Nature's Palette: From Databases to Networks for Flowers, Foliage, and Gemstones Classification

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IN

INTELLIGENT AUTOMATION AND ROBOTICS

By

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DECLARATION OF ORIGINALITY AND COMPLIANCE OF ACADEMIC ETHICS

I, **Ranadhir Das,** hereby declare that this thesis entitled, "**Nature's Palette: From Databases to Networks for Flowers, Foliage, and Gemstones Classification**" contains literature survey and original research work done by the undersigned candidate as a part of Master of Technology (M.Tech) in Intelligent Automation and Robotics offered by the Department of Electronics and Telecommunication Engineering.

All the information in this thesis are obtained and presented in accordance with existing academic rules and ethical conduct. I declare that, as required by these rules and conduct and ethical conduct, I have fully cited and referred all materials when required and none of the work represented in this thesis is fabricated.

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This is to certify that the thesis entitled **—** "**Nature's Palette: From Databases to Networks for Flowers, Foliage, and Gemstones Classification**" has been carried out by **Ranadhir Das** (Class Roll No: **002110704001**, Examination Roll No.: **M6IAR24002** and Registration No: **160219** of **2021-2022**) under my guidance and supervision and be accepted in partial fulfilment of the requirement for the degree of Master of Technology in Intelligent Automation and Robotics offered by the Department of Electronics and Telecommunication Engineering.

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The forgoing thesis titled − "**Nature's Palette: From Databases to Networks for Flowers, Foliage, and Gemstones Classification**" is here approved as a creditworthy study of an engineering subject conducted and presented satisfactorily to warrant its acceptance as a precondition to the degree for which it was submitted. It is understood that the undersigned does not automatically support or accept any argument made, opinion expressed, or inference is drawn in it by this approval, but only approve the thesis for the reason for which it was submitted.

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[3]. Sriparna Banerjee, **Ranadhir Das**, Bidisha Samanta, Swati Chowdhuri and Sheli Sinha Chaudhuri, "Herbal Leaf Repository: Unveiling Nature's Pharmacy", Dairy Number: 12120/2024-CO/L (Communicated). (Database is publically available at the following link: https://data.mendeley.com/datasets/rryf548b6p/1)

[4]. **Ranadhir Das**, Sriparna Banerjee and Sheli Sinha Chaudhuri, "The Gem Atlas: A Pictorial Database of Precious Stones", Dairy Number: 14873/2024-CO/L (Communicated). (Database is publically available at the following link: https://data.mendeley.com/datasets/6crrpfxvn8/1)

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[1]. **Ranadhir Das**, Sriparna Banerjee, Bidisha Samanta, Swati Chowdhuri, Aruna Pavate, Smita Chavan, Varsha Damodar Jadhav, Sheli Sinha Chaudhuri, Rupali Mahajan ,Invention:"DEEP LEARNING-BASED METHOD AND SYSTEM FOR DETECTING INSULIN LEAF DISEASES ", Application No. 202331078058, The Patent Office Journal No. 47/2023, Publication Date : 24th November, 2023.

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Abstract

The thesis entitled "**Nature's Palette: From Databases to Networks for Flowers, Foliage, and Gemstones Classification**" primarily focuses on real-life leveraging of smart agriculture and artificial intelligence. The work conducted in this thesis is mostly focused on curation of several databases which is essential for authenticated training of deep neural networks in order to prepare the networks to perform automated categorization tasks as well as design of light-weight dual attention network to achieve a perfect desired balance between computational and performance efficiencies.

This thesis has mostly concentrated on curation of new databases for identification of distinct floral species growing in my native place Ranaghat which plays a significant role in enhancing the annual revenue growth of the floriculture industry of West Bengal as well as India. The thesis work is also extended to designing new databases focused on categorization of healthy and damaged insulin leaves which have inherent hyperglycemic properties and serve as natural diabetes healer, classification of five different foliage species which have immense medicinal properties and curation of a novel vegetable database comprising of fresh, damaged and severely damaged vegetables which is prepared for performing automated freshness evaluation of edibility of vegetables.

The curation of databases have been one of the primary focus of this thesis owing to their notable significance in computer vision domain.

Apart from curating new databases, the focus of thesis also lies in designing new deep neural based architecture for performing categorization task.

This thesis also mentions a novel database of the precious gemstones which is created for performing automated classification task. This mentioned gemstone database fills the research gaps for designing an identification system in this domain.

The novelties of this thesis work is highlighted as follows:

- ***Newly curated databases***

1. BongFloralpedia: A comprehensive collection of diverse types of flowers growing in fields of Ranaghat, Bengal

2. Nature's Diabetes Helpers: Insulin Leaves Repository

3. Herbal Leaf Repository: Unveiling Nature's Pharmacy

4. The Gem Atlas: A Pictorial Database of Precious Stones

5. Nature's Best vs. Bruised: A Veggie Evaluation

- **Deep neural architecture**

6. GreenMedNet which is designed to perform categorization of damaged and healthy insulin leaves.

Chapter 1

1. Introduction

This chapter provides a concise overview of each work examined in the thesis, delving into the significance of the problems they address in the real world, supported by statistical data from credible sources. It discusses the motivation driving the image processing tasks explored in this thesis. The chapter concludes with a thorough description of the thesis's organization.

1.1 BongFloralpedia : A comprehensive collection of diverse types of flowers growing in fields of Ranaghat, West Bengal

The productivity of crops is greatly threatened by various factors, including bacterial, viral, and fungal diseases etc. which serve as one of the major reason behind the reduction of the annual revenue earned by India as well as other countries from the agriculture industry there by causing financial distress to farmers.

According to a report published in [1], it has been stated that India ranks globally second after China and the country has earned a total of 774.41 crores in 2021-2022 by exporting flowers. The same report also stated that the earnings of India has increased at an average rate of 10%-15% annually with West Bengal, Maharashtra, Karnataka being the most significant flower growing states.

In [2], it has been stated that the Indian Government has identified floriculture as a significant upcoming industry as it has added a net amount of 701.81 crores to the total revenue earned by the country in 2022-2023. Floriculture industry has left its' mark in India only but according to a report published in [3], globally also the floriculture industry lead to an earning of eleven billion USD by exporting flower bouquets.

Despite of being such an important revenue earning industry, floriculture suffers from immense financial loss due to damages caused from undesired sources or because of uncontrolled use of pesticides. To mitigate these shortcomings, regular monitoring of different floral species is required for timely diagnosis of diseases to prevent undesired wastage of crops. For this reason, automated floral health monitoring systems are required to provide time-efficient and cost-effective solutions to this problem as manual inspection involves huge cost as well as time and is also subjected to human error. Moreover, due to the limited availability of experts, regular monitoring of flowers growing in fields located in remote locations by manual experts is often not feasible.

Overwhelming performances achieved by advanced computer vision networks in categorization and detection tasks in past decade have also served as an inspiration behind designing these automated systems. Databases play a crucial role in determining the performance efficiencies of the designed systems as the training of such systems are largely dependent on the varsity in characteristics among the samples belonging to different flower categories present in the databases.

For performing reliable classification of floral diseases, proper identification of distinct floral species are required. For this purpose, some researchers have developed databases whose details I have given in Chapter 2 in Section 2.1. These databases comprise of images of distinct

floral species. The image samples included within these databases are either captured by the creators themselves from real fields or are collected from publicly available sources.

To the best of my knowledge, none of these databases are created considering the floral species growing in West Bengal, India as it contributes a significant portion of the revenue earned by India due to flower exports. This has urged me to choose nine different types of floral species growing in Ranaghat, a well-known flower cultivation area of West Bengal for the curation of this database. The novel database which I have developed in this work is termed as "BongFloralpedia" dedicated to the place of origin of flowers whose images are included in this database. The floral species which are selected in this work for the creation of the database contributes largely to the revenues of the state as well as India as those flowers are exported to other countries and also have immense medicinal values.

1.2 Construction of Nature's Diabetes Helpers: Insulin Leaves Repository, GreenMedNet and Herbal Leaf Repository: Unveiling Nature's Pharmacy

Every year, farmers residing worldwide grapple with substantial monetary challenges stemming from crop yield losses caused by detrimental plant diseases. These diseases mostly occur due to attacks by unwanted causes (insects, pests, and overuse of pesticides etc.). According to findings from a 2016 article [4], India witnesses an approximate annual crop yield reduction of 15-25% due to diseases resulting from pest and mite infestations, along with bacterial, fungal, and viral infections. A corresponding report highlighted in [5] reveals that the associated annual financial loss due to crop damage reaches Rs 50,000 crore.

Prof. Maria Lodovica and a team of 10 scientists conducted a survey [6], revealing that around 40% of the global annual crop yield is lost to pest infestations. The Director-General of the UN Food and Agriculture Organization emphasized this information during their 2021 convention, noting that these losses lead to a reduction of global revenue by 70B$. Taking into consideration losses attributed to various plant diseases collectively, the cumulative annual financial impact reaches an astonishing 220 billion dollars.

To address this challenge with efficiently both from computational as well as time perspective, scientists have developed various advanced computer vision architectures for detecting plant diseases. In conjunction with these architectures, the choice of suitable databases utilized to train them is equally crucial in asserting the overall efficiency.

Owing to the pivotal role played by databases in this research domain, numerous scientists have organized collections featuring both diseased and healthy leaves across various crop species as well as curated different leaves repository for identification of the leaves as well as its disease. Brief details of noteworthy databases are given in Chapter 2 in Section 2.3. These databases predominantly emphasize plant disease classification, underscoring their importance in advancing research and development efforts in this critical field.

To develop a technologically advanced system for the reliable classification of various foliage species, diversity in samples within the databases used for training and validating the network often play a crucial factor as they significantly influences the network's performance, alongside the design aspects.

As far as my knowledge extends, there is currently no existing database containing images of insulin leaves. In response to these gaps, I have meticulously developed an entirely novel

repository titled "Nature’s Diabetes Helpers: Insulin Leaves Repository”. This well-balanced database comprises a total of 600 images, evenly distributed between two classes—diseased and healthy insulin leaves. This repository serves as a valuable resource for researchers and practitioners seeking to advance understanding and applications related to insulin leaf health and diseases.

In addition to the creation of the innovative "Nature’s Diabetes Helpers: Insulin Leaves Repository," the primary contribution of this study lies in the development of a computationally efficient and hyperparameter-optimized, attention based deep neural network known as "GreenMedNet." This network excels in the classification of damaged and healthy insulin leaves by incorporating multi-scale contextual spatial as well as channel-wise information that too using less number of parameters. The goal is to achieve a highly optimized, computationally efficient, and reliable deep neural network for enhanced insulin leaf classification.

Also I have introduced another database called “Herbal Leaf Repository: Unveiling Nature's Pharmacy”, as there is no such novel database in publicly available sources with new types of leaves to perform the identification or classification methods. The purpose of this database curation is to create new identification methods in future.

1.3 Nature's Best vs. Bruised: A Veggie Evaluation

The motivation behind the research in evaluating vegetable freshness lies in the significant impact it has on the food industry's revenue, both at the local and international levels. As consumers increasingly demand high-quality produce, ensuring the freshness of vegetables has become paramount for growers, distributors, and retailers alike. However, manual inspection methods are often labor-intensive, time-consuming, and subject to human error. Therefore, the development of automated techniques presents an opportunity to streamline this process while maintaining quality standards.

By leveraging advanced technologies such as deep learning, researchers aim to create efficient and cost-effective tools for assessing vegetable freshness. These methods focus on analyzing external morphology, texture, and colour, which are key indicators of freshness. Deep learning algorithms, with their ability to learn complex patterns and features from data, offer promising avenues for accurately categorizing vegetables into specific freshness classes.

Nevertheless, the effectiveness of these automated methods crucially depends on the quality and diversity of the datasets used for training and validation. As such, researchers face the challenge of sourcing or creating suitable databases that encompass the variability in vegetable appearance and freshness levels. Addressing this challenge is essential for ensuring the reliability and generalizability of the developed techniques, ultimately facilitating their adoption within the food industry.

In summary, the motivation behind this work stems from the need to improve the efficiency and accuracy of vegetable freshness evaluation, thereby enhancing the overall quality of produce and positively impacting the revenue of the food industry on a global scale. This is achieved through the development of automated methods, particularly leveraging advanced deep learning technologies, albeit with the challenge of acquiring comprehensive and diverse datasets for training and validation.

1.4 The Gem Atlas: A Pictorial Database of Precious Stones

According to 2020 data [7], India's gem and jewellery exports represent 3.5% of global exports, ranking it among the top seven exporters worldwide. The country leads in diamond jewellery exports, holding a 29.0% share of the global market, followed by silver-cut diamonds and lab-grown diamonds and synthetic stones, which have market shares of 22.0% and 32.7%, respectively. As one of the foremost exporters in this sector, the industry plays a significant role in contributing to India’s foreign exchange reserves. Reports indicate that India saw a substantial 54.13% growth in this sector over the previous year, reaching USD 39.14 billion in 2021-22. Furthermore, the Government of India aims to escalate jewellery exports to a landmark figure of US$ 100 billion by 2027.

So the automated methods for gemstones is required to identify the precious gemstones as well as to create systems to prevent the gemstone radiance and quality reduction due to physical and chemical restoration. So this work is introduced for presenting such classification methods in future for the sake of economic growth of country.

Chapter 2

2. Literature Survey

2.1 Existing floral databases:

17 category flowers[8] :

The developers of this database have curated it by incorporating images of flowers primarily found in the United Kingdom, categorized into 17 distinct types. This database can be described as "balanced" since it contains an equal distribution of 80 images for each flower category considered during its creation. The included images were taken from various camera perspectives and under diverse lighting conditions, resulting in both intra-class and inter-class variations within the dataset.



(a) Snowdrop **(b) Daffodil**

Fig.2.1. Some images incorporated in 17 category flowers dataset, (a) Snowdrop, (b) Daffodil

Edelweis Flower[9]:

The purpose of creating this database is to train machine learning algorithms. This dataset contains real-life photographed images in PNG format. It consists of a total of 4550 images, with 3500 images designated for training and 1050 images for testing. The images in the database specifically focus on three species of Edelweis Flower: Anaphalis Javanica (350 files), Leontopodium Alpinum (350 files), and Leucogenes Grandiceps (350 files).



(a)Anaphalis Javanica **(b) Leontopodium Alpinum** **(c) Leucogenes Grandiceps**

Fig.2.2. Some images incorporated in Edelweis Flower database, (a) Anaphalis Javanica , (b) Leontopodium Alpinum ,(c) Leucogenes Grandiceps

Five Flowers[10]:

The database contains a collection of 3670 images in .jpeg format, representing five distinct flower species: Daisy (633 files), Dandelion (898 files), Roses (641 files), Sunflower (699 files), and Tulips (799 files). The number of samples of different classes of flowers are unequal so it is imbalanced dataset.



(a) Daisy flower **(b) Dandelion flower** **(c) Rose flowers**



(d) Sunflower **(e) Tulip flowers**

Fig.2.3. Examples of images included in Five Flowers database, (a) Daisy, (b) Dandelion ,(c) Roses, (d) Sunflower, (e) Tulips

A.Flower classification version 1[11]:

The purpose of creating this dataset is to train machine learning and deep learning methods. It consists of flower images categorized into five different types: Daisy, Lavender, Rose, Lily, and Sunflower. The dataset is divided into three sets: a training set, a validation set, and a test set. The training and validation sets are considered "balanced" as they contain an equal number of images from each category. Specifically, the training set includes 1000 images per category, while the validation set contains 500 images per category.



(a) Daisy **(b) Lavender** **(c) Lily**



(d) Rose **(e) Sunflower**

Fig.2.4A. Examples of images included in Flower classification version 1 database, (a) Daisy, (b) Lavender ,(c) Lily, (d) Roses, (e) Sunflower

B. **Flower classification version 2[12]:**

The objective of creating this database is similar to Version 1, but Version 2 includes an additional five flower categories: Aster, Iris, Marigold, Poppy, and Orchid. Similar to Version 1, this dataset can also be considered "balanced" as the training and validation sets contain an equal number of images from each category. Specifically, the training set consists of 1500 images per category, while the validation set contains 500 images per category.



(a) Aster **(b) Marigold** **(c) Poppy**



(d) Orchid **(e) Iris**

Fig.2.4B. Examples of images included in Flower classification version 2 database, (a) Aster, (b) Marigold, (c) Poppy, (d) Orchid, (e) Iris

Flower Dataset 102 [13] :

The purpose of creating this database is to achieve automated classification of flower images across 102 diverse categories. The database consists of a total of 8189 images in .jpg format; however, it suffers from a data imbalance issue as the number of samples varies across different classes. In other words, the inclusion of samples for each class in this database is not equal, leading to an uneven distribution.



Fig.2.5. Examples of images included in Flower Dataset 102 database

Flower image[14]

This database contains images from 102 distinct categories in .jpg format; however, the specific names of these categories are not explicitly provided within the database.



Fig.2.6. Examples of images included in Flower image database

Flower Image Dataset[15]

This imbalanced database consists of 733 images of flowers categorized into 10 different types in .jpg format, including Tulips, Orchids, Peonies, Hydrangeas, Lilies, Gardenias, Garden Roses, Daisies, Hibiscus, and Bougainvillea. Some examples of this dataset are given below explicitly.



(a) Bougainvillea **(b) Daisies**

Fig.2.7. Examples of images included in Flower Image Dataset, (a) Bougainvillea, (b) Daisies

Flower Photos [16]

This database is created by the Tensorflow Team and comprises of images belonging to five different flower categories namely, Tulips, Daisy, Dandelion, Roses and Sunflowers. All the images included in this database are in .jpg format.



(a) Daisy **(b) Dandelion** **(c) Roses**



(d) Sunflowers **(e) Tulips**

Fig.2.8. Examples of images included in Flower Photos Database, (a) Daisy, (b) Dandelion, (c) Roses, (d) Sunflowers, (e) Tulips

Flower_classification_dataset[17]:

The database consists of 18,540 images in .jpg format, encompassing 102 distinct flower categories with explicitly mentioned names.



(a) Passion Flower

Fig.2.9. Example of images included in Flower_classification_dataset, (a) Passion Flower

Flower_Recognition_HE[18]

The database contains images of flowers from 102 different classes. The dataset is divided into train and test sets, each containing a collection of these images.



Fig.2.10. Some images incorporated in Flower_Recognition_HE database

Flowers[19]

The database is constructed by incorporating images of flowers from 18 distinct categories, which include Astilbe, Bellflower, Black_eyed_susan, Calendula, California_poppy, Carnation, Common_daisy, Coreopsis, Daffodil, Daisy, Dandelion, Iris, Lotus, Magnolia, Rose, Sunflower, Tulip, and Water_lily in .jpg format.



(a) Astilbe **(b) Bellflower**

Fig.2.11. Examples of images included in Flowers database, (a) Astilbe, (b) Bellflower

Flowers Dataset[20]

The database consists of images of flowers belonging to five distinct categories: Daisy, Dandelion, Rose, Sunflower, and Tulip. The files containing in the database are presented in .jpg format.



(a) Sunflower **(b) Rose** **(c) Dandelion**

Fig.2.12. Some images incorporated in Flowers Dataset, (a) Sunflower, (b) Rose, (c) Dandelion

Flowers Recognition[21]

This database is a compilation of 4,242 images distributed among five diverse flower categories: Daisy (764 files), Dandelion (1052 files), Rose (784 files), Sunflower (733 files), and Tulip (984 files). The images within this database have been sourced from publicly available platforms such as Flickr, Yandex images and Google images. Termed as "imbalanced," this database contains various number of images for each flower category.



(a) Daisy **(b) Dandelion** **(c) Rose**

Fig.2.13. Examples of images included in Flowers Recognition database, (a) Daisy, (b) Dandelion, (c) Rose

Flowers299 [22]

The creators of this database have meticulously collected 115,944 images representing 299 distinct flower categories from Google images in .jpg format. The database, known as Flowers299, exhibits a data imbalance issue, characterized by an uneven distribution of samples across the categories. The explicit category names are mentioned within the database.



(a) Abutilon **(b) Acacia**

Fig.2.14. Examples of images included in Flowers299 database, (a) Abutilon, (b) Acacia

Hackathon Blossom (Flower Classification) [23]

This database encompasses flower images from 102 different categories. The names of these flower categories are explicitly stated in a separate .json file that is included within the database.



Fig.2.15. Examples of images included in Hackathon Blossom (Flower Classification) database

Indian subcontinent flowers[24]

This database comprises an extensive collection of flower images found in the South Asian region, predominantly in the Indian subcontinent. It encompasses a wide range of 4,951 diverse categories. The images in this database have been sourced from publicly available internet platforms. It is important to note that this database is currently under construction, and as a result, some of the included images may be corrupted.

Oxford 102 Flower Dataset[25]

This database consists of images of flowers primarily found in the United Kingdom, covering 102 different flower categories. The images included in this database exhibit diverse intra-class and inter-class variations, as they have been captured from various camera positions and under varying illumination conditions. However, it should be noted that this database suffers from a class imbalance issue, with an unequal distribution of the number of images across the different flower categories.



Fig.2.16. Examples of images included in Oxford 102 Flower Dataset

Purple Flower Photos[26]

This database contains a total of 5,341 image samples specifically focusing on purple-coloured flowers in .jpg format. These images have been sourced and downloaded from various publicly available platforms.



Fig.2.17. Examples of images included in Purple Flower Photos

Rose Flowers[27]

This database consists of 73 images predominantly showcasing red and yellow roses in .jpg format.



Fig.2.18. Examples of images included in Rose Flowers

White Flowers[28]

This database encompasses a collection of 514 images featuring real-world white flowers from 13 diverse flower categories. Through an extensive survey of existing flower databases in this research area, we have discovered that all related databases consist of flower images belonging to various categories. The images included in these existing databases are sourced either from real-world captures or are synthetically generated. The database contains 509 image files in .png format as well as 5 image files in .jpg format.



Fig.2.19. Examples of images included in White Flowers

Full Descriptions of 900 Flowers [Flower Database][29]

This database consists of image files of 900 different categories of flowers in .jpg format. The database faces data imbalanced issue due to unequal distribution of image files belonging to each class.



(a)Aeonium 'Emerald Ice' (b) Aeonium 'Jolly Clusters' (c)Aloe 'Orange Marmalade'

Fig.2.20. Examples of images included in Full Descriptions of 900 Flowers [Flower Database], (a)Aeonium 'Emerald Ice', (b) Aeonium 'Jolly Clusters', (c)Aloe 'Orange Marmalade'

Flower Classification[30]:

This database encompasses a collection of 3669 images of five different categories of flowers: daisy, dandelion, roses, sunflowers and tulips in JPG format. This database is considered as "balanced" as each category of flowers contains equal number of images.



