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A Context-Aware Hybrid Model for Sentiment Analysis

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Abstract: The rapid growth of social media and online platforms has generated large volumes of opinion-rich text, increasing the need for automated sentiment analysis. Traditional machine learning methods can efficiently classify text but often have limited ability to capture semantic context, negation, sarcasm, and domain-specific expressions, whereas modern contextual models such as BERT provide richer representations at higher computational cost. This paper surveys research on context-aware sentiment analysis published from 2020 to 2026 and categorizes existing approaches according to their representation and classification techniques. Based on the identified trends and limitations, a hybrid opinion-mining framework is proposed that combines text preprocessing, TF-IDF statistical features, TextBlob lexical polarity, BERT contextual representations, and CNN-BiLSTM with attention mechanisms for sentiment classification and emotion recognition. The surveyed studies, datasets, reported findings, advantages, and limitations are comparatively discussed to identify research gaps. The analysis highlights the potential of combining complementary statistical, lexical, contextual, and sequential representations while also emphasizing challenges related to computational complexity, sarcasm, negation, multilingualism, and domain adaptation. The proposed framework provides a structured basis for future empirical evaluation across multiple domains.

Keywords: Sentiment Analysis, Context-Aware Computing, Natural Language Processing, BERT, Hybrid Deep Learning, Opinion Mining

I INTRODUCTION

Due to the rapid development of Internet technologies, the interaction and exchange of opinions and experiences about likes and dislikes among individuals have grown exponentially. A significant number of textual reviews has been published on e-commercial portals and websites, discussion forums, blog comments, social networks, and customer feedback sites. The availability of vast amounts of textual opinions in digital mode allows companies to carry out extensive research on customers' feedback, products/services, market trends, and customers' sentiments and opinions. Since the analysis of the affective or opinionated content of text provides valuable insights automatically, sentiment analysis has become a vital research field within the context of Natural Language Processing (NLP) [1].

In the initial phases of research on building a sentiment analysis system, classical machine learning algorithms such as Naive Bayes, Support Vector Machine (SVM), Decision Tree,

Logistic Regression, were widely used. The described methods were combined with handcrafted text representation techniques such as the Bag of Words (BoW), n-grams, Term Frequency–Inverse Document Frequency (TF–IDF), and sentiment lexicon dictionaries to yield satisfactory results. The described methods showed promising results in terms of speed and efficiency but underperformed in terms of modeling the semantic connection between words and capturing the contextual information of utterances [1], [2].

Later, the paradigm of deep learning was incorporated to address the shortcomings of traditional machine learning methods. Recurrent Neural Network (RNN) was used to capture sequential information from given text data with better accuracy than conventional text representation methods. The variations of RNNs such as Long Short Term Memory (LSTM) and Bidirectional Long Short Term Memory (BiLSTM) demonstrated the ability to encode the temporal information from text data for various natural language understanding tasks.

However, these techniques were not computationally efficient enough while capturing long-range temporal information [1], [3].

Besides RNNs and their variations, another promising deep learning technique called Convolutional Neural Network (CNN) has made a remarkable improvement in performing sentiment analysis. Specifically, CNNs were used to learn high-level semantic features by focusing on local text patterns. Researchers have demonstrated that CNNs combined with BiLSTM have achieved outstanding performance on the task of sentiment classification [4], [5]. On the other hand, the mentioned techniques failed to address the problem of text with ambiguous context, negation, sarcasm, implicit sentiment, and context-dependent opinions [6].

Later, the self-attention mechanism and Transformer architecture were introduced to improve the context-aware representation of text. The Transformer architecture focuses on relevant input tokens by leveraging the attention mechanism to perform downstream natural language understanding tasks efficiently. Bidirectional Encoder Representations from Transformers (BERT) take the contextual representation of text to a new level by encoding text's contextual information from both directions with the help of the Transformer architecture [7]. Different variations of BERT have been proposed to modify the contextual representation of text and incorporate hybrid learning mechanisms to enhance the performance of various natural language understanding tasks [7], [8].

The recent advances in context-aware representations of text have motivated researchers to design several context-aware sentiment analysis frameworks with different combinations of contextual embedding strategies, CNNs, BiLSTM, recurrent attention networks, and statistical/lexical features to represent text for sentiment analysis [1], [8]. Contextual BERT embeddings were combined with CNN and BiLSTM networks for e-commerce review sentiment analysis [4]. Some researchers utilized the Transformer-based approaches with recurrent networks for cross-domain and social media sentiment analysis [9], [10]. Others have adopted various BERT variants along with recurrent networks and attention mechanisms for contextual feature extraction and sentiment prediction for different downstream tasks [11], [12]. The combination of the described methods for text representation showed better performance than using individual techniques in isolation.

