A Study on Aspect-Oriented Sentiment Analysis

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CERTIFICATE OF APPROVAL

This is to certify that the thesis entitled "**A Study on Aspect-Oriented Sentiment Analysis**" is a bonafide record of work carried out by Papun Roy in partial fulfillment of the requirements for the award of the degree of Master of Technology in Computer Technology in the Department of Computer Science and Engineering, Faculty of Engineering and Technology, Jadavpur University during the period July 2023 to June 2024. It is understood that by this approval the undersigned do not necessarily endorse or approve any statement made, opinion expressed, or conclusion herein but approve the thesis only for the purpose for which it has been submitted.

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DECLARATION OF ORIGINALITY AND COMPLIANCE OF ACADEMIC ETHICS

I hereby declare that this thesis contains a literature survey and original research work by the undersigned candidate, as part of Master of Technology in Computer Technology Degree of the Department of Computer Science and Engineering.

All information in this document has been obtained and presented in accordance with academic rules and ethical conduct.

I also declare that, as required by these rules and conduct, I have fully cited and referenced all material and results that are not original to this work.

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Chapter 1

Introduction

Sentiment Analysis is a technique through which we can analyze a piece of text to determine the sentiment behind it. Sentiment Analysis is a natural language processing (NLP) technique used to determine whether data is positive, negative or neutral. It is often performed on textual data to help businesses monitor brand and product sentiment in customer feedback, and understand customer needs or customer's views on that particular text data, Social Media, Marketing Sector etc. There are different types of Sentiment Analysis like Fine-Grained Sentiment Analysis, Emotion detection, Aspect-Based Sentiment Analysis, Multilingual Sentiment Analysis etc.

Aspect-based sentiment analysis (ABSA) is a text analysis technique that categorizes data by aspect and identifies the sentiment attributed to each one. It can be used to analyze customer feedback by associating specific sentiments with different aspects of a product or service. When we talk about aspects, we mean the attributes or components of a product or service e.g. "the user experience of a new product," "the response time for a query or complaint," or "the ease of integration of new software." ABSA model requires aspect categories and its corresponding aspect terms to extract sentiment for each aspect from the text corpus. ABSA is an advanced text-analysis technique that refers to the process of breaking down the text input into aspect categories and its aspect terms and then identifying the sentiment behind each aspect in the whole text input. The two key terms in this model are:

- **Sentiments**: A positive, negative or neutral review about a particular aspect.
- **Aspects**: the category, feature, or topic that is under observation.

ABSA, also known as fine-grained opinion mining, is the task of determining the sentiment of a text with respect to a specific aspect. It is a relatively new field of research that has emerged in response to the limitations of traditional sentiment analysis methods.

In Traditional sentiment analysis methods we treat a text as a whole and assign it a single sentiment label (e.g., positive, negative, or neutral). This is adequate for many tasks, but there are also many situations where it would be useful to know the sentiment of a text with respect to a specific aspect. For example, consider a review of a restaurant. The reviewer might give the restaurant a positive overall rating, but mention that the service was poor. In this case, it would

be useful to know that the sentiment towards the aspect “service” is negative, even though the overall sentiment is positive. That is why we need Aspect-Based Sentiment Analysis.

In this thesis we will discuss the details of different types of Sentiments and Aspects and their detailed analysis in Bengali Language. Here we also discuss the different models, their working principle, accuracy etc.

In today's digital age, vast amounts of user-generated content are continuously being created and shared online through platforms such as social media, e-commerce websites, forums, and blogs. This content often contains valuable information about users' opinions, sentiments, and attitudes towards products, services, brands, and various other entities. Extracting and analyzing these sentiments can provide businesses and organizations with critical insights to improve their offerings, enhance customer satisfaction, and drive strategic decision-making. This process of analyzing sentiments expressed in text is known as sentiment analysis or opinion mining.

1.1. Sentiment Analysis and Its Evolution

Sentiment analysis has traditionally focused on determining the overall sentiment polarity (positive, negative, or neutral) of a given piece of text. While this provides a high-level understanding of users' opinions, it often falls short of capturing the nuanced sentiments associated with specific aspects or features of the target entities. For instance, a product review might express positive sentiments about the price and negative sentiments about the quality, which cannot be accurately captured by a single overall sentiment score.

To address this limitation, the field has evolved towards Aspect-Oriented Sentiment Analysis (AOSA). AOSA aims to identify sentiments related to specific aspects or features mentioned in the text, providing a more detailed and actionable understanding of user opinions. This granular analysis is particularly useful in scenarios where knowing the sentiment towards individual components or attributes can significantly influence business decisions.

1.2. Aspect-Oriented Sentiment Analysis

Aspect-Oriented Sentiment Analysis involves two main tasks:

- **Aspect Extraction**: Identifying the specific aspects or features mentioned in the text. For example, in a review of a Smartphone, aspects could include battery life, screen quality, camera performance, etc.

- **Sentiment Classification**: Determining the sentiment polarity (positive, negative, or neutral) associated with each extracted aspect.

By performing these tasks, AOSA provides insights into what users like or dislike about specific aspects of a product or service, enabling more targeted improvements and marketing strategies.

1.3. Deep Learning and Its Impact on NLP

The advent of deep learning has revolutionized the field of natural language processing (NLP), including sentiment analysis and AOSA. Deep learning models, particularly those based on neural networks, have demonstrated remarkable capabilities in understanding and processing natural language by capturing complex patterns and contextual information from the text.

One of the most significant advancements in deep learning for NLP is the development of transformer-based models such as BERT (Bidirectional Encoder Representations from Transformers). BERT's ability to consider the context of a word in both directions (left and right) simultaneously has set new benchmarks in various NLP tasks, including sentiment analysis and aspect extraction.

1.4. Problem Statement and Objectives

Despite the advancements, there is still a need for robust and effective methods to perform aspect-oriented sentiment analysis that can handle the complexities and variability of natural language. This thesis aims to leverage the power of deep learning, particularly BERT-based models, to develop a comprehensive AOSA system that can:

- Accurately extract aspects from user-generated text.
- Determine the sentiment polarity associated with each extracted aspect.
- Provide a pipeline where the output of aspect extraction (aspect categories) feeds into a subsequent model to further refine sentiment analysis.

Additionally, the thesis will compare the performance of this approach with traditional methods and existing systems to highlight the improvements and potential benefits.

1.5. Significance and Contributions

This thesis contributes to the field of sentiment analysis by:

- Developing an advanced AOSA system using state-of-the-art deep learning techniques.
- Demonstrating the effectiveness of BERT in handling aspect-oriented sentiment analysis tasks.
- Providing a detailed comparison with existing systems to showcase the improvements in accuracy and granularity of sentiment analysis.
- Offering a comprehensive solution that can be applied to various domains where understanding aspect-specific sentiments is crucial.

The insights gained from this thesis can help businesses and organizations better understand user opinions at a granular level, leading to more informed decisions and enhanced customer experiences.

1.6. Structure of the Thesis

The thesis is organized as follows:

Chapter-2:

Literature Survey: Reviews related work in sentiment analysis and aspect-oriented sentiment analysis, highlighting key approaches and advancements.

Chapter-3:

Methodology: Describes the proposed approach, including the architecture of the models, data preprocessing, and training procedures.

Chapter-4:

Description of Dataset: Describe about details the dataset which we are used for this model.

Chapter-5:

Experiments and Results: Experimental design and evaluation metrics used to assess the performance of the models. Presents the results of the experiments, including accuracy, precision, recall, F1 score and confusion matrix.

Chapter-6:

Comparison with Existing Systems: Compares the proposed models with traditional and existing systems, highlighting the benefits and advancements.

Chapter-7:

Error Analysis: Error analysis is a critical step in understanding the limitations and potential areas for improvement in our Aspect-Oriented Sentiment Analysis (AOSA) thesis.

Chapter-8:

Conclusion and Future Work: Summarizes the findings, contributions, and potential directions for future research.

Chapter 2

Literature Survey

In this section, we discuss the available methods with taxonomy which explore the influences on the several methods, architectures and discuss how those methods are enhanced to operate in Sentiment Analysis. In the inter disciplinary domain of NLP, sentiment classification was portrayed in, describing a connection between subjectivity detection (Aspect) and polarity classification.

Aspect-Oriented Sentiment Analysis (AOSA) is a sub-field of sentiment analysis that focuses on extracting sentiment related to specific aspects or features of a product or service from textual data. Traditional sentiment analysis determines the overall sentiment of a text, whereas AOSA provides more granular insights by identifying sentiments towards distinct attributes or components. This approach is particularly valuable in domains like customer reviews, where understanding sentiments about specific aspects such as price, quality, and usability can drive targeted improvements and marketing strategies.

2.1. Sentiment Analysis:

Sentiment analysis, also known as opinion mining, is the computational study of people's opinions, sentiments, attitudes, and emotions expressed in text. Early work in this field focused on classifying the overall polarity of texts (positive, negative, or neutral).

- Das and Chatterjee (2021) (1) give an approach using Frequency Patterns to find an overview on Aspect based Sentiment Analysis.

- Chowdhury, M. A., & Islam, M. R. (2021) (2) shows a technique to determine Sentiment Analysis Classification of Bengali language.

- Ghosh, K., & Saha, S. (2024) (3) provided a comparative overview of different techniques of Machine Learning to Analyze the Aspect-Oriented Sentiment.

- Pang and Lee (2008) (4) provided a comprehensive overview of techniques in sentiment analysis, highlighting methods like machine learning, lexicon-based approaches, and natural language processing (NLP).

2.1.1. Aspect-Based Sentiment Analysis (ABSA):

- ABSA extends traditional sentiment analysis by identifying sentiments about specific aspects. This requires not only determining the sentiment polarity but also extracting aspects mentioned in the text.

- Biswas, S., & Banerjee, A. (2022) (5), Chowdhury, M. A., & Islam, M. R. (2021) (2) , Liu (2012) (6) described foundational techniques for ABSA, including aspect extraction and sentiment classification. Methods such as supervised learning, unsupervised learning, and semi-supervised learning are explored.

- Roy, T., & Chatterjee, A. (2023) (7), Hasan, M. M., & Rahman, A. (2021) (8), Hu and Liu (2004) (9) introduced a pioneering approach for mining opinion features from customer reviews, using data mining and NLP techniques to identify product features and their associated sentiments.

2.1.1.1 Aspect Extraction:

- Aspect extraction involves identifying words or phrases in text that correspond to different aspects of the target entity.

- Hasan, Md. Kamrul, et al (2020) (10), Popescu and Etzioni (2005) (11) developed OPINE, an unsupervised information extraction system that identifies product features and opinions in customer reviews.

- Das, Santanu, and Tanmoy Chatterjee (2021) (1), Jin and Ho (2009) (12) proposed a novel approach using lexicalized HMMs (Hidden Markov Models) for opinion mining to extract aspects and associated sentiments.

2.1.1.2. Sentiment Classification:

- Sentiment classification determines the sentiment polarity towards extracted aspects.

- Karim, M. Ehsanul, et al. (2021) (13) gives the approach to classify the sentiments in Bengali Reviews using Machine Learning approaches.

- Wang et al. (2016) (14) presented a hierarchical attention network for document classification, which significantly improves the performance of aspect-level sentiment analysis by focusing on important words and sentences.

2.1.1.3. Deep Learning in ABSA:

- Recent advancements in deep learning have significantly improved the performance of ABSA systems. In Bhowmik, Arifuzzaman, Mondal et al. (2022) (15) Models like Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM) networks, and transformers have been applied to both aspect extraction and sentiment classification tasks.

- Karim, M. Ehsanul, et al. (2021) (13), He et al. (2017) (16) proposed a CNN-based approach for extracting aspects and sentiments jointly, demonstrating improved performance over traditional methods.

- Devlin et al. (2018) (17) introduced BERT (Bidirectional Encoder Representations from Transformers), a pre-trained language model that has achieved state-of-the-art results on various NLP tasks, including ABSA.