(a) Daisy flower (b) Dandelion flower



(c) Rose flower (d)Sunflower (e) Tulip flower

Fig.2.21. Examples of images included in Flower Classification database, (a)Daisy, (b) Dandelion, (c) Rose, (d) Sunflower, (e) Tulip

2.2 Existing methodologies for floral identification:

In the study [31] the author utilized the Visual Geometry Group's 102 category flower dataset from Oxford University, containing 8189 images of 102 categories. In their study [31] deep learning network consists of two parts: image segmentation and classification. They compared

the performance of GoogleNet and AlexNet architectures for classification using the same hyperparameters. GoogleNet achieved Top-1 and Top-5 accuracies of 47.15% and 69.17%, respectively, while AlexNet achieved 43.39% and 68.68%. These accuracies significantly outperform the random classification accuracy of 0.98%. Their method mentioned in [31] can be implemented in real-time applications and aids botanists in research and camping enthusiasts in flower identification.

The paper [32] showcases the effectiveness of designed architecture in recognising floral images. Flowers are highly distinguishable and stable in appearance, making them ideal for identification purposes. Traditional feature-based approaches often overlook natural cues and require expert knowledge. Through a comparative study, the authors found that GoogLeNet achieves the highest performance among CNN architectures like AlexNet and CaffeNet. By tuning network parameters, GoogLeNet achieved an accuracy rate of 67.45% at rank 1 and 90.82% at rank 10 for a flower dataset of 967 species from PlantCLEF 2015, outperforming conventional Kernel Descriptor (KDES) techniques by six times. This approach holds promise for image-based search applications in botanical classification, ecological monitoring, and multimedia fields.

In the study [33] the author introduces a two-step deep learning classifier for accurate flower classification, overcoming challenges posed by similar shapes and surrounding objects. Firstly, flower regions are segmented using a binary classifier within a convolutional network framework. Then, a robust CNN classifier is employed to distinguish different flower types. Novel training steps ensure accuracy and real-time classification. Evaluation on three flower datasets demonstrates classification results exceeding 97%, outperforming existing methods in this field.

Flower classification techniques primarily rely on colour, shape, and texture features, but they often require extensive manual parameter tuning due to small inter-class and large intra-class variations among different flower species. This process frequently results in datasets with inadequate qualitative and quantitative measures. In this study [34] the author introduces a CNN to improve the accuracy of identifying white flowers of Fragaria × ananassa from three other wild flower species. The CNN architecture comprises eight layers, including five convolutional layers and three fully connected layers, taking 227 × 227 pixel true colour flower images as input. It achieves average accuracies of 99.2% and 95.0% in training and testing, respectively. Compared to traditional methods like scale-invariant feature transform (SIFT)+ Support Vector Machine (SVM) and pyramid of histogram of gradients (PHOG)+SVM, the CNN model significantly outperforms, achieving average accuracies of 82.9% and 55.6% in training and 78.3% and 63.1% in testing, respectively. This demonstrates the capability of artificial intelligence for precise flower image classification, with potential applications in discriminating white wild flowers in fields.

In study [35] the author introduces a hybrid method using DCNN for flower species classification, addressing the need for accurate digital flower catalogues. The technique combines feature extraction using pre-trained DCNN models (AlexNet and VGG16), concatenates the extracted features, and applies the minimum Redundancy Maximum Relevance (mRMR) algorithm for feature selection. A SVM classifier with Radial Basis Function (RBF) kernel is then utilized for classification. Experimentation on Flower17 and

Flower102 datasets yields accuracy rates of 96.39% and 95.70%, respectively, showcasing the effectiveness of the proposed approach.

The study [36] focuses on automating plant phenology recording through autonomous systems, aiming to reduce labor-intensive manual efforts. In this paper [36] the author compares a lightweight CNN with deeper CNNs for flower detection and classification tasks using a dataset of Dryas flowers from Greenland. The lightweight CNN is proposed for both tasks, employing a sliding window approach for flower detection in test images. The comparison includes evaluation based on mean average precision (mAP) scores, accuracy, as well as training and prediction times.

Current flower image recognition techniques lack detection capabilities for scenes with multiple targets, limiting their applicability. In complex environments with diverse flower types, traditional computer vision techniques are inefficient and imperfect. Additionally, certain applications require real-time interaction with flower location information. In the study [37] the author presents Single Shot Detectors (SSD) deep learning technology for flower detection and identification, addressing limitations in traditional computer visual methods. Using the Oxford University flower dataset for training and testing, the method achieves average accuracies of 83.64% (Pascal VOC2007) and 87.4% (Pascal VOC2012). With a processing time of 0.13s per image on PC, the approach enables high-quality automatic detection and recognition, facilitating agricultural plant information retrieval and dissemination of flower-related information.

Computer vision methods are essential for extracting significant information from images through automated processes. In this paper [38] the author presents a hybrid methodology employing multiple kernel-learning support vector machine (MKL-SVM) for multi-label classification, applied to a dataset of 25,000 flower images spanning 102 species. Features including colour, size, texture, and petal characteristics are extracted to enhance classification accuracy. Various classifiers are tested, with MKL-SVM achieving a promising accuracy rate of 76.92%. Overall, in study [38] the author explores novel morphology-based feature extraction and symbolic representation schemes for effective multi-label classification of flower species.

In plant science and agroforestry, accurate flower identification is essential. To overcome the limitations of manual and traditional computer vision techniques, in this study [39] authors developed a modified tiny Darknet for flower classification. Using a dataset of seventeen flower types from Oxford University, the deep network model automatically extracts image features and employs a softmax classifier for classification. Results demonstrate a classification accuracy of 92%, outperforming original and mainstream models. The model's simplicity, few training parameters, and high accuracy make it suitable for automatic flower classification and agricultural database retrieval.

Flowers, with their diverse species and colours, require expertise to identify. Integrating artificial intelligence, specifically convolutional neural networks, into flower identification can revolutionize industries like pharmaceuticals and cosmetics. In the paper [40] the author introduces a system where uploading a flower image enables efficient recognition through a simple click through web application, benefiting from the medicinal properties recognized in many flowers by ancient Ayurveda. This study [40] mentions that a flower recognition system is developed using a CNN for efficient image classification. CNN models are trained with

labeled flower images using batches, with a batch size of 32 and 150 epochs. The model automatically preprocesses input images, including resizing and augmentation methods like rotation and shear. During training, the model learns features and patterns to classify new flower images. Categorical cross entropy is used as the loss function, gradually reducing loss values through weight adjustments. Once classified, the system displays the flower's common name, family name, and major uses. To enhance user-friendliness, the model is deployed in a web application where users can upload flower images for prediction with a single click.

In paper [41] the author addresses the challenge of flower category recognition using a novel attention-driven residual network deep learning model. To overcome limitations like lack of training samples and intra-class similarity, the model employs image augmentation techniques and integrates human visual attention mechanisms. The model can leverage diverse channel features and spatial dimensions while retaining the ability for few-shot learning to address insufficient training samples. Specifically, the proposed model in [41] consists of multiple weighted visual attention learning blocks, enhancing the network's learning and discriminating abilities. The model achieves an accuracy of 85.7% on the Flowers 17 dataset, demonstrating its effectiveness in flower category recognition.

Flowers, integral to ecological balance, offer various benefits to humans. With approximately 400,000 known varieties, distinguishing between them poses a challenge due to shape and colour similarities. Flower classification faces difficulties stemming from shape variations, colour distribution, and lighting conditions. Human perception struggles with discerning similar flowers, often relying on specific morphological features. Recently, CNN-based transfer learning methods have gained traction for flower species recognition. According to authors the study [42] evaluates popular pre-trained models like VGG16, VGG19, SqueezeNet, DenseNet-121, DenseNet-201, and InceptionResNetV2 for flower classification. Experimental results show InceptionResNetV2 outperforming other models, achieving 92.25% accuracy. Inception-ResNet combines features from both the Inception and ResNet architectures. With 164 layers, the InceptionResNetV2 model comprises 55,855,205 trainable parameters. Increasing the number of deep layers also increases the trainable parameters [42].

In [43], the project aims to classify flowers using text recognition, utilizing flower dimensions provided in the dataset. The goal is to extract flower features and evaluate their advantages and disadvantages. K-Nearest Neighbour (KNN) and Random Forest algorithms were selected and compared based on their performance, achieving the highest accuracy among other algorithms examined. The author in [43] used iris dataset comprising three flower species: setosa, versicolour, and virginica for this work. The training dataset comprises 80% of the data, with the remaining 20% used for testing. Using Random Forest and KNN algorithms, the maximum accuracy achieved is 93.33%. The user interface allows users to input flower names and displays their advantages, such as medicinal values. Histograms illustrating classification results are shown in the study [43]. Advantages include obtaining information on therapeutic and medicinal uses of flowers. However, the dataset's limitation lies in its inclusion of only a few flower species.

Flower species recognition can be challenging due to various features like leaves and grass. Traditional methods rely on attributes such as colour, shape, and texture. According to authors the study [44] employs CNNs to classify flower species accurately. The authors deployed in [44] the CNN models like Sequential Model, Inception-V3 and VGG-16 on dataset of 4242

images across 5 classes which is utilized, with Tensor Flow and Image Data Generator aiding in training set augmentation to prevent overfitting, resulting 85%, 83%, 81% accuracy respectively.

A method for grading fresh cut flowers based on their maturing status was proposed in [45], using deep learning and depth information. Colour as well as depth images of floral buds were fused to form RGBD information and fed into CNNs for classification. Four CNN models VGG16, ResNet18, MobileNetV2, and InceptionV3 were adapted for 4D (four dimensional) RGBD input, showing improved classification accuracy with depth information. InceptionV3 achieved the highest accuracy (up to 98%) with RGBD data, indicating the effectiveness of depth information in reflecting flower characteristics for intelligent classification and sorting.

In today's world, data generated across various platforms serves diverse domains such as Floriculture, Agriculture, and Finance. Real-time analysis in Floriculture is crucial due to its increasing cultivation globally. Data analysis involves parameters like shape, colour, and size of flowers, aiding in species recognition and analysis. Deep learning methods offer effective flower species detection. In this paper [46] the author reviews pattern classification and detection algorithms, comparing their performance with various datasets to explore different approaches for flower detection under different scenarios. According to the survey in [46] CNNs are effective for image classification, they struggle with detecting multiple objects. Variants of Region-Based Convolutional Neural Network (R-CNN) algorithms like SSD, You Only Look Once (YOLO) are used for this purpose, each with its advantages and drawbacks. YOLO, for instance, detects objects based on coordinates (X,Y), width (W), height (H), and confidence (C). Conditional probabilities for different classes are assigned to each bounding box in YOLO, with confidence scores based on Intersection over Union (IOU). However, YOLO has limitations in detecting small objects within grid cells, requiring high-quality images for accurate detection.

Manual flower identification and classification is labor-intensive and often yields low accuracy. Traditional computer vision and artificial intelligence methods also face challenges in database search queries due to high recognition costs and low efficiency. In article [47] the author addresses these issues using five common flower image datasets and a CNN framework. The process includes image information import, preprocessing, feature extraction, and classification. Through training and verification, the model achieves a recognition accuracy rate of 75%, overperforming traditional methods.

Recognizing plant species from images is complex due to diverse plant types and environmental factors. The paper [48] employs a CNN for plant species recognition, leveraging its efficiency in feature extraction and image recognition. According to this paper [48] the author used publically available Kaggle dataset for classification. The CNN model achieved 96.95% accuracy in distinguishing plant leaf images after running for various epochs.

In [49] the proposed work aims to classify flower species using machine learning techniques, particularly CNNs. Pre-trained CNNs are utilized to extract complex features from flower images, followed by classification using machine learning classifiers like Logistic Regression or Random Forest. This hybrid approach reduces the computational burden associated with training CNNs. The process of identifying flower species involves three main steps. First, image characteristics are extracted from the training dataset using a CNN and stored in Hierarchical Data Format, Version 5 (HDF5) format. Next, the network is trained using various

machine learning classifiers, including Bagging Trees, Gaussian Naive Bayes, Linear Classification Analysis, Logistic Regression, Decision Trees, KNN, Stochastic Gradient Boosting and Random Forests. Finally, random test images are inputted into the network to predict labels and evaluate the accuracy of the system. Results show a 64.28% accuracy rate using Random Forest as the classifier on the FLOWERS17 dataset.

Deep neural networks are widely used in computer vision for object detection tasks, including flower identification. The authors in this study [50] proposes a DCNN utilizing Faster-RCNN and SSD architectures for accurate flower detection, localization, and classification. Pretrained models like ResNet-50, ResNet-101, Inception-V2, and MobileNet-V2 are employed and trained on a dataset comprising 2000 images, with 70% used for training, 25% for validation, and 5% for testing. The Faster-RCNN model, through transfer learning, achieves an mAP score of 83.3% with 300 and 91.3% with 100 proposals across ten flower classes, providing essential details such as flower name, class classification, and multilabeling techniques. While the model demonstrates high accuracy, challenges remain, especially in distinguishing visually similar flower classes. Further training with visually similar classes is suggested for future improvement.

CNNs are instrumental in identifying plant species by leveraging deep learning techniques that analyze properties like colour and shape. The study [51] focuses on classifying five categories of flora: daisy, rose, dandelion, sunflower, and tulip. Utilizing a CNN with skip connections like Residual Network (ResNet), the methodology aims for intuitive recognition of flora images. A ResNet containing nine deep layers is employed for classification, addressing various approaches and implementations. The author in [51] performed data mining techniques to design the dataset comprising total 4242 flower images. Experimental methodologies using PyTorch and datasets are detailed, with results and graphical analyses presented.

In study [52] the author explores the effectiveness of Deep CNNs using a transfer learning approach for flower recognition. Using a benchmark dataset from Kaggle, two popular image classification models, AlexNet and VGG16, were analysed. Results indicate that CNNs perform well for object recognition, with model performance influenced by image type and CNN architecture depth. VGG16 achieved the highest accuracy at 95.02%, followed by AlexNet at 85.69%. The model's applicability extends to other areas, including Taman Negara, a diverse flora ecosystem. Feature extraction processes were discussed, applicable beyond the trained dataset.

The author in the paper [53] proposes an efficient flower classification system that combines handcrafted features with deep features to address challenges such as intra-class variation and interclass similarity. Fundamental features like colour, directional and textural are extracted using Centre Symmetric Local Binary Pattern (CSLBP), Colour Coherent Vector (CCV), and Edge Histogram Descriptor (EHD), while deep features Centre Symmetric Local Binary Pattern (CSLBP)are obtained from ResNet-50 and AlexNet followed by utilization of Multiclass SVM for performing classification. Experimental results on various datasets show high accuracy, with 100%, 95.3%, 94%, and 92% achieved on the Corel-1K, Oxford Flower 17, Kaggle, and Flower102 datasets, respectively, and an impressive 86.4% accuracy on the pooled dataset.

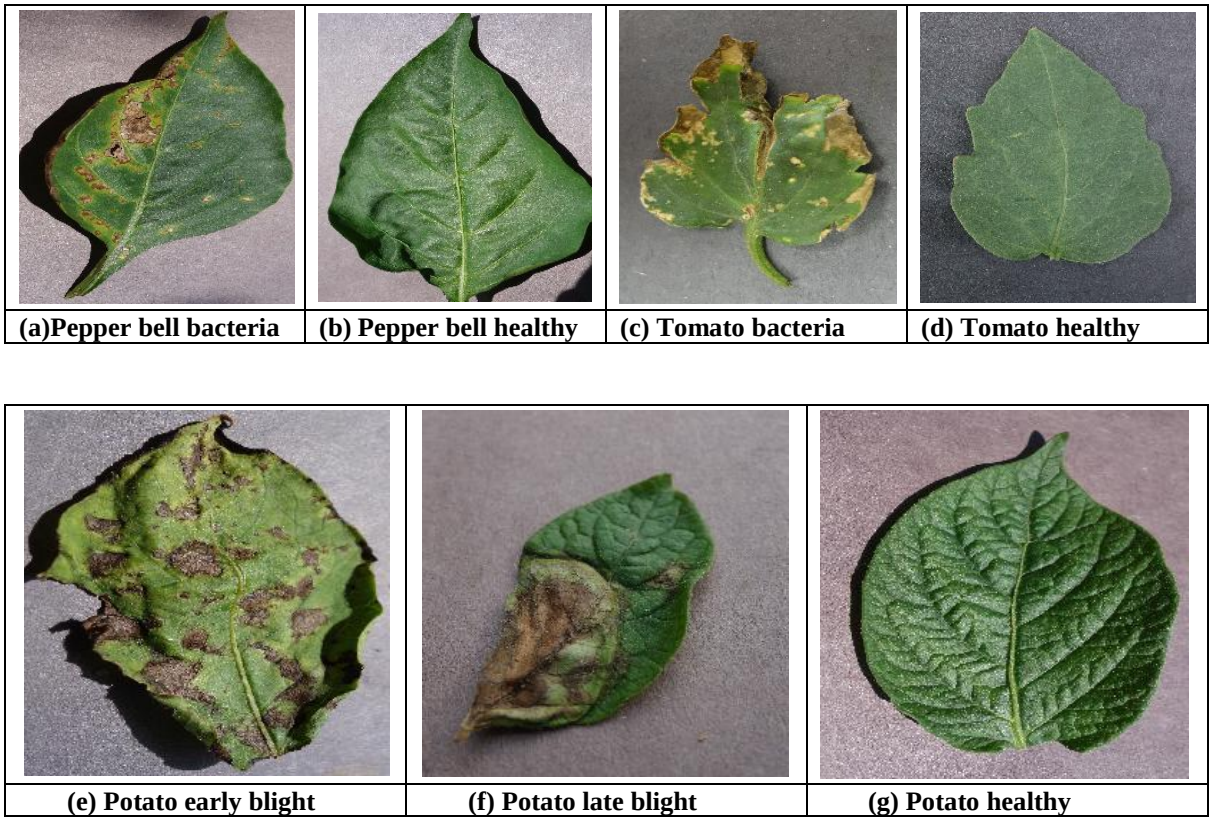
The study [54] focuses on using machine learning algorithms to classify iris flower subclasses in the Iris dataset, which contains three classes: Versicolour, Setosa, and Virginica including

total 50 occurrences. Various algorithms including KNN, Logistic Regression, Decision Tree, Linear SVC, Gaussian Naive Bayes, and Random Forest are employed for analysis, with Linear SVC achieving the highest accuracy of 97.778% with a Cross-Validation Score (CVS) of 98.67%.

2.3 Existing databases to perform foliage disease identification:

PlantVillage Dataset[55]:

The PlantVillage Dataset is a valuable resource for crop health monitoring and knowledge exchange among researchers. It comprises over 54,000 images from 14 crop species, such as Apple, Corn, and Tomato, captured at research stations affiliated with US Land Grant Universities. These images depict leaves from various angles and under different lighting conditions. Contributions to the platform are scored, allowing high-scoring researchers to edit others' contributions. The dataset provides information on 1,800 diseases affecting more than 150 crop types, contributed mainly by plant pathologists. Images were taken using a Sony DSC-Rx 100/13 digital camera with 20.2 megapixels against a uniform gray background. Plant diseases, including those caused by viruses, mites, bacteria, and fungi, are documented, with samples artificially infected under controlled laboratory conditions.



(a)Pepper bell bacteria	(b) Pepper bell healthy	(c) Tomato bacteria	(d) Tomato healthy

(e) Potato early blight	(f) Potato late blight	(g) Potato healthy

Fig.2.22. Examples of images included in PlantVillage Dataset, (a)Pepper bell bacteria, (b) Pepper bell healthy, (c) Tomato bacteria, (d) Tomato healthy, (e) Potato early blight, (f) Potato late blight, (g) Potato healthy

Cassava Leaf Disease Detection Dataset [56]

The Cassava Leaf Disease Detection Database stands as a pivotal resource in leaf disease detection research, specifically focusing on cassava crops. Cassava serves as a vital source of carbohydrates in Africa, with approximately 80% of small-scale farmers in Sub-Saharan Africa relying on it. However, cassava is highly vulnerable to viral diseases, leading to significant financial losses for farmers. Traditional disease detection methods involve manual visual inspections by experts, incurring substantial costs, manual labour, and potential errors. In response, a collaborative effort between the National Crops Resources Research Institute (NaCRRI) and the AI lab at Makerere University, Kampala, resulted in the creation of this database.

Comprising 21,637 labeled images collected from agricultural fields in Uganda, the database features cassava leaf images captured by farmers using their mobile cameras. Plant pathologists then provided labeling and annotations. The database categorizes cassava leaf images into five groups: Cassava Bacterial Blight, Cassava Brown Streak Disease, Cassava Green Mottle, Cassava Mosaic Disease, and Healthy leaves. In contrary to PlantVillage database, this database offers cassava leaf images from real fields, making it conducive to developing machine learning and deep learning models tailored for real-world applications.



(a)Cassava Bacterial Blight	(b)Cassava Brown Streak Disease	(c) Cassava Green Mottle	(d) Cassava Mosaic Disease	(e)Cassava healthy leaves

Fig.2.23. Examples of images included in Cassava Leaf Disease Detection Dataset, (a) Cassava Bacterial Blight, (b) Cassava Brown Streak Disease, (c) Cassava Green Mottle , (d) Cassava Mosaic Disease, (e) Cassava healthy leaves

PlantDoc Dataset [57]:

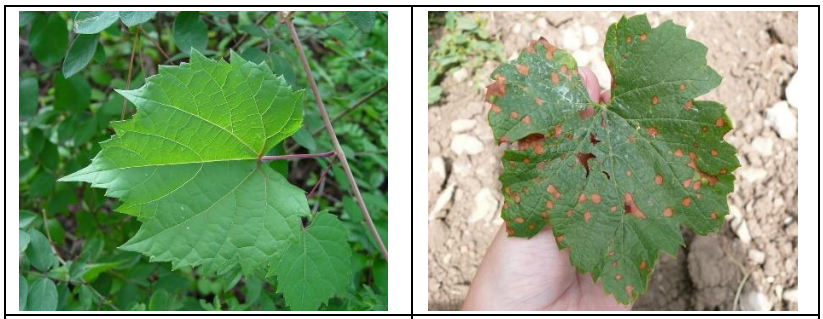
To address limitations in the PlantVillage dataset, which mainly consisted of single leaf images with uniform gray backgrounds, the authors developed a more practical dataset. They gathered 20,900 images from Ecosia and Google Images, considering both scientific and common names. These images underwent meticulous filtering by four users using website metadata and ASPNet guidelines. The resulting PlantDoc dataset comprises 2,598 labeled and annotated images across 27 classes (17 diseased and 10 healthy) from 13 crop species. Labeling relied on ASPNet and other public sources, while annotations were added using the LabelImg tool, with bounding box information stored in XML files for supervised leaf disease classification and detection tasks. Additionally, the authors introduced the Cropped-PlantDoc dataset, featuring 9,216 cropped leaf images prepared from the original PlantDoc dataset. These images resemble PlantVillage images but with diverse backgrounds and lower resolution.