On the other hand, the mentioned techniques failed to address the challenges of sarcasm detection, negation processing, multilingualism, domain-specific terms, language ambiguity, computational complexity, and model interpretability in analyzing the sentiment of text [1], [6]. Given the demand for context-aware sentiment analysis, the current research study

proposes a context-aware hybrid framework for sentiment analysis with an advanced text preprocessing technique, TF-IDF text representation, contextual BERT embeddings, CNN, BiLSTM, and attention mechanisms for a hybrid CNN-BiLSTM attention deep learning model to perform sentiment and emotion analysis. The proposed context-aware hybrid approach can be used in different real-life domains, including but not limited to customers' opinion mining, business and social media analytics, financial opinion mining, and recommendation systems.

II. LITERATURE REVIEW

Recent advancements in Natural Language Processing have empowered the representation and analysis of opinion-rich data collected from online reviews, social media, blogs, forums, and customer feedback sources. Research on opinion mining and sentiment analysis has witnessed exponential growth in recent years. Early studies were primarily focused on employing traditional machine learning algorithms and hand-crafted textual features such as Bag-of-Words and TF-IDF. Recent studies have focused on deep learning algorithms and particularly employed the Transformer encoder for capturing context and semantics in text [7], [8].

Hybrid architectures that include the Transformer encoder with convolutional, recurrent, and attention mechanisms have been widely explored for feature extraction and sentiment classification [4], [16], [18]. BERT variants with BiLSTM, TextCNN, and attention modules have been widely adopted for fine-grained contextual representations and sentiment classification [4], [16], [18]. Hybrid approaches that combine BERT with recurrent, attention-based, and other networks were widely explored for analyzing sentiments from customers' reviews [11], [12]. Experimental results have shown that hybrid approaches generally outperform single-representation learning models. However, sentiment analysis still encounters several challenges and limitations, including negation, sarcasm, ambiguity, and domain-specific terminology. Additionally, there is a need to consider multilingual texts and computational complexity when developing such systems [6], [19]. On the other hand, recent studies have focused on addressing sentiment analysis challenges with an emphasis on explainability and robustness to domain shifts [6], [19]. Therefore, the present study focuses on hybrid approaches for sentiment analysis, which have the potential to capture context-dependent information with comparable performance in terms of computational complexity.

A. Background and Definitions

Sentiment analysis is a natural language processing (NLP) task, which aims to identify opinions, attitudes, and sentiments contained within a document. The task of opinion mining is

performed on customer reviews, social media, and other platforms containing user comments with positive, negative, and neutral polarity. At the same time, the task of sentiment analysis has attracted researchers' attention due to its ability to consider contextual information and affect-related features in addition to simple polarity classification, e.g., word-level, sentence-level, and aspect-based [1], [6]. The problem can be resolved at diverse levels, depending on the granularity and specific requirements of a particular application. Document-level sentiment classification extracts text polarity at the whole-document level, while sentence-level analysis focuses on the sentence as the basic processing unit. Aspect-based approaches detect aspects and corresponding sentiment toward them, thus providing more fine-grained results [6]. Traditional approaches to the problem employed handcrafted features such as Bag-of-Words, n-grams, TF-IDF, and other lexical features. Such approaches allow one to estimate words' relevance, while context is only partially taken into account, which prompted the advent of deep learning-based methods [1], [2]. Various deep learning architectures, including convolutional, recurrent, and attentive networks, were used for sentiment analysis tasks. Convolutional neural networks (CNN) can effectively capture local word patterns, while recurrent layer types, such as Long Short-Term Memory (LSTM) and Bidirectional LSTM (BiLSTM), were introduced to model sequential information. Stacking convolutional and recurrent layers together allows one to learn both local and sequential features and was shown to improve the performance of the sentiment analysis task [3]–[5]. BERT is a language model based on the transformer architecture, which allows one to pretrain contextual text representations. Contextual representations enable BERT to capture information from both left and right contexts of a particular word, which makes the encoder suitable for downstream NLP tasks, including sentiment analysis e.g., [7], [8]. The BERT encoder has been used with BiLSTM, attention modules, and CNNs [4], [11], [16] to harness contextual information and achieve higher performance in opinion mining tasks. However, the problem of opinion mining is not fully resolved and remains a challenging one, especially with regard to ambiguous texts containing negation, sarcasm, implied sentiment, and domain-specific terminology. Complexity is increased with the inclusion of multiple languages and advanced methods requiring powerful GPU resources. At the same time, recent studies showed that hybrid approaches combining statistical, contextual, and neural features tend to perform better on various NLP tasks [4], [6].

B. Related Work

As can be seen from Table 1, the research area of sentiment analysis has evolved from feature engineering to the use of state-of-the-art deep learning algorithms. Traditional approaches based on machine learning algorithms and handcrafted features allow one to highlight the most relevant terms using Bag-of-Words, n-grams, and TF-IDF representation. On the other hand, neural networks demonstrated effectiveness in terms of utilizing contextual information for sentiment classification [1], [2]. Deep learning approaches, such as CNN, BiLSTM, attention-based modules, and other architectures, were used to learn local and sequential features, identify relevant phrases, and classify text according to sentiment polarity. BERT was combined with CNN, BiLSTM, TextCNN, and other architectures to leverage contextual information and achieve better performance [3]–[5]. Hybrid BERT-attention and BERT-recurrent networks were utilized for multiple tasks, including social media sentiment classification, customer reviews analysis, financial opinion mining [11], [12], [14].