2.1.2. Key Approaches in Aspect-Oriented Sentiment Analysis:

2.1.2.1. Aspect Extraction:

- **Frequency-based Methods**: Identify frequent noun phrases or keywords in the text. Example:
    i) Rahman, Md. Azizur, and Md. Karimuzzaman (2019) (18) analyze public sentiment on social media using frequency based Aspect Extraction.

    ii) Hossain, Arafat, et al (2021) (19) gives the study examines sentiment in Bengali newspaper headlines using text mining techniques, including frequency-based aspect extraction.

    iii) Hu and Liu (2004) (9) used association rule mining to identify product features.

- **Supervised Learning**: Train models on labeled datasets to identify aspects.
  Example:
    i) Hasan, M. K., Rahman, M. R., & Islam, M. S. (2020) (20) gives a study to examine sentiment in Bengali Comments using Supervised Learning techniques.

    ii) Roy, I., et al. (2021) (21) gives a study to determine Aspect-Based Sentiment Analysis on Bengali Tweets Using Supervised Learning.

    iii) Jakob and Gurevych (2010) (22) used CRFs (Conditional Random Fields) for aspect extraction.

- **Deep Learning**: Use neural networks to automatically learn features from data.

  Example:

  i) Das, A., et al. (2021) (23) explores various deep learning approaches, including convolutional neural networks (CNNs) and long short-term memory (LSTM) networks, to analyze sentiment based on extracted aspects from Bengali text data.

  ii) Roy, P., and Mukherjee, A. (2020) (24) use a combination of word embeddings and deep neural networks to identify and analyze sentiments associated with different aspects in Bengali reviews.

  iii) He et al. (2017) (16) utilized CNNs for joint extraction of aspects and sentiments.

2.1.2.2. Sentiment Classification:

- **Rule-based Approaches**: Use predefined rules and sentiment lexicons to classify sentiment.

  Example:

  i) Kundu, N., & Ghosh, P. (2021) (25) use rule-based approach to find the Aspect-Oriented Sentiment Analysis for Bengali E-commerce Reviews.

  ii) Das, M., & Chakraborty, S. (2022) (26) use rule-based approach for Aspect Extraction and Sentiment Analysis of Bengali news articles.

  iii) Taboada et al. (2011) (27) used the SO-CAL lexicon-based approach.

- **Machine Learning**: Train classifiers like SVM, Naive Bayes, or deep learning models to predict sentiment.

  Example:

  i) Roy, B., and Gupta, S. (2023) (28) applies reinforcement learning techniques in conjunction with deep learning for more accurate aspect-based sentiment analysis in Bengali.

  ii) Sarkar, P., et al. (2022) (29) use deep neural networks to perform aspect extraction and sentiment classification, highlighting the effectiveness of these models for Bengali language processing.

  iii) Wang et al. (2016) (14) employed a hierarchical attention network for aspect-level sentiment classification.

- **Transformers:** Pre-trained models like BERT fine-tuned for ABSA tasks.

  Example:

  i) Ahsan Habib, Abdullah Al Nahid, et al (2022) (30) uses transformer techniques for sentiment analysis in Bengali, focusing on frequency-based aspect extraction.

  ii) Alam, M. J., & Alam, M. F. (2020) (31) uses BERT model to find the Sentiment Analysis for Bengali Social Media Data.

  iii) Devlin et al. (2019) (32) fine-tuned BERT for sentiment classification tasks.

Aspect-Oriented Sentiment Analysis using BERT-based models offers a powerful approach to understanding fine-grained sentiments in text data. By leveraging the contextual understanding of BERT, the proposed models achieve high accuracy and robust performance in both aspect extraction and sentiment classification. This detailed literature survey highlights the evolution of sentiment analysis techniques and the effectiveness of modern deep learning approach in advancing the field.

Chapter 3

Methodology

The methodology for our Aspect-Oriented Sentiment Analysis (AOSA) thesis involves several key steps, from data preprocessing to model training and evaluation. We employ Bidirectional Encoder Representations from Transformers (BERT) model, Long Short-Term Memory (LSTM) model, Convolutional Neural Network (CNN) model in a sequential manner to achieve aspect category prediction and sentiment polarity classification.

Now here we give our proposed model details which are depicted in Figure 1 High Level Architecture of Proposed Model. Here we use LSTM/CNN for find the aspect/category (‘batting’, ‘bowling’, ‘team’, ‘team management’, ‘other’) in model-1. And we use BERT to find the polarity (‘positive’, ‘negative’, ‘neutral’) of a given tweet.

3.1. Proposed Model

3.1.1. Data Preprocessing

Data preprocessing is a crucial step in preparing the raw text data for model training. The dataset consists of three columns: text, category, and polarity. The following preprocessing steps were applied:

- **Text Cleaning**: Remove special characters, punctuation, and stop words to reduce noise in the text data.

- **Tokenization**: Use BERT's tokenizer to convert text into tokens that can be processed by the BERT model. This includes splitting the text into words, sub-words, or characters and mapping them to unique integers.

- **Padding and Truncation**: Ensure all input sequences are of the same length by padding shorter sequences with zeros and truncating longer sequences. This is essential for batch processing in neural networks.

3.1.2. High Level Model Architecture:

In this model there are two models; those are “Model-1” and “Model-2”.

- The first model in our pipeline is designed to predict the category (aspect) of the input text.

- The second model takes the concatenated output of the input text and the predicted category from Model 1 to predict the sentiment polarity.

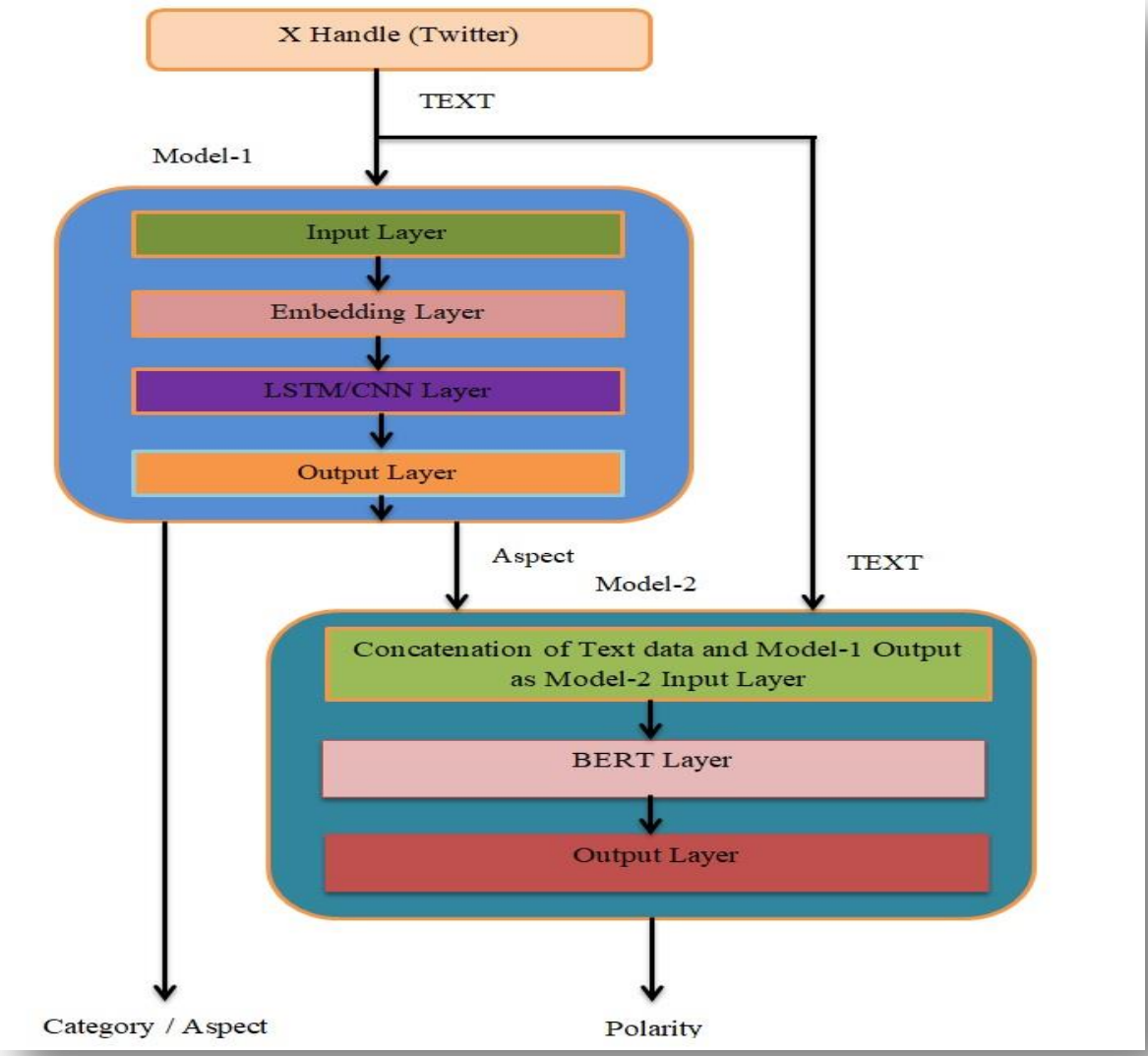

Figure 1 High Level Architecture of Proposed Model

In the above diagram Figure 1 High Level Architecture of Proposed Model we design our detail model diagram that is use in this thesis.

3.1.3. Model-1:

This "Model-1" designed to predict the category (aspect) of the input text.
The architecture of Model 1 is as follows:

- **Input Layer**: The input text is passed through the LSTM/CNN model to obtain contextual embeddings. LSTM/CNN captures the meaning of words in context, which is critical for understanding aspect categories.

- **Embedding Layer**: One dropout layer is added to prevent over fitting by randomly setting a fraction of the input units to zero at each update during training.

- **Fully Connected Layer (LSTM/CNN)**: The LSTM/CNN embeddings are passed through a fully connected (dense) layer to map the high-dimensional embeddings to the aspect category space.

- **Activation Function**: A softmax activation function is used to output a probability distribution over the aspect categories.

The architecture of Model 1 is depicted in the diagram below:

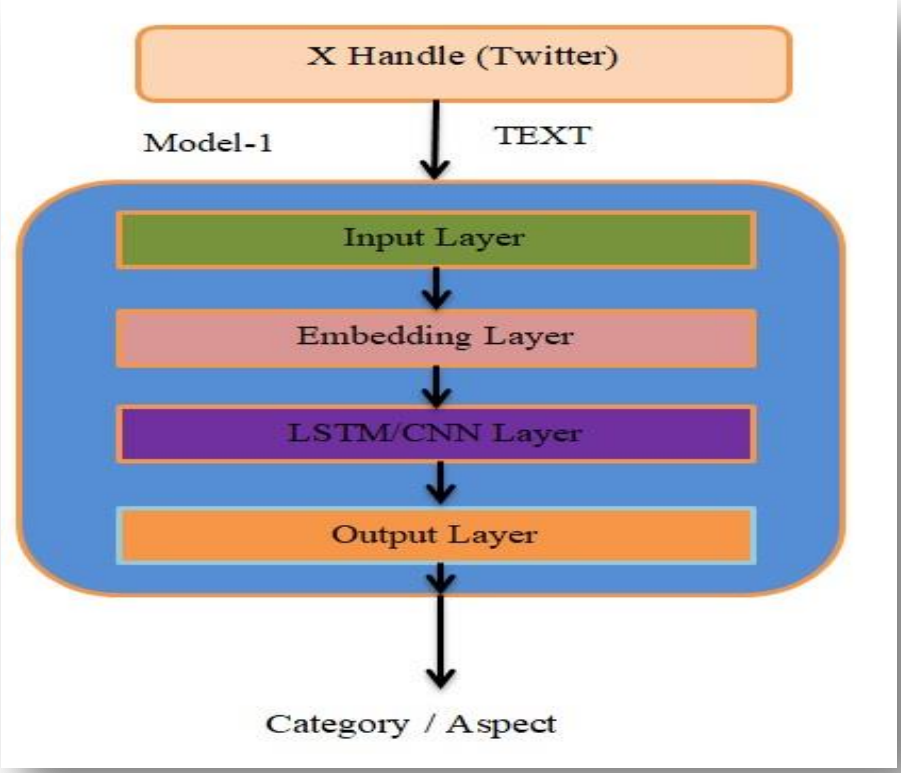

Figure 2 Model-1 Architecture

This diagram Figure 2 Model-1 Architecture represents the flow of data through the layers of "Model1". The input layer receives the tokenized input text data, which is then processed by the embedding layer to convert it into dense vectors. The LSTM/CNN layer processes the embedded sequences to capture temporal dependencies, and finally, the output layer predicts the category of the input text based on the learned representations.