(a) Apple leaf healthy Disease | (b) Apple rust leaf Disease | (c) Apple scab leaf Disease



(d) Corn gray leaf spot Disease | (e) Corn leaf blight Disease | (f) Corn rust leaf Disease



(g) grape leaf healthy Disease | (h) grape leaf black rot Disease

Fig.2.24. Examples of images included in PlantDoc Dataset, (a) Apple leaf healthy, (b) Apple rust leaf, (c) Apple scab leaf, (d) Corn gray leaf spot, (e) Corn leaf blight, (f) Corn rust leaf, (g) grape leaf healthy, (h) grape leaf black rot

Leaf disease detection and moss species identification dataset [58]

In the paper, the authors propose a one-shot learning approach for plant disease detection and moss species identification. They employ a Siamese network with a triplet loss function and three network branches, utilizing MobileNetV2 as the base network for these branches. To support their research, the authors have curated two distinct databases.

The first dataset, created for plant disease detection and available at http://pdd.jinr.ru/, comprises 935 images sized at 256x256 pixels. It covers 25 different classes from five diverse crop species, including cotton, cucumber, wheat, corn, and grape.

The second dataset, designed for moss species identification and accessible at http://moss.jinr.ru/, consists of 599 images, also sized at 256x256 pixels. It represents five different moss species: Abietinella Abietina, Hypnum Cupressiforme, Hylocomium Splendens, Pluerozium Schreberi, and Pseudoscleropodium Purum.



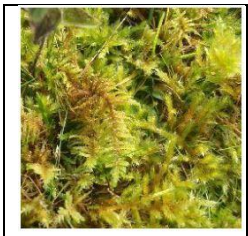
(a) Alternaria leaf blight



(b) Cherry leaf spot



(c) Marginal leaf necrosis



(d)Abietinella Abietina



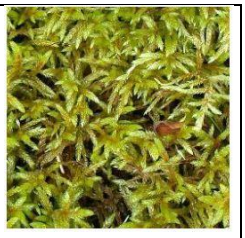
(e)Hypnum Cupressiforme



(f)Hylocomium Splendens,



(g)Pluerozium Schreberi



(h)Pseudoscleropo-dium Purum

Fig.2.25. Examples of images included in Leaf disease detection and moss species identification dataset, (a) Alternaria leaf blight, (b) Cherry leaf spot, (c) Marginal leaf necrosis, (d) Abietinella Abietina, (e) Hypnum Cupressiforme, (f) Hylocomium Splendens, (g) Pluerozium Schreberi, (h) Pseudoscleropodium Purum

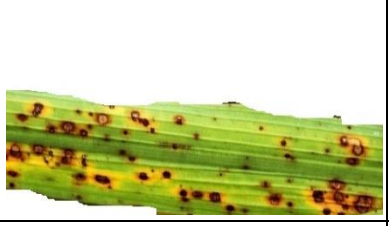
Rice Leaf Disease Dataset [59]:

In this study, the authors devised a machine learning-based approach to classify three types of rice diseases: Bacterial leaf blight, Leaf smut, and Brown Spot. This methodology involved segmenting diseased regions of leaves from healthy ones, accomplished through centroid-based clustering technique. Subsequently, they categorized infected leaves into the aforementioned three classes by utilizing features derived from shape, colour, and texture extracted from the segmented image regions.

To support their research, the authors curated their own database, comprising a total of 120 images. Each disease class was represented by 40 images. These images were sourced from rice fields in Shertha, a village near Gandhinagar, Gujarat, India, during the early stages of rice crop harvesting in November 2015. All images in the database were captured using a NIKON D90 12.3-megapixel digital SLR camera, with uniform white backgrounds in direct sunlight, and saved in JPEG format with consistent dimensions of 2848x4288 pixels.



(a) Bacterial leaf blight



(b) Brown spot



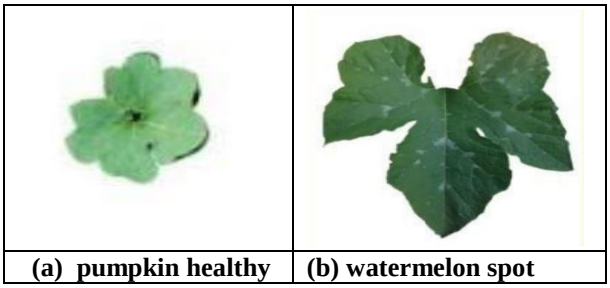
(c) Leaf smut

Fig.2.26. Images included in the Dataset, (a) Bacterial leaf blight disease, (b) Brown spot disease, (c) Leaf smut disease

Leaf Disease Detection Dataset (Cucurbitaceae family) [60]

In this study, the authors developed a deep neural network-based method to detect healthy and diseased leaves from multiple species within the cucurbitaceous family, such as cucumber, watermelon, squash, and pumpkin. They chose to focus on this family due to its significant importance, encompassing 965 species known for being among the most widely consumed and economically crucial edible vegetables worldwide. The authors aimed to contribute specifically to the detection of diseases affecting these crop species, which play a vital role in the economic growth of the food industry.

In their research, as detailed in [60], the authors crafted a seven-layer CNN for the classification of diseased leaves. To support their work, they curated a database by collecting images of both healthy and diseased leaves from various publicly available online sources.



(a) pumpkin healthy	(b) watermelon spot

Fig.2.27. Examples of images included in Leaf Disease Detection Dataset (Cucurbitaceae family), (a) pumpkin healthy, (b) watermelon spot

Grape Leaf Disease Dataset (GLDD) [61]:

In this study, the authors introduced a deep learning-based model called Faster DR-ICANN for detecting four types of diseased grape leaves: Black rot, Leaf blight, Black measles, and Mites of grape. Drawing inspiration from the architecture of Faster RCNN, their model consisted of three key modules. The first module, INSE-ResNet, integrated residual structures, SE blocks, and inception modules to effectively extract multi-scale features. This enabled the detection of minute leaf spots that might otherwise be overlooked. The second module, the Region Proposal Network (RPN), utilized the multi-scale features from the first module to pinpoint the locations of diseased spots on the leaves. The third module comprised Fully Connected layers responsible for predicting class scores and bounding box coordinates. To support their research, the authors assembled the GLDD dataset, comprising 4,449 labeled and annotated images of diseased grape leaves across four distinct disease classes. These images were collected from both laboratory settings and actual grape vineyards located in nearby areas. The dataset encompassed samples gathered under various climatic conditions, allowing for the assessment of temperature and humidity's impact on grape leaf diseases. It also facilitated year-round monitoring of grape leaf health, recognizing that the prevalence of these diseases varies in response to shifts in climatic conditions. For instance, Black rot disease can cause significant damage during humid and hot weather but has a reduced impact in dry conditions, while Leaf

blight tends to occur predominantly in September when temperatures are lower and rainfall is frequent.



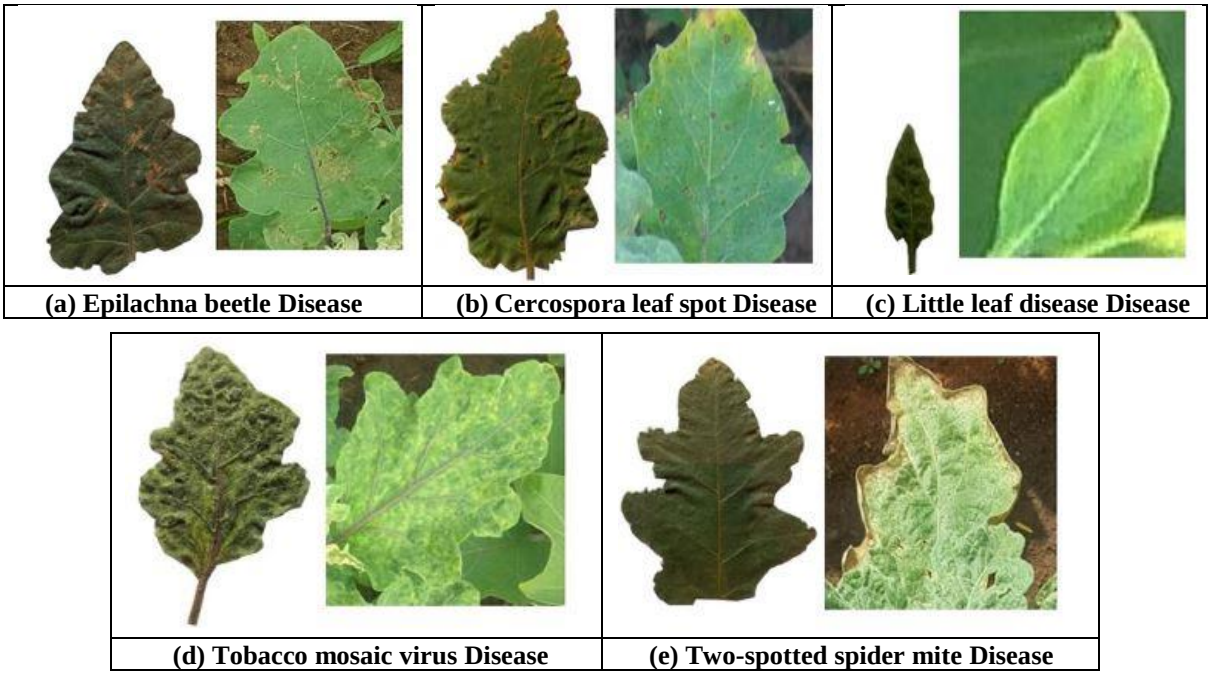
(a) Black rot Disease	(b) Black measles Disease	(c) Leaf blight Disease	(d) Mites of grape Disease

Fig.2.28. Examples of images included in Grape Leaf Disease Dataset (GLDD), (a) Black rot, (b) Black measles, (c) Leaf blight, (d) Mites of grape.

Eggplant Leaf Disease Detection dataset [62]

In this study, the authors employed the pre-trained VGG16 model as a feature extractor and a Multi-Class Support Vector Machine (MSVM) as the classifier for classifying diseased eggplant leaves. To support their research, they curated a dataset comprising 1,088 labeled images of diseased eggplant leaves, representing five distinct types of diseases whose names are explicitly mentioned in Fig.27.

The dataset includes both isolated leaf images captured in laboratory conditions using smartphones against a uniform white background and real field images captured with the same smartphones. Unlike the isolated leaf images, the real field images feature backgrounds consisting of overlapping leaves from plants of the same species, as well as other species, soil, weeds, and more. Experienced plant pathologists performed the labeling of the images in this dataset.



(a) Epilachna beetle Disease	(b) Cercospora leaf spot Disease	(c) Little leaf disease Disease

(d) Tobacco mosaic virus Disease	(e) Two-spotted spider mite Disease

Fig.2.29. Examples of images included in Eggplant Leaf Disease Detection dataset, (a) Epilachna beetle, (b) Cercospora leaf spot, (c) Little leaf disease, (d) Tobacco mosaic virus, (e) Two-spotted spider mite.

Diseased Tea Leaf dataset [63]

In [63], researchers presented an enhanced RetinaNet architecture named AX-RetinaNet for detecting four types of tea leaf diseases: Tea algae leaf spot (TALS), Tea white scab (TWB), Tea leaf blight (TLB) and Tea bud blight (TBB). Since no such dataset was present previously, the authors meticulously constructed their own dataset, comprising 700 infected tea leaf images, with each disease class represented by 175 images captured from tea gardens located in China. These images were captured using a Canon EOS 80D camera (with an image resolution of 6000x4000 pixels) and a Sony DSC-W55 camera (with an image resolution of 3072x2304 pixels). The cameras were positioned at a height of 0.4 meters above the tea tree canopy during image acquisition. Due to the complexity of the backgrounds in the images utilized in this study, conventional CNNs were deemed inadequate for accurate detection of diseased tea leaves. To overcome this challenge, the authors introduced AX-RetinaNet, incorporating an X-module for feature map extraction with rich information content, supporting multi-scale feature fusion. Additionally, they integrated a channel attention module called Attention to optimize feature extraction by emphasizing the most relevant features and reducing redundancy across channels in the generated feature map.



(a) Tea algae leaf spot	(b) Tea bud blight	(c) Tea white scab	(d) Tea leaf blight

Fig.2.30. Some image samples present in Diseased Tea Leaf dataset, (a) Tea algae leaf spot, (b) Tea bud blight, (c) Tea white scab, (d) Tea leaf blight

Bean Disease Detection dataset [64]:

The dataset, a collaborative effort between Makerere AI Lab and NaCRRI, consists of 990 images directly obtained from bean fields. These images are divided into three classes: Bean rust, Angular leaf spot, and healthy, with an even distribution of 330 images per class.



(a) Angular leaf spot	(b) Bean rust leaf	(c) Bean healthy leaf

Fig.2.31. Some image samples incorporated in Bean Disease Detection dataset, (a) Angular leaf spot, (b) Bean rust leaf, (c) Bean healthy leaf

Corn Leaf Infection Dataset [65]

The dataset comprises 4,226 images depicting corn leaves. Among them, 2,226 images portray partially infected corn leaves resulting from pest attacks like the Fall Armyworm, while the remaining 2,000 images showcase healthy corn leaves.

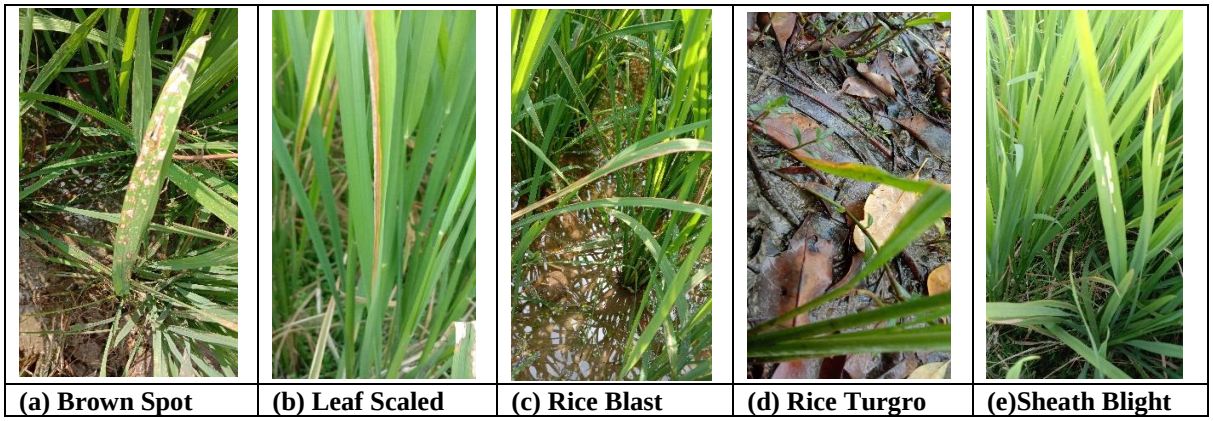


(a) Infected corn leaf	(b) Healthy corn leaf

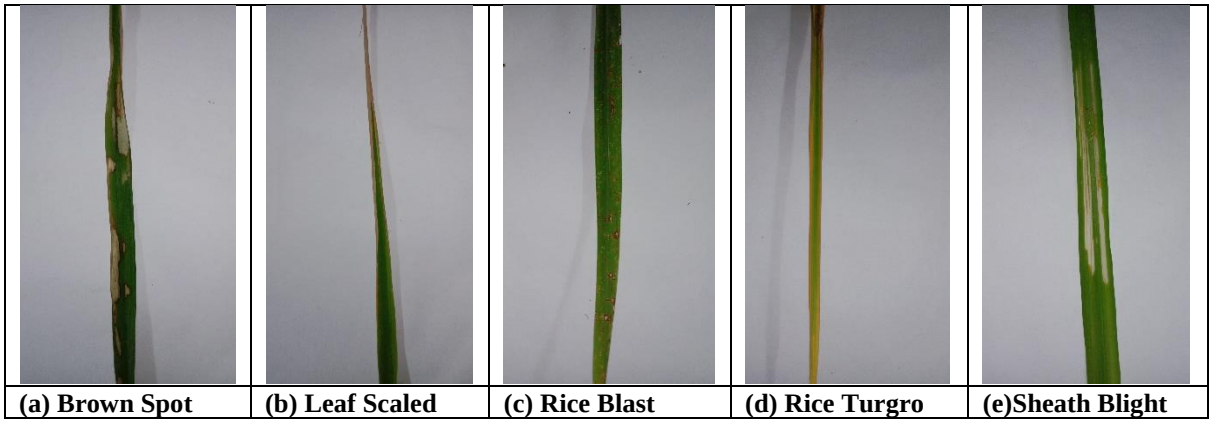
Fig.2.32. Examples of images included in Corn Leaf Infection Dataset, (a) Infected corn leaf, (b) Healthy corn leaf

Dhan-Shomadhan: A Dataset of Rice Leaf Disease Classification for Bangladeshi Local Rice [66]:

The dataset was meticulously curated with the aim of improving the detection of diseases impacting rice crops in Bangladesh. It consists of 1,106 images showcasing diseased rice crops, covering five distinct types of diseases: Brown spot, Rice blast, Rice tungro, Sheath blight, and Leaf scald. Noteworthy is the inclusion of images captured against two diverse backgrounds: a white background and a field background.



(a) Brown Spot	(b) Leaf Scaled	(c) Rice Blast	(d) Rice Turgro	(e)Sheath Blight



(a) Brown Spot	(b) Leaf Scaled	(c) Rice Blast	(d) Rice Turgro	(e)Sheath Blight

Fig.2.33. Examples of images included in Dhan-Shomadhan: A Dataset of Rice Leaf Disease Classification for Bangladeshi Local Rice, (a) Brown Spot, (b) Leaf Scaled, (c) Rice Blast, (d) Rice Turgro, (e) Sheath Blight

Wheat Leaf dataset [67]:

The dataset was created with a central objective of distinguishing between two diseases affecting wheat crops: Stripe rust and Septoria, alongside healthy wheat leaves. It contains a total of 407 images, with 97 representing Septoria, 208 depicting Stripe rust, and 102 showcasing healthy wheat leaves. These images were directly sourced from wheat farms.



(a) wheat leaf healthy	(b) wheat leaf septoria	(c) wheat leaf stripe rust

Fig.2.34. Examples of images included in Wheat Leaf dataset, (a) wheat leaf healthy, (b) wheat leaf septoria, (c) wheat leaf stripe rust

Sun Flower Fruits and Leaves dataset for Sunflower Disease Classification through Machine Learning and Deep Learning [68]:

The dataset encompasses 467 images portraying both diseased and healthy Sunflowers, categorized into four classes: Downy mildew, Gray mold, Leaf scars, and Healthy. These leaf samples were gathered from the demonstration farm at the Bangladesh Agricultural Research Institute in Gazipur and meticulously labeled with the guidance of domain experts. Additionally, alongside the primary dataset, the creators have provided a secondary dataset containing 1,668 images. These supplementary images were produced using data augmentation techniques applied to the original dataset images.



(a) Downy mildew



(b) Fresh Leaf



(c) Gray mold



(d) Leaf scars

Fig.2.35. Examples of images included in Sun Flower Fruits and Leaves dataset for Sunflower Disease Classification through Machine Learning and Deep Learning, (a) Downy mildew, (b) Fresh Leaf, (c) Gray mold, (d) Leaf scars

Nsukka Yellow Pepper_Healthy dataset [69]:

The dataset comprises 21 images showcasing healthy Nsukka yellow pepper leaves. These databases represent some of the most widely recognized collections in the current research domain.

To our knowledge, none of the existing databases include images of both healthy and diseased insulin leaves, despite their significant medical importance. Tables 1 and 2 present the images of healthy and diseased insulin leaves incorporated in this database, respectively.

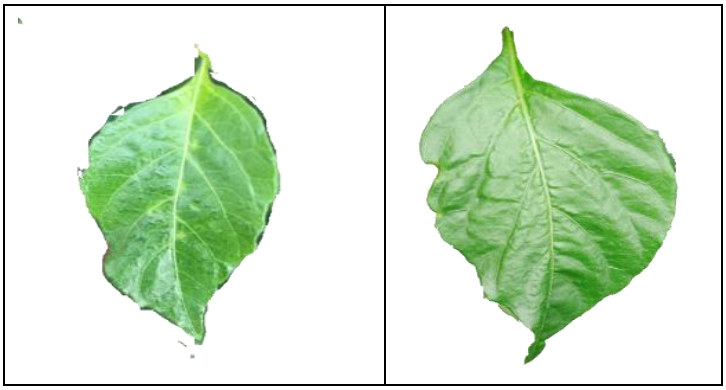


Fig.2.36. Examples of images included in Nsukka Yellow Pepper_Healthy dataset

Sugarcane leaf dataset: A dataset for disease detection and classification for machine learning applications[70]:

In this study [70] authors presented the "Sugarcane Leaf Dataset" comprising 6748 high-resolution JPEG leaf images each with dimension of 768 x 1024 pixels categorized into nine disease types, healthy leaves, and dried leaves. Diseases include smut, yellow leaf disease, pokkah boeng, mosale, grassy shoot, brown spot, brown rust, banded cholorsis, and sett rot. This dataset aids in developing machine learning algorithms for disease detection, enhancing sugarcane production. Image datasets are crucial for various fields, providing valuable visual information for training models and gaining insights. Specific datasets like this one play a significant role in agricultural research, aiding in disease identification and management. The dataset contains high-quality images captured from sugarcane-growing regions, ensuring comprehensive coverage of disease manifestations. Each category is organized in separate folders for easy access, facilitating research and development efforts.