BERT-based sentiment analysis approaches were widely used for analyzing social media data, such as tweets, with a focus on extracting contextual features for improving classification performance. Multiple transformer-based approaches were employed for analyzing short texts, tweets, customer reviews, financial comments, and other text types with the focus on extracting contextual features to improve sentiment classification e.g., [8], [10], [20]. At the same time, issues of computational complexity, contextual ambiguity, including negation and sarcasm, domain-specific data, and multilingualism remain relevant and should be considered when designing opinion mining systems e.g., [1], [6]. It was reported that no particular model demonstrates clear advantages in terms of accuracy and robustness; thus, it is rational to combine multiple approaches that utilize traditional statistical features, contextual encoder-based representations, and sequential information for better performance. According to the related works section, it can be concluded that a hybrid approach combining TF-IDF, CNN, BiLSTM, attention modules, and BERT contextual encoder would be beneficial for improving sentiment analysis in terms of utilizing features from diverse sources. The following study will focus on feature engineering and highlight the importance of statistical and contextual representations for opinion mining tasks.

Table 1: Representative studies on context-aware sentiment analysis (2020–2026)

Year	Author	Method	Dataset / Application	Major contribution	Research limitation
2026	Mahim [4]	BERT–CNN–BiLSTM	E-commerce Reviews	Combined BERT contextual representations with CNN and BiLSTM to improve contextual representation and sentiment classification of e-commerce reviews.	The integration of multiple deep learning components increases computational complexity.
2026	Kumar [9]	Transformer-Enhanced Hybrid	Customer Reviews	Proposed a Transformer-enhanced hybrid framework for cross-domain sentiment analysis of customer reviews.	Cross-domain deployment may require substantial computational and training resources.
2025	Zhang [10]	BERT–LSTM–Attention	Twitter	Integrated BERT, LSTM, and attention mechanisms for robust multi-class sentiment classification on Twitter data.	The combined architecture introduces additional computational requirements.
2025	Deng and Liu [11]	RoBERTa–BiLSTM–Attention	Online Public Opinion	Combined RoBERTa, BiLSTM, and attention mechanisms for sentiment analysis of online public opinion.	The combination of Transformer and recurrent architectures can increase computational complexity.
2025	Thekkekara and Yongchareon [13]	BERT–CNN–BiLSTM–Attention	Social Media Text	Applied an attention-based BERT–CNN–BiLSTM architecture to social media text analysis.	The multi-component architecture increases computational requirements.
2024	Jahin [12]	Transformer + Attention + RNN	Tweets	Combined Transformer representations with recurrent neural networks and attention mechanisms to improve robustness and interpretability in tweet sentiment analysis.	The multi-component architecture increases model complexity and training requirements.
2024	Xiao and Luo [8]	Transformer–BERT Hybrid	Short Texts	Developed an automatic sentiment analysis method based on a Transformer–BERT hybrid architecture for short textual content.	Further cross-domain evaluation is required to establish broader generalization.
2024	Duan [14]	Hybrid Neural Network + Attention	Financial Texts	Combined topic extraction, pre-trained representations, and enhanced attention mechanisms for financial sentiment analysis.	The combination of topic extraction and deep learning components increases computational complexity.
2023	Talaat [15]	Hybrid BERT Models	Sentiment Classification	Proposed a hybrid BERT-based sentiment classification system that combines transformer-based representations for sentiment analysis.	The use of multiple BERT-based components may increase computational requirements.
2023	Jiang [16]	BERT–ETextCNN–ELSTM	Comment Data	Developed a hybrid BERT–ETextCNN–ELSTM model to combine contextual representations with convolutional and recurrent features for sentiment analysis.	The hybrid architecture introduces additional model complexity and computational cost.
2022	Li [17]	BiLSTM + Self-Attention	Sentiment Classification	Used BiLSTM with self-attention to capture sequential dependencies and contextual information for sentiment classification.	Recurrent attention-based architectures may require substantial computational and training resources.