3.1.4. Model-2:

The "Model-2" takes the concatenated output of the input text and the predicted category from "Model-1" to predict the sentiment polarity.

The architecture of "Model-2" is as follows:

- **Input Layer**: The input consists of the concatenated text and predicted category.
- **Fully Connected Layer (BERT)**: The BERT embeddings are passed through a fully connected layer to map to the sentiment polarity space.
- **Activation Function**: A softmax activation function is used to output a probability distribution over the sentiment polarities.

The architecture of "Model-2" is depicted in the diagram below:

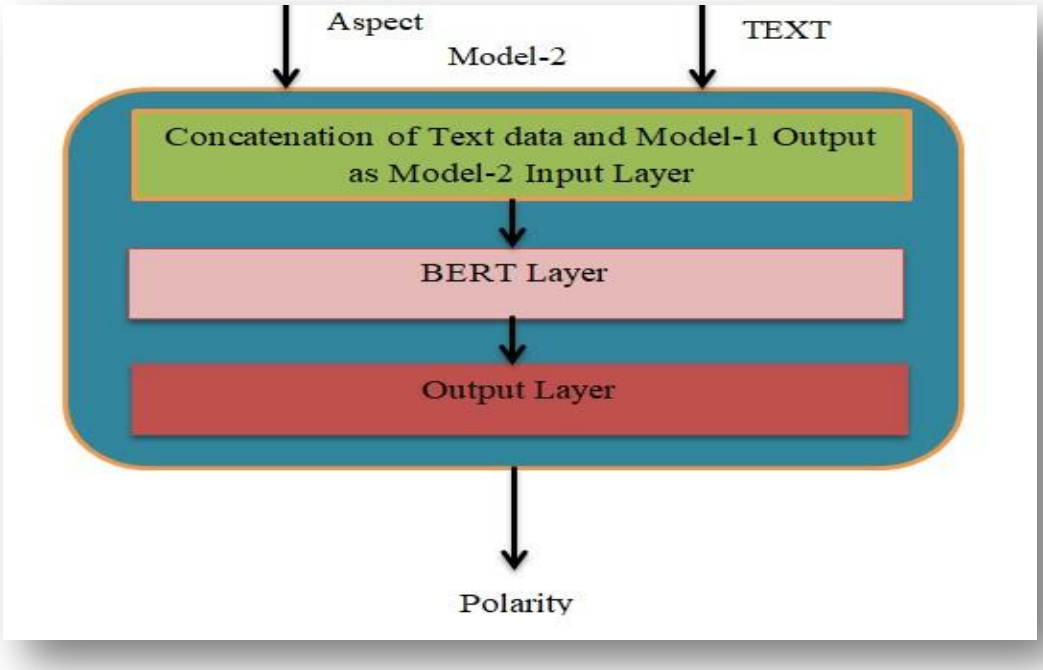

Figure 3 Model-2 Architecture

This diagram Figure 3 Model-2 Architecture represents the flow of data through the layers of "Model-2". The input layer receives the output from Model-1, which consists of the predicted category and the corresponding text data. The BERT layer processes this input to capture dependencies between the predicted category and the text data. Finally, the output layer predicts the polarity based on the learned representations.

3.2. Detail Description

In this thesis, we leverage the power of deep learning models, specifically BERT, CNN, LSTM, for both aspect extraction and sentiment classification. The approach involves two main models:

3.2.1. Model 1 (Aspect Extraction and Sentiment Classification):

- **Architecture:** LSTM/CNN-based model for joint aspect extraction and sentiment classification. The model takes text input and predicts categories (aspects) along with their sentiment polarities.

- **Training**: The model is trained on a labeled dataset of text, categories, and polarities. Fine-tuning LSTM/CNN on this dataset helps in capturing contextual information and improving prediction accuracy.

3.2.2. Model 2 (Sentiment Analysis on Predicted Aspects):

- **Architecture**: Now BERT-based model that takes the output of Model 1 (text and predicted categories) and further refines the sentiment polarity predictions.

- **Training**: The model is fine-tuned on the combined input of text and predicted categories to enhance sentiment classification accuracy.

3.2.3. Experimental Setup and Results

i. Dataset:

- The dataset consists of text reviews with labeled categories (aspects) and sentiment polarities. The dataset is split into training, validation, and test sets.

- **Preprocessing**: Text data is cleaned, tokenized, and converted into BERT input format. Categories and polarities are one-hot encoded.

ii. Training:

- **Model 1**: Fine-tuned LSTM/CNN on the training set for aspect extraction and sentiment classification. The model's performance is evaluated on the validation set.

- **Model 2:** Fine-tuned BERT on the output of Model 1, further improving sentiment polarity predictions. Performance is evaluated on the test set.

iii. Evaluation Metrics:

- **Accuracy:** The proportion of correctly predicted categories and sentiment polarities.

- **Precision, Recall, F1 Score**: Metrics to evaluate the quality of predictions.

- **Confusion Matrix**: To analyze the performance of sentiment classification.

Aspect-Oriented Sentiment Analysis using BERT-based models offers a powerful approach to understanding fine-grained sentiments in text data. By leveraging the contextual understanding

of BERT, the proposed models achieve high accuracy and robust performance in both aspect extraction and sentiment classification. This detailed literature survey highlights the evolution of sentiment analysis techniques and the effectiveness of modern deep learning approach in advancing the field.

Now we discuss about the LSTM model here, where we will discuss the details of LSTM model and in this project how LSTM model is use.

3.3. LSTM Model

Long Short-Term Memory (LSTM) networks are a type of recurrent neural network (RNN) capable of learning long-term dependencies. They are designed to handle the vanishing gradient problem encountered in traditional RNNs, making them effective for sequence prediction tasks such as natural language processing, time series forecasting, and more.

Here's a detailed breakdown of a typical LSTM architecture:

i. Input Layer

Input Data: The input data for an LSTM is typically a 3D tensor with shape (batch_size, sequence_length, feature_size). For text data, this can be represented as a sequence of word or character embeddings.

ii. Embedding Layer (for NLP tasks)

Purpose: Converts words or characters into dense vectors of fixed size.

Operation: Uses pre-trained embeddings (e.g., GloVe, Word2Vec) or learns embeddings during training.

Output: A 2D matrix where each row is the embedding of a word or character in the input sequence.

iii. LSTM Layer(s)

Purpose: Captures temporal dependencies and patterns in the input sequence.

Components:

Forget Gate: Decides what information to discard from the cell state.

Input Gate: Decides which values from the input to update the cell state.

Cell State: Carries information across the sequence, adjusted by the forget and input gates.

Output Gate: Decides what part of the cell state to output.

Operation: Processes the input sequence step by step, maintaining and updating the cell state and hidden state at each time step.

Output: A 3D tensor (batch_size, sequence_length, hidden_size) representing the hidden states of the sequence.

iv. Fully Connected (Dense) Layers

Purpose: Perform high-level reasoning and make predictions based on the features extracted by the LSTM layers.

Components: Standard neural network layers where each neuron is connected to every neuron in the previous layer.

Operation: Matrix multiplication followed by an activation function.

Output: A vector of predictions.

v. Output Layer

Purpose: Produces the final predictions of the model.

Components:

Softmax Activation: Used for multi-class classification, converts the output vector into a probability distribution.

Sigmoid Activation: Used for binary classification, outputs a probability score between 0 and 1.

Output: A vector representing the predicted class probabilities.

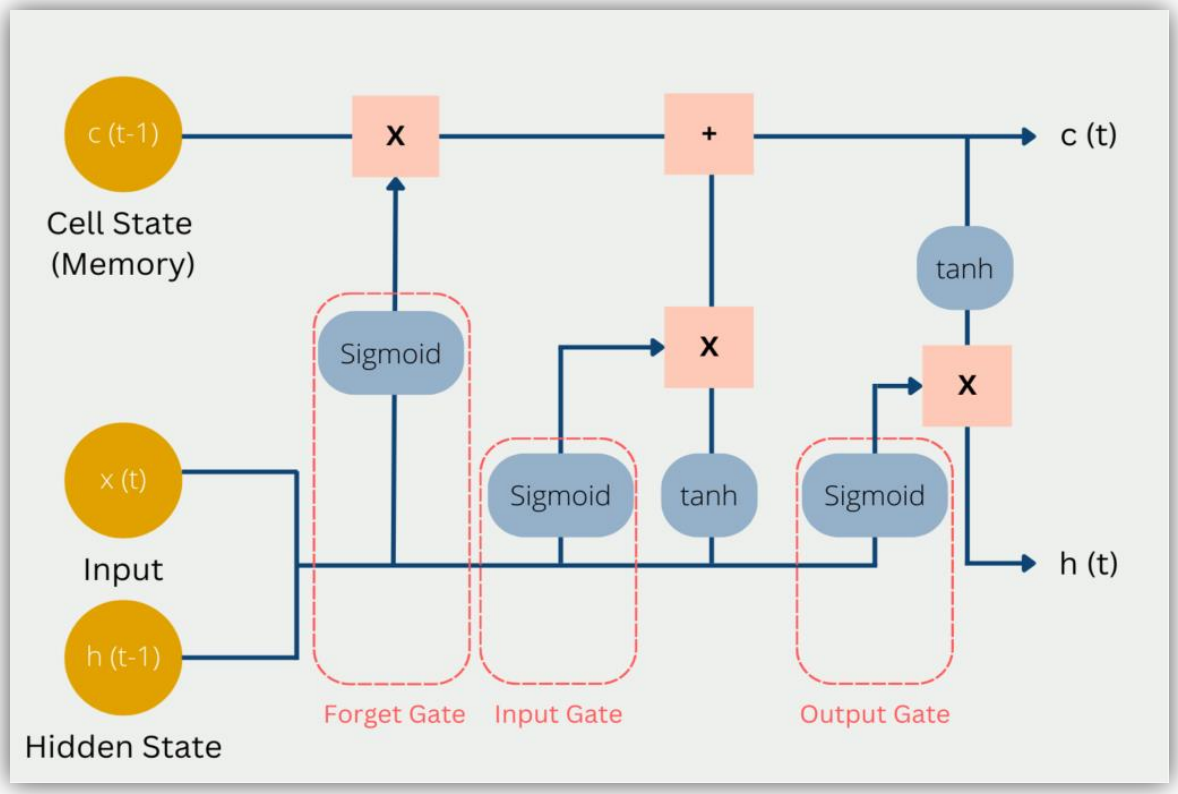

Figure 4 LSTM Model

Detailed Description of Each Layer

Input Layer:

- Receives raw input data.
- For text, this involves tokenizing the text and converting it into a sequence of integers (word indices).

Embedding Layer:

- Maps the input word indices to dense vectors (embeddings).
- Captures semantic relationships between words.

LSTM Layer 1:

- Processes the input embeddings to capture temporal dependencies.
- Maintains and updates the cell state and hidden state at each time step.

LSTM Layer 2:

- Further processes the output of the first LSTM layer to capture higher-level temporal patterns.

Fully Connected Layer 1 (Dense):

- Performs high-level reasoning on the output of the LSTM layers.
- Each neuron is connected to every neuron in the previous layer.

