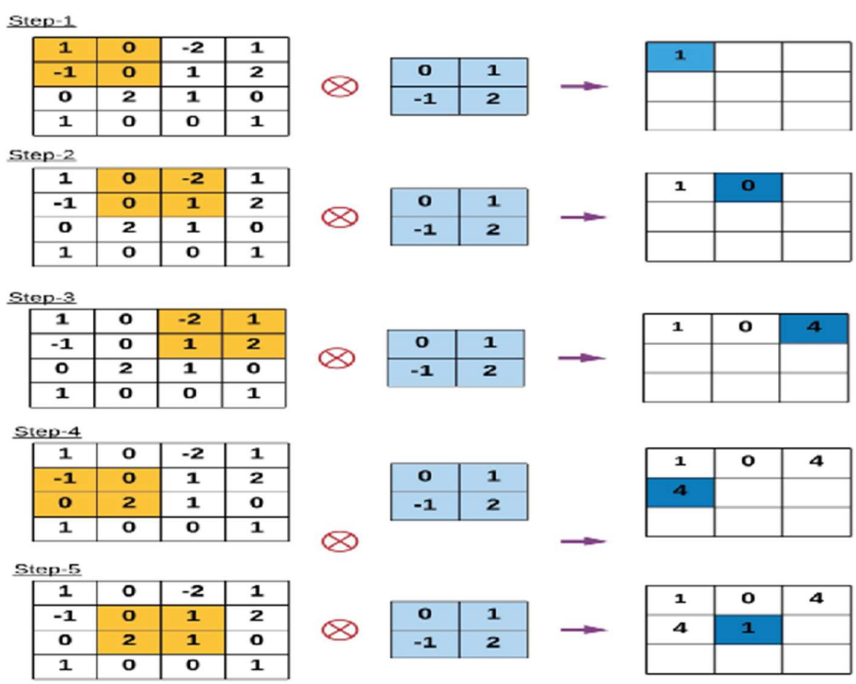


Figure 3.4. Illustrating The Steps of Convolution Operation

Now, to understand the convolution operation [10], if we take a gray scale image of 4 x 4 dimension, shown in Fig.3.4 and an 2 x 2 kernel with randomly initialized weights as shown in Fig.3.4. Now, in convolution operation, we take the 2 x 2 kernel and slide it over all the complete 4 x 4 image horizontally as well as vertically and along the way we take the dot product between kernel and input image by multiplying the corresponding values of them and sum up all values to generate one scaler value in the output feature map. This process continues until the kernel can no longer slide further. To understand the thing more clearly, let's do some initial computations performed at each step graphically as shown in Fig. 3.4, where the 2 x 2 kernel (shown in light blue color) is multiplied with the same sized region (shown in yellow color) within the 4 x 4 input image and the resulting values are summed up to obtain a corresponding entry (shown in deep blue) in the output feature map at each convolution step.

In the previous example, we applied the convolution operation to the input image with no padding and a stride of 1. However, it's essential to note that we can adjust the stride value in the convolution operation, impacting the resulting feature map's dimensions. When we increase the stride of the convolution operation, it leads to a lower-dimensional feature map. This is because the convolutional kernel moves over the input data with larger steps, resulting in fewer output activations.

Padding [11] plays a crucial role in convolutional operations by giving more importance to border size information in the input image. Without padding, features at the border of the input image may be washed away too quickly during the convolution process. Additionally, padding can be used to increase the input image size, thereby increasing the output feature map size. For instance, consider Figure 3.5, which illustrates the convolution operation with zero-padding and a stride value of 3. In this example, you can observe how padding ensures that the border features of the input image receive adequate consideration during the convolution process. Moreover, the increased stride value results in a sparser feature map, reflecting the impact of larger steps taken by the convolutional kernel. The formula to find the output feature map size after convolution operation as below.

$$h' = \left\lfloor \frac{h - f + p}{s} + 1 \right\rfloor$$
$$w' = \left\lfloor \frac{w - f + p}{s} + 1 \right\rfloor \quad (3.1)$$

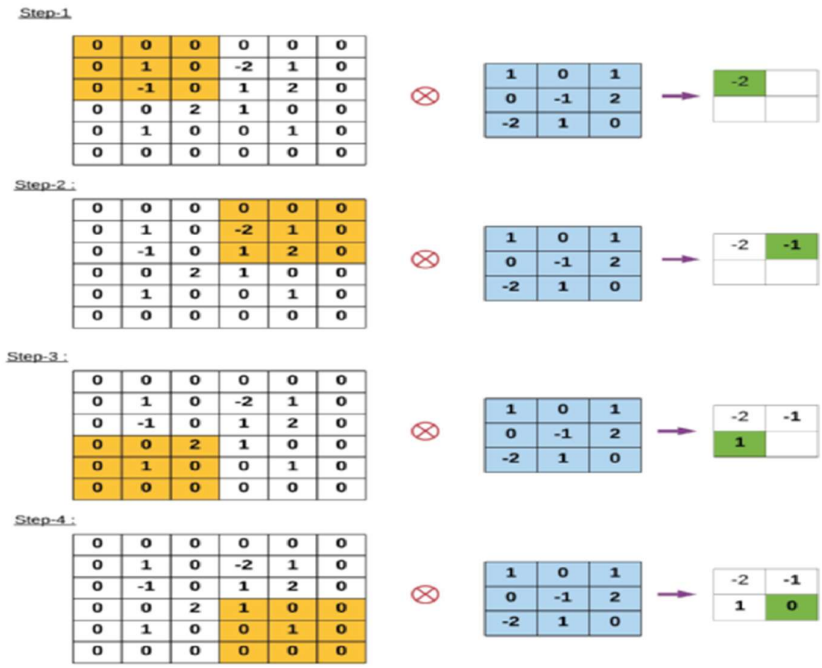


Figure 3.5. The computations performed at each step, where the 3X3 kernel (shown in light blue color) is multiplied with the same sized region (shown in yellow color) within the 6X6 input image (where we applied zero-padding to the original input image of 4X4 dimension and it becomes of 6X6 dimensional) and values are summed up to obtain a corresponding entry (shown in deep green) in the output feature map at each convolution step.

Where h' denotes the height of the output feature map, w' denotes the width of the output feature map, h denotes the height of the input image, w denotes the width of the input image, f is the filter size, p denotes the padding of convolution operation and s denotes the stride of convolution operation.

The convolution layers in Convolutional Neural Networks (CNNs) offer several key advantages:

- **Sparse Connectivity**

Unlike fully connected neural networks where each neuron in one layer connects to every neuron in the next layer, CNNs exhibit sparse connectivity. This means that only a small number of weights are present between two layers. Consequently, the number of connections and weights required is significantly reduced, leading to efficient memory usage. Moreover, the computational cost

of the dot (.) operation used in convolution is lower compared to traditional matrix multiplication, further enhancing computational efficiency.

- **Weight Sharing**

CNNs leverage weight sharing, a technique where no dedicated weights exist between neurons in adjacent layers. Instead, a set of weights is shared across all neurons and applied to every pixel of the input matrix. This means that instead of learning new weights for each neuron, CNNs learn a single set of weights for all inputs. This approach drastically reduces training time and associated computational costs, making CNNs more efficient and scalable for large datasets and complex tasks.

3.2.3.5 Pooling Layer

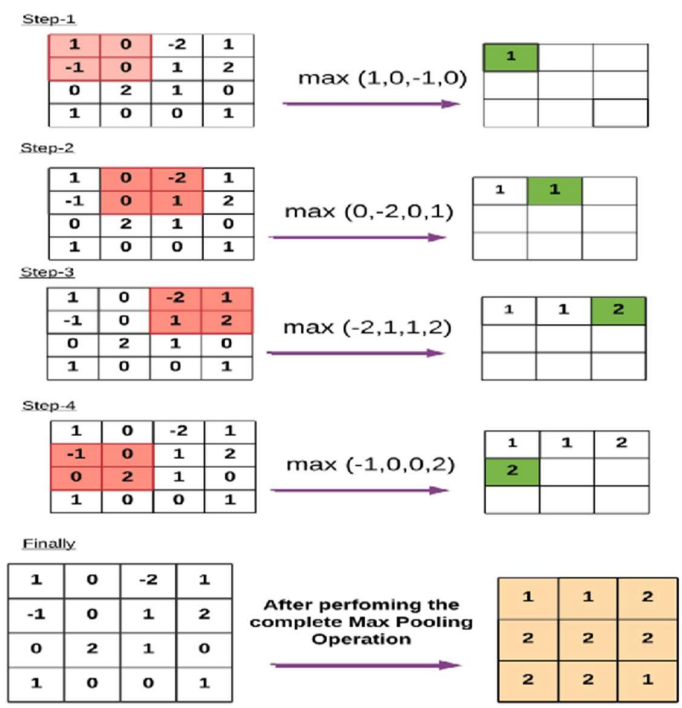


Figure 3.6. Illustrating an example that shows some initial steps as well as the final output of max-pooling operation, where the size of the pooling region is 2 2 (shown in orange color, in the input feature map) and the stride is 1 and the corresponding computed value in the output feature map (shown in green)

Pooling layers [12] in Convolutional Neural Networks (CNNs) play a vital role in subsampling the feature maps generated after convolution operations. Their primary function is to reduce the size of the feature maps while retaining the most dominant features or information in each pooling step. Pooling achieves this by specifying the size of the pooled region and the stride of the operation, similar to the convolution operation. Various pooling [13] techniques exist, including max pooling, min pooling, average pooling, gated pooling, and tree pooling. Among these, max pooling is the most popular and widely used technique. However, it's important to note that pooling layers can sometimes negatively impact the overall performance of a CNN. "The pooling operation used in convolutional neural networks is a big mistake and the fact that it works so well is a disaster" Said Geoffrey Hinton.