C. Research Gap

The literature review highlighted the tendency to transition from traditional machine learning approaches to deep learning and take advantage of contextual encoders for improved

performance in sentiment analysis. Statistical algorithms, such as TF–IDF, allow one to identify relevant terms, but their use is limited by the absence of effective semantic information exploitation. On the other hand, the use of contextual encoders leads to an increase in computational complexity, which is

reported to be a challenge for sentiment analysis e.g., [1], [6]. At the same time, the literature review also highlighted the fact that further research is needed to combine various sources of information for opinion mining. In particular, while most of the discussed approaches focus on analyzing contextual representations obtained with transformer-based language models [4], [10], [11], statistical and lexical features are not always considered. While hybrid approaches, such as BERT-CNN, BERT-BiLSTM, and BERT-attention, have proven to be effective for the task of opinion mining, there is still room for improvement in terms of combining statistical and contextual information with sequential features e.g., [3]–[5]. Another research gap is the analysis of complex language phenomena, such as linguistic negation, ambiguity, and sarcasm, as well as domain-specific jargon. The latter presents a challenge for many sentiment analysis methods, as it often leads to decreased performance due to the inability of the algorithms to properly handle specialized terms. On the other hand, many architectures are limited in their ability to generalize across different domains and text types, making it challenging to design robust and accurate sentiment analysis systems e.g., [6], [9]. A potential solution to the aforementioned problems would be to combine statistical information, represented by TF-IDF, with deep contextual embeddings and employ additional sequential layers, such as CNN and BiLSTM, for mining local patterns. Such an approach has been proven effective in multiple tasks of sentiment analysis e.g., [3]–[5]. Thus, the current study will address the research gap of designing a hybrid architecture that takes advantage of statistical information, contextual BERT embeddings, and sequential features extracted with CNN, BiLSTM, and attention mechanisms. This system will allow one to evaluate the effectiveness of complementary representations for analyzing sentiment and perform practical emotion recognition and opinion mining tasks.

III. METHODOLOGY

The proposed Context-Aware Hybrid Sentiment Analysis framework utilizes a multi-stage methodology for representing and classifying textual reviews. The methodology comprises statistical text representation, lexical polarity information, contextual language representation, and deep learning classification. The combination of these stages helps represent complementary information from different text representation strategies to predict sentiment. Overall, the methodology is comprised of six main stages, including data collection, text preprocessing, hybrid feature extraction, sentiment classification, emotion recognition, and result visualization. In the first three preprocessing stages, raw reviews undergo text preprocessing to standardize the input format and represent text in statistical, lexical, and contextual representations. The four

stages of feature extraction, classification, emotion recognition, and visualization utilize the processed text inputs to visualize the predicted sentiment and emotion classification results.

A. Proposed Context-Aware Hybrid Model

Our proposed context-aware hybrid model utilizes statistical, lexical, contextual, and deep learning representations for accomplishing the task of reviews sentiment and emotion analysis. The whole architecture consists of review acquisition, review preprocessing, TF-IDF and TextBlob feature extraction, BERT contextual representation, feature fusion, CNN-BiLSTM classification, attention-based feature weighting, sentiment and emotion prediction, database storage, and visualization modules. The motivation behind using such a hybrid approach comes from the recent finding that transformer, recurrent, convolutional, and attention mechanisms achieve promising results in the task of sentiment analysis [1], [4], [6], [9], [11], [12].

TF-IDF, TextBlob, and BERT representations can provide statistical, lexical, and contextual information about the text [7], [8], [15], [20]. Afterward, these representations are fused together and fed into the CNN-BiLSTM classifier, where CNN extracts local features from the text, and BiLSTM learns long-range bidirectional dependencies of the words [3], [5], [16], [17]. In addition, an attention mechanism is employed to assign importance weights to the extracted features for improving the performance of the classifier [10], [14], [21]. Finally, the softmax activation function predicts the positive, negative, and neutral classes of the given review. In addition, the proposed model can predict the emotion information of the review [2], [13]. The final sentiment results, including the predicted class, the predicted confidence score, emotion, and other relevant information, can be stored in the database and visualized in the dashboard for further analysis.

B. Datasets and Experimental Setup

To evaluate the proposed Context-Aware Hybrid Sentiment Analysis model across different textual domains, three publicly available review datasets are considered: Amazon Reviews, Yelp Reviews, and IMDb Movie Reviews. These datasets provide textual reviews representing different types of user opinions, including product-related, service-related, and entertainment-related experiences. The use of multiple datasets enables the proposed model to be evaluated across different domains and helps examine its generalization capability.

The overall evaluation process consists of data collection, text preprocessing, negation handling, lexical sentiment analysis, contextual sentiment analysis, context scoring, emotion detection, and hybrid sentiment decision-making. Each dataset is processed independently using the same analysis pipeline to ensure consistent evaluation.

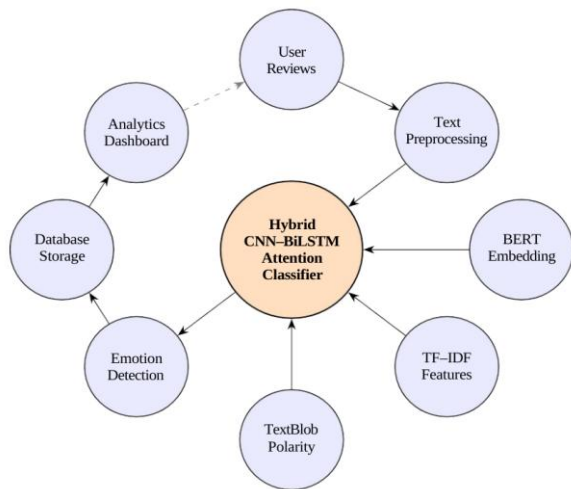


Figure 1: Circular architecture of the proposed Context-Aware Hybrid Sentiment Analysis framework. User reviews are preprocessed before extracting contextual (BERT), statistical (TF-IDF), and lexical (TextBlob) features. The extracted representations are fused within a hybrid CNN-BiLSTM with an attention mechanism to generate sentiment and emotion predictions. The results are stored in the database and presented through an analytics dashboard.