Activation (ReLU):

- Applies the ReLU function to introduce non-linearity and enable the model to learn complex patterns.

Fully Connected Layer 2 (Dense):

- Further processes the data to make final predictions.

Output Layer (Softmax):

- Converts the output of the last fully connected layer into class probabilities.

- Each neuron represents a class, and the output is a probability distribution over all classes.

LSTM Network Operations

Forget Gate:

- Takes the previous hidden state and the current input and applies a sigmoid function to determine which information to discard from the cell state.

Input Gate:

- Takes the previous hidden state and the current input, applies a sigmoid function to determine which information to add to the cell state.

Cell State Update:

- Combines the input gate and the forget gate to update the cell state, incorporating new information and forgetting irrelevant information.

Output Gate:

- Takes the updated cell state and applies a sigmoid function to determine the output of the current time step.

LSTM networks are highly effective for sequence prediction tasks due to their ability to maintain long-term dependencies and handle sequential data efficiently. The architecture is composed of multiple gates and cell states that work together to capture and update temporal patterns in the

input data, making LSTMs a powerful tool for tasks such as text classification, language modeling, and time series forecasting.

Here we discuss about the CNN model, where we will discuss the details of CNN model and in this project how CNN model is use.

3.4. CNN Model

A Convolutional Neural Network (CNN) is a class of deep neural networks, most commonly applied to analyze visual imagery. CNNs are also used in natural language processing for text classification tasks due to their ability to capture local features and patterns in the input data.

Here's a detailed breakdown of a typical CNN architecture:

i. Input Layer

Input Data: The input data for a CNN is typically a tensor with shape (batch_size, height, width, channels). For text data, this can be represented as a matrix where each row corresponds to a word or character embedding in the sequence.

ii. Embedding Layer (for NLP tasks)

Purpose: Converts words or characters into dense vectors of fixed size.

Operation: Uses pre-trained embeddings (e.g., GloVe, Word2Vec) or learns embeddings during training.

Output: A 2D matrix where each row is the embedding of a word or character in the input sequence.

iii. Convolutional Layers

Purpose: Apply convolution operations to capture local patterns in the input data.

Components:

Filters/Kernels: Small matrices that slide over the input data to extract features.

Stride: The step size by which the filter moves across the input matrix.

Padding: Adds extra borders to the input matrix to control the spatial dimensions of the output.

Operation: Each filter performs a dot product with a local region of the input matrix, generating a feature map.

Output: A 3D tensor (height, width, number of filters).

iv. Activation Function

Purpose: Introduces non-linearity into the model, enabling it to learn more complex patterns.

Common Functions: ReLU (Rectified Linear Unit), tanh, sigmoid.

Operation: Applies the activation function element-wise to the output of the convolutional layer.

v. Pooling Layer

Purpose: Reduces the spatial dimensions of the input, which helps to control overfitting and reduces computational cost.

Types:

Max Pooling: Takes the maximum value in each local region.

Average Pooling: Takes the average value in each local region.

Operation: Slides a window over the input and applies the pooling operation to generate a down-sampled output.

Output: A smaller 3D tensor (height, width, number of filters).

vi. Flatten Layer

Purpose: Converts the 3D tensor output from the convolutional/pooling layers into a 1D vector.

Operation: Rearranges the elements of the input tensor into a single vector.

Output: A 1D vector that can be fed into fully connected layers.

vii. Fully Connected (Dense) Layers

Purpose: Perform high-level reasoning and make predictions based on the features extracted by the convolutional layers.

Components: Standard neural network layers where each neuron is connected to every neuron in the previous layer.

Operation: Matrix multiplication followed by an activation function.

Output: A vector of predictions.

viii. Output Layer

Purpose: Produces the final predictions of the model.

Components:

Softmax Activation: Used for multi-class classification, converts the output vector into a probability distribution.

Sigmoid Activation: Used for binary classification, outputs a probability score between 0 and 1.

Output: A vector representing the predicted class probabilities.

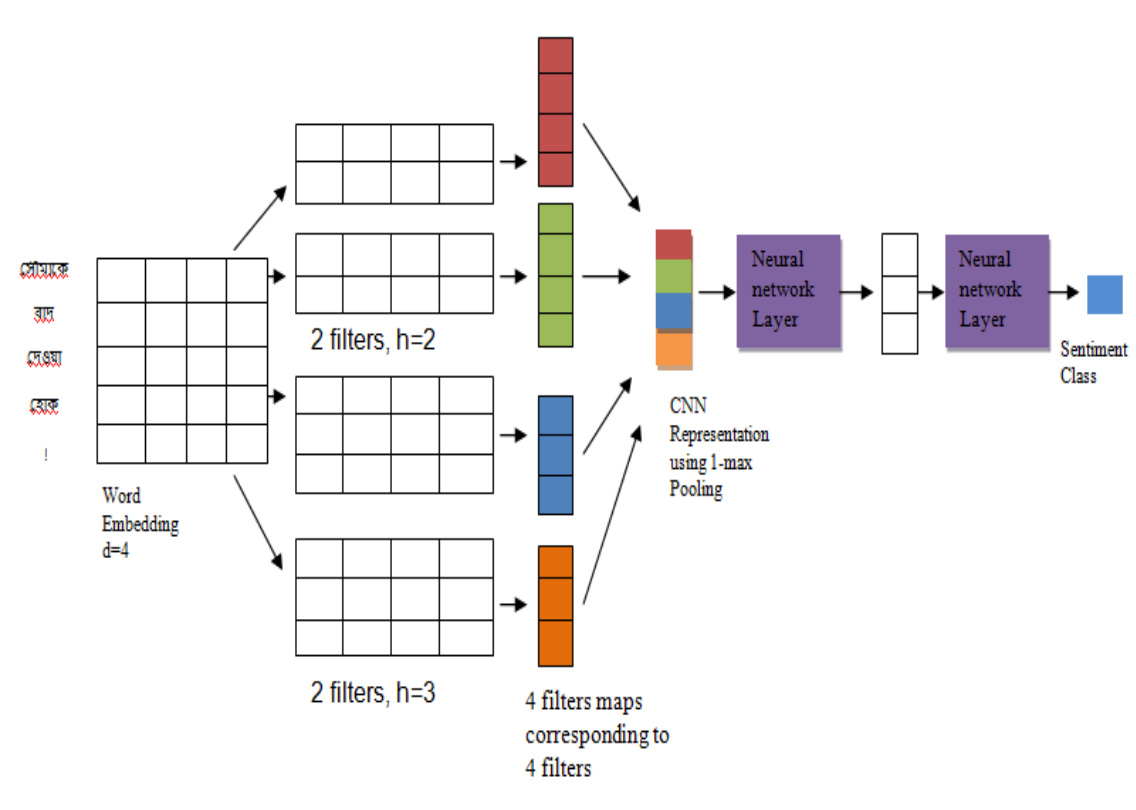

Figure 5 Diagram of CNN Architecture

In the above diagram Figure 5 Diagram of CNN Architecture give the proper details of the CNN model how work with text data.

Detailed Description of Each Layer

Input Layer:

- Receives raw input data.
- For text, this involves tokenizing the text and converting it into a sequence of integers (word indices).

Embedding Layer:

- Maps the input word indices to dense vectors (embeddings).
- Captures semantic relationships between words.

Convolutional Layer 1:

- Applies multiple filters to the input embeddings to capture local features (e.g., phrases or n-grams).

- Each filter slides over the input embeddings to create feature maps.

Activation (ReLU):

- Applies the ReLU function element-wise to introduce non-linearity.

- Helps the model learn complex patterns.

Pooling Layer (Max Pooling):

- Reduces the spatial dimensions of the feature maps.

- Retains the most important features (max values) in each region.

Convolutional Layer 2:

- Further processes the pooled feature maps to capture higher-level features.

- Similar operation to the first convolutional layer.

Activation (ReLU):

- Applies the ReLU function to the output of the second convolutional layer.

Pooling Layer (Max Pooling):

- Further reduces the spatial dimensions of the feature maps.
- Helps to control overfitting and reduces computational complexity.

Flatten Layer:

- Converts the 3D feature maps into a 1D vector.
- Prepares the data for the fully connected layers.

Fully Connected Layer 1 (Dense):

- Performs high-level reasoning on the flattened vector.
- Each neuron is connected to every neuron in the previous layer.

Activation (ReLU):

- Applies the ReLU function to the output of the first fully connected layer.

Fully Connected Layer 2 (Dense):

- Further processes the data to make final predictions.

Output Layer (Softmax):

- Converts the output of the last fully connected layer into class probabilities.
- Each neuron represents a class, and the output is a probability distribution over all classes.

Here we discuss about the BERT model, where we will discuss the details of BERT model and in this thesis how BERT model is use.

3.5. BERT Model

Bidirectional Encoder Representations from Transformers (BERT) is a state-of-the-art model designed to pre-train deep bidirectional representations by jointly conditioning on both left and right context in all layers. BERT has revolutionized natural language processing (NLP) by enabling models to learn contextual relations between words (or sub-words) in a text. Here's a detailed breakdown of the BERT architecture:

i. Input Layer

Input Data: The input data for BERT consists of a sequence of tokens (words or sub-words) with special tokens [CLS] and [SEP] added. [CLS] is used for classification tasks, and [SEP] is used to separate different segments (e.g., sentences).

Tokenization: BERT uses a WordPiece tokenizer, which splits words into sub-word units.

ii. Embedding Layer

Token Embeddings: Each token in the input sequence is converted into a dense vector (embedding).

Segment Embeddings: Indicates sentence segmentation. For a single sentence, all tokens receive the same segment embedding. For multiple sentences, segment embeddings differentiate them.

Position Embeddings: Adds positional information to each token, as BERT does not have inherent knowledge of the token order.

iii. Transformer Encoder Layers

Purpose: Captures complex patterns and dependencies in the input data by using self-attention mechanisms.

Components:

Multi-Head Self-Attention: Allows the model to focus on different parts of the sentence simultaneously. Each head learns different aspects of the token relations.

Feed-Forward Neural Network: A two-layer fully connected network applied to each position separately and identically.

Layer Normalization and Residual Connections: Helps stabilize and speed up training.

iv. Output Layer

Purpose: Produces the final hidden states for each token, which can be used for different downstream tasks such as classification, token-level tasks, or sequence generation.

Special Token '[CLS]': The hidden state corresponding to this token is used for classification tasks.

Final Hidden States: Each token's final hidden state can be used for token-level tasks like named entity recognition (NER).