(a) Sugarcane Diseases	(b) Sugarcane Dried	(c) Sugarcane Healthy

Fig.2.37. Examples of images included in Sugarcane leaf dataset: A dataset for disease detection and classification for machine learning applications, (a) Sugarcane Diseases, (b) Sugarcane Dried, (c) Sugarcane Healthy

SoyNet: A high-resolution Indian soybean image dataset for leaf disease classification[71]:

In this study [71] the "SoyNet" dataset offers over 9000 high-quality images of soybean leaves, comprising both healthy and diseased samples. Captured from soybean fields using Nikon digital cameras and Motorola mobile phone cameras, the dataset covers various angles, lighting conditions, and backgrounds. Images are organized into two folders: "SoyNet Raw Data" and "SoyNet Pre-processing Data," containing healthy and diseased leaf images. The latter folder includes resized (256×256 pixels) and grayscale versions of the images. This dataset serves as a valuable resource for testing and training soybean leaf disease classification models. In India, soybean cultivation, particularly in Madhya Pradesh, faces challenges from diseases and pests, necessitating accurate diagnosis and prompt intervention for crop protection. The SoyNet

dataset aids in addressing these challenges by providing a comprehensive collection of soybean leaf images for model development and validation.

			
(a) Diseased Preprocessing data	**(b) Healthy Preprocessing data**	**(c) Healthy raw data**	**(d) Diseased raw data**

Fig.2.38. Examples of images included in SoyNet: A high-resolution Indian soybean image dataset for leaf disease classification for diseased and healthy leaves

PSFD-Musa: A dataset of banana plant, stem, fruit, leaf, and disease [72]:

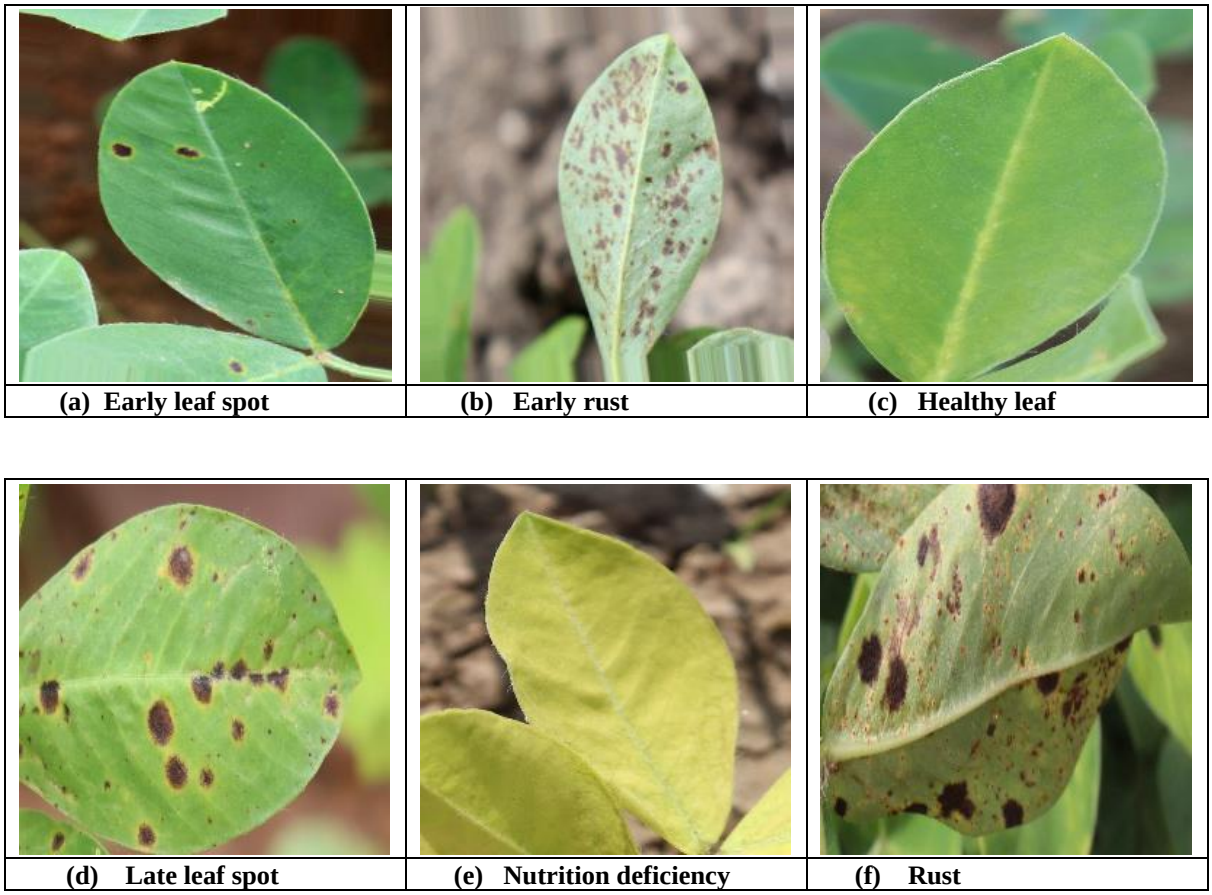
In [72] introducing the PSFD-Musa dataset, comprising more than eight thousand images of banana plants and associated diseases. Varieties include Malbhog (Musa assamica), Jahaji (Musa chinensis), Kachkol (Musa paradisiaca L.), and Bhimkol (M. Balbisiana Colla), with diseases like Bacterial Soft Rot, Black Sigatoka, Panama disease, Banana Aphids and Pseudo-Stem Weevil. The dataset is structured into three subfolders: one containing images of 7 types of banana plants, another with images of seven diseases affecting banana plants, and the last one dedicated to a single class representing deficiencies that affect the plants. The dataset also covers Potassium deficiency. Banana plants, globally distributed, are known for their susceptibility to various bacterial, fungal, and viral diseases. This dataset aids researchers and students in understanding banana plant varieties and common diseases. Organized into three subfolders, it includes images of plant varieties, diseases, and deficiencies in .jpg format, suitable for classification and machine learning models.

		
(a) BANANA DEFICIENCY	**(b) BANANA DISEASE**	**(c) BANANA VARIETY**

Fig.2.39. Examples of images included in PSFD-Musa: A dataset of banana plant, stem, fruit, leaf, and disease, (a) BANANA DEFICIENCY, (b) BANANA DISEASE, (c) BANANA VARIETY

Dataset of groundnut plant leaf images for classification and detection[73]:

This dataset consists of 10,361 digital photographs of groundnut plant leaves collected in the Koppal area of Karnataka, India. Images are categorized into six groups: healthy leaves (1871 images), early leaf spot (1731 images), late leaf spot (1896 images), nutrition deficiency (1665 images), rust (1724 images), and early rust (1474 images). Each category represents specific leaf conditions related to diseases and nutritional deficiencies. The dataset aids in training and validating deep learning and machine learning algorithms for groundnut leaf disease classification. Detailed descriptions of each leaf condition, such as early leaf spot, late leaf spot, nutrition deficiency, and rust, are provided, along with corresponding images captured using a digital camera. The dataset is freely accessible online and includes images from both Kharif and Rabi seasons, capturing various stages of groundnut plant development and disease manifestation.



(a) Early leaf spot | **(b) Early rust** | **(c) Healthy leaf**

(d) Late leaf spot | **(e) Nutrition deficiency** | **(f) Rust**

Fig.2.40. Examples of images included in Dataset of groundnut plant leaf images for classification and detection, (a) Early leaf spot, (b) Early rust, (c) Healthy leaf, (d) Late leaf spot, (e) Nutrition deficiency, (f) Rust

CoLeaf-DB: Peruvian coffee leaf images dataset for coffee leaf nutritional deficiencies detection and classification[74]:

This work presents the CATIMOR, CATURRA, and BORBON datasets of Peruvian coffee leaf images, collected from plantations in La Palma Central and San Miguel de las Naranjas, Cajamarca, Jaén province, Perú. The dataset contains 1006 images categorized by nutritional deficiencies, including Boron (101 images), Iron (65 images), Potassium (96 images), Calcium (162 images), Magnesium (79 images), Manganese (83 images), Nitrogen (64 images), and

others. These images facilitate the training of deep learning algorithms for recognizing and classifying coffee plant leaf nutritional deficiencies. The dataset is publicly available and organized into ten folders representing various deficiencies and healthy leaves. The images are captured and classified by agronomists based on leaf characteristics in a controlled environment. Each folder contains annotated images depicting specific deficiencies, with dimensions of 3000×4000 px, compressed in JPEG format with a resolution of 180 dpi, both horizontally and vertically, and with a colour depth of 24 bits. The dataset aids in understanding and addressing nutritional deficiencies in coffee plants, contributing to improved cultivation practices and crop yield.



(a) Boron deficiency	(b) Calcium deficiency	(a) Healthy leaves	(a) Iron deficiency

Fig.2.41. Examples of images included in CoLeaf-DB: Peruvian coffee leaf images dataset for coffee leaf nutritional deficiencies detection and classification, (a) Boron deficiency, (b) Calcium deficiency, (a) Healthy leaves, (a) Iron deficiency

Coffee and cashew nut dataset: A dataset for detection, classification, and yield estimation for machine learning applications [75]:

The dataset comprises high-quality coffee and cashew plants' images collected utilizing Unmanned Aerial Vehicle (UAV) equipment from farms across Uganda. It includes 3000 coffee and 3086 cashew nut images, annotated with classes like unripe, ripening, ripe, spoilt, and coffee_tree for coffee, and tree, flower, premature, unripe, ripe, and spoilt for cashew nuts. Images are approximately 4000 by 3200 pixels with bounding box annotations in YOLO format. The dataset aids in performing several computer vision tasks like yield estimation, flowering intensity analysis, and disease diagnosis. It's the first publicly available dataset of its kind for machine learning yield estimation in coffee and cashew nuts, collected using UAV equipment.



(a) Cashew	(b) Coffee

Fig.2.42. Examples of images included in Coffee and cashew nut dataset: A dataset for detection, classification, and yield estimation for machine learning applications, (a) Cashew, (b) Coffee

Black gram Plant Leaf Disease (BPLD) dataset for recognition and classification of diseases using computer-vision algorithms [76]:

The Black gram Plant Leaf Disease (BPLD) dataset focuses on common diseases affecting black gram crops, including Anthracnose, Leaf Crinkle, Powdery Mildew, and Yellow Mosaic. It contains 1000 images captured in agricultural lands located at Nagayalanka which is in Andhra Pradesh, with categories for each disease and healthy leaves. The dataset, partially associated with the referenced article, consists of images captured using a high-resolution camera. Images were taken at various daytime, resulting in diversely illuminated scenarios. The original RGB images, with varying dimensions due to different devices, were standardized to 512 × 512 during preprocessing. Uploaded to Mendeley data, the dataset comprises five folders representing different disease categories. Each folder contains images corresponding to the specific disease, with varying quantities ranging from 150 to 230 images per category. The dataset aids in the development of automated classification algorithms using image processing and deep learning techniques. Anthracnose causes dark lesions on plant parts, while Leaf Crinkle results in extreme leaf crinkling and puckering. Powdery Mildew leads to white powdery patches on leaves, and Yellow Mosaic causes yellowing and leaf withering. Each category contains images showcasing disease symptoms for research and development purposes.



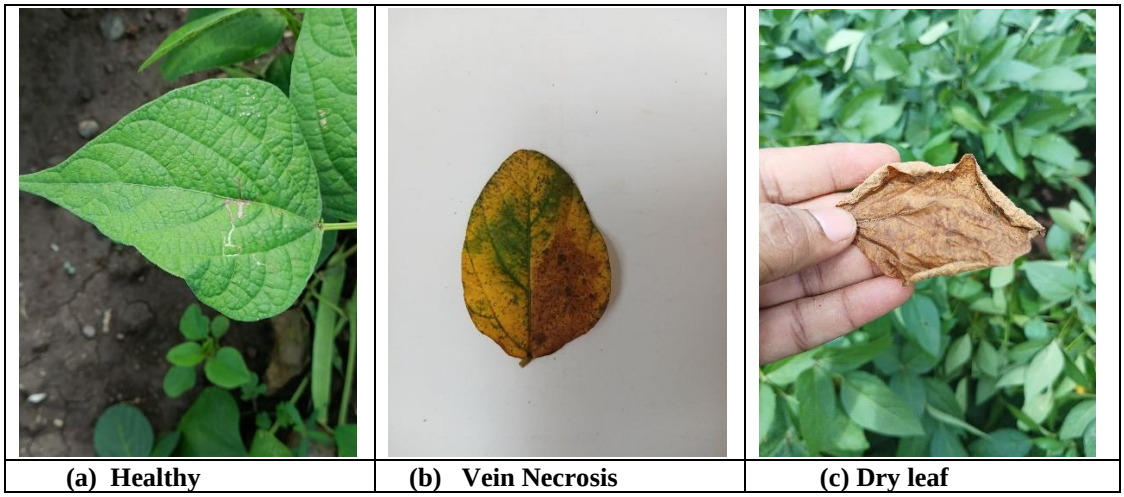
(a) Anthracnose	(b) Healthy	(c) Leaf Crinckle	(d)Powdery Mildew	(e) Yellow Mosaic

Fig.2.43. Examples of images included in Black gram Plant Leaf Disease (BPLD) dataset for recognition and classification of diseases using computer-vision algorithms, (a) Anthracnose, (b) Healthy, (c) Leaf Crinckle, (d) Powdery Mildew, (e) Yellow Mosaic

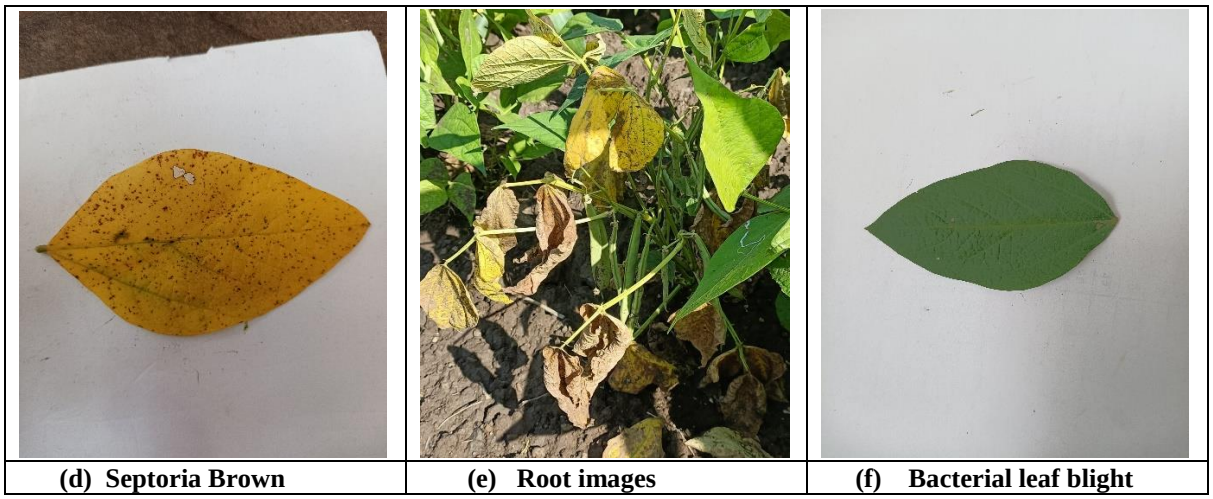
An India soyabean dataset for identification and classification of diseases using computer-vision algorithms[77]:

This study introduces a dataset of soybean plant leaves, encompassing both healthy specimens and those afflicted by various diseases, such as vein necrosis, dry leaf, Septoria brown spot, root images, and bacterial leaf blight. The dataset comprises 3363 images collected over multiple seasons from farms in Maharashtra, India. The dataset includes seven folders with varying numbers of images: the first folder contains 288 healthy images, the second has 138 images of vein necrosis, the third comprises 230 images of dry leaves, the fourth folder contains 284 images of Septoria brown spot, the fifth folder includes 10 root images, the sixth folder has 226 images of bacterial leaf blight, and the last folder contains 2187 raw leaf images.. The dataset aims to support academic research and student projects in the field of machine learning

for agricultural disease recognition. An analysis of the distinct symptoms of these diseases, illustrated with examples from the dataset, is also provided. These include vein necrosis, bacterial leaf spot, and Septoria brown spot, each with characteristic symptoms identifiable in the leaf images.



(a) Healthy **(b) Vein Necrosis** **(c) Dry leaf**



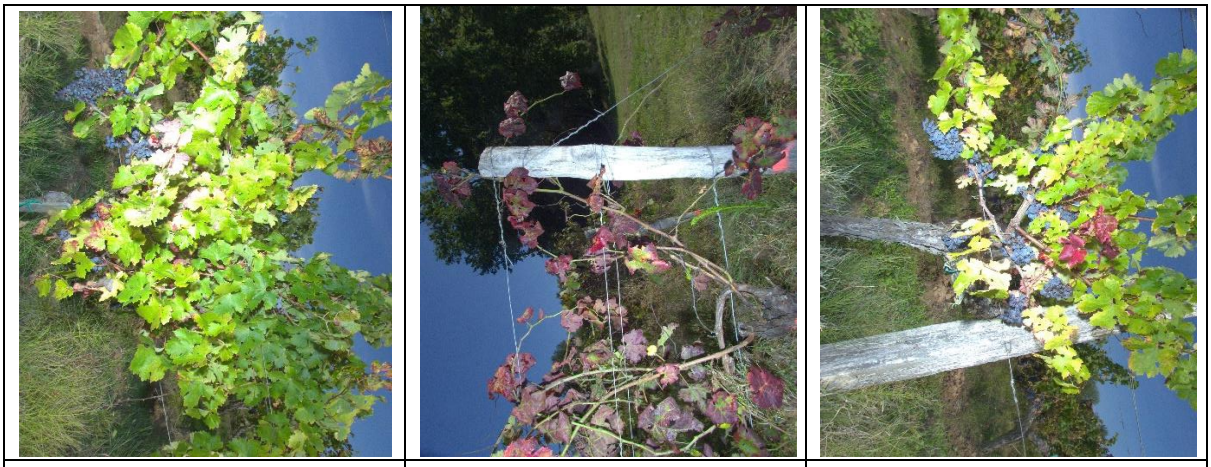
(d) Septoria Brown **(e) Root images** **(f) Bacterial leaf blight**

Fig.2.44. Examples of images included in An India soyabean dataset for identification and classification of diseases using computer-vision algorithms, (a) Healthy, (b) Vein Necrosis, (c) Dry leaf, (d) Septoria Brown, (e) Root images, (f) Bacterial leaf blight

An expertized grapevine disease image database including five grape varieties focused on Flavescence dorée and its confounding diseases, biotic and abiotic stresses[78]:

The dataset comprises 1483 RGB images of grapevines affected by various diseases and stresses, including Flavescence dorée (FD). It includes images of five grape varieties acquired over two years (2020 and 2021). Expert diagnosis and symptom annotations were made at both the grapevine and symptom scales. Annotations include bounding boxes and line strips for symptoms such as FD, ESCA, and confounding leaves, as well as segmentation masks for symptomatic shoots and bunches. The dataset is organized into three main folders: 'image_scale' for annotations at the grapevine scale, 'symptom_scale_box' for symptom annotations with bounding boxes, and 'symptom_scale_mask' for segmentation masks. Each

folder is further divided based on grape variety and acquisition year. The dataset enables the development and evaluation of machine learning algorithms for grapevine disease detection and classification.

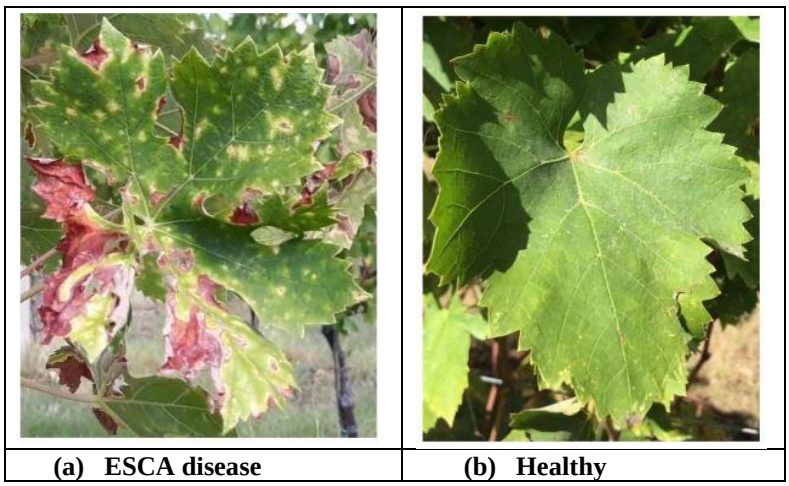


(a) ESCA **(b) FD** **(c) CONF+**

Fig.2.45. Examples of images included in An expertized grapevine disease image database including five grape varieties focused on Flavescence dorée and its confounding diseases, biotic and abiotic stresses, (a) ESCA, (b) FD, (c) CONF+

A grapevine leaves dataset for early detection and classification of esca disease in vineyards through machine learning[79]:

The dataset comprises 1770 images of grapevine leaves, categorized into two classes: healthy leaves and leaves affected by Esca disease. It was collected during the July-September period using smartphones and a tablet, with images having resolutions of 1920×1080 pixels and 1280×720 pixels. The dataset is freely available and includes annotations indicating the class of each image. Images are organized into two main folders: "esca" for Esca-affected leaves and "healthy" for healthy leaves. Each folder contains image files named according to their class and the camera source. Additionally, an annotation file (.csv) listing the filenames and corresponding class IDs is provided, along with a Jupyter notebook for data augmentation and CNN training. This study provides a breakdown of the dataset by class, including the size before and after augmentation. This dataset can aid researchers in developing computer vision and machine learning algorithms for early detection of grapevine diseases, particularly Esca.



(a) ESCA disease **(b) Healthy**

Fig.2.46. Examples of images included in A grapevine leaves dataset for early detection and classification of esca disease in vineyards through machine learning, (a) ESCA disease, (b) Healthy.

2.4 Existing methodologies for foliage identification:

Rapid identification of crop diseases is challenging globally due to limited infrastructure. However, leveraging the widespread use of smartphones and advancements in deep learning-based computer vision enables smartphone-assisted diagnosis. According to authors in the paper [80], using a dataset of 54,306 images of diseased and healthy plant leaves, a convolutional neural network was trained to identify 14 crop species and 26 diseases with 99.35% accuracy on a test set. Testing on images from diverse sources yielded an accuracy of 31.4%, indicating the need for more varied training data to enhance general accuracy. In [80] authors primarily focused on AlexNet and GoogLeNet architectures for the classification problem. This underscores the potential of training deep learning models on large, publicly available datasets for widespread smartphone-assisted crop disease diagnosis.