This drawback stems from the fact that pooling layers focus solely on identifying whether specific features are present in the input image, disregarding their precise spatial positions. While pooling layers effectively reduce the dimensionality of feature maps and help identify dominant features, they may occasionally lead to a loss of spatial information, potentially affecting the CNN's performance on certain tasks. Consequently, careful consideration should be given to the use of pooling layers within CNN architectures to ensure optimal performance.

3.3 Activation Function

The primary role of an activation function [20] in any neural network, including Convolutional Neural Networks (CNNs), is to map the input to the output. This mapping occurs by calculating the weighted sum of the input neurons and adding bias (if applicable). In essence, the activation function determines whether a neuron will fire or not for a given input, thereby producing the corresponding output. In CNN architectures, non-linear activation functions are applied after each learnable layer, which includes layers with weights such as convolutional and fully connected (FC) layers. The non-linear behaviour introduced by these activation functions enables the CNN model to learn more complex patterns and map inputs to outputs non-linearly.

An important characteristic of activation functions [21] is their differentiability, which is essential for error backpropagation during model training. This process allows the network to adjust its parameters based on the calculated error and improve its performance over time. Several activation

functions are commonly used in deep neural networks, including CNNs. Some of these functions are described below:

- **Step**

The step function is a binary activation function outputting 1 for inputs greater than or equal to zero and 0 otherwise, primarily used in binary classification. However, its lack of gradient makes it unsuitable for gradient-based optimization

- **Sigmoid**

The sigmoid function squashes the input values between 0 and 1, which is useful for binary classification tasks where the output needs to be interpreted as a probability.

- **Tanh (Hyperbolic Tangent)**

Tanh function is similar to the sigmoid function but squashes the input values between -1 and 1. It is commonly used in hidden layers of neural networks. Both Sigmoid and Tanh are suffering from vanishing gradient problem .To overcome this , we have ReLu, Elu etc.

- **ReLU (Rectified Linear Unit)**

ReLU is the most widely used activation function due to its simplicity and effectiveness. It replaces all negative values in the input with zero, while leaving positive values unchanged.

- **Leaky ReLU**

Leaky ReLU is a variant of ReLU that allows a small, positive slope for negative input values, preventing the "dying ReLU" problem where neurons stop updating during training.

- **Softmax**

Softmax function is often used as the activation function in the output layer of a neural network for multi-class classification tasks. It converts the raw scores into probabilities, with each output representing the likelihood of belonging to a particular class.

- **ELU (Exponential Linear Unit)**

Exponential Linear Unit is a variant of ReLU with a smooth curve for negative inputs, addressing the "dying ReLU" problem and providing non-zero mean gradients. ELU's range extends from negative infinity to positive infinity, offering improved performance and robustness in training deep neural networks compared to ReLU, albeit with some computational overhead.

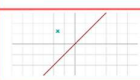
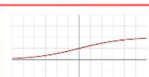
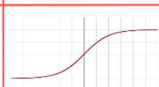
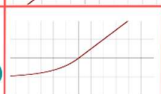
ACTIVATION FUNCTION	PLOT	EQUATION	DERIVATIVE	RANGE
Linear		f(x) = x	f'(x) = 1	(-∞, ∞)
Binary Step		$f(x) = \begin{cases} 0 & \text{if } x < 0 \\ 1 & \text{if } x \geq 0 \end{cases}$	$f'(x) = \begin{cases} 0 & \text{if } x \neq 0 \\ \text{undefined} & \text{if } x = 0 \end{cases}$	{0, 1}
Sigmoid		$f(x) = \sigma(x) = \frac{1}{1+e^{-x}}$	$f'(x) = f(x)(1-f(x))$	(0, 1)
Hyperbolic Tangent(tanh)		$f(x) = \tanh(x) = \frac{e^{x}-e^{-x}}{e^{x}+e^{-x}}$	$f'(x) = 1 - f(x)^2$	(-1, 1)
Rectified Linear Unit(ReLU)		$f(x) = \begin{cases} 0 & \text{if } x<0 \\ x & \text{if } x\geq 0 \end{cases}$	$f'(x) = \begin{cases} 0 & \text{if } x < 0 \\ 1 & \text{if } x > 0 \\ \text{undefined} & \text{if } x = 0 \end{cases}$	[0, ∞)
Softplus		$f(x) = \ln(1+e^{x})$	$f'(x) = \frac{1}{1+e^{-x}}$	(0, 1)
Leaky ReLU		$f(x) = \begin{cases} 0.01x & \text{if } x < 0 \\ x & \text{if } x \geq 0 \end{cases}$	$f'(x) = \begin{cases} 0.01 & \text{if } x < 0 \\ 1 & \text{if } x \geq 0 \end{cases}$	(-1, 1)
Exponential Linear Unit(ELU)		$f(x) = \begin{cases} \alpha(e^{x}-1) & \text{if } x \leq 0 \\ x & \text{if } x > 0 \end{cases}$	$f'(x) = \begin{cases} \alpha e^{x} & \text{if } x < 0 \\ 1 & \text{if } x > 0 \\ 1 & \text{if } x = 0 \text{ and } \alpha = 1 \end{cases}$	[0, ∞)

Figure 3.7. Some Activation Functions And Their Properties

These activation functions contribute to the expressive power of CNNs by introducing non-linearity [22] , enabling them to model complex relationships in the data and achieve superior performance on various tasks.

3.4 Fully Connected Layer

Typically, the last layers of CNN architectures, used for classification, consist of fully-connected layers. Here, each neuron connects with every neuron from the previous layer. These layers, similar to feed-forward artificial neural networks (ANNs), adopt the principles of traditional multi-layer perceptron neural networks (MLPs). They receive input from the final convolutional or pooling layer, in the form of feature map matrices. These matrices are flattened into vectors, then passed to the FC layer to produce the CNN's final output, as depicted in Figure 3.8.

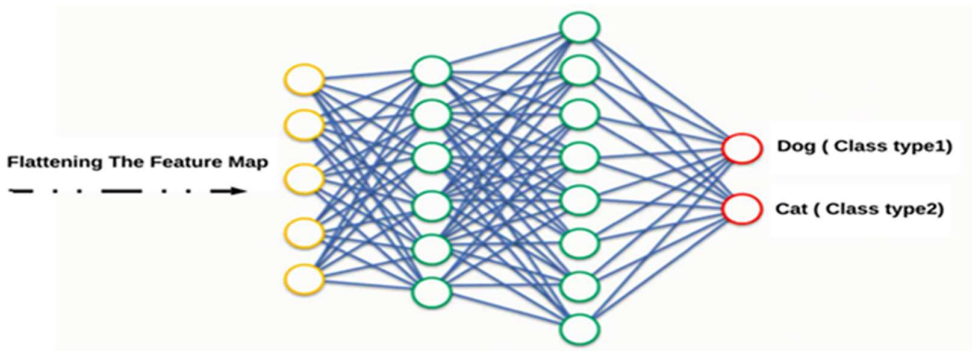


Figure 3.8. The Architecture Of Fully Connected Layers

3.5 Training process of Convolutional Neural Network

In the preceding section, we delved into the fundamental concepts of Convolutional Neural Networks (CNNs) along with the various crucial components comprising CNN architecture. In this section, our focus shifts to elucidating the training or learning procedure of a CNN model, accompanied by specific guidelines aimed at curtailing the requisite training duration while enhancing model accuracy. The training process encompasses the following sequential steps:

1. Data Pre-processing and Augmentation.

2. Parameter Initialization.
3. Regularization Techniques for CNN.
4. Selection of Optimizer.

These steps are elaborated upon in the subsequent subsections

- **Data Pre-processing and Augmentation**

This initial step involves preparing the dataset for training. Data pre-processing may include tasks such as normalization, resizing, or cropping images to ensure uniformity and facilitate efficient training. Augmentation techniques such as rotation, flipping, or adding noise to the images are employed to artificially increase the diversity of the dataset, thereby enhancing the model's ability to generalize to unseen data.

- **Parameter Initialization**

In this step, the parameters (weights and biases) of the CNN model are initialized. Proper initialization is crucial as it can significantly impact the convergence and performance of the model during training. Common initialization methods include random initialization, Xavier initialization, or He initialization, which aim to set initial parameter values in a way that promotes stable and effective learning.