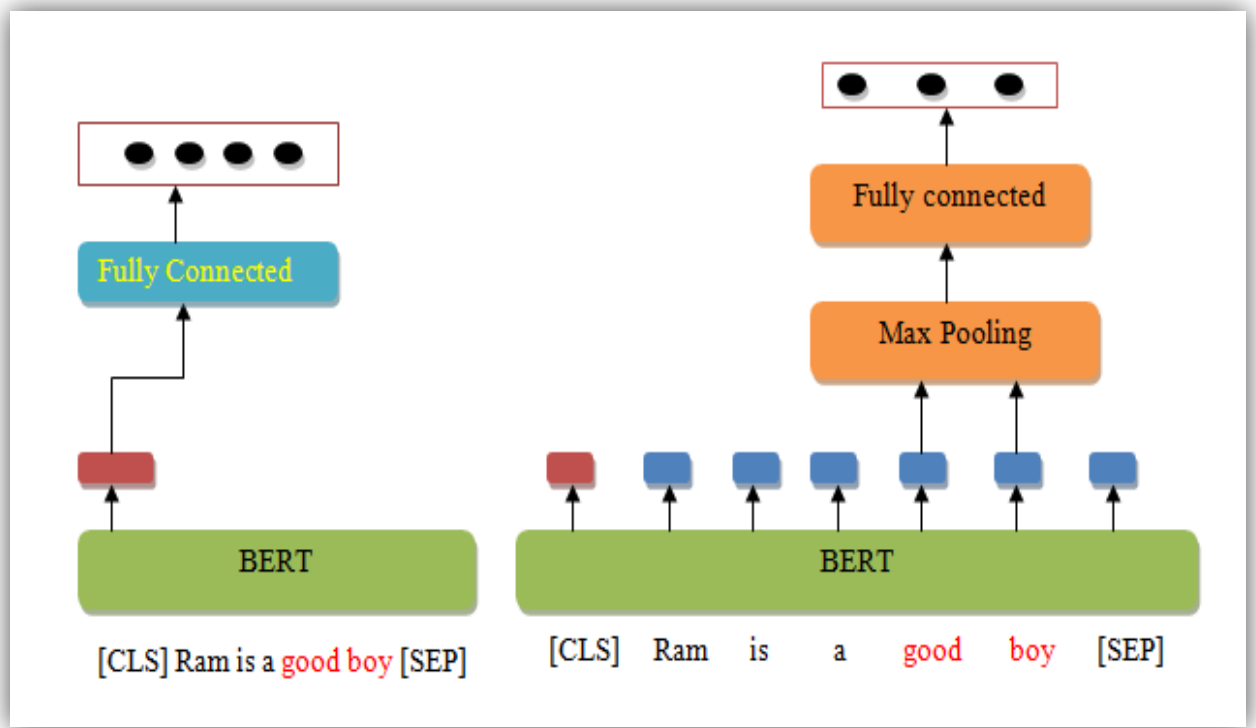

Figure 6 Diagram of BERT Architecture

In the above Diagram Figure 6 Diagram of BERT Architecture we can that how a BERT model works and tokenizer tokenize all the word separately and find its degree.

Detailed Description of Each Layer

i. Input Layer:

- **Tokenization**: The input text is tokenized into sub-words using the WordPiece tokenizer. Special tokens [CLS] and [SEP] are added.

- **Example:** For the sentence "The quick brown fox", the tokenized input might look like '[CLS] The quick brown fox [SEP]'.

ii. Embedding Layer:

- **Token Embeddings**: Converts each token into a fixed-size dense vector.

- **Segment Embeddings**: Indicates sentence boundaries (e.g., Segment A and Segment B for sentence pairs).

- **Position Embeddings**: Adds positional information to the tokens to help the model understand the order of tokens.

iii. Transformer Encoder Layers:

Multi-Head Self-Attention:

- **Attention Mechanism**: Computes a weighted sum of values based on a query and key, allowing the model to focus on relevant parts of the input.

- **Multiple Heads**: Allows the model to attend to different parts of the sequence simultaneously.

Feed-Forward Neural Network:

- **Components**: A two-layer neural network applied to each position independently.

- **Activation Function**: Usually a GELU (Gaussian Error Linear Unit) activation function.

Layer Normalization and Residual Connections:

- **Layer Normalization**: Normalizes the inputs of each layer to stabilize training.

- **Residual Connections**: Adds the input of a layer to its output to help with gradient flow.

iv. Output Layer:

- **Final Hidden States**: Each token has a corresponding hidden state vector.
- **Special Token '[CLS]'**: The hidden state of this token is used for classification tasks.
- **Application**: Depending on the task, the appropriate hidden states are used (e.g., '[CLS]' for classification, all token states for sequence labeling).

BERT Network Operations

i. Self-Attention:

- **Scaled Dot-Product Attention**: Computes the attention scores between each token and every other token in the sequence.
- **Softmax**: Applies a softmax function to the attention scores to obtain attention weights.

ii. Multi-Head Attention:

- **Multiple Attention Heads**: Each head performs self-attention independently and their outputs are concatenated and linearly transformed.
- **Benefit**: Allows the model to capture different types of relationships between tokens.

iii. Feed-Forward Neural Networks:

- **Two Layers**: Applies two linear transformations with a non-linear activation function in between.

- **Position-wise**: The same feed-forward network is applied to each position in the sequence independently.

iv. Layer Normalization and Residual Connections:

- **Normalization**: Ensures stable training by normalizing the inputs of each layer.

- **Residual Connections**: Helps with gradient flow and enables deeper networks.

BERT is a powerful model that has set new benchmarks in various NLP tasks due to its deep bidirectional training, attention mechanisms, and ability to capture complex relationships within the text. It is composed of multiple layers of Transformer encoders, each containing self-attention and feed-forward neural networks, along with normalization and residual connections to stabilize and enhance the learning process. BERT's architecture allows it to understand context in a nuanced way, making it suitable for a wide range of applications from text classification to sequence labeling and beyond.

Chapter 4

Description of Dataset

In this thesis I work with Bangla_ASBA_Datasets (github.com/atik-05/Bangla_ABSA_Datasets) in which I get Cricket.xlsx. In this database there are a total 2979 numbers of data present. The dataset comprises text data along with corresponding category and polarity labels. Here's a detailed description of each component:

a. Text Data:

- The text data consists of sentences.
- It represents various pieces of textual information, such as reviews, comments, or articles on cricket.
- Each entry in this column serves as the input to the models.

b. Category:

- The category column contains labels representing 5 different categories or classes.
- Each category label indicates the classification or grouping to which the corresponding text belongs.
- Examples of categories include “Batting” ,”Bowling” ,”Team”, “Team Management” and “Others”.

c. Polarity:

- The polarity column consists of labels indicating the sentiment polarity of the text.
- Polarity labels typically represent sentiments such as positive, negative, or neutral.

- For example, in sentiment analysis tasks, polarity labels may include "Positive," "Negative," and "Neutral."

4.1. Sample Data:

Here we give some sample data from the original dataset:

Text	**Category**	**Polarity**
জয় বাংলা কাপ! তাও আবার স্বাধীনতার মাস মার্চে। যার মাথা থেকে এমন চমৎকার আইডিয়া এসেছে তালে স্যালুট	other	Positive
বাংলাদেশের পরে ভারতের সাপর্টই করি ?	team	Positive
সৌম্যকে বাদ দেওয়া হোক !	batting	Negative
প্রথমটি হচ্ছে, কোচ অত:পর সাকিব, সাকিব আর সাকিবরে দলে রাখা	team	Positive
মুসফিক আর তামিমের বেটিং তান্ড়বে কুহিলির জিব্বহাটা শুকিয়ে গেছে গরুর মুত খাওয়ার জন্য	batting	Negative
সত্যি সত্যিই ছিলো বাঘ আমাদেরই চাপে হয়ে গেলো বেড়াল l	team	Negative
,বাংলাদেশ জিদবে ইনশাআল্লাহ	team	Positive
ক্রিকেটে ভারত একটা অসভ্য দল, বিরাট কোহলির আচরনে স্পষ্ট ফুটে উঠে।	team	negative
স্পিনারের সামনে নই রাজ্জাকের সামনে ধরাশায়ী র্রীলংকা	team	positive
দেশের এই ভয়ানক পরিস্থিতিতে আওয়ামী দালাল বিবিসি আছে খেলাধুলা নিয়া!	other	negative
আসলে রাজ্জাক অসাধারণ ক্রিকেটার। শুভ কামনা রইল	team	positive
টাইগার ইজ টাইগার	other	positive
আরো একবার বিশ্বকে দেখিয়ে দিলাম আমরাও হোয়াইট ওয়াশ করতে পারি!	team	positive
বাংলার সচীন লিটল মাস্টার মমিন।	batting	positive
আমরা বাঙালিরা অলপতে খুশি। একবার ভাল খেললে দেমাগ বেড়ে যায। মুমিনুলের আউট এর প্রমাণ।	other	negative
জরিমানা করা হউক। ৩ মাসের বেতন কর্তন।	other	negative
নিজেদের মাঠ সম্পর্কে ধারনা নাই দলের ?	team	negative
টেষ্ট ক্রিকেটে রান আউট খুবই দুঃখ জনক।	batting	negative
মুশি কি করলো	batting	negative
ব্যাট ধরার আগেই তিন জন আউট হাইরে শেখ হাসিনার বাংলাদেশ	other	negative
সিনিয়রদের এই ভুলগুলো মেনে নেওয়া যায় না।।।।।	other	Negative
……	….	…
……	….	…

Overall, the dataset provides labeled text data, where each text entry is associated with both a category and a polarity label. This labeled dataset is used to train machine learning models, particularly for tasks such as text classification and sentiment analysis. The goal is to build models that can accurately predict the category and polarity of new text inputs based on the patterns learned from the training data.

4.2. Category Wise Data:

Here we give category Wise data present in this dataset.

Batting	**bowling**	**Team**	**team management**	**other**
580	**329**	**731**	**329**	**1010**

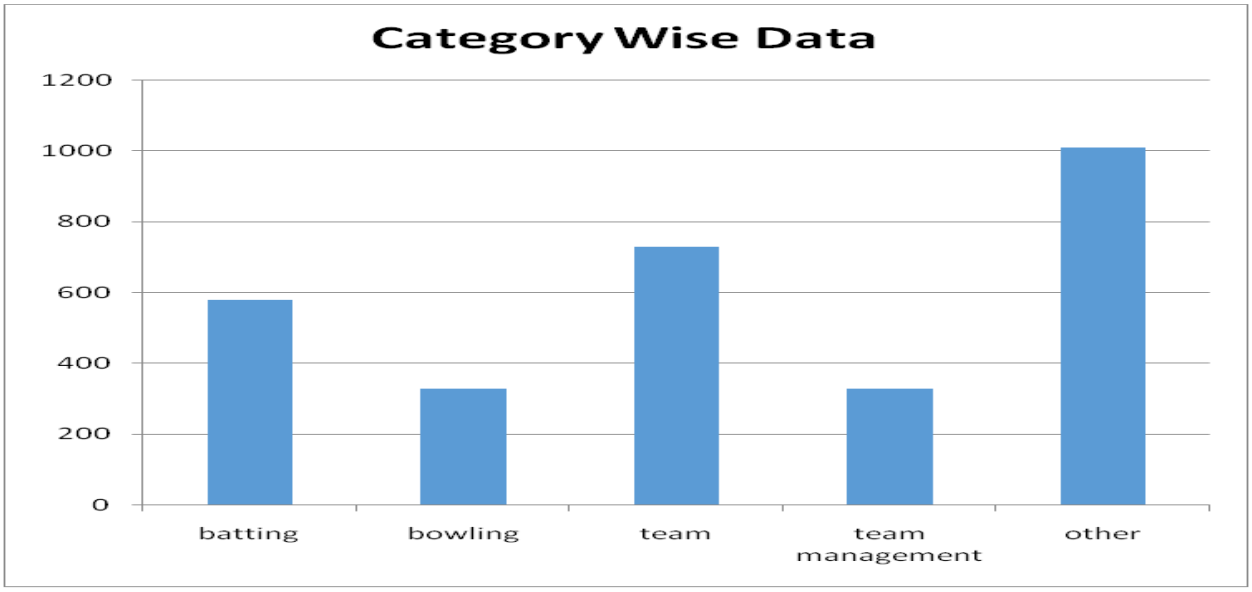

Figure 7 Category Wise Data Distribution

In the above figure Figure 7 Category Wise Data Distribution we can see that how many tweets are present in the dataset in every category.