Authors in article [81] introduces a prototype system for identifying and classifying three rice plant diseases: Bacterial leaf blight, Leaf smut and Brown spot using infected rice leaf images. The system includes experimental analysis of image processing techniques, such as background removal and segmentation. It employs centroid feeding based K-means clustering for accurate disease portion segmentation and utilizes SVM for multi-class classification. Training dataset accuracy is 93.33%, while test dataset accuracy is 73.33%. Cross-validation yields accuracies of 83.80% and 88.57% for 5 and 10-fold validations, respectively. The system is tested on leaf images collected from a rice field in Gujarat, India, and includes an easy-to-use GUI for visualization. Future work aims to enhance background removal techniques, explore alternative classifiers, and improve accuracy, particularly for distinguishing Leaf smut from Brown spot.

Authors, in the paper [82] introduces a novel plant disease recognition model based on CNNs named, specifically designed for leaf image classification. The model can identify 13 types of plant diseases and distinguish healthy leaves from diseased ones. CaffeNet, a deep CNN, comprises multiple layers that extract features from input images progressively. It consists of eight learning layers, including five convolutional and three fully connected layers. The architecture was adapted to accommodate 15 categories for this study [82], with modifications made to the last layer to align with the study's requirements. Specifically, the output of the softmax layer was customized accordingly. It outlines the steps for implementing the model, including image gathering and database creation, validated by agricultural experts. The architecture was trained using Caffe, achieving an average precision of 96.3% across separate class tests, with precision ranging from 91% to 98%.

In [83] authors present and assess a framework for plant leaf/stem disease detection. Traditional expert observation for disease detection can be costly, especially in developing regions. Their proposed image-processing-based framework aims to provide fast, affordable, and accurate solutions. It involves segmentation using the K-Means technique followed by processing through a pre-trained neural network. Testing utilized leaf images from the Al-Ghor area in Jordan, showing significant support for automatic disease detection. Their model is tested on

five plant diseases: Cottony mold, Early scorch, Ashen mold, Tiny whiteness and Late scorch. The neural network architecture proposed in [83] consists of 10 hidden layers. The number of inputs corresponds to the texture features listed. The network operates on feed-forward backpropagation. Mean Square Error (MSE) is used as the evaluation metric, with 10,000 iterations and a maximum error of 10^-5. The developed neural network classifier achieved a precision of approximately 93% in detecting and classifying tested diseases based on statistical classification.

Automating paddy disease recognition is crucial for economic growth in agriculture. In this research paper [84] author aims to develop an image recognition system for identifying three major diseases: Rice sheath blight, Rice blast and Brown spot. Images were taken in laboratory using a digital camera. Image processing is performed with segmentation using mathematical morphology. Features such as texture, shape, and colour are extracted from the diseased leaf images. Classification utilizes membership functions to distinguish between the diseases. Results indicate over 70% accuracy in classifying around 50 sample images.

This paper [85] focuses on automating the categorization of rubber tree leaf diseases using the RGB colour model. Images of various rubber tree leaf diseases are captured and processed to extract RGB colour information. An artificial neural network (ANN) is employed for image classification, with 600 samples used for training and 200 for testing. The research in [85] aims to distinguish corynespora from other diseases using feed-forward neural networks. The chosen network type is the multilayer perceptron (MLP) with one hidden layer, known for its successful application in similar diagnosis tasks. Two models are developed: one based solely on dominant pixel RGB values and another applying principal component analysis (PCA) on pixel gradation values. Both models achieve approximately 70% diagnostic accuracy, with over 80% sensitivity. The PCA model has a smaller network size compared to the other model.

In [86] authors utilize deep convolutional neural networks (CNNs) to recognise plant species from photographs, assessing various factors influencing network performance. Three prominent CNN architectures like AlexNet, GoogLeNet and VGGNet are employed. Transfer learning fine-tunes pre-trained models using LifeCLEF 2015 plant datasets. Data augmentation techniques, such as rotation and scaling, mitigate overfitting. The optimized parameters and fused classifiers achieved an 80% validation set accuracy and a 0.752 inverse rank score on the official test set. This represents a 15% improvement in validation accuracy and a 0.1 improvement in test set performance compared to LifeCLEF 2015 results. Additionally, they outperform the top three competition participants across all categories.

Early disease detection in agriculture is crucial for maximizing crop yield. Diseases like bacterial spot, septoria leaf spot, late blight and yellow curved leaf can significantly impact tomato crop quality. The author in this paper [87] introduces a method using a CNN and Learning Vector Quantization (LVQ) algorithm for automatic detection and categorization of tomato leaf diseases. The dataset comprises 500 images with four disease symptoms. The CNN extracts features automatically from RGB channels, aiding in disease classification. The LVQ algorithm utilizes the CNN's output for training. rectified linear unit (ReLU) activation function and max pooling are used on output matrices. Experimental results confirm the method's effectiveness in recognizing the four types of tomato leaf diseases.

The paper [88] presents a novel plant leaf disease identification model based on a CNN. Trained on a dataset with 39 plant leaf classes, the model utilizes six data augmentation methods—gamma correction, image flipping, PCA colour augmentation, noise injection, rotation, and scaling—to enhance its performance. The model proposed in [88] was compared against logistic regression, SVM, decision tree, and K-NN classifiers. Various testing techniques were evaluated for model performance. Results indicate the superiority of the proposed model over the compared methods. Training parameters like epochs, batch sizes, and dropouts are optimized. Compared to transfer learning approaches, the model proposed in [88] demonstrates superior performance on validation data, achieving a classification accuracy of 96.46%. This accuracy surpasses that of traditional machine learning methods. Additionally, the model's consistency and reliability are tested and confirmed.

The author in the paper [89] introduces a novel visualization method for plant diseases classification using CNN. The method involves two deep classifiers: Teacher and Student, trained jointly through multitask learning. Communication between the Teacher and the Student classifiers yields representations used for visualization of key image regions. The VGG16 architecture serves as both Teacher and Student for simplicity, though alternative classification architectures can be employed. If utilizing a different architecture for Teacher/Student classifier, the decoder must be adjusted to reverse the Teacher's layers for reconstructing the input of the Student. Both the Teacher and the Student architectures resemble the standard VGG16 architecture. Skip connections, depicted as blue arrows, connect the Teacher to the decoder, concatenating input tensors of pooling layers with deconvolution block tensors. Experiments mentioned in [89] conducted on the PlantVillage dataset, demonstrate sharper visualizations compared to existing techniques in plant diseases context.

The proposed work in [90] focuses on developing a practical system for recognizing and quantifying biotic stress on coffee leaves. Biotic stress, caused by pests and pathogens, poses a threat to agricultural sustainability. Computer vision, powered by deep learning methods, allows for the early and accurate identification of stress-causing agents in various contexts. This capability enables prompt corrective measures to be taken, mitigating potential issues and improving outcomes. The proposed multi-task system in [90], based on CNNs, is augmented with data augmentation techniques for improved robustness and accuracy. A new dataset of coffee leaf images was created for experiments in [90]. Various CNN architectures were tested, with ResNet50 yielding the best results. However, the dataset's limited representation of coffee biotic stresses is a drawback. Expanding the dataset with additional stresses and images could balance out this limitation. Experimental results suggest that the system could serve as a valuable tool for experts and farmers in detecting and assessing biotic stresses in coffee plantations.

The author in this paper [91] addresses India's significant crop yield loss of 35% due to plant diseases by exploring computer vision approaches for early detection. The lack of large-scale non-laboratory datasets poses a challenge. The authors introduce PlantDoc, a dataset for visual plant disease detection, comprising 2,598 data points across 13 plant species and up to 17 disease classes. In paper [91], it is mentioned that the author utilized Faster R-CNN with InceptionResnetV2 model and MobileNet model to perform the experiments. Training models on this dataset can improve classification accuracy by up to 31%. The dataset aims to reduce the complexity and requirements for utilizing computer vision techniques in plant disease detection, making it more accessible to a wider range of users. According to authors the paper

[92] proposes an automatic algorithm for identifying grape varieties in vineyards, crucial for applications like robotic harvesting systems. Challenges include natural environmental conditions, limited image volume, and similarity among grape varieties. Transfer learning and fine-tuning techniques using the AlexNet architecture are evaluated in the study. Two vineyard image datasets from different locations and seasons are used, along with image processing methods like the four-corners-in-one algorithm. Experimental results show a 77.30% test accuracy using transfer learning with the four-corners-in-one method and an accuracy of 89.75% on the Flavia leaf dataset. These results offer promise for aiding Douro wine growers in grape variety identification.

The paper [93] introduces a system for classifying and detecting plant leaf diseases using deep learning techniques, utilizing images from the Plant Village dataset. Specifically targeting common plants like peppers, tomatoes, and potatoes, the dataset comprises 20,636 images. The proposed system in [93] employs CNN to classify 15 classes, including 12 disease classes and 3 healthy leaf classes. Achieving high accuracy, the system attains 98.29% accuracy in training and 98.029% accuracy in testing across the entire dataset.

The paper [94] addresses the challenge of plant disease diagnosis by leveraging artificial intelligence, particularly CNNs for leaf image classification. However, CNN performance can be hindered by noisy training data labels, leading to overfitting and reduced accuracy. To tackle this, the author proposed a framework in [94] which integrates a rectified meta-learning module into the CNN paradigm. This module prioritizes unbiased samples, enhancing convergence and classification accuracy. Notably, the method is versatile, effective across various types of label noise, and easily adaptable to different deep learning models. Extensive experiments demonstrate its superior performance compared to existing methods.

Early quantification of Tuta absoluta pest's effects in tomato plants is crucial for effective pest management and preventing significant crop damage. The author in study [95] proposes a CNN approach to assess the impact of Tuta absoluta in tomato plants. Four pretrained CNN architectures (VGG16, VGG19, ResNet, and Inception-V3) were trained on a dataset containing both healthy and infested tomato leaves. Inception-V3 achieved the highest accuracy of 87.2% in estimating the severity of Tuta absoluta. Specifically, it excelled in identifying high Tuta severity status compared to low and no Tuta severity. Evaluation metrics, including F1-score, precision, and recall accuracy, were utilized to assess model performance. Inception-V3 demonstrated superior accuracy, particularly in identifying high Tuta severity, with precision accuracy of 90.5% and recall accuracy of 96.5% on no Tuta images. Overall, Inception-V3 exhibited the highest accuracy of 87.2% on the test set among the trained models.

The authors in paper [96] introduced an unsupervised plant disease diagnosis technique using image data. Unlike supervised deep learning classifiers, their approach does not rely on large labelled datasets, making it more accessible. Their method is based on colour reconstructability, leveraging a deep encoder-decoder network trained to reconstruct healthy plant colours but fails on symptomatic regions. They employed a novel framework utilizing a conditional adversarial network (pix2pix) and a new anomaly score based on CIEDE2000 colour difference. Experimental results on the PlantVillage dataset demonstrate the superiority of their method over existing approaches in terms of accuracy, computational efficiency and interpretability. Their approach in [96] resembles AnoGAN in detecting anomalies in test data through unsupervised training of a generator and discriminator. However, their technique

focuses specifically on colour anomalies. Comparative analysis with AnoGAN shows improved performance in image-level anomaly detection. The simplicity and human interpretability of the CIEDE2000 anomaly score allow for intuitive visualization, effectively highlighting symptomatic regions. Notably, their method exhibits computational efficiency, eliminating the need for iterative computation in anomaly score calculation, thus making it suitable for real-time application. Further research is needed to explore the global-scale application of automatic diagnosis systems based on colour reconstructability.

Automated deep learning-based algorithms are crucial for plant identification but face challenges due to morphological similarities. In [97] authors compared custom CNN and vision transformer (ViT) models using PyTorch on a dataset of 88K and 16K images for genus and species classification respectively. ViT models outperformed CNN-based models like ResNet50 and ResNet-RS-420, achieving 83.3% accuracy at the genus level and 92.5% accuracy at the species level. Augmentation techniques significantly impacted classification success. They conclude that ViT models extract more features and augmentation enhances data quality and network robustness. A custom CNN-based model revealed misclassification of far-captured images compared to near ones. The experiments favored a custom softmax balanced loss function over cross-entropy loss for plant classification tasks.

The author of the paper [98] explores the application of CNNs for plant disease detection, focusing on fine-tuning pre-trained models like DenseNet-121, ResNet-50, VGG-16, and Inception V4. Experiments conducted on the PlantVillage dataset, consisting of 54,305 images across 38 disease classes, revealed DenseNet-121's superiority, achieving a remarkable classification accuracy of 99.81%. Comparative analysis with other state-of-the-art models confirmed its outstanding performance. DenseNet-121 stood out due to its smaller number of trainable parameters and reduced computational complexity, making it more suitable for plant disease identification. The proposed model in [98] achieved a classification accuracy and F1 score of 99.81% and 99.8%, respectively.

The author in the paper [99] introduces a robust as well as novel plant disease detection framework using DenseNet-77 as the base network. The technique involves three steps: annotation development for region of interest extraction, use of DenseNet-77 for deep keypoints extraction in an improved CenterNet, and application of CenterNet for disease detection and categorization. The approach in [99] is evaluated using the PlantVillage Kaggle database, demonstrating superior performance in identifying and categorizing plant diseases compared to other approaches. The framework introduced in [99] efficiently handles variations in light, intensity, size, color, orientation, and shapes of plant leaves. While achieving comparable results, the model currently lacks mobile deployment capability, prompting future work on developing lightweight models and reducing time complexity. Additionally, future plans include testing the model in real-world scenarios, extending its application to other plant parts, and exploring recognition performance on more complex datasets using state-of-the-art DL techniques.

The author in paper [100] introduces DF-Tiny-YOLO, a target detection model for apple leaf diseases based on deep learning methods, aiming to improve the speed and effectiveness of automatic detection. 1,404 images of four common apple leaf diseases were selected for data modeling .The model utilizes feature reuse with DenseNet to enhance feature propagation and detection accuracy. Additionally, Resize and Reorg techniques, along with convolution kernel

compression, reduce calculation parameters and increase detection speed. The network architecture employs 1 × 1 and 3 × 3 convolution kernels for dimensionality reduction without increasing complexity. Evaluation results demonstrate high mAP and average intersection over union (IoU) of 99.99% and 90.88% respectively, with a detection speed of 280 FPS. Compared to existing models, DF-Tiny-YOLO significantly enhances detection performance for apple leaf diseases while maintaining speed and effectiveness.

2.5 Existing vegetable databases:

VegNet: Dataset of vegetable quality images for machine learning applications[111]:

In this study [111] authors curated a dataset featuring four popular Indian vegetables: Bell Peppers, Tomatoes, Chili Peppers, and New Mexico Chiles. Each vegetable category is further divided into subcategories based on their quality: Unripe, Ripe, Old, Dried, and Damaged. The dataset comprises 6850 images captured using mobile phones, showcasing the colour-changing nature of these vegetables as they ripen. This dataset is valuable for training and evaluating machine learning models for vegetable categorization. The focus is on quick and accurate classification to meet the demands of the agricultural industry. The images were taken in various settings, both indoors and outdoors, with different lighting conditions. The dataset is structured according to vegetable quality rather than image quality.

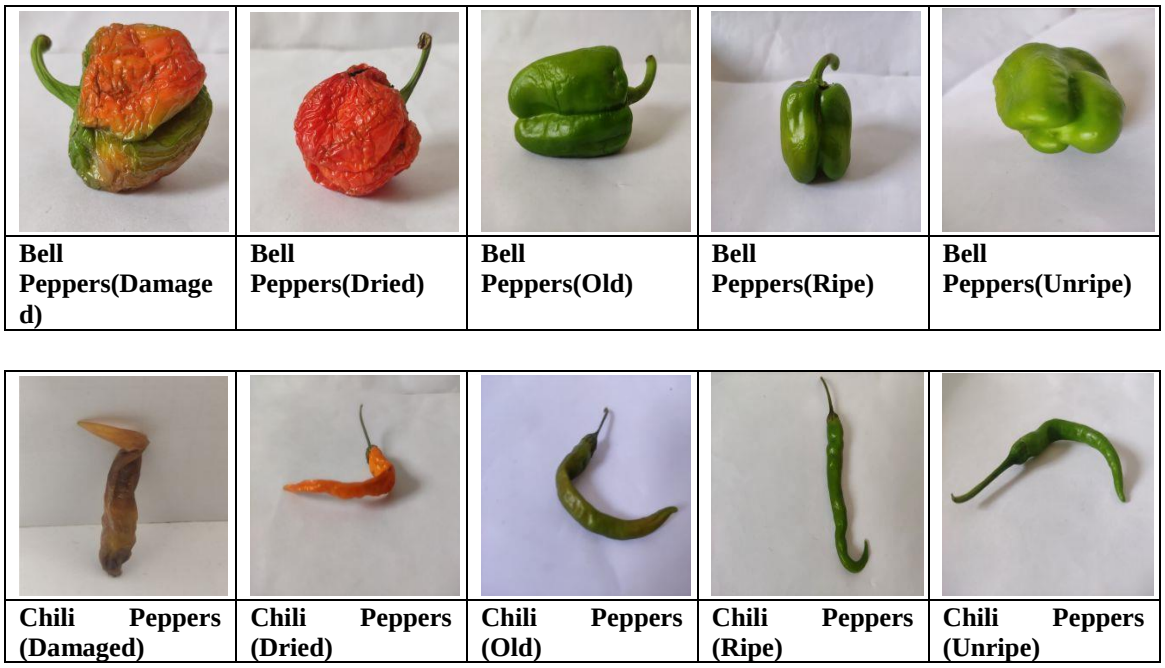


Fig.2.47. Examples of images included in VegNet: Dataset of vegetable quality images for machine learning applications, (a) Bell Peppers, (b) Chili Peppers

SeasVeg: An Image Dataset of Bangladeshi Seasonal Vegetables [112]:

The "SeasVeg" dataset comprises ten categories of seasonal vegetables from Pabna and Dhaka, Bangladesh: Carica Papaya, Momordica dioica, Abelmoschus esculentus, Lablab purpureus, Trichosanthes cucumerina, Trichosanthes dioica, Solanum lycopersicum, Brassica oleracea, Momordica charantia, and Raphanus sativus. It includes 1,500 original images and 3,000 augmented images, all captured under natural lighting conditions with suitable backgrounds.

This dataset offers significant potential for researchers utilizing machine learning and deep learning techniques in healthcare advancements, serving as a valuable resource for future investigations in these domains.



(a) Carica Papaya



(b)Momordica dioica



(c)Abelmoschus esculentus



(d)Lablab purpureus



(e) Trichosanthes cucumerina



(f)Trichosanthes dioica



(g)Solanum Iycopersicum



(h)Brassica oleracea



(i)Momordica charantia



(j)Raphanus sativus

Fig.2.48. Examples of images included in SeasVeg: An Image Dataset of Bangladeshi Seasonal Vegetables, (a) Carica Papaya, (b) Momordica dioica, (c) Abelmoschus esculentus, (d) Lablab purpureus, (e) Trichosanthes cucumerina, (f) Trichosanthes dioica, (g) Solanum Iycopersicum, (h) Brassica oleracea, (i) Momordica charantia, (j) Raphanus sativus

Fruits and Vegetables[113]:

The dataset comprises images of fruits and vegetables collected from the local market in Talegaon, Maharashtra. Captured using a Nikon digital DSLR camera over five months, the dataset includes images collected under various conditions on different days. Operations like cropping and resizing were performed on the collected images. It contains twenty categories: Apple, Bitter melon, Brinjal, Chilli, Cabbage, Fig, Khira, Kundru, Kiwi, Onion, Orange, Pepper Green, Pepper Red, Pomegranate, Tomato Green, Tomato Red, Sapodilla, Sponge Gourd, Strawberry, and Watermelon.



(a) Red Cabbage



(b) Tomato Green

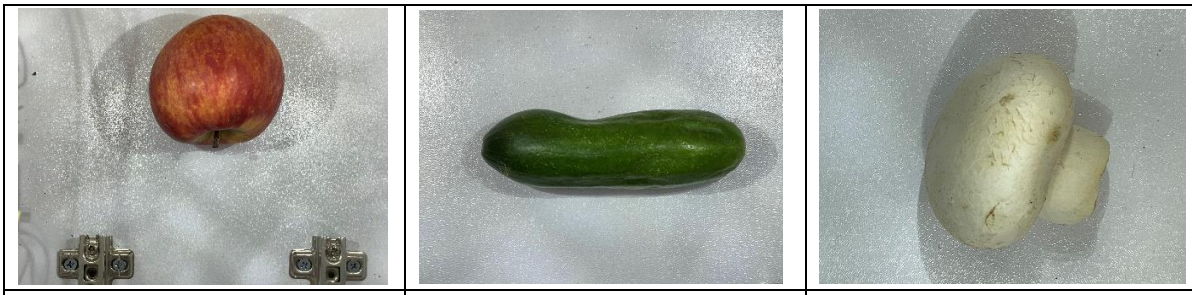


(c) Onion

Fig.2.49. Examples of images included in Fruits and Vegetables, (a) Red Cabbage, (b) Tomato Green, (c) Onion

Thermal and Visible database of organic and Non-organic fruits and vegetables[114]:

The database contains visible and thermal images of red apples, mushrooms, and cucumbers. It includes approximately 160 organic and non-organic apples, 120 organic and non-organic mushrooms, and 30 organic and non-organic cucumbers. Each fruit was rotated 360 degrees at different levels to capture various surfaces, resulting in 3 to 4 photos per fruit. The dataset comprises a total of 1150 visible images and 1166 thermal images. Images were captured using a Dali-tech T4/T8 infrared thermal image camera with dimensions of 640 x 480 pixels, operating in the wavelength range of 8 to 14 μm with a minimum sensitivity of 0.04 °C. Visible images were captured using a 12-megapixel mobile phone camera (iPhone 12-pro) with output image dimensions of 4032*3024 pixels.



(a) Apple organic	(b) Cucumber organic	(c) Mushrooms organic

Fig.2.50. Examples of images included in Thermal and Visible database of organic and Non-organic fruits and vegetables, (a) Apple organic, (b) Cucumber organic, (c) Mushrooms organic

2.6 Existing gemstone databases:

Gemstones Images[115]:

This dataset features over 3,200 images of various gemstones, organized into 87 distinct categories and formatted for both training and testing purposes. All images are in JPEG format and come in a range of sizes and shapes, including round, oval, square, rectangle, and heart.