- **Regularization Techniques for CNN**

Regularization methods are employed to prevent overfitting, whereby the model memorizes the training data rather than learning generalizable patterns. Common regularization techniques for CNNs include dropout, which randomly disables a proportion of neurons during training to prevent co-adaptation, and weight decay (L2 regularization), which penalizes large parameter values to discourage overfitting. Dropout is one of the most used approach for regularization. In this approach, we randomly remove neurons from the network during each training epoch. By doing so, we aim to distribute the feature selection capability evenly among all neurons and compel the model to learn multiple independent features. When a unit or neuron is dropped, it doesn't contribute to either forward or backward propagation during training. However, during testing, the complete network is utilized

for making predictions. With the help of Figure 3.9 (a) and (b), we try to show the exact of dropout in networks architecture during training.



Figure 3.9. Illustration of Dropout Process a) A Normal Neural Network b) After Applying Dropout

- ## Selection of Optimizer

The choice of optimizer plays a crucial role in training a CNN model. Optimizers are algorithms responsible for updating the model parameters during training to minimize the loss function. Popular optimizers include, Gradient Descent Learning, Stochastic Gradient Descent (SGD), Adam, RMSprop, and AdaGrad. The selection of an optimizer depends on factors such as the nature of the dataset, the model architecture, and computational resources.

In the gradient descent algorithm, the model parameters are updated iteratively during each training epoch to minimize the training error. This update process involves calculating the gradient of the objective function with respect to the model parameters and adjusting the parameters in the opposite direction of the gradient. This is typically done through back-propagation, where the gradient at each neuron is propagated backward through the network layers. Mathematically, the parameter update for a specific weight wij in the network can be represented as:

$$w_{t,ij} = w_{t-1,ij} - \eta \partial E / \partial w_{ij} \tag{3.2}$$

where:

$w_{t,ij}$ is the updated weight in the current t th training epoch. $w_{t-1,ij}$ is the weight in the previous $(t-1)$ th training epoch. η(eta) is the learning rate, which determines the step size of parameter updates.

E is the prediction error, often represented by the loss function. Most commonly used Loss functions are :

3.5.1 Euclidean Loss Function

The Euclidean loss, also known as mean squared error, finds extensive application in regression tasks. It quantifies the average squared difference between the predicted output $p \in R^N$ and the actual output $y \in R^N$ in each neuron of the output layer of a CNN. Mathematically, the Euclidean loss $H(p,y)$ is defined as:

$$H(p,y) = \frac{1}{2N} \sum_{i=1}^{N} (p_i - y_i)^2 \tag{3.3}$$

Here, N represents the number of neurons in the output layer. The Euclidean loss provides an estimate of the discrepancy between the predicted and actual outputs, facilitating the assessment of model performance in regression scenarios.

3.5.2 Hinge Loss Function

The Hinge loss function serves as a cornerstone in binary classification problems, particularly in maximum margin-based classification tasks like support vector machines (SVMs). It is instrumental in maximizing the margin between two target classes, fostering robust classification boundaries. The Hinge loss $H(p,y)$ is defined as:

$$H(p,y) = \sum_{i=1}^{N} max(0, m(2y_i - 1)p_i) \tag{3.4}$$

Here, m denotes the margin, typically set to 1, p_i signifies the predicted output, and y_i represents the desired output. The Hinge loss penalizes misclassifications and incentivizes the model to correctly classify instances, thus facilitating effective binary classification.

This gradient descent equation represents how each weight in the network is adjusted based on the gradient of the error with respect to that weight, scaled by the learning rate η. By iteratively

updating the weights using this process, the model gradually learns to minimize the prediction error and improve its performance on the training data.

Now let's talk about a CNN architecture, LeNet. LeNet, short for LeNet-5, is a pioneering convolutional neural network architecture developed by Yann LeCun, Léon Bottou, Yoshua Bengio, and Patrick Haffner in the 1990s. It was primarily designed for handwritten digit recognition tasks, particularly for recognizing digits in check images for banking applications. LeNet laid the groundwork for modern CNN architectures and played a crucial role in popularizing deep learning for computer vision tasks. The LeNet architecture comprises seven layers, including three convolutional layers, two subsampling (pooling) layers, and two fully connected layers:

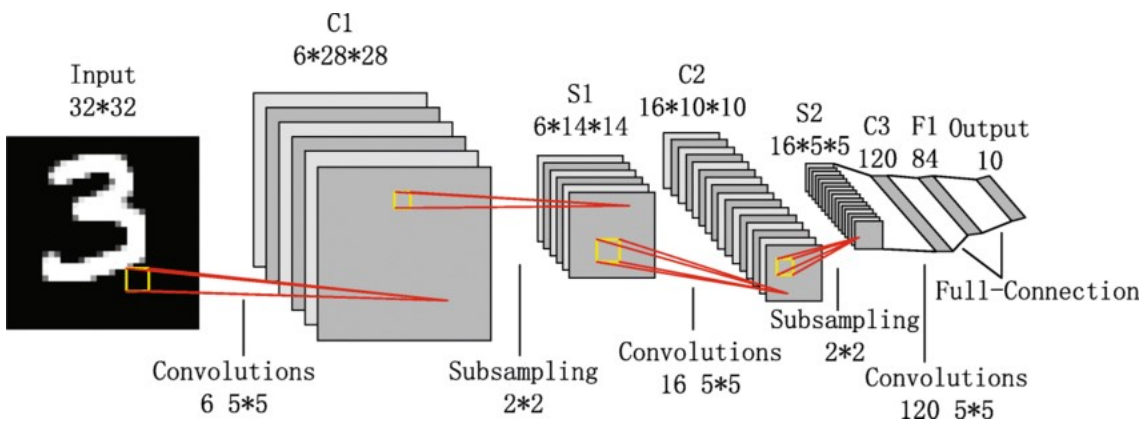


Figure 3.10. LeNet Architecture

- **Input Layer**

The network begins with an input layer, which receives the raw pixel values of the input image.

- **Convolutional Layers**

LeNet consists of three convolutional layers, each followed by a tanh activation function. These convolutional layers perform feature extraction by convolving learnable filters with the input image.

- **Subsampling (Pooling) Layers**

Following each convolutional layer, LeNet incorporates a subsampling (pooling) layer, typically using average pooling or max pooling operations. These layers reduce the spatial dimensions of the feature maps, enhancing computational efficiency and promoting translation invariance.

- **Fully Connected Layers**

LeNet includes two fully connected layers, also known as dense layers, towards the end of the network. These layers integrate the high-level features extracted by the convolutional layers and make predictions by mapping them to the output classes. The final fully connected layer typically employs a Softmax activation function to produce class probabilities.

- **Training**

LeNet is trained using the backpropagation algorithm, where the weights of the network are updated iteratively to minimize a chosen loss function, such as cross-entropy loss for classification tasks. The training process involves feeding input images through the network, comparing the predicted outputs with the ground truth labels, and adjusting the weights using optimization techniques like stochastic gradient descent (SGD) or its variants.

- **Impact**

LeNet's success in handwritten digit recognition tasks, particularly on the MNIST dataset, demonstrated the effectiveness of convolutional neural networks for image classification. Its architecture inspired subsequent CNN designs, including AlexNet, VGGNet, and ResNet, which achieved ground breaking results across various computer vision tasks. LeNet's legacy continues to influence advancements in deep learning and remains a foundational model in the field of convolutional neural networks.

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Chapter 4
Experiment And Result

4.1. Introduction

Clustering [1], a cornerstone in machine learning and data analysis, organizes data points into distinct groups based on their similarities, operating unsupervised and freeing from predefined labels. Its core objective is uncovering hidden structures within datasets by grouping similar data points. An intriguing dimension of clustering involves cluster shape detection, which enhances its effectiveness by considering the geometric arrangement of data points within clusters. This adaptability makes clustering applicable to various datasets, accommodating differences in shapes and densities. This study focuses on developing a cluster shape detection algorithm to further enhance the versatility and efficacy of clustering techniques. By integrating cluster shape detection into algorithms, clustering performance can be augmented, allowing for a more nuanced understanding of the data's underlying structures.

The existing literature [2][3] on clustering techniques primarily focuses on categorizing data points into distinct clusters. For instance, Chen et al. [2] introduced the Density-Based Spatial Clustering of Applications with Noise (DBSCAN) algorithm, tailored for boundary detection and plane segmentation in 3D point clouds. Another notable contribution by Kumar et al. [3] involves the application of a K-means clustering algorithm for automated acute leukemia detection. However, there remains a noticeable gap in works specifically addressing cluster shape detection. Although some notable works [4][5] have ventured into this realm, they often come with a significant computational expense. This study aims to address this gap by presenting a simple, effective, and computationally inexpensive approach to cluster shape detection.