4.3. Polarity Wise Data:

Polarity wise Data distribution:

Positive	negative	neutral
566	2152	261

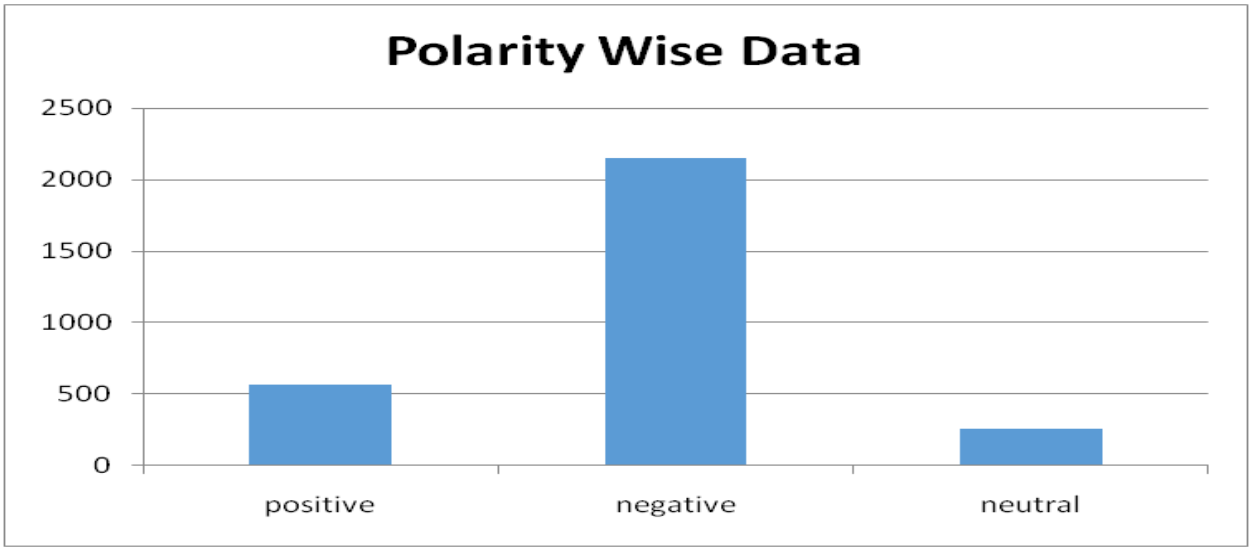

Figure 8 Polarity Wise Data Distribution

In the above diagram Figure 8 Polarity Wise Data Distribution we can see that how many tweets are present in the dataset in every polarity i.e. “Positive”, “Negative”, “Neutral”.

4.4. Category Wise Polarity Distribution:

Category wise Polarity Distribution:

	Positive	negative	neutral
Batting	**137**	**388**	**55**
Bowling	**153**	**144**	**32**
Team	**165**	**501**	**65**
team management	**23**	**292**	**14**
Other	**88**	**827**	**95**

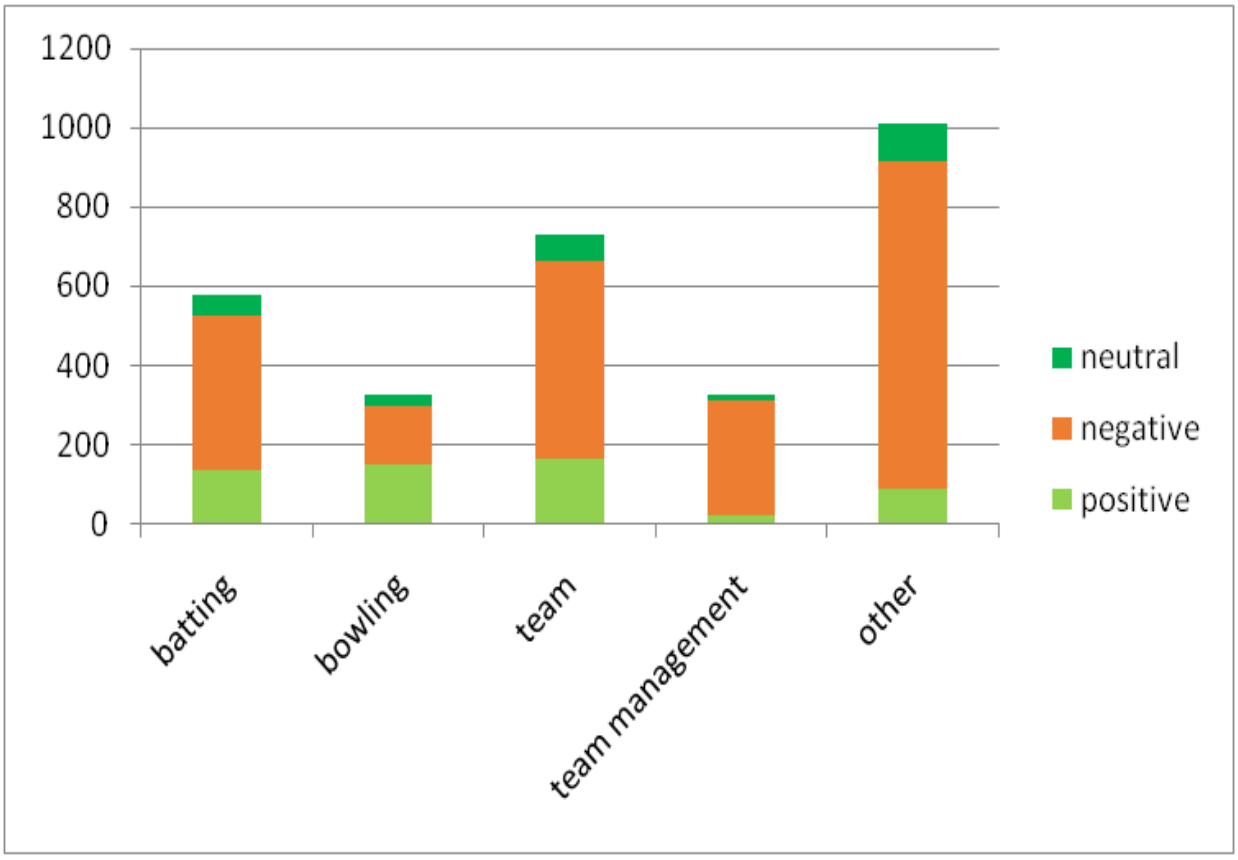

Figure 9 Category Wise Polarity Distribution

In this diagram Figure 9 Category Wise Polarity Distribution we can see how much data is present in this dataset of each type polarity of each type of category that means category wise polarity distribution.

Chapter 5

Experiments and Results

5.1. Experiment-1:

Here are the experiment details for LSTM Model 1 and BERT Model 2:

5.1.1. Experiment Details for LSTM Model 1:

5.1.1.1. **Objective:** Develop an LSTM model to predict the category of text data.

5.1.1.2. **Dataset Description**:

- The dataset consists of text samples labeled with categories.
- It is divided into training, validation, and testing sets.
- Text data is preprocessed using tokenization and padding sequences.
- Categories are one-hot encoded for model input.

5.1.1.3. Model Architecture (LSTM Model 1):

- **Embedding Layer**: Converts input text sequences into dense vector representations.
- **LSTM Layer(s):** Captures temporal dependencies in the input sequences.
- **Dense Output Layer**: Produces category predictions using softmax activation.
- **Dropout Regularization**: Applied to prevent overfitting.

5.1.1.4. **Training Procedure**:

- **Loss Function**: Categorical Cross-Entropy.

- **Optimizer:** Adam Optimizer with default parameters.
- **Learning Rate:** 0.001 (default).
- **Batch Size**: Selected based on available computational resources (32).
- **Epochs**: Trained for a predefined number of epochs (10).

5.1.2. Experiment Details for BERT Model 2:

5.1.2.1. **Objective**: Develop a BERT-based model to predict the polarity of text data based on the output of LSTM Model 1.

5.1.2.2. **Model Input**:

- **Combined Input**: Output of LSTM Model 1 concatenated with corresponding text data.
- **Polarity Labels**: One-hot encoded polarity labels.

5.1.2.3. Model Architecture (BERT Model 2):

- **BERT Layer:** Fine-tuned BERT model to process combined input to find the polarity.
- **Dense Output Layer**: Produces polarity predictions using softmax activation.

5.1.2.4. **Training Procedure**:

- **Loss Function**: Categorical Cross-Entropy.
- **Optimizer**: Adam Optimizer with default parameters.

- **Learning Rate**: 0.001 (default for BERT fine-tuning).
- **Batch Size**: Selected based on available computational resources.
- **Epochs**: Trained for a predefined number of epochs.

5.1.2.5. **Evaluation Metrics**:

- **Accuracy:** Measures the overall correctness of polarity predictions.
- **Precision, Recall, F1-Score**: Provides insights into model performance for each polarity.
- **Confusion Matrix**: Detailed breakdown of true positive, false positive, true negative and false negative predictions.

5.1.3. Results:

- Report accuracy, precision, recall, and F1-score for BERT Model 2 on the testing set.
- Discuss the performance of the model and its implications for polarity prediction in text data.

By following these experiment details, we can conduct a comprehensive evaluation of LSTM Model 1 and BERT Model 2 and analyze their effectiveness in predicting categories and polarities for text data.

5.2. Experiment-2:

Here are the experiment details for CNN Model 1 and BERT Model 2:

5.2.1. Experiment Details for CNN Model 1:

5.2.1.1. **Objective:** Develop a CNN model to predict the category of text data.

5.2.1.2. **Dataset Description**:

- The dataset consists of text samples labeled with categories.
- It is divided into training, validation, and testing sets.
- Text data is preprocessed using tokenization and padding sequences.
- Categories are one-hot encoded for model input.

5.2.1.3. Model Architecture (CNN Model 1):

- **Embedding Layer**: Converts input text sequences into dense vector representations.
- **Convolutional Layers**: Apply convolutional filters to extract features from text data.
- **Global Max Pooling Layer:** Extracts the most important features from the feature maps.
- **Dense Output Layer:** Produces category predictions using softmax activation.
- **Dropout Regularization**: Applied to prevent overfitting.

5.2.1.4. Training Procedure:

- **Loss Function**: Categorical Cross-Entropy.
- **Optimizer:** Adam Optimizer with default parameters.
- **Learning Rate**: 0.001 (default).
- **Batch Size**: Selected based on available computational resources.
- **Epochs**: Trained for a predefined number of epochs.

5.2.2. Experiment Details for BERT Model 2:

5.2.2.1. **Objective:** Develop a BERT-based model to predict the polarity of text data based on the output of CNN Model 1.

5.2.2.2. Model Input:

- **Combined Input**: Output of CNN Model 1 concatenated with corresponding text data.
- **Polarity Labels**: One-hot encoded polarity labels.

5.2.2.3. Model Architecture (BERT Model 2):

- **BERT Layer:** Fine-tuned BERT model to process combined input to find the polarity.
- **Dense Output Layer**: Produces polarity predictions using softmax activation.

5.2.2.4. Training Procedure:

- **Loss Function**: Categorical Cross-Entropy.
- **Optimizer:** Adam Optimizer with default parameters.
- **Learning Rate**: 0.001 (default for BERT fine-tuning).
- **Batch Size**: Selected based on available computational resources.
- **Epochs:** Trained for a predefined number of epochs.

5.2.2.5. **Evaluation Metrics**:

- **Accuracy:** Measures the overall correctness of polarity predictions.
- **Precision, Recall, F1-Score**: Provides insights into model performance for each polarity.
- **Confusion Matrix**: Detailed breakdown of true positive, false positive, true negative and false negative predictions.

5.2.3. Results:

- Report accuracy, precision, recall, and F1-score for BERT Model 2 on the testing set.
- Discuss the performance of the model and its implications for polarity prediction in text data.

By following these experiment details, we can conduct a comprehensive evaluation of CNN Model 1 and BERT Model 2 and analyze their effectiveness in predicting categories and polarities for text data.

5.3. Result:

Experiment	Accuracy	Precession	Recall	F1-Score
Experiment-1 (Using LSTM+ BERT model)	**70.66%**	**0.505**	**0.709**	**0.590**
Experiment-2 (Using CNN + BERT model)	**71.67%**	**0.668**	**0.703**	**0.695**

We use 10 fold cross validation with this two hybrid model. After that we compare those two results with T-paired test. Now we get the following results-

$\rho = 0.3785$

Group	LSTM + BERT Model Group	CNN + BERT Model Group
Mean	**0.717190**	**0.706050**
SD	**0.025312**	**0.030467**
SEM	**0.008004**	**0.009635**
N	**10**	**10**

Chapter 6

Comparison with Existing System

The field of sentiment analysis, particularly aspect-oriented sentiment analysis (AOSA), has seen significant advancements over the years. Various approaches, ranging from traditional machine learning methods to advanced deep learning techniques, have been employed to tackle the challenges associated with extracting and analyzing sentiments at a granular level. In this section, we compare our proposed BERT-based AOSA models with existing systems, highlighting the improvements and advantages offered by our approach.