The dataset is structured into two main directories:

Train (~56 MB): This directory holds approximately 2,800 images distributed across 87 subfolders. Each subfolder is dedicated to a specific type of gemstone.

Test (~8 MB): This directory contains around 400 images, also spread across 87 subfolders, with each subfolder featuring images of different gemstones.

The images given in the database are given below

				
(a) Alexandrite	**(b) Amber**	**(c) Bloodstone**	**(d) Cat's Eye**	**(e) Chrysocolla**

Fig.2.51. Examples of images included in Gemstones Images, (a) Alexandrite, (b) Amber, (c) Bloodstone, (d) Cat's eye, (e) Chrysocolla

Chapter 3

3. BongFloralpedia : A comprehensive collection of diverse types of flowers growing in fields of Ranaghat, West Bengal

3.1 Description of the Database:

This database is a collection of a total of 1920 images of flowers belonging to nine different types of flower species namely, Tuberose (247 images), Marigold (206 images), Ixora coccinea (202 images), Hibiscus (208 images), Crape jasmine (202 images), Dhatura (200 images), Bougainvillea (207 images), 4o' clock (208 images) and Rose (240 images) captured from real-fields located in Ranaghat, West Bengal, India.

The images incorporated in this dataset comprises of non-uniform backgrounds accommodating soil, weeds, etc. This database is created with the aim of providing a comprehensive collection of labelled floral images to train deep neural networks to perform automated classification of nine diverse types of floral species. The inclusion of flower images possessing complex backgrounds in this database enables it to train deep neural networks for performing highly accurate real-life identification of floral species.

The images incorporated in this database are captured using mobile phones, Samsung Galaxy S20 FE 5G (Camera specifications: 12 Mega Pixel with Dual Pixel OIS F 1.8 Wide Rear Camera + 8 Mega Pixel OIS Tele Camera + 12 Mega Pixel Ultra Wide 30 X Space Zoom) and Redmi Note 9 pro max (Camera specifications: AI Quad camera array 64MP+8MP+5MP+2MP).

The images of flowers incorporated in this dataset are specifically captured from real-fields situated in Ranaghat, West Bengal, India which is one of the most well-known flower cultivation areas of the state, so the name of this database is termed as BongFloralpedia considering the place of origin of flowers whose images are included in this database.

Brief descriptions of floral species whose images are included in this database are given as follows:

1. **Tuberose (Scientific name: Polianthes tuberosa):** This is a type of perennial plant belonging to Asparagus family which apart from serving as an important component of perfumes and other aromatic compounds, also have immense medical significance. It serves as an essential constituent of mostly ayurvedic medicines used for treating insomnia, cataract, anaemia, influenza and strep throat.

2. **Marigold (Scientific name: Tagetes):** This type of plant belongs to Tagetes family and is used to cure various dermatological diseases like varicose veins, bruises and contusions. It is used as an important constituent of ointment used for treating wounds caused due to eczema and sunburns.

3. **Ixora (Scientific name: Ixora coccinea)**: This plant belongs to Rubiaceae family and serves as an important ingredient of ayurvedic medicines which are used to treat loss of appetite, nausea, hiccup and also used as a constituent of ointment which are used for treating eczema, chronic ulcers and sores.

4. **Hibiscus (Scientific name: Hibiscus):** This plant belongs to Mallows family and has antiseptic, anti-spasmodic, blood pressure-lowering properties and serves as a well-known antioxidant agent. Its mild laxative and diuretic effects enable it to control constipation and urine production.

5. **Crape jasmine (Scientific name: Tabernaemontana divaricata):** This is an evergreen shrub which belongs to the Apocynaceae family. It is used for treating liver diseases like hepatitis, cirrhosis, etc., acts as a reliever of abdominal pain caused due to diarrhea and also used for treating cancer and preventing stroke.

6. **Datura (Scientific name: Datura):** This is an annual plant which belongs to Solanaceae family. It is used for treating fever, acts as pain reliever, enhance heart functions and also promotes skin and hair health.

7. **Bougainvillea (Scientific name: Bougainvillea):** This plant belongs to the four o'clock family, Nyctaginaceae. It is used for treating coughs and respiratory problems and also serves as an important constituent of botanical insecticides.

8. **Four o' clock (Scientific name:Mirabilis jalapa):** This plant belongs to the four o'clock family, Nyctaginaceae. It is used for treating dropsy and has diuretic and purgative properties. It acts as a healer and used for treating inflammation.

9. **Rose (Scientific name: Rosaceae):** This plant belongs to Rosaceae family and possess anti-depressant, anti-spasmodic, anti-bacterial, purgative and antiseptic properties.

Being a completely novel database BongFloralpedia is curated by including multiple images of nine diverse types of floral species growing in Ranaghat, West Bengal, India. The images of flowers included in this database are completely novel and are not collected from any publicly available sources. These images are captured by performing extensive field survey by the creators of this database. Some new floral species which are not incorporated in any of the publicly available databases are considered while curating BongFloralpedia. Some floral image samples of different species incorporated in this database are given below.

1. Tuberose





2. Marigold



3. Ixora



4. Hibiscus





5. Crape Jasmine



6. Datura



7. Bougainvillea





8. Four o’ clock



9. Rose



Fig.3.1. Examples of images incorporated in BongFloralpedia

3.2 <u>Application</u>: This database is developed to perform training of deep neural networks for automated identification of nine different types of floral species cultivated in fields located in Ranaghat, West Bengal, India. The inclusion of images having high inter-class and intra-class similarities and possessing complex backgrounds, captured using different camera angles and under diverse illumination conditions in this database have enabled it to perform efficient training of deep neural networks for automated, real-life identification of floral species.

3.3 Methodologies to perform the real-life effectiveness on BongFloralpedia:

In this work, I have chosen multiple deep neural networks designed following different methodologies, learning strategies to validate the effectiveness of the newly designed database. Brief details of the deep neural networks are given as follows:

(a) **AlexNet:** It considered one of the pioneering deep neural network models, made a significant impact on the computer vision domain. It gained popularity being one of the earliest models to revolutionize image analysis. Comprising a total of eight layers, the architecture consists of five convolutional layers followed by three fully connected layers. The convolutional layers employ diverse filters to extract meaningful features from input images, complemented by max-pooling layers that aid in down sampling the feature maps. This combination effectively preserves important features while reducing the computational load. However, due to its substantial parameter count of approximately 60 million, AlexNet requires significant memory resources to achieve its impressive performance.

(b) **Vgg16:** Similar to AlexNet, Vgg16 also has achieved desired performance in categorizing images within the computer vision field. The model consists of a total of sixteen layers, comprising thirteen convolutional layers followed by three fully connected layers. A notable characteristic of Vgg16 is its homogeneous architecture, where all convolutional layers employ 3x3 kernel size filters to extract features from the input data. With approximately 138 million parameters, the Vgg16 model faces a substantial computational burden, despite its impressive performance. The high parameter count contributes to increased memory and computational requirements, which can impact the model's efficiency. However, the trade-off is justified by the overwhelming performance Vgg16 delivers in various image classification tasks.

(c) **ResNet152:** ResNet152 is a CNN model belonging to the ResNet family. It is characterized by a sequence of residual blocks that consist of convolutional and batch-normalization layers. The activation function used in these layers is Rectified Linear Unit (ReLU). In contrary to AlexNet and Vgg16, which primarily concentrates on gaining information from previous layer activation maps, ResNet152 introduces skip-connections. These connections enable the network to learn residual functions, facilitating efficient preservation of multi-scale features.

With a total of 152 layers and over 11 billion parameters, ResNet152 incurs a significant computational cost. The large parameter count contributes to increased memory and computational requirements for the model. However, this trade-off is justified by the enhanced performance and the ability of ResNet152 to capture intricate features across different scales in various image analysis tasks.

(d) **MobileNetv2:** MobileNetv2 is a lightweight convolutional neural network (CNN) architecture that distinguishes itself by utilizing depth-wise separable convolution layers instead of standard convolutional layers. This architectural choice significantly reduces the computational burden of the network. Additionally, MobileNetv2 incorporates linear bottlenecks with a reduced number of channels, further decreasing its computational requirements.

To enhance performance and address the vanishing gradient problem MobileNetv2 includes skip-connections. These connections enable the network to learn residual functions, thereby increasing the stability of the network. The combination of depth-wise separable convolution layers, linear bottlenecks, and skip-connections contributes to the network's low computational complexity without compromising its impressive performance.

As a result, MobileNetv2 finds practical application in mobile devices for tasks such as object classification and detection. Its efficient design makes it well-suited for deployment on resource-constrained devices, enabling effective image analysis on mobile platforms.

(e) **Inceptionv3:** Inceptionv3 is a well-known CNN model that is built upon the core idea of parallel computations utilizing filters of various sizes. This architecture incorporates multiple inception modules, which consist of a fusion of 1x1, 3x3, and 5x5 convolutions. This unique combination enables the extraction of multi-scale feature maps, enhancing the model's ability to capture diverse information.

A noteworthy advantage of Inceptionv3 is the integration of 1x1 convolution blocks, which contribute to reducing the computational cost of the network. With approximately 23 million parameters, Inceptionv3 exhibits significant computational efficiency compared to models such as AlexNet and Vgg16.

The Inceptionv3 architecture is well-regarded for its ability to efficiently process and extract features at multiple scales. By leveraging the concept of parallel computations and employing a mixture of convolutional filters, Inceptionv3 demonstrates its prowess in various computer vision tasks.

(f) **Xception:** The CNN model known as "Extreme Inception" derives its design inspiration from the concept of inception modules used in Inceptionv3. However, a significant difference lies in the architecture of these networks. In Extreme Inception, the inception modules incorporate depth-wise convolutional layers instead of conventional convolutional layers. This architectural choice serves two purposes: reducing the computational burden and facilitating improved feature extraction by isolating spatial and channel-wise information.

Extreme Inception combines depth-wise separable convolutions, residual connections, and skip connections within its architecture. This combination not only enhances the model's memory efficiency but also proved to be highly effective in capturing intricate features and achieving remarkable accuracy in various tasks.

The integration of depth-wise separable convolutions allows for efficient processing and extraction of features, while residual connections and skip connections contribute to the model's stability and the preservation of valuable information throughout the network.

Overall, the "Extreme Inception" model presents a powerful solution with its memory-efficient design and the ability to capture complex features, leading to impressive accuracy in a range of applications.

(g) **ShuffleNetv2:** ShuffleNet is another computationally efficient network characterized by a low parameter count. Its architecture incorporates two key elements: channel shuffling and point-wise group convolutions.

Channel shuffling plays a significant role in the network by enabling the exchange of information between different channels. This process involves rearranging feature maps within the network, enhancing information flow and improving the model's capacity for learning complex representations.

ShuffleNet is structured with multiple stages, each comprising several ShuffleNet units. These units consist of point-wise group convolutions, channel shuffling, and depth-wise separable convolutions. Together, these components efficiently combine spatial and channel information, resulting in effective feature extraction and representation.

(h) **SqueezeNet:** The model at hand is also characterized by its computational efficiency, with a key highlight in its architecture being the incorporation of "squeeze and excitation" modules. These modules play a crucial role in striking a balance between computational complexity and performance efficiency.

The squeeze module, utilizing 1x1 point-wise convolutions, reduces the number of input channels, effectively compressing the information. On the other hand, the excitation modules perform adaptive weighting of the channels, enhancing the preservation of the most significant information and boosting the model's representation capabilities.

The model employs fire modules, which combine squeeze and expand layers, allowing for efficient execution of both 1x1 and 3x3 convolutions. This design choice contributes to its computational efficiency, making it well-suited for deployment on resource-constrained devices.

The utilization of "squeeze and excitation" modules and fire modules enhances the model's ability to capture meaningful features while maintaining computational efficiency. This advantageous combination allows for effective implementation in devices with limited computational resources.

(i) **DenseNet121:** DenseNet121 is a network that prioritizes information flow across layers by utilizing dense blocks instead of sequential flow. This design choice enables better preservation of information throughout the network. In addition, the architecture incorporates bottleneck layers, which consist of 1x1 convolutions, before each 3x3 convolution.

The combination of dense connectivity and bottleneck layers in DenseNet121 allows for a desirable balance between accuracy and computational efficiency. The dense blocks facilitate extensive information exchange between layers, enhancing the model's ability to capture complex features. The incorporation of bottleneck layers further improves computational efficiency by reducing the dimensionality of feature maps before applying 3x3 convolutions.

DenseNet121 demonstrates its effectiveness by achieving high accuracy while maintaining computational efficiency. This makes it a favourable choice for various tasks where the preservation of information and computational resources are both crucial considerations.

(j) **InceptionResNetv2:** This hybrid deep neural network combines the best features of Inceptionv3 and ResNet152, resulting in a powerful architecture. By incorporating inception modules and skip-connections, this model effectively preserves multi-scale contextual information while minimizing the computational parameters required.

With an approximate parameter count of 50 million, this network strikes a balance between complexity and computational efficiency. The integration of inception modules and skip-connections enables the network to capture intricate features and maintain contextual information across different scales.

By leveraging the strengths of both Inceptionv3 and ResNet152, this hybrid network demonstrates improved performance and robust feature representation. It is well-suited for various deep learning tasks where the preservation of multi-scale contextual information is crucial while optimizing computational resources.

(k) **NasNetLarge and NasNetMobile:** NasNetLarge and NasNetMobile are CNN models that belong to the Neural Architecture Search (NAS) family of neural network architectures. Unlike traditional manual design approaches, these models employ a reinforcement learning strategy to automatically select the most optimal network structure from a vast search space of potential architectures.

Both NasNetLarge and NasNetMobile are cell-based architectures, where cells are composed of separable convolutions, pooling operations, and skip connections. Through the reinforcement learning process, these models learn to choose and assemble the most effective combinations of these architectural elements.

NasNetLarge is a more complex model, while NasNetMobile is designed to be lightweight with a lower number of parameters. This characteristic makes NasNetMobile particularly suitable for deployment on resource-constrained devices.

By leveraging the power of neural architecture search, NasNetLarge and NasNetMobile achieve state-of-the-art performance without the need for manual design. The ability to automatically discover optimal network structures makes these models highly efficient and effective in various machine learning tasks.

(l) **EfficientNetB7:** The CNN model at hand is built with a deep hierarchical structure, consisting of stacked blocks that incorporate convolution and normalization layers, as well as non-linear activation functions. The primary goal of this design is to achieve maximum efficiency while maintaining a high level of effectiveness. This is achieved through a compound scaling method that scales the network's width, depth, and resolution.

Within the EfficientNet series, the "B7" variant stands out as the most powerful. It boasts the widest channels, the highest number of layers, and the largest image resolution compared to other variants in the series. This increased capacity enables the model to capture intricate features and perform highly effective classification tasks.

The hierarchical structure of this model facilitates the learning of complex and detailed features, contributing to its ability to achieve impressive classification performance. By leveraging the compound scaling method, the EfficientNet series strikes a balance between computational efficiency and effectiveness, making it a valuable asset in various deep learning applications.

(m) **GhostNetv2:** GhostNetv2 is a lightweight CNN model designed with a focus on efficient and reliable image recognition while minimizing computational resources. It is an advanced version of the original GhostNet architecture, named after the concept of using "ghost" feature maps, representing low-dimensional representations of the original feature maps.

GhostNetv2 incorporates several key concepts to enhance its performance. It adapts a split-attention mechanism, allowing for the extraction of multi-scale features. This capability enables the model to capture and leverage relevant information at multiple levels, improving its ability to recognize diverse patterns.

To reduce computational costs, GhostNetv2 incorporates different convolutional operations, including depth-wise and point-wise convolutions, as well as squeeze-and-excitation modules. These design choices efficiently process information while maintaining high accuracy.

The model further benefits from various efficient channel shuffling, linear bottleneck modules, and inverted residual connections, which facilitate better information flow. This increased feature extraction capacity contributes to improved overall performance.

Comparative analyses of networks like GhostNetv2 are crucial in showcasing the advancements in deep learning research and their impact on real-life problems. These networks differ significantly in their architectures and learning procedures, demonstrating the diversity and progress in the field of deep learning. GhostNetv2 stands out as an exemplary model that efficiently addresses image recognition tasks with reduced computational resources.

These networks are chosen for performing comparative analyses to portray how the advancements in deep learning research area is influencing the real-life problems and as most of the deep neural networks are designed focused on the low computation cost aspect, so the analyses' is performed to select the deep neural network which can be implemented in real-time systems.

3.4 Comparative analysis results obtained on BongFloralpedia database:

Here, I have validated the real-life effectiveness of my designed BongFloralpedia database in performing real-life identification of floral species possessing diverse characteristics. Here, I have also demonstrated the performances registered by 14 popular DNNs as shown in results in performing the categorization of images of floral species included in this database.

Comparative analysis is performed using four relevant quantitative parameters namely, Test Accuracy, Precision, Recall and F1 Score.

TABLE 3.1. COMPARATIVE ANALYSIS RESULTS

Parameters	AlexNet	Vgg16	ResNet152	EfficientNetB7	MobileNetv2	Inceptionv3
Test Accuracy (%)	12.8	12.8	76.14	12.8	99.4	98.8
Precision	0.017	0.017	0.779	0.017	0.994	0.988
Recall	0.129	0.129	0.761	0.129	0.994	0.988
F1 Score	0.0293	0.0293	0.750	0.0293	0.994	0.988

Parameters	ShuffleNetv2	SqueezeNet	Xception	InceptionResNetv2	NasNetLarge	NasNetMobile
Test Accuracy (%)	0.10	12.8	99.2	0.989	0.976	98.9
Precision	0.02	0.017	0.991	0.990	0.977	0.989
Recall	0.11	0.129	0.991	0.990	0.976	0.989
F1 Score	0.03	0.0293	0.991	0.990	0.976	0.989

Parameters	DenseNet121	GhostNetv2
Test Accuracy (%)	99.0	12.8
Precision	0.99	0.017
Recall	0.99	0.129
F1 Score	0.99	0.0293

N.B: DenseNet121 gives the best results among all the deep neural networks in terms of Test Accuracy (%), Precision, Recall and F1 Score. (Better results are highlighted.)

3.5 Conclusion: From the basis of my knowledge, BongFloralpedia is the first and novel dataset which is designed by incorporating 1920 images of floral samples belonging to nine different categories having vast diversities in their characteristics growing in West Bengal. The images of floral samples included in this database are captured by the creators from the real-fields located in Ranaghat, West Bengal which is one of the most popular flower cultivation areas of India. The samples are chosen from species having high export values and immense medicinal properties. The place of origin of these samples served as the main inspiration behind naming this database as "BongFloralpedia". The images included in this database are captured using different camera angles, under varied illumination conditions and possess complex backgrounds containing different ambiguities which facilitates efficient training of deep neural networks. Future work in this research area can be focused on creating more such databases for effective training of networks and to design more computationally efficient real-time applicable systems for floral health monitoring.

Chapter 4

4. Nature's Diabetes Helpers: Insulin Leaves Repository

4.1 Description of this database: This database comprises a total of 429 images depicting both healthy (265 images) and diseased (164 images) leaves of the insulin plant (Scientific name: Chamaecostus cuspidatus). All the images included in this database are captured by the creators of this database from the real fields located in and around Ranaghat of West Bengal, India.

The images in this database consist of intricate backgrounds that include elements like weeds, soil, and portions of other plants. The primary objective behind creating this database is to offer a comprehensive assortment of labeled foliage images of insulin plants. These images are intended for training deep neural networks to autonomously classify them into either diseased or healthy categories. The incorporation of foliage images with complex backgrounds and captured under varied illumination condition in this database enhances its capability to effectively train deep neural networks, enabling precise real-world identification for the specified task.

The images included in this database were captured using mobile phones, specifically the Samsung Galaxy S20 FE 5G with the following camera specifications: 12MP (Dual Pixel) OIS F 1.8 Wide Rear Camera, 8MP OIS Tele Camera, and 12MP Ultra Wide 30X Space Zoom, as well as the Redmi Note 9 Pro Max with a camera array featuring 64MP+8MP+5MP+2MP, utilizing Artificial Intelligence (AI) technology.

As this database contains the diseased and healthy leaves of insulin plants which serves as natural remedy for diabetes, so we have termed this database as “Nature’s Diabetes Helpers: Insulin Leaves Repository.”

Some potential medicinal aspects associated with insulin plant leaves are listed as follows:

Hypoglycemic Properties: Insulin plant leaves are believed to have compounds that may help lower blood sugar levels. Some studies suggest that certain phytochemicals in the leaves may mimic the action of insulin in the body or improve insulin sensitivity.

Antioxidant Activity: Insulin plant leaves contain antioxidants that can help combat oxidative stress in the body. Reducing oxidative stress is important for overall health, including diabetes management.

Anti-Inflammatory Effects: Inflammation plays a role in the development and progression of diabetes. Some research suggests that insulin plant leaves may possess anti-inflammatory properties.

Traditional Use: In traditional medicine, particularly in Ayurveda and traditional systems of medicine in Southeast Asia, insulin plant leaves have been used as part of diabetes management. However, traditional uses are not always supported by rigorous scientific research.

Some examples of healthy and diseased insulin leaves which are taken from the repository are shown below:

1. **Healthy insulin leaves:**



2. **Damaged insulin leaves:**



Fig.4.1. Examples of images incorporated in Nature's Diabetes Helpers: Insulin Leaves Repository

4.2 Application: This database has been designed for the purpose of training deep neural networks to autonomously categorize insulin leaves as either healthy or diseased, a task of great medical importance. The incorporation of images with intricate backgrounds, taken from various camera angles, and captured under diverse lighting conditions, empowers the database to facilitate effective training of deep neural networks for the real-world automated classification of foliage.

4.3 Conclusion: In conclusion, the "Nature's Diabetes Helpers: Insulin Leaves Repository" database serves as a valuable resource for advancing research at the intersection of technology and healthcare. Through its comprehensive collection of labeled foliage images, captured under diverse conditions using accessible mobile phone cameras, the database enables the training of deep neural networks for the automated classification of insulin leaves.

This database is completely novel database which is not found in any other publicly available sources before. To create insulin plant health monitoring methods this database is very much required so with this consideration the "Nature's Diabetes Helpers: Insulin Leaves Repository" database is made publicly available at this link: https://data.mendeley.com/datasets/t3tt7rjszv/1

The diverse nature of the dataset, encompassing both healthy and diseased leaves with intricate backgrounds, enhances its utility in real-world applications, such as precision agriculture and herbal medicine. By leveraging modern technology and focusing on a plant species with significant medicinal value, this database contributes to the ongoing efforts to harness the power of artificial intelligence for the benefit of human health.