The proposed methodology, known as the Dual Attention Induced Convolutional-Clustering (DAICC) algorithm, begins with a feature extraction strategy aimed at abstracting essential features for effective clustering. This extraction process involves two primary modules: an attention module and a convolutional module utilizing 2-dimensional (2D) convolution operations to abstract attention-induced features. The attention module comprises a combination of channel and spatial attention modules [6]. The channel attention module focuses on inter-channel relationships to identify significant features ('what'), while the spatial module explores inter-spatial relationships to determine the location of crucial information ('where'). The outputs from these modules are combined to produce refined features. These refined features then undergo 2D convolution to distill pertinent information

essential for clustering. Subsequently, the abstracted features are input into a Fuzzy C-Means clustering algorithm [7] to categorize them into respective clusters. Following the clustering process, a novel shape detection algorithm is employed to identify the shape of each cluster, thereby enhancing the overall robustness and interpretability of the clustering results.

The novelty inherent in the proposed work lies in the development of a cluster shape detection algorithm. This algorithm is composed of three major steps. Initially, two geometric figures, (e.g., ellipses), are considered, with one being designated as larger than the other. Both are initialized at the coordinates (0,0). Subsequently, both ellipses reach a cluster point before embarking on movement towards the clusters through a combination of translation and rotation at an angle of 5 degrees. Additionally, there is a progressive increase in their major and minor axes by a small value defined by the user. In the final step, an iterative checking process is employed, which entails examining whether the differences in the two major axes of the ellipse fall within the cluster data points, covering this area up to a user-defined threshold (e.g., 80%). If this condition holds true, it indicates that the cluster assumes an elliptical shape. A similar procedure is undertaken for other types of cluster shapes, such as rectangles and triangle.

The effectiveness of the proposed model over its traditional counterparts is substantiated through a thorough performance analysis, including ablation studies. The demonstrated efficacy positions the proposed method as promising for various applications, including the detection of microorganism oocysts in drinking water [8], segmentation of brain tumour images [9], and the identification of distinct characteristics of urban entities in public spaces [10]. Notably, the proposed method excels in these tasks without the need for time-consuming manual detection.

4.2. Problem Formulation and Approach

In this paper, the main objective is to identify cluster shape from a diverse dataset, expressed in block diagram (Figure 4.1). The journey starts with the raw dataset, undergoing a trans- formative phase in the attention layer featuring the Attention Module. Attention Module dynamically focuses on channel- wise and spatial-wise attention, enhancing critical features. This attention mechanism integrates seamlessly with a one- dimensional Convolutional Neural Network (CNN), featuring a Conv1D layer and followed by a Flatten layer, three hidden layers with 128, 64, and 32 neurons,

respectively, and an out- put layer. This CNN-Attention Module symbiotic relationship amplifies representational capabilities, allowing the CNN to extract features and delve into dataset variation. As features undergo metamorphosis, the journey advances to Fuzzy C- Means (FCM) clustering, FCM's iterative refinement handles complexities, resulting in three distinct cluster shapes that provide detailed insights into intrinsic structures. Following this, we develop an algorithm to assess and characterize these cluster shapes. The algorithm examines the geometries of the clusters, identifying patterns and structural nuances within each of the three shapes. This algorithmic evaluation gives us a comprehensive understanding of the cluster shapes, enabling precise classification based on their unique features. The detail procedure is outlined below, providing comprehensive insights into each step. This detailed explanation aims to facilitate a clear understanding and smooth execution of the process.

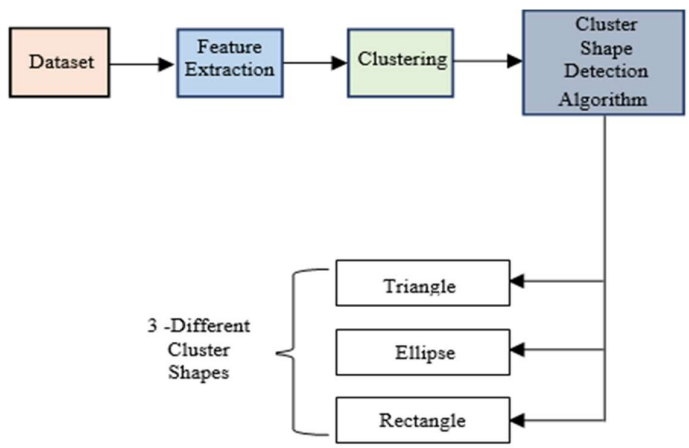


Figure 4.1 Block Diagram of Proposed Scheme

4.3. Proposed Dual Attention Induced Convolutional C -Means Clustering

In this section, a detailed breakdown of each step in our proposed dual attention induced convolutional clustering Figure 4.1. Block Diagram of the proposed scheme algorithm is provided within the procedure, aiming to provide a clear understanding and facilitate a smooth execution of the process.

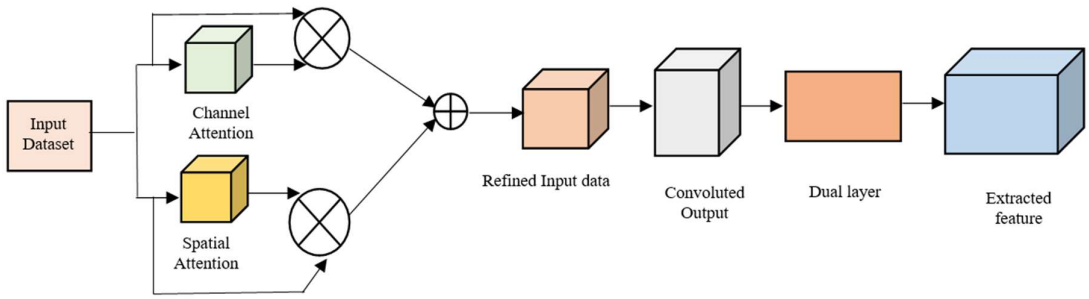


Figure 4.2 Block Diagram of Feature Extraction

4.3.1 Attention Module

An attention mechanism (denoted in Figure 4.2) is designed to enhance the representational power of Convolutional Neural Networks (CNNs) by focusing on both channel-wise and spatial-wise attention. Here's a breakdown of the attention module architecture and its components.

4.3.1.1 Channel Attention

This mechanism systematically analyzes interdependencies among input feature map channels. Global average pooling (F_{cavg}) and max pooling (F_{cmax}) operations are applied independently to capture channel-wise average and maximum values. A Multilayer Perceptron (MLP) with hidden activation size $R^{c/r}\times1\times1$, where r is the reduction ratio, reduces channel-wise dimensionality. Outputs from MLPs are combined and processed through sigmoid activation, yielding a channel-wise attention vector. This vector is then multiplied element-wise with the original feature map to highlight important channels. Mathematically, the channel attention M_C (F) is computed as:

$$M_C(F) = \sigma(W_1(W_0(F_{cavg})) + W_1(W_0(F_{cmax}))) \quad (4.1)$$

where σ denotes the sigmoid function, $W_0 \in R^{C/r\times C}$ and $W_1 \in R^{c\times c/r}$. Notably, the MLP weights are shared for both inputs, and the ReLU activation function follows W_0. The diagrammatic representation of the present module is shown in Figure 4.3.

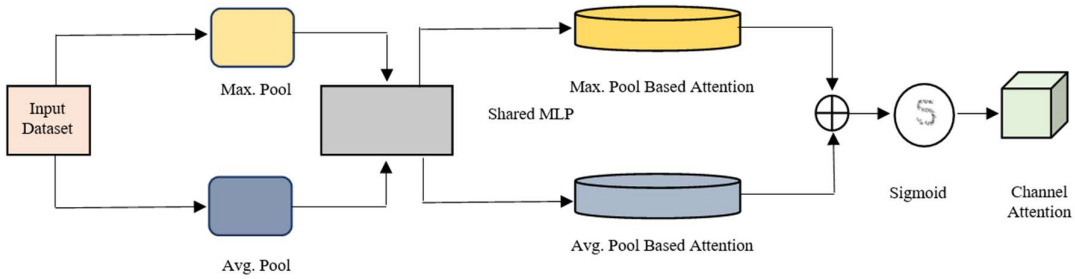


Figure 4.3 Block Diagram of Channel Attention

4.3.1.2 Spatial Attention

The spatial attention mechanism in Figure 4.4 focuses on the interdependencies between spatial locations in the input feature map. Two 2D maps $F_{savg} \in R^{1\times H\times W}$ and $F_{smax} \in R^{1\times H\times W}$, are generated through the average-pooling and max-pooling operations across the channel dimension. These maps represent the average-pooled and max-pooled features, respectively, encapsulating spatial information. Subsequently, these two maps are concatenated to form a consolidated representation of spatial features. This concatenated feature map undergoes convolution through a standard convolutional layer, producing a 2D spatial attention map denoted by Ms(F). Mathematically, the spatial attention is computed as:

$$Ms(F) = \sigma\,(f7\times7([F_{savg} + F_{smax}])) \tag{4.2}$$

where σ represents the sigmoid function, and f7×7 signifies a convolution operation with a filter size of 7×7. This convolutional operation allows the model to capture intricate spatial dependencies within the input data, emphasizing the significance of specific spatial regions. The resulting spatial attention map serves as a refined representation and prioritizes spatial information crucial for intricate pattern recognition and feature extraction in the input data.