- 1) **Dataset 1: Amazon Reviews:** Description: The Amazon Reviews dataset consists of user-generated product reviews collected from the Amazon e-commerce platform. The reviews cover different product categories and contain opinions related to product quality, performance, usability, reliability, price, and customer satisfaction. The dataset is suitable for evaluating sentiment analysis on product-oriented textual reviews.

Method: The Amazon reviews are provided as input to the proposed Context-Aware Hybrid Sentiment Analysis model. Each review is initially subjected to text cleaning, including the removal of URLs, HTML tags, numbers, punctuation, and unnecessary spaces. The cleaned text is then tokenized, followed by stopword removal and lemmatization. Negation handling is subsequently applied to preserve the effect of negative expressions.

The preprocessed review is analyzed using TextBlob to obtain lexical polarity and a pre-trained BERT-based sentiment model to obtain contextual sentiment predictions. In addition, manually constructed positive and negative sentiment lexicons are used to calculate a context score. The outputs of TextBlob, BERT, and the context layer are combined using the hybrid decision mechanism to determine the final sentiment. The emotion detection module further identifies the dominant emotion associated with the review. The resulting predictions

are compared with the corresponding dataset labels to calculate accuracy, precision, recall, and F1-score.

- 2) **Dataset 2: Yelp Reviews:** Description: The Yelp Reviews dataset contains user-generated textual reviews related to restaurants, businesses, products, and services. The reviews express opinions concerning service quality, food quality, customer experience, staff behavior, pricing, and overall satisfaction. The dataset represents a service-oriented domain and therefore provides a useful evaluation source for examining the ability of the proposed model to process sentiment expressed in a different context from product reviews.

Method: Each Yelp review is passed through the same Context-Aware Hybrid Sentiment Analysis pipeline. The input review is first cleaned by removing URLs, HTML elements, numerical values, punctuation, and extra spaces. Tokenization, stopword removal, and lemmatization are then performed to obtain a normalized textual representation. Negation handling is applied before sentiment analysis to preserve the semantic effect of negative expressions.

TextBlob is subsequently used to determine the lexical polarity of the review, while the pre-trained BERT sentiment model analyzes the contextual sentiment. The positive and negative sentiment lexicons contribute additional contextual information through the context score. The hybrid decision layer combines these outputs and determines the final sentiment class. The emotion detection module is also applied to identify the corresponding emotion. The predictions are compared with the ground-truth sentiment labels, and accuracy, precision, recall, and F1-score are calculated.

- 3) **Dataset 3: IMDb Movie Reviews:** Description: The IMDb Movie Reviews dataset contains user-written reviews of movies along with their associated sentiment labels. The reviews represent opinions regarding movie quality, acting, storyline, direction, entertainment value, and overall viewing experience. The dataset represents the entertainment domain and provides an additional domain for evaluating the proposed sentiment analysis model.

Method: Each IMDb review is processed using the proposed preprocessing and hybrid sentiment analysis pipeline. Initially, the review undergoes text cleaning to remove URLs,

HTML tags, numbers, punctuation, and unnecessary spaces. The cleaned text is tokenized, stopwords are removed, and the remaining words are lemmatized. Negation handling is then performed to preserve sentiment information associated with negative expressions.

The processed review is analyzed using TextBlob for lexical polarity and the pre-trained BERT model for contextual sentiment classification. The manually constructed positive and negative sentiment lexicons are used to calculate the context score. The hybrid decision mechanism combines the contextual and lexical outputs to determine the final sentiment. The emotion detection component is subsequently applied to identify the dominant emotion. The predicted sentiment is compared with the ground-truth sentiment label of each IMDb review, and accuracy, precision, recall, and F1-score are calculated for performance evaluation.

4) **Overall Evaluation Method:** The three datasets are evaluated independently using the same Context-Aware Hybrid Sentiment Analysis pipeline. The Amazon Reviews dataset represents the product and e-commerce domain, the Yelp Reviews dataset represents the restaurant and service domain, and the IMDb Movie Reviews dataset represents the entertainment domain. This multi-domain evaluation enables the proposed model to be examined under different types of textual opinions.

For each dataset, the actual sentiment labels are compared with the sentiment predictions generated by the proposed model. The evaluation results are reported using accuracy, precision, recall, and F1-score. The comparison of results across the three datasets is used to analyze the consistency, robustness, and generalization capability of the proposed approach.