Moving forward, this database opens doors for further exploration and innovation in the fields of image recognition, plant pathology, and medical diagnostics. By fostering collaboration and knowledge exchange, it paves the way for future developments in leveraging natural remedies for the management of chronic diseases like diabetes.

Chapter 5:

5. GreenMedNet: A computationally inexpensive hyperparameter optimised dual attention based insulin leaves categorization approach

5.1 Introduction: In addition to the creation of the innovative "Nature's Diabetes Helpers: Insulin Leaves Repository," the primary contribution of this study lies in the development of a computationally efficient and hyperparameter-optimized, attention based deep neural network known as "GreenMedNet." This network excels in the classification of damaged and healthy insulin leaves by incorporating multi-scale contextual spatial as well as channel-wise information that too using less number of parameters. The goal is to achieve a highly optimized, computationally efficient, and reliable deep neural network for enhanced insulin leaf classification.

5.2 GreenMedNet: a novel hyper-parameter optimized attention based deep neural architecture

GreenMedNet's architecture is strategically designed to enhance performance efficiency and reduce the total number of parameters. By incorporating Depth-wise separable convolutional layers and GlobalAveragePooling2D layers, the design effectively minimizes the model's parameter count, optimizing both the computational load and the efficiency of the network.

The integration of depth-wise and point-wise convolutional blocks as bottlenecks within the depth-wise separable convolutional layers significantly reduces the number of parameters needed for feature map extraction. This approach is more parameter-efficient compared to traditional convolutional layers.

The use of the GlobalAveragePooling2D layer has also significantly reduced the total parameter count compared to the Flatten layer. This layer effectively summarizes the spatial information of the activation maps from the preceding layer by condensing each channel into a single value, thus streamlining the network architecture and enhancing its efficiency.

The designed architecture includes Batch-Normalization layers to achieve faster convergence by reducing internal covariance shift. Additionally, the architecture incorporates the concept of Dropout to address the issue of overfitting, enhancing the model's generalization capabilities.

The architecture of GreenMedNet is finalized by selecting various hyper-parameters, such as the number of Depth-wise separable convolutional layers, the number of neurons in Dense Layers (D1 and D2), the dropout values applied in these two dense layers (Dp1 and Dp2), and the reduction ratio in the spatial attention block. This selection process utilizes the Random Search method.

The initial search space defined for the hyper-parameters includes the following ranges: the number of Depth-wise separable convolutional layers is set to [3, 4, 5]; the reduction ratio in the spatial attention block is [8, 10, 12]; the number of neurons in D1 ranges from [64, 128, 256]; the number of neurons in D2 is set to [32, 64, 128]; and the dropout values for Dp1 and Dp2 are [0.3, 0.4, 0.5] respectively.

The optimal architecture, determined using the Random Search strategy and based on the criteria of maximized validation accuracy, comprises four Depth-wise separable convolutional layers. It features a reduction ratio of 8, 256 neurons in D1, 128 neurons in D2, with dropout rates of 0.4 for Dp1 and 0.5 for Dp2.

In this work, Categorical Cross Entropy and the Adam optimizer with momentum values (β1=0.92 and β2=0.98) are utilized as the loss function and optimization technique, respectively. The Exponential Rectified Linear Unit (EReLU) serves as the activation function in intermediate layers to mitigate issues like vanishing gradients and the dying ReLU problem. For the final classification layer, the softmax function is employed as it effectively handles multiclass classification. Additionally, L2 regularization is implemented in the Convolutional and Dense layers to prevent overfitting. Fig. 1 and Fig.2 provide a visual representation of GreenMedNet's architecture and the detailed architecture of the Dual spatial and channel attention block, respectively.

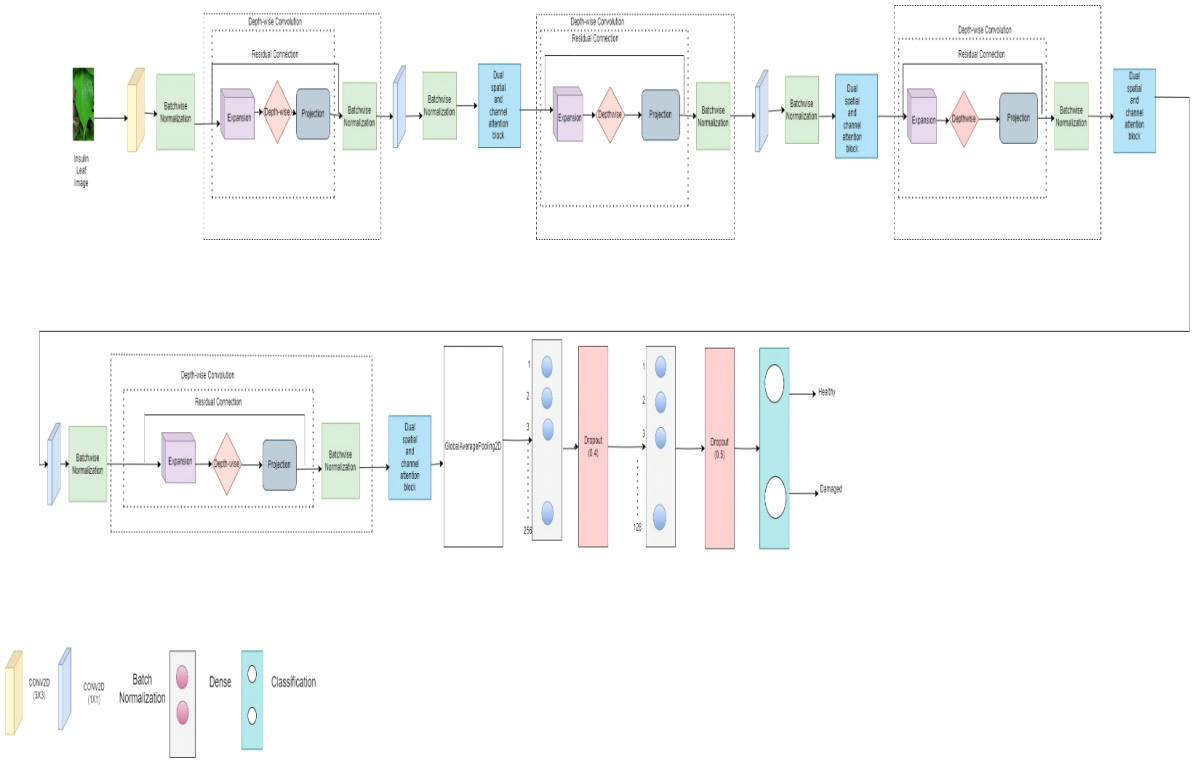


Fig.5.1. Pictorial representation of detailed architecture of GreenMedNet

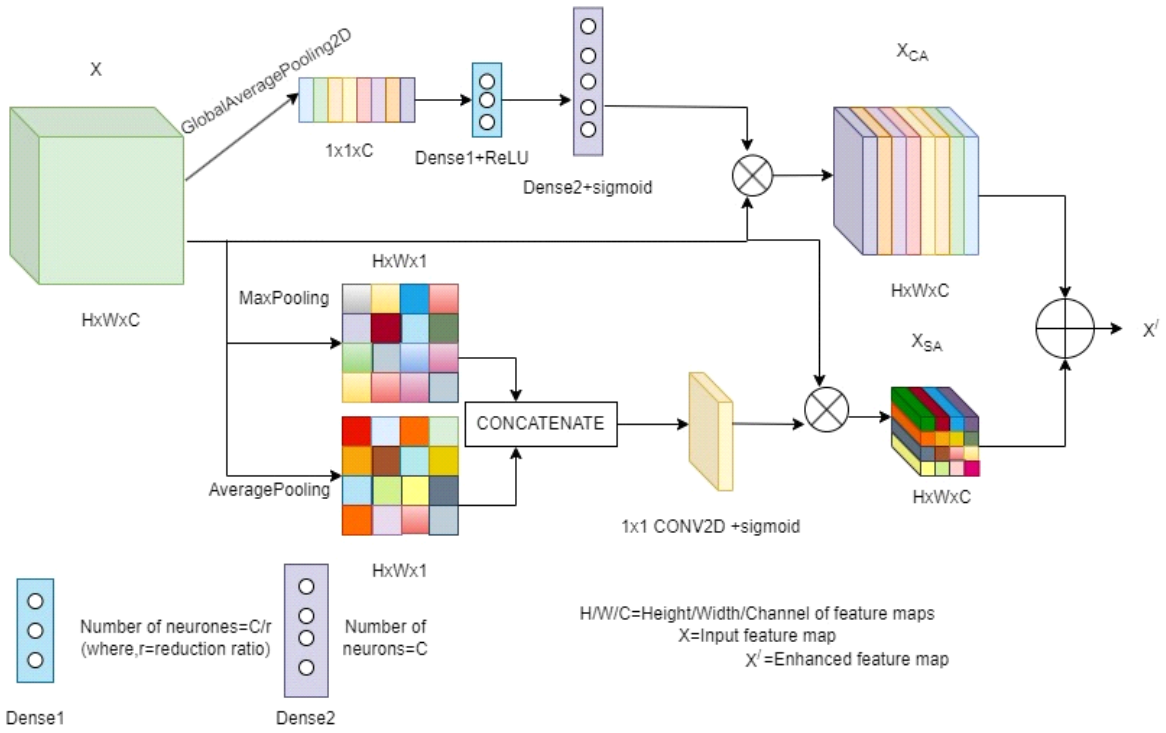


Fig.5.2. Detailed overview of the Dual spatial and channel attention block

5.3 <u>Comprehensive comparative results:</u> In this study, I thoroughly validated the performance efficiency of our newly designed network by comparing it with several established deep neural networks: AlexNet, ResNet152, MobileNetV2 , InceptionV3, DenseNet121, InceptionResNetV2, NasNetLarge, and NasNetMobile. We assessed performance using a variety of significant qualitative metrics such as Test Accuracy, Precision, Recall, and F1 score. The experimental results are detailed in table below.

<u>TABLE 5.1. COMPREHENSIVE COMPARATIVE RESULTS</u>

Model Name	Precision	Recall	F1 Score	Test Accuracy (%)	Total parameters
AlexNet	0.944	0.943	0.942	94.29	44562890
ResNet152	0.828	0.767	0.828	76.78	24106107
MobileNetv2	0.94	0.94	0.94	94.03	7523
Inceptionv3	0.914	0.914	0.914	91.46	458923
DenseNet121	0.913	0.913	0.913	90.90	4314289

Model Name	Precision	Recall	F1 Score	Test Accuracy (%)	Total parameters
InceptionResNetV2	0.922	0.922	0.922	92.75	1114482
NasNetLarge	0.948	0.948	0.948	94.88	1324501
NasNetMobile	0.943	0.943	0.943	94.3	369104
EfficientNetB7	0.86	0.81	0.84	86.01	1072216
GreenMedNet	0.995	0.995	0.995	99.47	6521

5.4 <u>Conclusion:</u> To my knowledge, this study is a ground breaking endeavour in the realm of leaf disease detection, particularly targeting leaves with significant medicinal properties. A notable achievement of this research is the creation of the Nature's Diabetes Helpers: Insulin

Leaves Repository. This repository contains both diseased and healthy leaf samples from selected species known for their potent blood sugar reduction effects.

The comprehensive analysis demonstrates that GreenMedNet effectively balances performance efficiency with total parameter count at both document and word levels. This balance is largely due to the integration of Depth-wise separable convolutions and GlobalAveragePooling2D layers, which significantly reduce the total parameter count. Additionally, the implementation of a dual attention mechanism, which operates both spatially and channel-wise, enhances the network's performance by focusing on the most pertinent features according to their attention scores. The inclusion of Batch-Normalization, Dropout layers, and an L2 regularization strategy further contributes to rapid convergence and reduced overfitting.

Future research in this field may focus on several critical areas:

1. **Improving Accuracy:** While the designed network already performs commendably, there is room for further improvement by exploring advanced learning techniques. This could include experimenting with deeper neural network models, exploring innovative neural architectures, or employing ensemble learning strategies to combine predictions from multiple models.
2. **Expansion to Other Crops and Diseases:** The current study primarily focuses on specific crop species and their leaf diseases. Future research could broaden this focus to include a wider variety of crops and leaf diseases. This would help in developing more comprehensive databases and neural network models that can detect and classify a broader spectrum of leaf diseases across different crops.
3. **Real-time Data Integration:** Current leaf disease detection models primarily use static databases. An exciting area for future exploration is the integration of real-time data into the detection process. This could involve using sensors or cameras to capture live images of leaves, which would then be directly fed into the model for instant disease detection.
4. **Development of a Mobile Application for Leaf Disease Detection:** Another promising direction is to develop a mobile application based on the leaf disease detection model. Such an application would allow farmers and other users to easily take photos of leaves with their mobile devices, submit these photos to the application, and quickly receive disease detection and classification results.

Chapter 6

6. Herbal Leaf Repository: Unveiling Nature's Pharmacy

6.1 Description of this database: This database contains a comprehensive collection of images showcasing both healthy and diseased leaves of Curry tree (Scientific name: Murraya koenigii), Neem (Scientific name: Azadirachta indica), Longevity spinach (Scientific name: Gynura), Red spinach (Scientific name: Amaranth Dubius) and Holy Basil (Scientific name: Ocimum tenuiflorum). All the images featured in this database were taken by the creators directly from fields situated in the Ranaghat district of West Bengal, India.

The images within this database feature detailed backgrounds, including elements such as weeds, soil, and sections of other plants. The main goal of creating this database is to provide a wide range of labelled foliage images of diverse plant species. These images are designed for training deep neural networks to classify them automatically into different plant categories. By incorporating foliage images with complex backgrounds and captured under various lighting conditions, this database enhances its ability to effectively train deep neural networks, enabling precise real-world identification for the specified task.

The images in this database were taken using mobile phones, specifically the Samsung Galaxy S20 FE 5G with the following camera specifications: a 12MP (Dual Pixel) OIS F 1.8 Wide Rear Camera, an 8MP OIS Tele Camera, and a 12MP Ultra-Wide 30X Space Zoom. Additionally, images were captured using the Redmi Note 9 Pro Max, which features a camera array comprising 64MP+8MP+5MP+2MP, utilizing Artificial Intelligence (AI) technology.

This database, which includes both diseased and healthy leaves of plants known for their natural medicinal properties, is appropriately named "Herbal Leaf Repository: Unveiling Nature's Pharmacy." Some potential medicinal aspects associated with plant leaves whose images are included in this database are listed as follows:

Certainly, here are the medicinal properties associated with each of the mentioned plants:

1. Curry Tree (Murraya koenigii):

- Anti-inflammatory properties
- Antioxidant activity
- Aids in digestion
- Supports heart health
- May help in managing diabetes

2. Neem (Azadirachta indica):

- Antibacterial and antiviral properties
- Antifungal activity
- Supports oral health
- Skin healing and anti-acne properties

- Helps in managing diabetes

- Supports liver health

3. Longevity Spinach (Gynura):

- Rich in antioxidants

- Anti-inflammatory properties

- Supports cardiovascular health

- May aid in managing diabetes

- Immune-boosting properties

4. Red Spinach (Amaranth Dubius):

- High in vitamins and minerals

- Supports eye health

- May help in lowering blood pressure

- Antioxidant properties

- Supports bone health

5. Holy Basil (Ocimum tenuiflorum):

- Adaptogenic properties (helps the body adapt to stress)

- Anti-inflammatory and antioxidant properties

- Supports respiratory health

- May help in managing anxiety and depression

- Supports digestive health

- Anti-diabetic properties

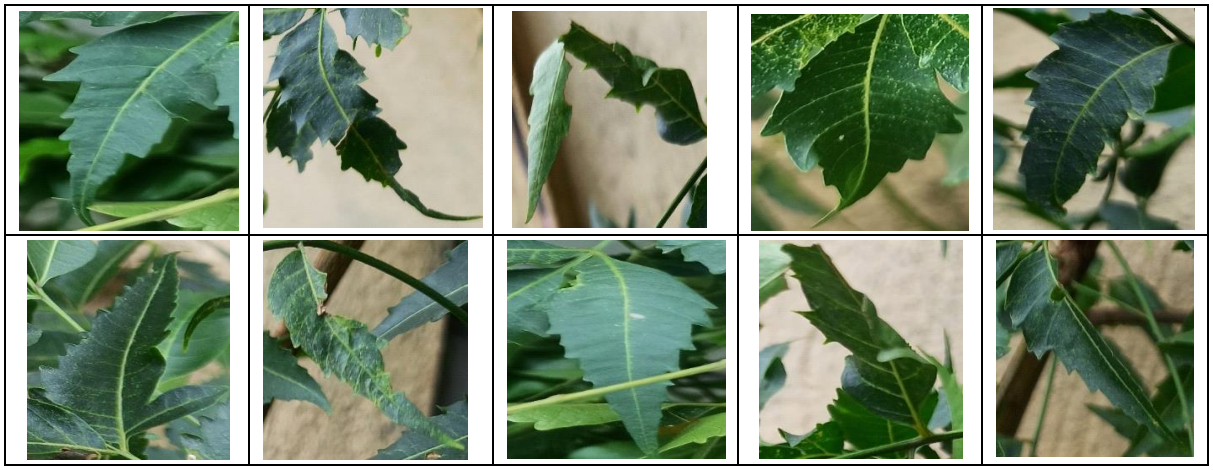
Some examples of the database "Herbal Leaf Repository: Unveiling Nature's Pharmacy" is given below:

1. Curry Tree (Murraya koenigii):





2. Neem (Azadirachta indica):



3. Longevity Spinach (Gynura):



4. Red Spinach (Amaranth Dubius):





5. Holy Basil (Ocimum tenuiflorum):



Fig.6.1. Examples of images incorporated in Herbal Leaf Repository: Unveiling Nature's Pharmacy

6.2 Application: This database has been created for training deep neural networks to autonomously categorize healthy or diseased leaves belonging to five different plant species having immense medical significance. By incorporating images with intricate backgrounds, taken from various camera angles, and captured under diverse lighting conditions, the database enables effective training of deep neural networks for the real-world automated classification of foliage.

6.3 Discussion: The "Herbal Leaf Repository: Unveiling Nature's Pharmacy" database represents a significant effort towards harnessing the potential of deep learning in plant classification, particularly focusing on species known for their medicinal properties. With a comprehensive collection of images showcasing both healthy and diseased leaves from five diverse plant species, this database serves as a valuable resource for training deep neural networks to autonomously categorize foliage.

One notable strength of this database is its inclusivity, encompassing a range of plant species renowned for their medicinal benefits. From the Curry tree with its anti-inflammatory and antioxidant properties to Holy Basil with its adaptogenic and anti-diabetic properties, each species offers unique therapeutic potentials. By providing labeled images of leaves from these plants, the database enables the development of AI models capable of identifying and distinguishing between different medicinal herbs, facilitating their utilization in various healthcare applications.

Furthermore, the incorporation of detailed backgrounds in the images adds complexity to the dataset, mirroring the natural environments in which these plants grow. This diversity in backgrounds, coupled with variations in lighting conditions and camera angles, enhances the robustness of the dataset and prepares AI models for real-world scenarios where environmental factors may affect image quality and classification accuracy.

The use of mobile phone cameras for image acquisition highlights the accessibility and scalability of the data collection process. By utilizing widely available devices such as the Samsung Galaxy S20 FE 5G and Redmi Note 9 Pro Max, the creators have ensured that the dataset can be expanded and updated with relative ease, fostering ongoing research and development in the field of plant classification and medicinal herb identification.

6.4 Conclusion: In conclusion, the "Herbal Leaf Repository: Unveiling Nature's Pharmacy" database represents itself as a valuable resource for advancing research at the intersection of technology and traditional medicine. By providing a diverse collection of labeled images showcasing healthy and diseased leaves from five medicinal plant species, the database enables the training of deep neural networks for automated plant classification.

The inclusion of detailed backgrounds, diverse lighting conditions, and variations in camera angles enhances the dataset's suitability for real-world applications, ensuring that AI models trained on this dataset are robust and reliable. As technology continues to evolve, and the demand for natural remedies grows, databases like this play a crucial role in bridging the gap between traditional knowledge and modern computational techniques.

Moving forward, this database sets the stage for further exploration and innovation in plant classification, herbal medicine, and healthcare. By fostering collaboration between experts in botany, medicine, and artificial intelligence, it paves the way for the development of novel diagnostic tools, drug discovery methods, and personalized healthcare solutions rooted in the rich diversity of nature's pharmacy.

Chapter 7

7. Nature's Best vs. Bruised: A Veggie Evaluation

7.1 Introduction: In the realm of evaluating vegetable freshness, automated methods that assess external morphology, texture, and colour have emerged as efficient and cost-effective tools. These methods play a crucial role in sorting high-quality vegetables for both export and local consumption, significantly impacting the revenue of the food industry worldwide. Researchers have recognized the importance of this area, leading to the development of various automated techniques, particularly leveraging advanced deep learning technologies to categorize vegetables into specific classes. However, the effectiveness of these methods heavily relies on the databases used for training and validation, posing a challenge due to the lack of suitable datasets.

7.2 Specification Table

Subject	Smart Agriculture, Vegetable freshness evaluation, Deep Neural Networks
Specific Subject area	Automated Vegetable freshness quality evaluation
Data type	Images of vegetables from Fresh to Damaged to Severely Damaged
Data acquisition	Images of vegetables included in this dataset are acquired using varied camera angles, non-uniform illumination and consistent white background.
Data format	Raw
Dataset preparation	Various freshness stages of vegetables were captured using the high-resolution rear cameras of three different mobile phones. These images were saved in JPG format after resizing to a fixed dimension of 256 × 256 using a Python script. The resized images were organized into six folders: Cowpea, Snake Gourd, Spiny Gourd, Ivy Gourd, Taro root and Turmeric. Within these folders, the vegetable images were further categorized into six subfolders based on their freshness level: Fresh, Damaged, and Severely Damaged. All images were captured under different lighting conditions against a white background. This meticulously curated vegetable image dataset serves a vital purpose in the testing, training, and validation of automated models designed for evaluation of freshness levels of vegetables. Researchers and developers can utilize this dataset to enhance the accuracy and efficiency of their vegetable-related projects, benefiting from the diverse quality and type variations captured in the images.