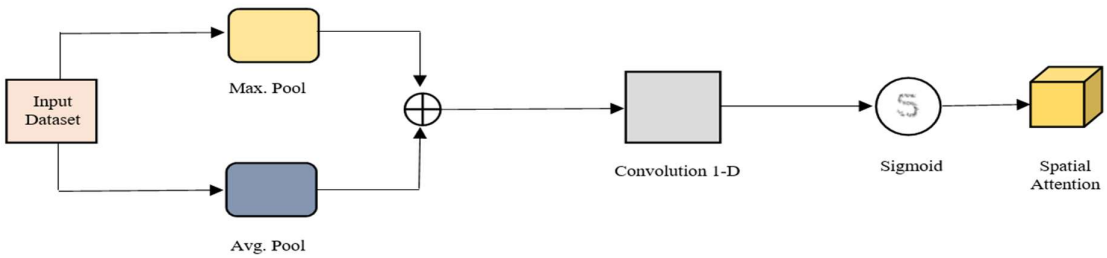


Figure 4.4 Block Diagram of Spatial Attention

4.3.1.3 Combination of Channel and Spatial Attention

Both the channel attention and spatial attention components operate independently on the input feature map. The final output is obtained by element-wise addition of the channel-wise attention and spatial-wise attention feature maps. This combined attention is used to refine the original input feature map, providing a more focused and context-aware representation.

4.3.1.4 Integration into a Neural Network

The attention module is integrated into a neural network architecture by inserting it as a layer within the network. In the provided code, an example usage is demonstrated where the attention module is applied to an input tensor, and a model is constructed with the attention module-enhanced feature map as the output.

4.3.2 Convolutional Neural Network for Feature Extraction

This methodology employs Convolutional Neural Networks (CNNs) for hierarchical feature extraction. Initially, a one-dimensional Convolutional layer is employed to capture localized patterns within the input feature matrix X (dimensions N × 2, representing features 'X' and 'Y'). Following this, the data is normalized using Min-Max scaling:

$$X_{\text{scaled}} = [\, X - \min(X)] / [\max(X) - \min(X)] \tag{4.3}$$

This normalization step ensures that the values in the feature matrix are scaled to a range between 0 and 1, which aids in stable and efficient training of the neural network. Subsequently, the normalized data is passed through Flatten and densely connected layers for further complex feature extraction, ultimately resulting in a condensed data representation suitable for subsequent processing.

The constructed neural network, as a Sequential model, comprises a Conv1D layer. Within this layer, there are F filters (32 in this case), each with a kernel size of a (1 in this case). Each filter is designed to learn a distinct feature from the input data, allowing the layer to train F different features. The convolution operation is expressed as:

$$v^j = f_a(b_j + \sum_i w^{ij} \times u^i) \tag{4.4}$$

where, u^i and v^j are the i-th input feature map and the j-th output feature map respectively. bj denotes the bias, " × " denotes the convolution operation, wij are the weights of the convolution filter, and $f_a(\cdot)$ represents the activation function of the j-th output feature map. For a given (M×N) input (M=340 sample points and N is the number of channels selected), the output of this layer is a $((M-a+1)\times F)$ matrix. The activation function introduces non-linearity to the output of the convolution, which is represented as:

$$\mathrm{ReLu(u)} = \max(\mathrm{u}, 0) = \begin{cases} u_i, if\ u_i \geq 0 \\ 0, if\ u_i < 0 \end{cases} \tag{4.5}$$

This is followed by a Flatten layer and Dense layers with 128, 64, and 32 neurons, all employing ReLu activation. These layers perform a reduction operation on a vector of length F to generate an output vector of length C, representing the number of classes to be predicted. The reduction operation is expressed as:

$$v^j = f_a(\sum_{i=1}^{F} w^{ij}\, u^i + b) \tag{4.6}$$

where, u^i and v^j are the i-th input feature map and the j-th output feature map. Here, u^i represents the i-th neuron of an mm-dimensional input vector, v^j denotes the j-th neuron of a C-dimensional output vector, w is a C×F weight matrix, b is the bias term, and $f_a(\cdot)$ represents the non-linear activation function applied to the output. This formulation implies that each neuron in the output

vector y is influenced by a weighted sum of the input neurons x where the weights are determined by the matrix w, and the bias term b is added. The non-linear activation function $f_a(\cdot)$, which is basically ReLu, introduces non-linearity to the output of each neuron in the C-dimensional vector.

The output layer comprises two neurons with linear activation. The model is compiled with the Adam optimizer and Mean Squared Error (MSE) loss, and training spans 100 epochs with a batch size of 32. Use the trained model to predict features from the input data. The Mean Squared Error (MSE) is represented as:

$$\mathrm{MSE} = \frac{1}{n}\sum_{j=1}^{n}(v^j - \hat{v}^j)^2 \tag{4.7}$$

Where n is the number of data points in the dataset. vj represents the actual value for the j-th data point, and $\hat{v}^j$ denotes the predicted value for the j-th data point. The MSE quantifies the average squared difference between the actual and predicted values across all data points, providing a measure of the model's accuracy in approximating the true relationship between the input features and the target variable.

4.3.3 Fuzzy C- Means Clustering

In the subsequent stage of our methodology, Fuzzy C-Means (FCM) clustering is applied to the features extracted by the CNN. Consider a set of unlabelled patterns $X=\{x_1, x_2,...,x_N\}$, where $x_i \in R^f$, N is the number of patterns, and f is the dimension of pattern vectors (features). The FCM algorithm focuses on minimizing the value of an objective function. The objective function measures the quality of the partitioning that divides a dataset into C clusters. The FCM algorithm measures the quality of the partitioning by comparing the distance from pattern x to the current candidate cluster center Wj with the distance from pattern x to other candidate cluster centers. The objective function is an optimization function that calculates the weighted within-group sum of squared errors (WGSS) as follows:

$$J_m(U,W) = \sum_{j=1}^{C}\sum_{i=1}^{N}(\mu_{ij})^{\,m}\, d_{ij}^2 \tag{4.8}$$

Where N is the number of patterns in X, C is the number of clusters, U is the membership function matrix; the elements of U are μ_{ij}, μ_{ij} is the value of the membership function of the i-th pattern belonging to the j-th cluster, d_{ij} is the distance from x_i to w_{tj} viz., $d_{ij}=||x_i-w_{tj}||$ where w_{tj} denotes the cluster center of the j-th cluster for the t-th iteration, W is the cluster center vector, m is the exponent on μ_{ij} to control fuzziness or the amount of cluster overlap. The FCM algorithm focuses on minimizing J_m, subject to the following constraint on U:

$$\mu_{\mathrm{ij}} \in [0,1], \mathrm{i} = 1,2, \dots \dots, \mathrm{N} \text{ and } \mathrm{j} = 1,2, \dots \dots, \mathrm{C} \tag{4.9}$$

$$\sum_{j=1}^{\mathrm{C}} \mu_{\mathrm{ij}} = 1, \mathrm{j} = 1,2, \dots \dots, \mathrm{C} \tag{4.10}$$

$$0 < \sum_{\mathrm{i}=1}^{\mathrm{N}} \mu_{\mathrm{ij}} < \mathrm{N}\,, \mathrm{i} = 1,2, \dots \dots, \mathrm{N} \tag{4.11}$$

Function (4.8) describes a constrained optimization problem, which can be converted to an unconstrained optimization problem by using the Lagrange multiplier technique.

$$\mu_{ij}^{(t)} = \frac{1}{\sum_{l=1}^{C} \left(\frac{d_{ij}}{d_{il}}\right)^{\frac{1}{(m-l)}}} . 1^{\left(\frac{2}{m-l}\right)} \tag{4.12}$$

$$i = 1,2, \dots \dots, N \; and \; j, \mathrm{l} = 1,2, \dots \dots, C$$

$$if \; d_{ij} = 0 \,, then \; \mu_{ij} = 1 \; and \; \mu_{ij} = 0 \; for \; l \neq j \tag{4.13}$$

$$w_j^t = \frac{\sum_{i=1}^{N} (\mu_{ij}^{(t-l)})^{\,m} x_i}{\sum_{i=1}^{N} (\mu_{ij}^{(t-l)})^{\,m}}, j = 1,2, \dots \dots, C \tag{4.14}$$

The FCM algorithm starts with a set of initial cluster centers (or arbitrary membership values). The complete algorithm consists of the following steps:

- Step 1: Given a fixed number C, initialize the cluster center matrix W_0 by using a random generator from the dataset. Record the cluster centers, set t=0, m=2, and decide E, where E is a small positive constant.
- Step 2: Initialize the membership matrix U_0 by using functions (4.9) and (4.10).
- Step 3: Increase t by one. Compute the new cluster center matrix W^t by using (4.11).
- Step 4: Compute the new membership matrix U^t by using function (4.12) and (4.13).
- Step 5: If $||U^t - U^{t-1}|| < E$ then stop, otherwise go to step 3.