Table 2: Summary of datasets used for evaluation

Dataset	Domain	Purpose
Amazon Reviews	Products and E-commerce	Primary evaluation of product-related sentiment
Yelp Reviews	Restaurants and Services	Cross-domain service sentiment evaluation
IMDb Reviews	Movies and Entertainment	Cross-domain sentiment evaluation

C. Overview of the Proposed Model

The proposed framework processes each textual review through the following stages:

- 1) Collecting textual reviews from the selected dataset for the experimental study
- 2) Preprocessing the input text using NLP preprocessing techniques
- 3) Extracting statistical text representations using TF-IDF
- 4) Extracting contextual text representations using BERT [10]
- 5) Extracting lexical polarity information using TextBlob
- 6) Fusing statistical, lexical, and contextual text representations

- 7) Classifying text using CNN-BiLSTM with attention mechanism
- 8) Predicting the sentiment label and confidence score
- 9) Using the emotion recognition module to extract additional information about the input reviews
- 10) Storing the predicted sentiment labels, confidence scores, emotion class labels, and other relevant information about the input reviews in a relational database
- 11) Visualizing the results using an analytical dashboard

D. Evaluation Metrics

The proposed context-aware hybrid framework is evaluated using standard multi-class classification metrics to measure its performance in terms of Positive, Negative, and Neutral. Accuracy, Precision, Recall, and F1-score are calculated based on the final predicted results generated by the Softmax classification layer of the proposed CNN-BiLSTM-Attention model. Accuracy indicates the percentage of reviews predicted correctly by the classification model. It is calculated using the following formula:

$$\text{Accuracy} = (\text{TP} + \text{TN}) / (\text{TP} + \text{TN} + \text{FP} + \text{FN}) \quad (1)$$

In this case, each class has TP, TN, FP, and FN, so their values should be substituted in the formula to calculate the Accuracy for each class. Using this classification metric, one can estimate what proportion of reviews classified as Positive, Negative, and Neutral are predicted correctly by the proposed framework. In general, this metric provides an overall prediction performance of the framework for each class. Precision indicates the percentage of reviews predicted as Positive, Negative, or Neutral that are actually Positive, Negative, or Neutral. It is calculated using the following formula:

$$\text{Precision} = \text{TP} / (\text{TP} + \text{FP}) \quad (2)$$

Recall aims to calculate the percentage of actual Positive, Negative, and Neutral reviews that are predicted correctly by the proposed classification framework. It is calculated using the formula below:

$$\text{Recall} = \text{TP} / (\text{TP} + \text{FN}) \quad (3)$$

The F1-Score represents the harmonic mean of Precision and Recall and provides an insight into the prediction performance of the proposed framework. It is calculated using the formula below:

$$\text{F1-Score} = 2 \times \text{Precision} \times \text{Recall} / (\text{Precision} + \text{Recall}) \quad (4)$$

where TP, TN, FP, and FN represent true positive, true negative, false positive, and false negative predictions, respectively.

Since the proposed framework deals with the three-class sentiment classification, one can compute Precision, Recall, and F1-Score for each class, namely Positive, Negative and Neutral. Then, the overall performance of the framework can be estimated using Macro, Micro, or Weighted average. Typically, Weighted average is the most commonly used one when the number of instances in each class is not equal. Another effective way to visualize and analyze the performance of the proposed framework is to create a confusion matrix. A confusion matrix is a tabular representation that describes the performance of a classification model. Its rows represent the actual class labels, while its columns represent the predicted class labels. Using the values in a confusion matrix, one can easily find out how many reviews were predicted correctly and incorrectly for each class label. Moreover, one can find TP, FP, and FN for each class and compute evaluation metrics, such as Precision, Recall, and F1-Score. In addition, it is possible to compare the performance of the proposed framework to conventional approaches to text sentiment analysis using the same set of evaluation metrics. Comparing Accuracy, Precision, Recall, and F1-Score, allows us to estimate the effectiveness of using TF-IDF and BERT features representation followed by the CNN-BiLSTM-Attention architecture for Text Sentiment Analysis. Moreover, using the same set of evaluation metrics, we can compare the performance of the proposed approach to each conventional approach. On the other hand, a confusion matrix allows to estimate the prediction performance of the proposed approach in more detail and understand how well it classifies Positive, Negative, and Neutral reviews. To be more specific, using a confusion matrix, one can see whether the proposed model tends to confuse Positive and Negative reviews, Negative and Neutral reviews, or Positive and Neutral reviews.

E. Proposed Hybrid Model's Benefits

The proposed framework has several design-level benefits over the existing approaches for analysing textual reviews.

First, the framework considers multiple types of text representations for improving the accuracy of the classifier. Second, the framework has a modular design that allows individual modules to be replaced or modified as needed. Third, the framework includes a separate module for organising and visualising the results, making it suitable for use in different application domains.

The benefits of the proposed framework can be summarised as follows:

- Using contextual representations helps the framework to learn contextual meanings of words [10].
- Using TF-IDF helps the framework to retain statistical representations of terms.