Data source location	This dataset is prepared at Jadavpur University, Kolkata, India. $22.4989^{\circ}N, 88.3714^{\circ}E$
Data accessibility	Repository name: Nature's Best vs. Bruised: A Veggie Evaluation Data Identification Number (doi): 10.17632/b2mvj3kjfx.2 Direct URL to data: https://data.mendeley.com/datasets/b2mvj3kjfx/2

7.3 Data description: The research has pioneered the creation of a unique database named " Nature's Best vs. Bruised: A Veggie Evaluation," featuring **4464** images representing six commonly consumed vegetables in India: Cowpea (Scientific name: Vigna sinensis Savi), Snake Gourd (Scientific name: Trichosanthes cucumerina), Spiny Gourd (Scientific name: Momordica dioica), Ivy Gourd (Scientific name: Coccinia grandis), Taro root (Scientific name: Colocasia esculenta) and Turmeric (Scientific name: Curcuma longa). These specific vegetables were chosen due to their widespread consumption and affordability, particularly in rural areas, and notably, they were absent from existing databases.

The images within our database authentically capture the natural progression of these vegetables, showcasing their transition from Fresh state to Damaged to Severely Damaged conditions, without any external manipulation. We classified these images into three distinct categories: Fresh, Damaged, and Severely Damaged. To ensure diversity, the photographs were captured utilizing varied camera angles, non-uniform illumination conditions and consistent white background.

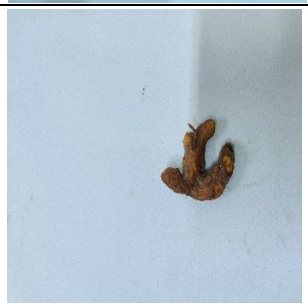
This comprehensive database stands as a valuable resource for researchers in the field, addressing the crucial need for robust datasets and facilitating advancements in automated vegetable quality assessment techniques.

Value of Data

1. This database contains a total of **4464** high-quality images of six different types of vegetables namely, Cowpea, Snake Gourd, Spiny Gourd, Ivy Gourd, Taro root and Turmeric.
2. Images included within each vegetable category are further categorized into three classes namely, Fresh, Damaged, and Severely Damaged.
3. The provided dataset offers a valuable resource for researchers working on deep learning solutions focused on classifying vegetables according to their freshness levels.
4. The dataset holds immense potential in the development of high-quality vegetable freshness evaluation applications.

Examples of images included in this newly curated database are given below:

1. Turmeric:

Fresh			
Damaged			
Severely Damaged			

2. Spiny Gourd:

Fresh			
Damaged			

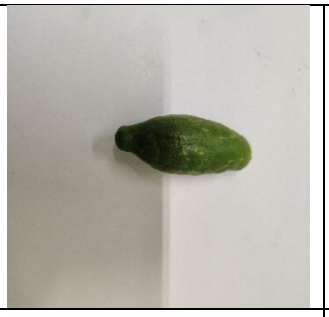
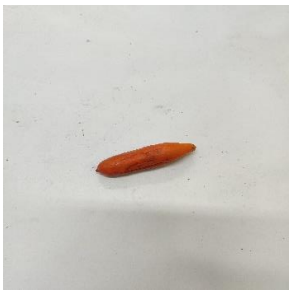
Severely Damaged			

3. Taro Root:

Fresh			
Damaged			
Severely Damaged			

4. Cocinia:

Fresh			

Damaged			
Severely Damaged			

5. **Snake Gourd:**

Fresh		
Damaged		
Severely Damaged		

6. Cowpea:

Fresh		
Severely Damaged		

Fig.7.1. Examples of images incorporated in Nature's Best vs. Bruised: A Veggie Evaluation

7.4 Experimental Design, Materials and Methods

The high-definition rear cameras of OnePlus7T, Redmi Note 9 pro max and OnePlus Nord mobile phones were employed to capture the photographs of the vegetables. After capturing the images, they are resized to a fixed dimension of 256x256 using a python script and are stored in appropriate folders in .jpeg format.

Materials or Specification of Image Acquisition System

OnePlus7T camera specifications: 48 MP Ultra-wide Triple camera

Redmi Note 9 pro max camera specifications: AI Quad camera array 64 MP+8 MP+5MP+2MP

OnePlus Nord camera specifications: 48 OIS+8+5+2 MP Quad Camera, 32+8 MP Dual Front Camera.

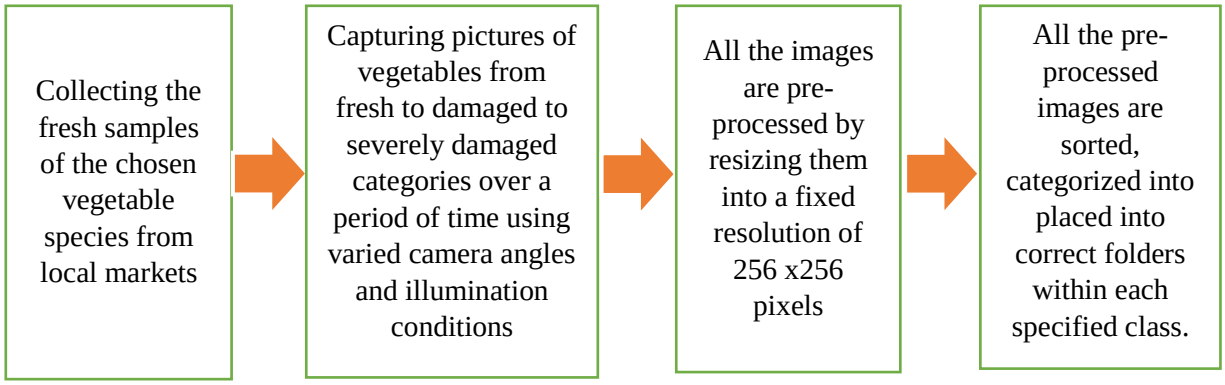


Fig.7.2. Steps adapted to curate the Nature's Best vs. Bruised: A Veggie Evaluation dataset

Table 7.1

Specification of image acquisition devices

Sl.No	Properties	Camera 1	Camera 2	Camera 3
1	Device name	OnePlus7T	Redmi Note 9 pro max	OnePlus Nord
2	Camera specifications	**Rear camera** 48 megapixel (f/1.6,0.8 micron) +16 megapixel(f/2.2) +12 megapixel (f/2.2) **Front camera** 16 megapixel (f/2.0,1.0 micron)	**Quad camera** 64 megapixel (f/1.9, 0.8 micron) +8 megapixel (f/2.2)+5 megapixel (f/2.4)+2 megapixel (f/2.4)	**Quad camera** 48 megapixel (f/1.8, 0.8 micron) +5 megapixel (f/2.3)+5 megapixel (f/2.4)+2 megapixel (f/2.4)

Table 7.2

Sl.No.	Image details	Image quality
1	Dimension	256x256 pixels
2	Height	256
3	Width	256
4	Vertical resolution	72 dpi
5	Horizontal resolution	72 dpi
6	Bit depth	24
7	Resolution unit	2
8	Colour representation	sRGB

Table 7.3

Nature's Best vs. Bruised: A Veggie Evaluation: Dataset details

Classes	Vegetable Species	Camera angles, illumination and image background specifications	Number of images included under each class for each vegetable species
Fresh Damaged Severely Damaged	**Cowpea** (*Scientific name: Vigna sinensis Savi*), **Snake Gourd** (*Scientific name: Trichosanthes cucumerina*), **Spiny Gourd** (*Scientific name: Momordica dioica*), **Ivy Gourd** (*Scientific name: Coccinia grandis*), **Taro root** (*Scientific name: Colocasia esculenta*) and **Turmeric** (*Scientific name: Curcuma longa*)	Images are captured using varied camera angles, non-uniform illumination conditions in the presence of artificial light and using consistent white background, thereby ensuring the diversity in samples.	**Fresh** *Cowpea:203* *Snake Gourd:122* *Spiny Gourd:418* *Ivy Gourd:246* *Taro root:228* *Turmeric:350* **Damaged** *Cowpea:NIL* *Snake Gourd:124* *Spiny Gourd:487* *Ivy Gourd:254* *Taro root:186* *Turmeric:335* **Severely Damaged** *Cowpea:204* *Snake Gourd:123* *Spiny Gourd:420* *Ivy Gourd:254* *Taro root:186* *Turmeric:324*

Method: All the vegetable species considered for designing this database are brought from local markets in fresh condition and are transformed from Fresh to Damaged to Severely Damaged stages under constant supervision in the laboratory. The images included in this database are captured using varied camera angles, non-uniform illumination and consistent white background. The images captured for each class under each vegetable category are included into suitable folders after resizing them into a fixed resolution of 256x256 pixels. The inclusion of these diverse types of samples have enhanced the real-life effectiveness of this database enabling it to serve as a reliable one to perform training, validation and testing of methods designed to automatic freshness evaluation of vegetables.

7.5 Discussion: The creation of the "Nature's Best vs. Bruised: A Veggie Evaluation" database represents a significant advancement in the field of automated vegetable freshness assessment. With 865 images representing six commonly consumed vegetables in India, this database fills

a critical gap by providing a comprehensive and diverse collection of images showcasing the natural progression of vegetables from fresh to damaged and severely damaged conditions.

One of the key strengths of this database is its authenticity. The images authentically capture the natural progression of vegetables, reflecting real-world scenarios without any external manipulation. This authenticity enhances the reliability and applicability of the database, ensuring that AI models trained on this dataset are capable of accurately assessing vegetable freshness under varying conditions.

Furthermore, the inclusion of commonly consumed vegetables such as Cowpea, Snake Gourd, and Turmeric, among others, ensures the relevance and practicality of the database for the Indian context. These vegetables are not only widespread but also affordable, particularly in rural areas, making them vital components of the local diet. By focusing on these specific vegetables, the database addresses the need for datasets that are relevant to the target population, thereby enhancing the effectiveness of automated freshness assessment techniques in real-world settings.

The diversity in image acquisition, including varied camera angles, non-uniform illumination conditions, and consistent white background, further enriches the dataset and prepares AI models for the complexities encountered in real-world applications. This variability ensures that the trained models are robust and capable of generalizing to different environmental conditions, thereby enhancing their practical utility in sorting high-quality vegetables for both export and local consumption.

7.6 Conclusion: In conclusion, the "Nature's Best vs. Bruised: A Veggie Evaluation" database serves as a valuable resource for researchers and practitioners in the field of automated vegetable freshness assessment. By providing a comprehensive collection of images representing the natural progression of commonly consumed vegetables in India, the database addresses the critical need for robust datasets in this area.

The authenticity of the images, coupled with the inclusion of diverse vegetables and variability in image acquisition conditions, enhances the database's reliability and real-world effectiveness. As a result, AI models trained on this dataset are well-equipped to accurately assess vegetable freshness, contributing to improvements in food quality control, supply chain management, and ultimately, the revenue of the food industry worldwide.

Moving forward, this database lays the foundation for further advancements in automated vegetable quality assessment techniques, paving the way for enhanced efficiency, cost-effectiveness, and sustainability in the food industry. By fostering collaboration and knowledge exchange, it empowers researchers to develop innovative solutions that address the evolving challenges in vegetable production, distribution, and consumption.

Chapter 8

8. The Gem Atlas: A Pictorial Database of Precious Stones

8.1 Description of the newly curated database: This database contains a comprehensive collection of 700 images belonging to five diverse types of gemstones namely, Red Coral Moonga (Scientific name: Corallium rubrum) (134 images), Yellow sapphire (Pukhraj) (Scientific name: Hessonite (Gomed)) (158 images), Navi Sankh (Gomati) (Scientific name: Cat's Eye Shell) (125 images), Blue Sapphire (Neelam) (Scientific name: Corundum) (156 images) and Emerald (Panna) (Scientific name: Beryl) (127 images).

The images of gemstones which are included in this newly curated database are not present in any of the existing databases and are captured by the curators themselves.

These images have uniform white background and are captured using the Redmi Note 9 Pro Max is equipped with an advanced camera array consisting of 64MP, 8MP, 5MP, and 2MP lenses, enhanced by Artificial Intelligence (AI) technology.

The gemstones listed in the newly curated database hold unique significance and value in various cultural, astrological, and geological contexts:

1. Red Coral (Moonga) - Corallium rubrum:

Cultural/Astrological Significance:

In astrology, Red Coral is believed to provide energy and vigour to its wearer. It's associated with the planet Mars and is often recommended to boost courage, overcome procrastination, and achieve success in endeavours.

Geological Significance:

Red Coral is not a stone but an organic product formed from the skeletal remains of marine animals called polyps. This gives it a distinct place among gemstones, valued for its vibrant red colour and rarity.

2. Yellow Sapphire (Pukhraj) - Hessonite (Gomed):

Cultural/Astrological Significance:

Yellow Sapphire is thought to attract wealth and bring prosperity to the home. It is especially revered in Vedic astrology where it's believed to enhance wisdom, virtue, and future foresight.

Geological Significance:

It's important to note that traditionally, Yellow Sapphire refers to the yellow variety of the mineral corundum. Hessonite, often confused here, is actually a different gemstone known as the "cinnamon stone" and is a variety of grossular garnet.

3. Navi Sankh (Gomati) - Cat's Eye Shell:

Cultural/Astrological Significance:

This is believed to remove the Vastu Dosh (architectural astrological defects) and negative energies in homes. It is also worn as a charm for prosperity and protection.

Geological Significance:

Technically, Navi Sankh is a shell rather than a crystalline gemstone, making it unique for its organic origin and is often collected from rivers or sea beds.

4. Blue Sapphire (Neelam) - Corundum:

Cultural/Astrological Significance:

Blue Sapphire is renowned for its powerful astrological benefits, including bringing mental clarity, financial rewards, and healing properties. It is also known for its fast-acting effects in Vedic astrology.

Geological Significance:

As a variety of corundum, Blue Sapphire is second only to diamond in hardness, making it highly prized for both its durability and its stunning deep blue hue.

5. Emerald (Panna) - Beryl:

Cultural/Astrological Significance:

Emeralds are believed to aid in intellectual growth, enhance memory and increase focus. They are thought to have rejuvenating and healing properties, making them popular among scholars and artists.

Geological Significance:

Emeralds are valued for their rich green colour, which is rare in the gem world. They are particularly prized when they exhibit transparency and depth of colour.

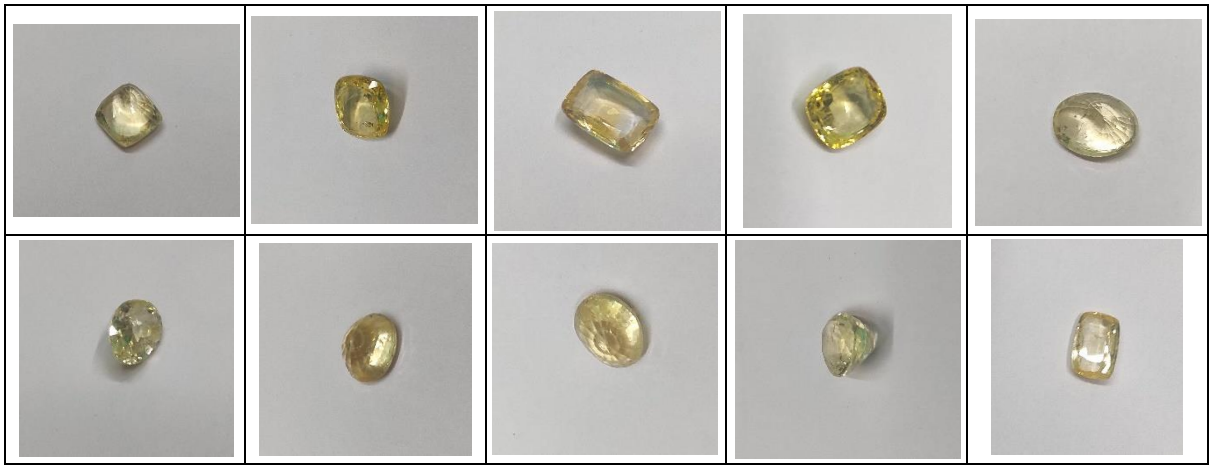
Each of these gemstones not only adds aesthetic value but also carries deep symbolic meanings, enhancing their appeal in jewellery and astrological practices.

Examples of the database "The Gem Atlas: A Pictorial Database of Precious Stones" is shown below:

1. Red Coral (Moonga):



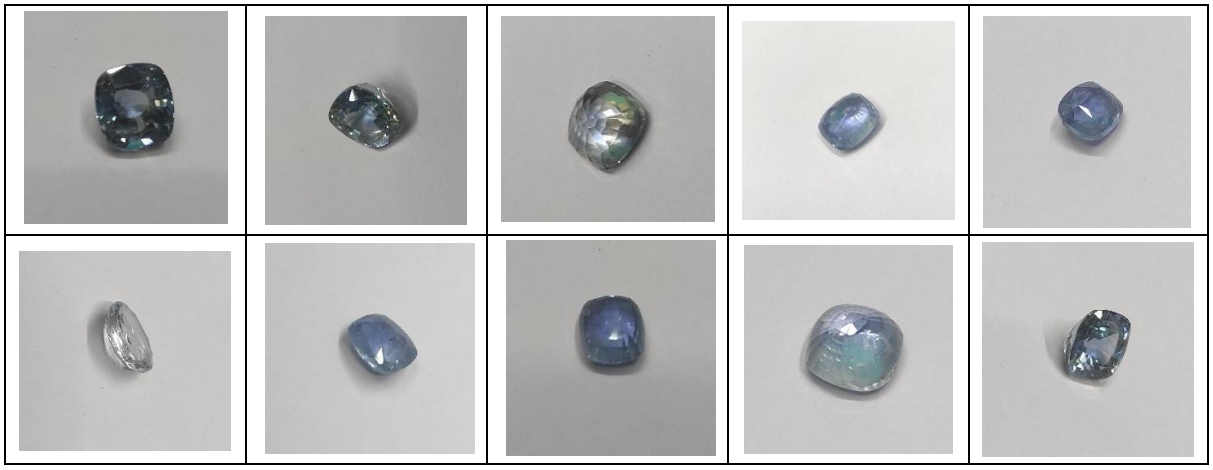
2. Yellow Sapphire (Pukhraj):



3. Navi Sankh (Gomati):



4. Blue Sapphire (Neelam):



5. Emerald (Panna):



Fig.8.1. Examples of images incorporated in The Gem Atlas: A Pictorial Database of Precious Stones

8.2 Applications: This database, with its extensive collection of gemstone images, plays a crucial role in facilitating automated gemstone classification by providing a rich, diverse dataset for training machine learning models. Here are several ways in which this database aids in automated classification:

1. Diverse Types and Forms: By including images of five different types of gemstones namely, Red Coral, Yellow Sapphire, Navi Sankh, Blue Sapphire, and Emerald providing a broad range of data. This variety helps in developing a robust model capable of recognizing and classifying various gemstones accurately, even when they come in different shapes and colours.

2. High-Quality Images in Standard Formats: All images are in JPEG format, a common standard that ensures compatibility with most image processing and machine learning tools. The varied sizes of the images allow the model to learn from and adapt to different resolutions and scales, enhancing its ability to classify images in real-world scenarios where gemstone photos may not always be uniform.

3. Support for Feature Extraction: The detailed images allow for intricate feature extraction, which is crucial for machine learning models. Features such as colour, texture, shape, and size of gemstones can be learned and recognized by the model, aiding in more accurate classifications.

4. Design and Customization: Virtual Try-On: Retailers can use the images to create virtual try-on solutions that allow customers to see how jewellery with these gemstones would look on them through augmented reality (AR) apps.

Custom Jewellery Design: Designers can use detailed images to create or modify jewellery pieces in software, allowing customers to customize their jewellery with different gemstone options before the final piece is made.

8.3 Automated classification of gemstones is essential from an economic perspective for several reasons:

1. Increased Efficiency and Speed: Automation significantly speeds up the process of gemstone classification compared to manual methods. This rapid classification allows businesses to process and catalogue larger volumes of gemstones faster, which is crucial for scaling operations and meeting market demands promptly.

2. Enhanced Accuracy and Consistency: Humans are prone to error, especially when dealing with the subtle distinctions between gemstone types, grades, and qualities. Automated systems can be trained to recognize these nuances with high precision, ensuring consistent and reliable classifications. This accuracy is particularly important in maintaining quality standards and trust, which directly impact customer satisfaction and loyalty.

3. Improved Traceability and Compliance: In the gemstone industry, provenance and legal compliance are paramount. Automated classification systems can integrate with tracking technologies to ensure that each gemstone's journey from mine to market is documented, supporting compliance with international trade laws and ethical standards.

4. Facilitating Global Trade: As gemstones are often traded on international markets, standardized automated classification systems help bridge the understanding between different markets and cultural preferences. This standardization supports smoother transactions and clearer communications regarding product quality and characteristics.

5. Enabling Personalization and Innovation: With advanced classification capabilities, companies can offer more personalized product offerings based on specific gemstone characteristics that are accurately identified by automated systems. Furthermore, these systems can drive innovation in gemstone processing and jewellery design, creating new opportunities for differentiation in a competitive market.

6. Enhanced Accuracy and Consistency: Human evaluation of gemstones can often be inconsistent, particularly when discerning the fine differences in type, grade, and quality. Automated systems, utilizing advanced Colour and light analysis, can be meticulously trained to detect these subtle variances with superior accuracy. This precision is crucial for upholding stringent quality standards and fostering trust, both of which are key to enhancing customer satisfaction and loyalty.

8.4 <u>Conclusion</u>: In conclusion, the newly curated database featuring a comprehensive collection of 700 images of five diverse types of gemstones fills a critical gap in existing datasets and plays a crucial role in advancing automated gemstone classification technology. By providing high-quality images with uniform backgrounds captured using advanced camera technology, this database facilitates the training of machine learning models for accurate and efficient gemstone classification.

The diversity of gemstone types included in the database ensures that the trained models are robust and capable of recognizing and classifying various gemstones accurately, even when they come in different shapes and colours. Moreover, the standardized format of the images enables compatibility with most image processing and machine learning tools, enhancing the adaptability of the models to real-world scenarios.

Automated gemstone classification offers numerous economic benefits, including increased efficiency and speed, enhanced accuracy and consistency, improved traceability and compliance, and facilitation of global trade. By automating the classification process, businesses can scale operations, maintain quality standards, and foster trust with customers, ultimately driving innovation and differentiation in the competitive gemstone market.

Moving forward, the availability of this database will stimulate further research and development in automated gemstone classification, leading to the adoption of more advanced technologies and methodologies in the gemstone industry. As automation continues to revolutionize various sectors, the integration of automated classification systems will undoubtedly contribute to the efficiency, accuracy, and sustainability of gemstone trading and processing practices globally.

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