The synergy between CNN-based feature extraction and FCM clustering embodies a symbiotic relationship, where the flexibility of FCM in handling complex datasets and the hierarchical feature learning capabilities of CNNs collectively contribute to a robust framework for data analysis and exploration.

The algorithm employs an iterative approach to fit two ellipses to the dataset, aiming to identify a cluster as an ellipse based on a predefined coverage target. It initializes parameters for two ellipses: a small ellipse with axes (semi-major, semi-minor), angle 0, and center [0, 0], and a large ellipse with the same properties. A target coverage is defined, with the initial coverage set to 0.0. The iterative process involves rotating the ellipses by a fixed angle increment, visualizing the data along with the ellipses, updating the angles, and displaying the current coverage. This rotation can be described mathematically using a rotation matrix. Let θ represent the current angle of rotation, and Δθ denote the fixed angle increment applied in each iteration. The rotation operation is performed as follows:

1) **Rotation Matrix:** The 2D rotation matrix is given by:

$$R = \begin{bmatrix} cos\theta & -sin\theta \\ sin\theta & cos\theta \end{bmatrix} \quad (4.15)$$

This matrix represents a counter-clockwise rotation by an angle theta (θ).

2) **Iterative Rotation:** In each iteration, the current angle angle θ is updated by adding the fixed angle increment mentioned as:

$$\theta \leftarrow \theta + \Delta\theta \quad (4.16)$$

3) **Ellipse Rotation:** The ellipse parameters, such as the semi-major and semi-minor axes (a, b) are rotated using the rotation matrix:

$$\begin{pmatrix} a' \\ b' \end{pmatrix} = R(\theta) \begin{pmatrix} a \\ b \end{pmatrix} \tag{4.17}$$

Here, (a', b') represents the rotated ellipse parameters. By iteratively updating the rotation angle and applying the rotation matrix to the ellipse parameters, the algorithm dynamically rotates the ellipses in a controlled manner, providing a visual representation of the adjustment process and facilitating convergence to an optimal orientation that captures the cluster structure. Points within the ellipses and in the gap between them are identified. The ellipse centers are gradually moved towards the cluster centroid, and the ellipse sizes are increased iteratively. Let c represent the current center of the ellipse, and $C_{centroid}$ denote the cluster centroid. The movement towards the cluster centroid is performed gradually over each iteration as follows:

$$c \leftarrow (1 - \alpha).c \; + \; \alpha.C_{centroid} \tag{4.18}$$

Here, α is a small positive constant, and the operation is performed element-wise for each dimension of the center. The sizes of the ellipses can be increased iteratively by adjusting their semi-major and semi-minor axes. Let (a, b) represent the current axes of the ellipse, and $(\Delta a, \Delta b)$ denote the incremental changes in the axes. The size increase operation is performed iteratively as follows:

$$(a, b) \leftarrow (a + \Delta a, b + \Delta b) \tag{4.19}$$

Here, $(\Delta a, \Delta b)$ is determined based on the algorithm's design and the specific requirements for size adjustments. The coverage ratio is calculated. The coverage ratio is computed as:

$$Current\ Coverage = \frac{\mathrm{N_{total}}}{\mathrm{N_{within\ ellipses\ or\ gap}}} \tag{4.20}$$

And the algorithm updates the coverage while decrementing rotation attempts. If the current coverage surpasses or equals the target coverage, the cluster is declared as an ellipse; otherwise, the algorithm indicates that the cluster could not be declared as an ellipse. This dynamic adjustment of

ellipse parameters, coupled with visual feedback and iterative refinement, ensures a tailored and accurate representation of the cluster structure.

4.4 Experiment And Result

In the experimental phase, the proposed model underwent rigorous assessments to ascertain its effectiveness in cluster shape detection. Leveraging a synthetic dataset enriched with diverse shapes and intentional noise, the model's adaptability and accuracy were meticulously evaluated. The results, validated through prominent metrics, demonstrated the model's robust performance and its potential to uncover the patterns within the cluster data. The experimental details are as follows:

4.4.1 Dataset

In the synthetic dataset created using NumPy, Pandas, and Matplotlib, the data points span the range of 0 to 200 for both X and Y coordinates. The dataset, with dimensions of 340 × 2, exhibits three distinguishable shapes: a triangle, an ellipse, and a rectangle. While these shapes lack precise geometrical boundaries, their collective emergence suggests an inherent structural organization within the dataset. We purposely added some noise, like random tweaks, to make things interesting and realistic.

4.4.2 Experimental Setup

The experimental settings utilized for the represent scenario include the input tensor with shape (340 × 2×1). The channel attention module incorporates global average pooling, global max pooling, and shared dense layers with a reduction ratio of 16. The spatial attention module includes global average pooling, global max pooling, concatenation, reshaping, and convolution with a kernel size of 7. The Sequential model of the neural network is composed of a Conv1D layer with 32 filters, utilizing a kernel size of 1 and ReLU activation. Subsequently, a Flatten layer is employed, followed by Dense layers featuring 128, 64, and 32 neurons, all activated by ReLU. The output layer consists of two neurons with a linear activation function. During the model compilation phase, the Adam optimizer is applied alongside Mean Squared Error (MSE) loss. Training the model extends over 100 epochs, with a batch size set at 32.

4.4.3 Results of Cluster Shape Detection

After incorporating an attention module into the dataset and utilizing the output in a CNN-induced clustering algorithm, the resulting clusters are triangle, ellipse and rectangle in shape (Figure 4.5).Figure 4.6 (b) illustrates a cluster resembling a triangle, and Figure 4.6 (a) depicts an elliptical cluster. Upon applying our shape detection algorithms to each cluster, it is evident that the algorithm excels in identifying elliptical clusters, which is our main motivation, with an efficiency exceeding 80 percentage. Additionally, the algorithm was evaluated for detecting triangle and rectangle shapes, yielding consistent results. However, due to space restrictions, we are unable to present the detailed results here. For detecting Ellipse shape only the algorithm correctly detect ellipse shape as shown in Fig 4.6 (a) but for other shapes (triangle, rectangle) it correctly detect that they are not ellipse shape in Fig 4.6 (b) and Fig 4.6 (c).

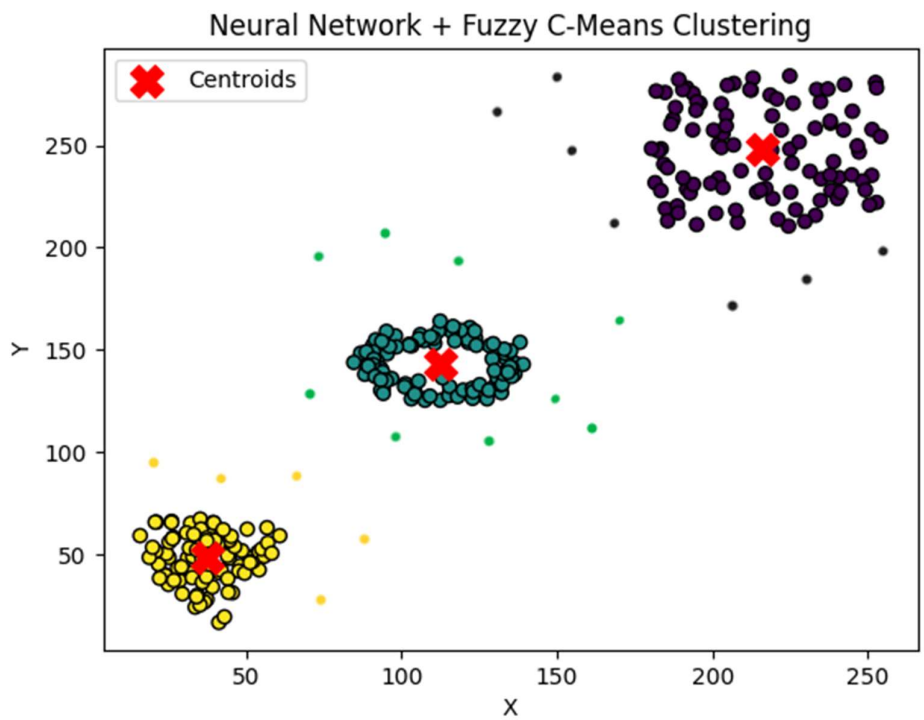
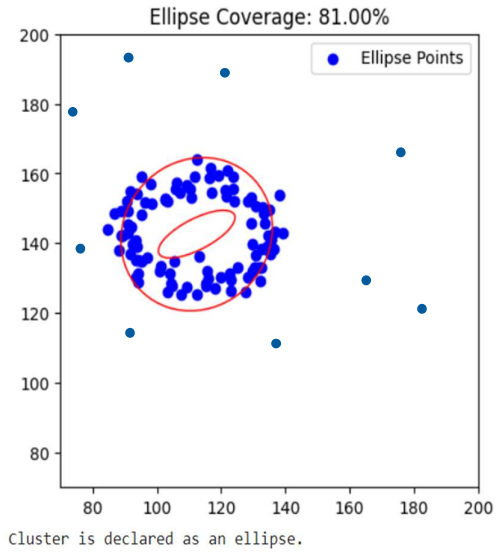
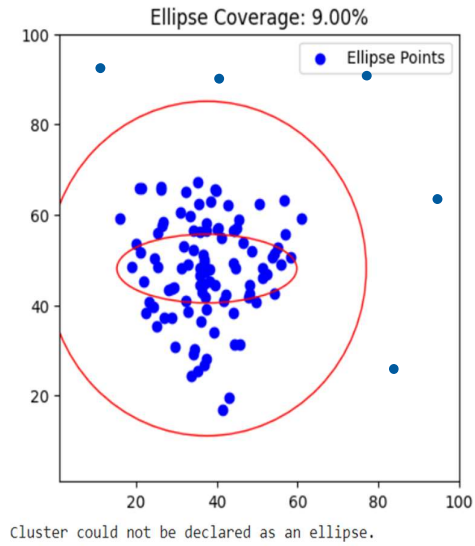