- Using TextBlob helps the framework to extract lexical polarity information.
- Using CNN-BiLSTM helps the framework to learn local patterns and bidirectional contextual dependencies.
- Using attention mechanism helps the framework to capture informative text representations.
- The framework provides both sentiment and emotion analysis in a single system.
- The framework has a modular design that allows individual modules to be replaced or modified.
- The framework can be evaluated on different domains and datasets.
- The framework includes a relational database that stores the results for future use.
- The framework includes a dashboard that helps users to visualise the results and use them for downstream tasks.

F. Experimental Evaluation

The evaluation process follows the standard procedure for training and testing machine learning models. In this step, the datasets used for training the framework are divided into training, validation, and test sets. The training set is used to train the model. The validation set is used to select the best model based on the values of Accuracy and Precision. The test set is used to report the final performance of the model. By following this procedure, overfitting of the model can be avoided.

The proposed framework will be evaluated using Accuracy, Precision, Recall, F1-score, and a confusion matrix. The same evaluation metrics will be used to compare the performance of the proposed framework to the performance of the existing approaches for opinion mining and sentiment analysis. This step is important to highlight the benefits of the proposed framework. The evaluation results should be described in detail to ensure that the benefits of the proposed framework are apparent.

The comparison analysis should highlight the benefits of the proposed approach over conventional machine learning approaches, such as Naïve Bayes and Support Vector Machine, as well as deep learning approaches, such as CNN, LSTM, BiLSTM, and BERT. This analysis will demonstrate that the combination of different types of text representations and the use of CNN-BiLSTM improve the performance of the framework.

It may be beneficial to conduct additional experiments to report the computational performance of the framework. For instance, the time required for processing different input sizes can be reported. In addition, the robustness of the framework can be

evaluated using reviews that include negation, sarcasm, and other figures of speech. Finally, it is important to report the actual evaluation results rather than hypothesizing about the expected results.

G. Mathematical Formulation

The proposed Context-Aware Hybrid Sentiment Analysis framework integrates statistical, lexical, contextual, convolutional, recurrent, and attention-based representations for sentiment and emotion analysis. The mathematical formulation is divided into two main parts. First, the mathematical formulation of the previous base model is presented. Second, the mathematical formulation of the proposed model is developed by introducing the additional TextBlob lexical representation and an explicit emotion prediction branch. Finally, the two formulations are compared to clearly identify the mathematical contribution of the proposed model.

Input Representation

Let an input review be represented as a sequence of tokens:

$$X = \{x_1, x_2, \dots, x_n\} \quad (5)$$

where x_i represents the i th token and n denotes the total number of tokens in the input review.

The input review is processed through statistical, lexical, and contextual representation branches. These representations are subsequently combined and supplied to the hybrid deep learning classifier. The proposed mathematical pipeline can therefore be expressed as

$$X \rightarrow \{F_{TFIDF}, F_{TB}, F_{BERT}\} \rightarrow F_{proposed} \rightarrow CNN \rightarrow BiLSTM \rightarrow Attention \rightarrow Softmax \quad (17)$$

In addition, the learned attention representation is supplied to a separate emotion classification branch.

Previous Base-Model Mathematical Formulation

The previous base model combines TF-IDF statistical features with BERT contextual representations. Its mathematical formulation is presented first to establish the baseline against which the proposed model is compared.

- 1) **Base TF-IDF Representation:** For a term t in document d , the TF-IDF value is defined as

$$TFIDF(t, d) = TF(t, d) \times \log(N / (1 + DF(t))) \quad (6)$$

where $TF(t, d)$ represents the frequency of term t in document d , $DF(t)$ represents the number of documents containing term t , and N denotes the total number of documents.

The resulting TF-IDF feature vector is represented as

$$F_{TFIDF} = [f_1, f_2, \dots, f_m] \in R^m \quad (7)$$

where m denotes the number of TF-IDF features.

- 2) **Base BERT Representation:** The token sequence X is supplied to the BERT model to obtain contextual representations:

$$F_{BERT} = BERT(X) \quad (8)$$

where

$$F_{BERT} \in R^{(n \times d)} \quad (9)$$

and d denotes the dimensionality of the BERT embedding. BERT provides contextual representations by considering the relationships between tokens in both directions.

- 3) **Base Feature Fusion:** The statistical TF-IDF representation and contextual BERT representation are combined using feature concatenation:

$$F_{base} = [F_{TFIDF} \parallel F_{BERT}] \quad (10)$$

where $\parallel$ denotes the feature concatenation operator. Thus, the previous model can be summarized as

$$X \rightarrow \{F_{TFIDF}, F_{BERT}\} \rightarrow F_{base} \rightarrow CNN \rightarrow BiLSTM \rightarrow Attention \rightarrow Softmax \quad (11)$$

- 4) **Base Attention Mechanism:** The attention representation in the base formulation is expressed as

$$A = \text{softmax}(QK^T / \sqrt{d_k}) \quad (12)$$

where Q and K denote the query and key matrices, respectively, K^T represents the transpose of the key matrix, and d_k denotes the dimensionality of the key vectors.