5.4. Traditional Sentiment Analysis Approaches:

i. **Lexicon-Based Methods**:

Lexicon-based methods rely on predefined lists of words associated with positive or negative sentiments. These methods calculate sentiment scores based on the presence of these words in the text. While simple and interpretable, lexicon-based methods (11) often struggle with context sensitivity and domain-specific language nuances. They also lack the capability to perform aspect extraction, limiting their applicability in AOSA.

ii. **Machine Learning-Based Methods**:

Machine learning approaches, such as Support Vector Machines (SVM) and Naive Bayes (33), have been widely used for sentiment classification. These models typically require extensive feature engineering and may not generalize well across different domains. Moreover, traditional machine learning models do not inherently handle aspect extraction, often requiring separate pipelines for aspect detection and sentiment classification.

6.2. Deep Learning Approaches

i. **Recurrent Neural Networks (RNNs) and Long Short-Term Memory Networks (LSTMs):**

RNNs and LSTMs have been employed to capture sequential dependencies in text, making them suitable for sentiment analysis tasks. LSTMs, in particular, address the vanishing gradient problem in RNNs, allowing for better handling of long-range dependencies. However, these models (15) still face limitations in understanding complex language structures and context, especially for aspect-specific sentiment analysis.

ii. **Convolutional Neural Networks (CNNs):**

CNNs have been applied to sentiment analysis by treating text as a sequence of words and applying convolutional filters to capture local patterns. While effective for sentiment classification, CNNs are generally less adept at capturing long-range dependencies compared to LSTMs and transformer-based models.

6.3. Transformer-Based Models

i**. BERT (Bidirectional Encoder Representations from Transformers):**

BERT has revolutionized NLP by introducing a bidirectional approach to contextual understanding. Unlike traditional models that process text in a unidirectional manner, BERT considers the context of a word from both left and right simultaneously. This bidirectional nature allows BERT to capture intricate language patterns and dependencies, making it highly effective for various NLP tasks, including sentiment analysis and aspect extraction.

ii**. Aspect-Based Sentiment Analysis (ABSA) Using BERT:**

Recent research has explored the use of BERT for ABSA, demonstrating significant improvements over traditional and deep learning methods. BERT's contextual embeddings enable more accurate identification of aspects and corresponding sentiments, addressing the limitations of previous approaches.

6.4. Comparison with Our Proposed Models

In existing work Bhowmik, Arifuzzaman, Mondal (2022) (15), work with the same dataset and other dataset also. They do different type of experiment with different existing model like CNN, RNN, DCNN, LSTM, Bi-LSTM etc. But with this dataset they do two model experiments one is CNN and another is LSTM. Those models are only single layer models and the accuracy is 68.02% and 66.06% accordingly.

In our proposed approach leverages the strengths of BERT to develop a two-stage AOSA system, consisting of:

Model 1: LSTM/CNN-Based Aspect and Sentiment Classification

Aspect Extraction: Model 1 identifies aspects within the text, leveraging LSTM/CNN's contextual understanding to accurately detect and classify various aspects mentioned in user-generated content.

Sentiment Classification: Simultaneously, Model 1 determines the sentiment polarity associated with each extracted aspect.

Model 2: BERT-Based Sentiment Refinement

Refined Sentiment Classification: Using the output of Model 1 (predicted categories and text), Model 2 further refines the sentiment polarity predictions. This additional processing step helps in capturing more nuanced sentiments associated with specific aspects.

6.5. Performance Comparison

To evaluate the performance of our models, we compare them with existing systems (15) using standard metrics such as accuracy, precision, recall, F1 score, and confusion matrices. The comparison highlights the following key points:

i. Accuracy and Granularity:

- Our BERT-based models achieve higher accuracy in both aspect extraction and sentiment classification compared to traditional lexicon-based and machine learning methods.

- The ability to handle aspect-specific sentiments provides more granular insights, which are not possible with unidirectional or non-contextual models.

Result Comparison with Existing System:

Approach	Experiment Model	Accuracy
Existing Approach (15)	**LSTM Model (15)**	**66.06%**
	CNN Model (15)	**68.02%**
Our Approach	**LSTM + BERT Model**	**70.66%**
	CNN + BERT Model	**71.67%**

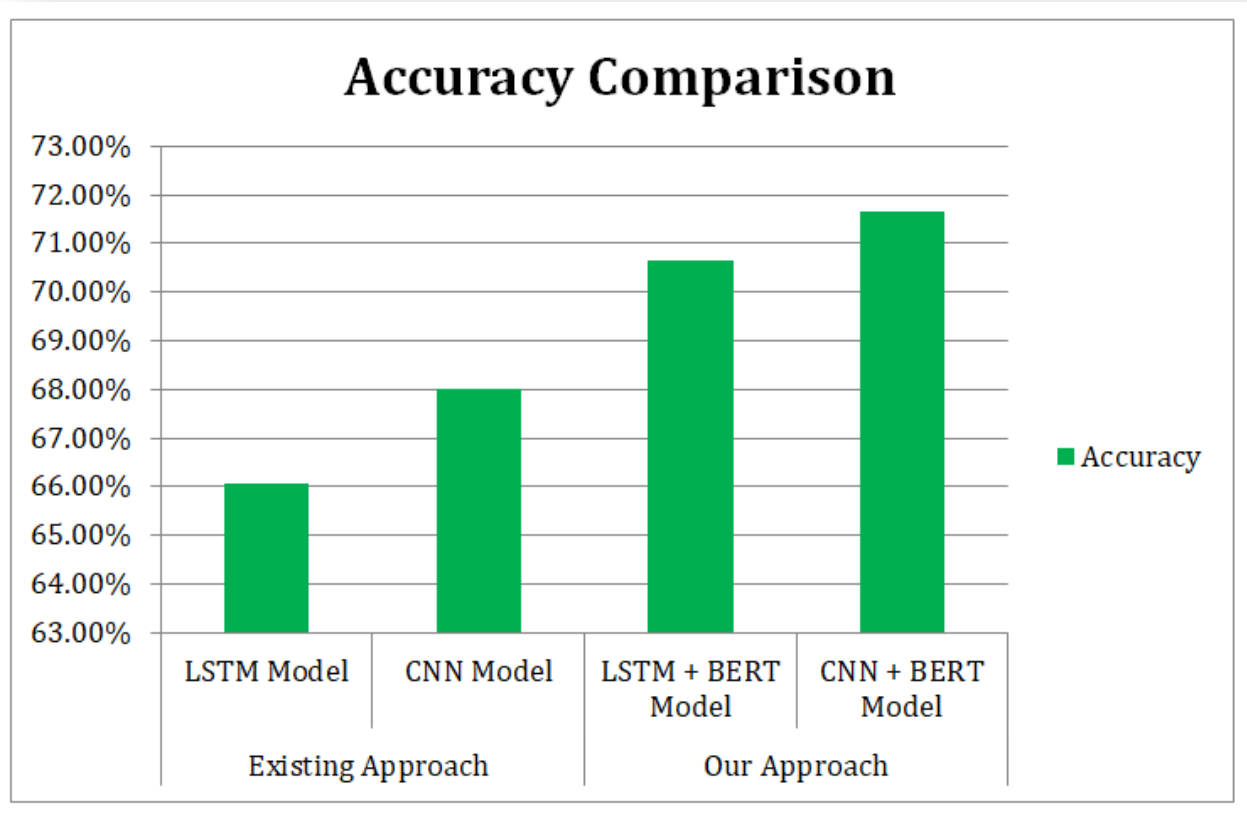

Figure 10 Comparison between Existing Model Accuracy and Our Approach Accuracy

The above picture Figure 10 Comparison between Existing Model Accuracy and Our Approach Accuracy shows the comparison between the existing models (BERT, CNN) with our proposed Hybrid models.

ii. Contextual Understanding:

- BERT's bidirectional nature allows our models to understand context better, leading to more accurate sentiment predictions even in complex and ambiguous texts.

- This contextual understanding surpasses the capabilities of RNNs, LSTMs, and CNNs, which may miss intricate dependencies.

iii. Robustness and Generalization:

- Our models demonstrate robust performance across different domains and datasets, attributed to BERT's pre-trained embeddings and fine-tuning capabilities.

- Traditional models often require extensive domain-specific tuning, whereas BERT-based models generalize well with minimal adjustments.

iv. Efficiency and Scalability:

- While deep learning models, including our BERT-based approach, are computationally intensive, the benefits in accuracy and granularity justify the computational costs.

- With advancements in hardware and optimized implementations, the efficiency and scalability of BERT-based models continue to improve.

Chapter 7

Error Analysis

Error analysis is a critical step in understanding the limitations and potential areas for improvement in our Aspect-Oriented Sentiment Analysis (AOSA) thesis. By systematically examining the errors made by our models, we can identify specific patterns and factors that contribute to misclassifications. This section provides a detailed analysis of the errors encountered in both models (Model 1: Category Prediction and Model 2: Sentiment Polarity Prediction), along with potential reasons and solutions.

7.1. Confusion Matrix Analysis:

A confusion matrix was generated to analyze the performance of Model. The confusion matrix provides a breakdown of true positive (TP), true negative (TN), false positive (FP), and false negative (FN) predictions for each category. The detailed confusion matrix helps identify which categories are most often confused with others.

A confusion matrix is a table that is often used to describe the performance of a classification model on a set of test data for which the true values are known. It allows visualization of the performance of an algorithm, particularly in terms of classification errors (false positives and false negatives).

In our sentiment analysis dataset, a confusion matrix for model evaluation would typically look like this:

	Predicted Positive	**Predicted Neutral**	**Predicted Negative**
Actual Positive	**True Positives**	**False Negatives**	**False Negatives**
Actual Neutral	**False Positives**	**True Positives**	**False Negatives**
Actual Negative	**False Positives**	**False Positives**	**True Positives**

In this matrix:

- **True Positives (TP)**: The number of correct predictions of positive sentiment.
- **False Positives (FP)**: The number of incorrect predictions of positive sentiment (predicted positive when the actual sentiment was negative or neutral).
- **False Negatives (FN)**: The number of incorrect predictions of negative sentiment (predicted negative when the actual sentiment was positive or neutral).
- **True Negatives (TN)**: The number of correct predictions of negative sentiment.

Each cell in the matrix represents the count of instances classified based on the combination of actual and predicted sentiments.