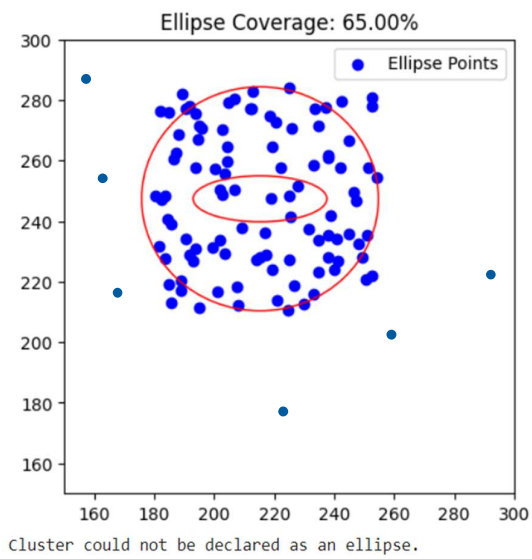
Figure 4.5 After Feature Extraction and C- means Clustering



(a)



(b)



(c)

Figure 4.6. Cluster shape detection results for ellipse (a) The cluster is identified as ellipse (b) The cluster is not identified as ellipse (c) The cluster is not identified as ellipse.

4.4.4 Comparative Study with State-Of-The-Art Methods

In this section, we evaluate the performance of our proposed algorithm in comparison to other relevant algorithms, employing metrics such as Silhouette Score and Davies-Bouldin Index. These metrics serve as key indicators for assessing the efficiency, accuracy, and overall performance of algorithms. As illustrated in Table 4.1, the proposed technique outperforms its traditional counterparts by a huge margin with respect to both Silhouette Score and Davies-Bouldin Index. Moreover, the proposed technique also proves to be computationally efficient as compared to most of the state-of-the-art methods.

TABLE 4.1: Comparative Analysis of The Proposed Model With Traditional Algorithms

Algorithms	Silhouette Score (%)	Davies – Bouldin Index (%)	Run Time Complexity (ms)
K- Means Clustering [3]	60.21	56.51	26.52
FCM [7]	68.30	48.87	35.78
Gaussian Mixture Model [4]	78.36	38.17	47.14
DBSCAN [2]	79.14	36.34	46.87
DAICC	**83.47**	**29.03**	**45.32**

4.4.5 Ablation Study

In our ablation study, we systematically examined the effectiveness of various architectural configurations. Initially, we considered a baseline architecture involving a combination of CNN for feature extraction, followed by clustering and a shape detection algorithm. Subsequently, we explored an alternative approach incorporating spatial attention in conjunction with CNN, clustering, and the

shape detection algorithm. In further iterations, we replaced spatial attention with channel attention to assess its impact on performance. Notably, we introduced our proposed attention module, which combines both spatial and channel attention, integrated with CNN, clustering, and the shape detection algorithm. Through rigorous experimentation, our results indicate that this latter configuration generated the most favourable outcomes, demonstrating the effectiveness of our proposed attention module in enhancing the overall performance of the system.

TABLE 4.2: Ablation Study of the Proposed Model

Architecture	Silhouette Score (%)	Davies – Bouldin Index (%)
CNN + FCM + Shape Detection Algorithm	80.06	35.56
Spatial Attention + CNN + FCM + Shape Detection Algorithm	81.11	33.37
Channel Attention + CNN + FCM + Shape Detection Algorithm	81.27	34.61
Attention Module (Spatial Attention + Channel Attention) + CNN + FCM + Shape Detection Algorithm	**83.47**	**29.03**

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Chapter 5

Conclusion

Cluster analysis is a fundamental task in data mining and machine learning, with applications spanning various domains such as pattern recognition, image processing, and anomaly detection. In this study, we proposed and evaluated the Dual Attention Induced Convolutional-Clustering (DAICC) algorithm, designed to address the challenge of cluster shape detection in datasets exhibiting complex structural organization. The effectiveness of the DAICC algorithm was demonstrated through rigorous experimentation and comparative analysis with state-of-the-art methods. By integrating attention mechanisms with convolutional neural networks (CNNs) and clustering algorithms, DAICC offers a novel approach to cluster shape detection, surpassing traditional techniques in terms of both accuracy and computational efficiency.

Our experimental results on synthetic datasets revealed the robustness of DAICC in identifying various cluster shapes, including triangles, ellipses, and rectangles. Through the incorporation of attention modules, DAICC demonstrated superior performance in distinguishing elliptical clusters, achieving an efficiency exceeding 80%. Furthermore, the algorithm exhibited consistent results for triangle and rectangle shapes, highlighting its versatility and applicability across different data distributions.

A key contribution of this study lies in the comparative analysis with established clustering algorithms, where DAICC outperformed traditional methods by a significant margin in terms of metrics such as Silhouette Score and Davies-Bouldin Index. Notably, DAICC exhibited computational efficiency comparable to or better than state-of-the-art algorithms, demonstrating its suitability for real-world applications with large-scale datasets.

The ablation study conducted in this research further underscored the significance of each component within the DAICC architecture. By systematically examining various architectural configurations, we confirmed the effectiveness of the proposed attention module, which combines spatial and channel attention mechanisms. This attention module, integrated with CNNs, clustering, and shape detection algorithms, yielded the most favourable outcomes in terms of cluster shape detection accuracy. In conclusion, the DAICC algorithm represents a significant advancement in the field of cluster analysis, particularly in the context of shape detection. By leveraging attention mechanisms and deep learning techniques, DAICC offers a versatile and efficient solution for identifying complex cluster shapes in diverse datasets. Beyond the synthetic datasets used in our

experiments, DAICC holds promise for real-world applications across domains such as urban planning, medical imaging, and environmental monitoring.

In urban structure analysis, DAICC provides insights into urban environments, aiding urban planners and architects in optimizing designs and fostering sustainable development. In healthcare, it assists in detecting and characterizing pathological structures from medical images, empowering informed decision-making in diagnoses and treatment planning. By analyzing water samples, it contributes to monitoring water quality and safeguarding public health against waterborne diseases. DAICC also tracks environmental changes, aiding in biodiversity conservation, ecosystem management, and climate change research. In industrial applications, it optimizes processes, enhances product quality, and minimizes inefficiencies, bolstering competitiveness and operational excellence. Additionally, DAICC aids in spatial data exploration, disaster management, and resource allocation, fostering resilience and prosperity. It analyzes traffic patterns, aiding in optimizing transportation networks and improving mobility in urban areas. Moreover, DAICC optimizes store layouts and marketing strategies, enhancing customer experiences and driving business growth. In natural disaster response and emergency management, it supports emergency responders in assessing impact and coordinating response efforts during disasters. By analyzing soil and crop data, it enables data-driven decision-making in farming practices, promoting sustainability and food security. Furthermore, DAICC identifies optimal locations for renewable energy installations, contributing to energy independence and sustainability. It aids in prioritizing conservation actions and protecting endangered species by analyzing spatial patterns of species distribution. Additionally, DAICC identifies suspicious financial transactions, mitigating risks and safeguarding against financial losses.

The findings presented in this study pave the way for future research directions in cluster analysis and machine learning. Further investigations could focus on extending the applicability of DAICC to multi-dimensional datasets, exploring alternative attention mechanisms, and adapting the algorithm for specific domain-specific challenges. Additionally, efforts to validate DAICC on real-world datasets and integrate it into practical systems would contribute to its adoption and impact in various fields.

Overall, the DAICC algorithm stands as a testament to the potential of combining attention mechanisms with deep learning for addressing complex data analysis tasks. With its robust

performance, efficiency, and versatility, DAICC represents a valuable tool for researchers and practitioners seeking to extract meaningful insights from high-dimensional data and tackle real-world challenges in data-driven decision-making.