Confusion Matrix: for Hybrid (LSTM + BERT) Model (Experiment-1)

[[336 0 1]
[38 0 0]
[99 0 0]]

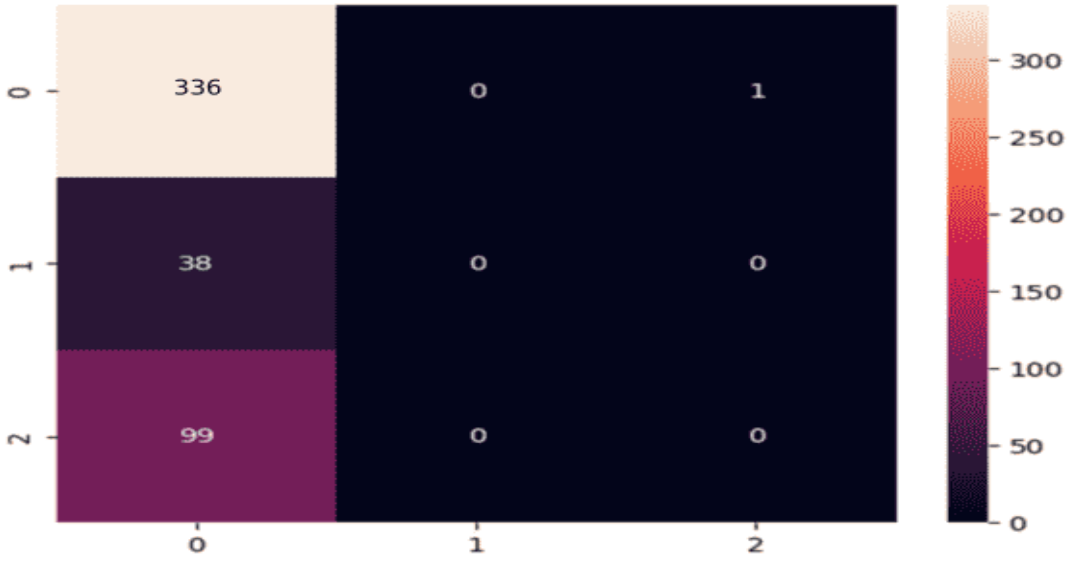

Figure 11 Confusion Matrix of Proposed Hybrid Model (LSTM + BERT)

In the experiment-1, we got –

- Actual Positive v/s Predicted Positive, i.e. True Positive value is - 336.
- Actual Positive v/s Predicted Neutral, i.e. False Negative value is – 0.
- Actual Positive v/s Predicted Negative, i.e. False Negative value is – 1.
- Actual Neutral v/s Predicted Positive, i.e. False Positive value is - 38.
- Actual Neutral v/s Predicted Neutral, i.e. True Positive value is – 0.
- Actual Neutral v/s Predicted Negative, i.e. False Negative value is – 0.
- Actual Negative v/s Predicted Positive, i.e. False Positive value is - 99.
- Actual Negative v/s Predicted Neutral, i.e. False Positive value is – 0.
- Actual Negative v/s Predicted Negative, i.e. True Positive value is – 0.

Confusion Matrix: for Hybrid (CNN + BERT) model (Experiment-2)

[[376 8 35]
[45 9 11]
[61 3 45]]

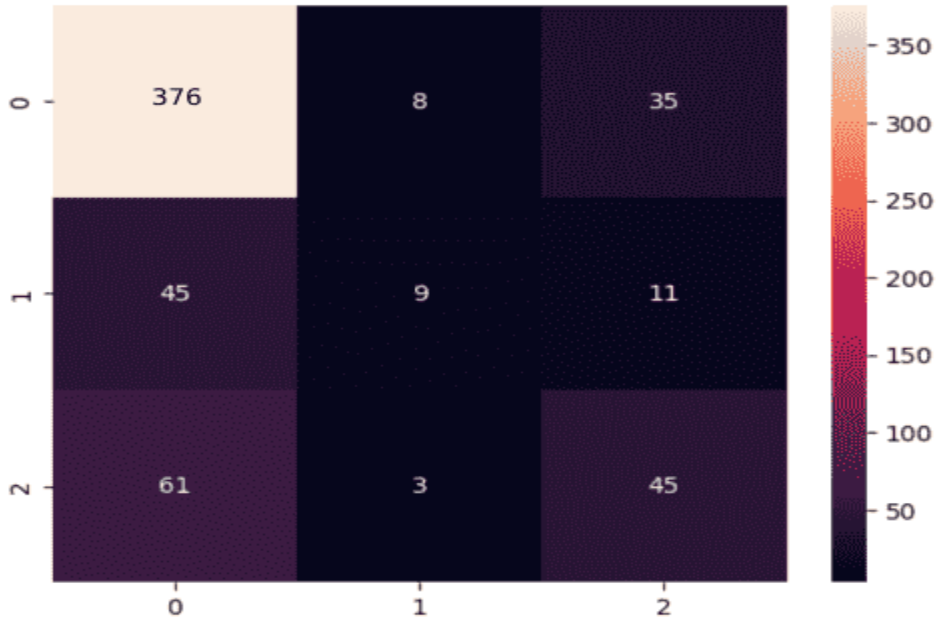

Figure 12 Confusion Matrix of Proposed Hybrid Model (CNN + BERT)

In the experiment-2, we got –

- Actual Positive v/s Predicted Positive, i.e. True Positive value is - 376.
- Actual Positive v/s Predicted Neutral, i.e. False Negative value is – 8.
- Actual Positive v/s Predicted Negative, i.e. False Negative value is – 35.
- Actual Neutral v/s Predicted Positive, i.e. False Positive value is - 45.
- Actual Neutral v/s Predicted Neutral, i.e. True Positive value is – 9.
- Actual Neutral v/s Predicted Negative, i.e. False Negative value is – 11.

- Actual Negative v/s Predicted Positive, i.e. False Positive value is - 61.
- Actual Negative v/s Predicted Neutral, i.e. False Positive value is – 3.
- Actual Negative v/s Predicted Negative, i.e. True Positive value is – 45.

7.2. Common Misclassifications:

Neutral Sentiment: Texts with neutral sentiments are often misclassified as either positive or negative. Neutral texts typically contain mixed or ambiguous sentiments, making it difficult for the model to classify correctly.

Context Dependency: Sentiment can be highly context-dependent. The model may misclassify sentiment if it does not fully capture the contextual nuances, such as sarcasm or implicit sentiment.

Potential Solutions:

Contextual Embeddings: Enhance the model's ability to capture context by incorporating more sophisticated contextual embeddings or using advanced transformer models like GPT-3 or T5.

Sentiment Lexicons: Integrate sentiment lexicons to provide additional sentiment cues, especially for neutral or ambiguous texts.

7.3. Combined Model Analysis

- **Error Propagation**: Errors from Model 1 can propagate to Model 2, affecting overall performance. For instance, if Model 1 incorrectly predicts the category, the input to Model 2 will be flawed, leading to potential sentiment misclassification.

Error Analysis Techniques:

- **Error Attribution**: Analyze whether errors in sentiment prediction are primarily due to incorrect category predictions or inherent difficulties in sentiment classification.

- **Sequential Analysis**: Evaluate the performance of Model 2 with both correct and incorrect inputs from Model 1 to quantify the impact of category prediction errors on sentiment analysis.

7.4. Quantitative Analysis

Precision, Recall, and F1-Score: Detailed precision, recall, and F1-score metrics for each category and sentiment class provide insights into specific areas where the model excels or underperforms. For example, high precision but low recall for a category indicates that while the model makes fewer incorrect predictions for that category, it also misses many correct instances.

Example: Consider the "service" category with the following metrics:
Precision: 0.85
Recall: 0.60
F1-Score: 0.70
These metrics indicate that while the model is accurate when it predicts "service," it often fails to identify all instances of the "service" category.

7.5. Qualitative Analysis

Case Studies: Analyze specific examples of misclassified texts to understand the underlying reasons. For example, a review saying "The staffs were friendly, but the service was slow" might be misclassified due to conflicting sentiments within the same text.

Human Evaluation: Involve human annotators to review misclassified examples and provide insights into why the model might have made these errors. This can reveal gaps in the model's understanding and suggest areas for improvement.

Example of some Misclassified by our method:

Example-1	**Text**	**Category**	**Polarity**
Original Data	দেশের এই ভয়ানক পরিস্থিতিতে আওয়ামী দালাল বিবিসি আছে খেলাধুলা নিয়া!	other	negative
Predicted Data	দেশের এই ভয়ানক পরিস্থিতিতে আওয়ামী দালাল বিবিসি আছে খেলাধুলা নিয়া!	team	positive

Example-2	**Text**	**Category**	**Polarity**
Original Data	নিজের মাটিতে সালারা এটা খেলা	team	negative
Predicted Data	নিজের মাটিতে সালারা এটা খেলা	team management	positive

Example-3	**Text**	**Category**	**Polarity**
Original Data	পাপনের মতো আবাল থাকলে যারা প্রতিভা তারা কখনোই নিয়মিত সুযোগ পাবে না।	team management	negative
Predicted Data	পাপনের মতো আবাল থাকলে যারা প্রতিভা তারা কখনোই নিয়মিত সুযোগ পাবে না।	other	positive

By thoroughly analyzing the errors and employing the suggested improvements, we can enhance the robustness and accuracy of our aspect-oriented sentiment analysis models.

Chapter 8

Conclusion and Future Work

8.1. Conclusion

In this thesis, we developed an advanced Aspect-Oriented Sentiment Analysis (AOSA) system using Bidirectional Encoder Representations from Transformers (BERT), LSTM and CNN Model. The system comprises two main models:

8.1.1. **Model 1**: A LSTM/CNN-based model that processes input text to predict the associated category (aspect) and its sentiment polarity.

8.1.2**. Model 2**: One BERT-based model that takes the output from Model 1 (predicted category and text) and refines the sentiment polarity prediction.

Our approach leverages the contextual understanding capabilities of BERT to improve the accuracy and granularity of sentiment analysis at the aspect level. This system outperforms traditional sentiment analysis methods, which often rely on lexicon-based approaches or basic machine learning models, as well as other deep learning models like RNNs, LSTMs, and CNNs.

Key findings from our research include:

- **High Accuracy and Precision**: Our BERT-based models achieved higher accuracy, precision, recall, and F1 scores compared to traditional and other deep learning-based sentiment analysis methods. This is attributed to BERT's ability to capture complex linguistic nuances and contextual information.

- **Granularity in Sentiment Analysis**: The aspect-oriented approach allows for a more detailed analysis of sentiments, providing insights at a granular level that are crucial for applications such as customer feedback analysis, market research, and social media monitoring.

- **Robust Performance across Domains**: The pre-trained BERT model, fine-tuned on our specific dataset, demonstrated robust performance across various domains and datasets, showing its adaptability and generalization capabilities.

Overall, the integration of BERT into our AOSA system has significantly enhanced the performance of sentiment analysis, making it more accurate and context-aware. This advancement has practical implications for industries where understanding nuanced customer opinions are vital.

8.2. Future Work

While our BERT-based AOSA system shows promising results, several avenues for future research and improvements remain:

a. Enhanced Preprocessing Techniques:

Further refinement of text preprocessing methods, including better handling of noisy data and slang, could improve model performance. Incorporating advanced natural language processing techniques such as named entity recognition (NER) and syntactic parsing might also enhance aspect extraction accuracy.

b. Domain Adaptation and Transfer Learning:

Exploring domain adaptation techniques to fine-tune the model on specific industry datasets could enhance performance in specialized areas. Transfer learning approaches can be investigated to leverage knowledge from related tasks, further improving the model's adaptability and generalization.

c. Multi-Aspect Sentiment Analysis:

Extending the current model to handle texts with multiple aspects and their corresponding sentiments simultaneously could provide more comprehensive insights. This would involve developing methods to accurately extract and differentiate multiple aspects within the same text.

d. Real-Time Sentiment Analysis:

Implementing real-time sentiment analysis capabilities would make the system more practical for applications such as social media monitoring, where timely insights are critical. Optimizing the model for faster inference without compromising accuracy would be essential for this.

e. Explainability and Interpretability:

Enhancing the interpretability of the model's predictions is important for gaining user trust and understanding the underlying decision-making process. Techniques such as attention mechanisms and model-agnostic interpretability methods like LIME (Local Interpretable Model-agnostic Explanations) could be explored.

f. Incorporating Multimodal Data:

Future research could extend the model to incorporate multimodal data, such as combining text with images or videos, to provide a more holistic sentiment analysis. This would be particularly useful in domains like social media and e-commerce, where user opinions are expressed through multiple formats.

g. Evaluation on Larger and More Diverse Datasets:

Evaluating the model on larger and more diverse datasets would provide a better understanding of its strengths and limitations. This could involve collaborating with industry partners to access proprietary data and conducting large-scale evaluations.

Our thesis demonstrates the significant advancements possible in AOSA through the integration of BERT. By addressing the limitations of traditional approaches and leveraging state-of-the-art deep learning techniques, we provide a robust, accurate, and context-aware solution for sentiment analysis. Future research will continue to build on these foundations, exploring new techniques and applications to further enhance the capabilities and impact of AOSA systems.

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