Chapter 6

Future Scope of the Work

The future scope of work for the DAICC (Dual Attention Induced Convolutional-Clustering) algorithm are rich and multifaceted, offering promising avenues for further research and development in the field of spatial data analytics. These future endeavours extend beyond the algorithm's current capabilities, aiming to enhance its efficacy, applicability, and scalability across diverse domains and applications. Here's a more descriptive exploration of the future scope of work for the DAICC algorithm.

1. Enhanced Feature Representation

Future research could delve into refining the feature extraction process to capture nuanced spatial patterns with greater fidelity. By exploring advanced techniques such as deep learning architectures or spatial-temporal modelling, the algorithm can achieve more comprehensive feature representation, leading to improved accuracy in detecting cluster shapes.

2. Real-Time Implementation

There's a growing demand for real-time analytics in various domains, including urban planning, disaster management, and transportation. Future endeavours could focus on optimizing the DAICC algorithm for real-time implementation, enabling it to analyse streaming data and provide timely insights for decision-making processes. This would involve developing efficient algorithms and data structures capable of processing high-volume data streams in near real-time.

3. Multi-Modal Data Integration

As data sources become increasingly diverse and complex, there's a need to develop techniques for integrating multi-modal data sources into the DAICC algorithm. This could include incorporating satellite imagery, sensor data, social media feeds, and other heterogeneous data sources to enrich the analysis and provide a more comprehensive understanding of spatial phenomena.

4. Scalability and Efficiency

With the proliferation of big data, scalability and efficiency are paramount for data analytics algorithms. Future research could focus on optimizing the DAICC algorithm to handle large-scale datasets efficiently, leveraging parallel computing paradigms, distributed processing frameworks, and optimization techniques to improve scalability and performance.

5. Domain-Specific Customization

Different application domains pose unique challenges and requirements for cluster shape detection. Future research could explore domain-specific customization of the DAICC algorithm to address the specific needs of diverse fields such as healthcare, environmental monitoring, cybersecurity, and finance. This could involve adapting the algorithm's parameters, features, and methodologies to suit the characteristics of each domain, thereby enhancing its effectiveness and applicability.

6. Interpretability and Explainability

As data-driven algorithms are increasingly deployed in critical decision-making processes, there's a growing demand for transparency and interpretability. Future research could focus on enhancing the interpretability and explainability of the DAICC algorithm's results, enabling stakeholders to understand how the algorithm arrives at its conclusions and trust the insights generated. This could involve developing visualization techniques, model explanations, and uncertainty quantification methods to provide meaningful interpretations of the algorithm's outputs.

7. Adaptive Learning and Self-Improvement

Continuous learning and adaptation are essential for data analytics algorithms to stay relevant in dynamic environments. Future research could explore methods for incorporating adaptive learning mechanisms into the DAICC algorithm, allowing it to adapt and improve over time based on feedback from real-world deployments, user interactions, and changing data distributions. This could involve techniques such as online learning, reinforcement learning, and evolutionary algorithms to enable self-improvement and adaptation in response to evolving data patterns and user needs.

8. Collaborative Research and Interdisciplinary Applications

Addressing complex societal challenges often requires interdisciplinary collaboration and expertise from diverse domains. Future research could foster collaborative efforts between researchers from fields such as computer science, engineering, social sciences, and environmental science to explore interdisciplinary applications of the DAICC algorithm. By bringing together expertise from different disciplines, researchers can leverage the algorithm to address multifaceted challenges such as urban planning, environmental conservation, public health, and social welfare, leading to more holistic and impactful solutions.

9. Privacy-Preserving Data Analytics

With growing concerns about data privacy and security, there's a need to develop techniques for conducting data analytics while preserving individuals' privacy and confidentiality. Future research could focus on privacy-preserving data analytics methods for the DAICC algorithm, ensuring that sensitive information remains protected while still extracting valuable insights from the data. This could involve techniques such as differential privacy, homomorphic encryption, and federated learning to enable secure and privacy-preserving data analysis in sensitive domains such as healthcare, finance, and telecommunications.

10. Open-Source Development and Community Engagement

Open-source development fosters collaboration, innovation, and knowledge sharing within the research community. Future efforts could focus on promoting open-source development of the DAICC algorithm, encouraging community contributions, and facilitating collaboration among researchers, developers, and practitioners. By building an open and inclusive ecosystem around the algorithm, researchers can accelerate innovation, drive adoption, and address emerging challenges in the field of spatial data analytics.

By delving into future scope, researchers can unlock new possibilities for advancing cluster shape detection and spatial analysis, paving the way for innovative solutions to complex real-world challenges.

Appendix

User guide to run the codes

This section provides step wise step guidance for the execution of the codes given in the accompanying CD at the end of the thesis.

- **Step 1:**

For our work we are using Google Colab .First we have to upload our required dataset as shown in Fig: 5.1

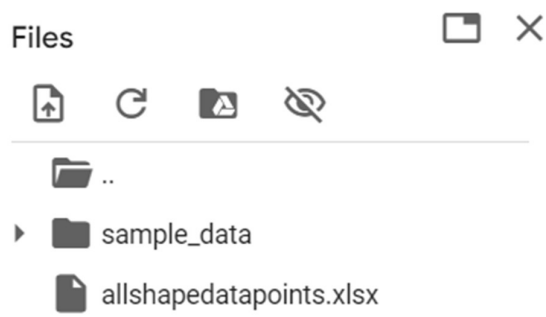


Fig: 5.1 Upload The Required Data

- **Step 2:**

In the context of Python programming, ensure to import all required libraries. If a library is not available, install it using the pip command before importing it for subsequent use.

```
!pip install -U scikit-fuzzy
```

```
import pandas as pd
import numpy as np
import skfuzzy as fuzz
import matplotlib.pyplot as plt
from sklearn.preprocessing import MinMaxScaler
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv1D, MaxPooling1D, Flatten, Dense
```

Fig: 5.2 Install And Import Required Libraries

- **Step 3:**

Now write the python code for the attention module and save the output data in an excel format for further use

```
# Assuming your data has two columns 'X' and 'Y'
input_data = data[['X', 'Y']].values

# Reshape the data to match the input shape of the model
input_data = input_data.reshape((input_data.shape[0], input_data.shape[1], 1))

def channel_attention(input_tensor, reduction_ratio=16):
    avg_pooled = layers.GlobalAveragePooling1D()(input_tensor)
    max_pooled = layers.GlobalMaxPooling1D()(input_tensor)

    shared_layer_1 = layers.Dense(input_tensor.shape[-1] // reduction_ratio, activation='relu')
    shared_layer_2 = layers.Dense(input_tensor.shape[-1])

    avg_att = shared_layer_2(shared_layer_1(avg_pooled))
    max_att = shared_layer_2(shared_layer_1(max_pooled))

    channel_attention = layers.Activation('sigmoid')(avg_att + max_att)

    return layers.Multiply()([input_tensor, channel_attention])

def spatial_attention(input_tensor):
    avg_pooled = layers.GlobalAveragePooling1D()(input_tensor)
    max_pooled = layers.GlobalMaxPooling1D()(input_tensor)

    concatenated = layers.Concatenate()([avg_pooled, max_pooled])
    reshaped = layers.Reshape((1, -1))(concatenated)
```

Fig 5.3: Screen Displaying The Programs To Be Written In Python

- **Step 4:**

Now use the Output data and write the python code for Convolutional C- means Clustering and evaluate the quality of cluster results. Also save the datapoints belong to different shaped cluster in excel files.

```
# Extract features for clustering
features = data[['X', 'Y']].values

# Normalize data using Min-Max scaling
scaler = MinMaxScaler()
features_scaled = scaler.fit_transform(features)

# Reshape data for Conv1D input as Conv1D layer in Keras expects a three-dimensional input with the shape (num
features_scaled = features_scaled.reshape(features_scaled.shape[0], features_scaled.shape[1], 1)

# Neural network for feature extraction
model = Sequential()
model.add(Conv1D(filters=32, kernel_size=1, activation='relu', input_shape=(2, 1)))
#each input sample has two features, and each feature is represented by a one-dimensional array (shape (1,)).
model.add(Flatten())#flatten the output from the convolutional layer into a one-dimensional vector.
model.add(Dense(128, activation='relu'))
model.add(Dense(64, activation='relu'))
model.add(Dense(32, activation='relu'))
model.add(Dense(2, activation='linear'))
model.compile(optimizer='adam', loss='mse')
```

Fig 5.4: Screen Denoting The Method For Running The Codes In Python

- **Step 5:**

After step 4, we are getting different shaped clusters' datapoints. Now use that data and write an algorithm that can check your required shape.

```
# Decide whether to declare the cluster as an ellipse or rotate and recheck
target_coverage = 0.85
current_coverage = 0.0
rotation_step = 5
max_rotation_attempts = 360 // rotation_step

while current_coverage < target_coverage and max_rotation_attempts > 0:
    small_ellipse_angle += rotation_step
    large_ellipse_angle += rotation_step

    fig, ax = plt.subplots()
    plt.scatter(cluster_data[:, 0], cluster_data[:, 1], c='b', label='Ellipse Point
```

Fig 5.5: Cluster Shape Detecting Code Writing In Python