- 5) **Base Sentiment Classification:** The final sentiment logits are represented by

$$z = W_c A + b_c \quad (13)$$

where W_c and b_c represent the classification weights and bias, respectively.

The probability of sentiment class c is calculated using the Softmax function:

$$P(y = c | X) = \exp(z_c) / \sum_{j=1}^C \exp(z_j) \quad (14)$$

where C represents the total number of sentiment classes. For this study,

$$C = 3 \quad (15)$$

corresponding to Positive, Negative, and Neutral sentiment. The predicted sentiment class is therefore

$$\hat{y} = \arg \max_{c \in \{1, \dots, C\}} P(y = c | X) \quad (16)$$

Proposed Mathematical Formulation

Unlike the previous base formulation, the proposed model introduces an additional lexical polarity representation generated using TextBlob. The three representations, namely TF-IDF, TextBlob, and BERT, are fused before being supplied to the CNN-BiLSTM-Attention classification architecture.

- 1) **TF-IDF Statistical Representation:** For term t in document d , the TF-IDF weight is defined as

$$\text{TFIDF}(t, d) = \text{TF}(t, d) \times \log(N / (1 + \text{DF}(t))) \quad (18)$$

The complete statistical representation is therefore

$$F_{\text{TFIDF}} = [\text{TFIDF}_1, \text{TFIDF}_2, \dots, \text{TFIDF}_m] \in \mathbb{R}^m \quad (19)$$

where m denotes the number of TF-IDF features.

- 2) **TextBlob Lexical Polarity Representation:** TextBlob is employed as an additional lexical sentiment feature. For an input review X , the TextBlob polarity score is represented as

$$F_{\text{TB}} = p(X) \quad (20)$$

where $p(X)$ denotes the polarity score generated by TextBlob. The polarity value provides a lexical sentiment signal that complements the statistical TF-IDF representation and contextual BERT representation.

- 3) **BERT Contextual Representation:** The token sequence X is supplied to BERT to obtain contextual embeddings:

$$F_{\text{BERT}} = \text{BERT}(X) \quad (21)$$

with

$$F_{\text{BERT}} \in \mathbb{R}^{(n \times d)} \quad (22)$$

where n represents the number of tokens and d denotes the embedding dimension.

- 4) **Proposed Feature Fusion:** The three complementary representations are combined through feature concatenation:

$$F_{\text{proposed}} = [F_{\text{TFIDF}} \parallel F_{\text{TB}} \parallel F_{\text{BERT}}] \quad (23)$$

where $\parallel$ represents the concatenation operator. The proposed representation therefore contains statistical, lexical-polarity, and contextual semantic information.

- 5) **CNN Feature Extraction:** The fused representation is supplied to a one-dimensional convolutional layer. For the k th convolutional filter, the convolution operation is defined as

$$C_k = \sigma(W_k * F_{\text{proposed}} + b_k) \quad (24)$$

where W_k represents the weights of the k th convolutional filter, b_k denotes its bias, $*$ represents the convolution operation, and $\sigma(\cdot)$ denotes the activation function. The CNN extracts local discriminative patterns from the fused representation.

- 6) **BiLSTM Contextual Modeling:** The CNN output is supplied to the BiLSTM layer. The forward hidden state is represented as

$$h_{\rightarrow t} = \text{LSTM}(C_t, h_{\rightarrow (t-1)}) \quad (25)$$

and the backward hidden state is represented as

$$h_{\leftarrow t} = \text{LSTM}(C_t, h_{\leftarrow (t+1)}) \quad (26)$$

The bidirectional contextual representation is obtained by concatenating the two hidden states:

$$H_t = [h_{\rightarrow t} \parallel h_{\leftarrow t}] \quad (27)$$

where H_t represents the contextual feature at position t .

- 7) **Attention-Based Feature Weighting:** The attention mechanism assigns a relevance score to each contextual representation. The unnormalized attention score is calculated as

$$e_t = v_a^T \tanh(W_a H_t + b_a) \quad (28)$$

where W_a and b_a are trainable parameters and v_a is the attention vector. The normalized attention weight is calculated using Softmax:

$$\alpha_t = \exp(e_t) / \sum_{j=1}^n \exp(e_j) \quad (29)$$

The final attention-weighted representation is obtained as

$$H_{\text{att}} = \sum_{t=1}^n \alpha_t H_t \quad (30)$$

where α_t determines the contribution of the contextual representation at position t .

- 8) **Sentiment Classification:** The attention-weighted representation is supplied to the fully connected sentiment classification layer:

$$z = W_c H_{\text{att}} + b_c \quad (31)$$

where W_c and b_c denote the classification weights and bias. The probability of sentiment class c is obtained using Softmax:

$$P(y = c | X) = \exp(z_c) / \sum_{j=1}^C \exp(z_j) \quad (32)$$

where $C = 3$ for the Positive, Negative, and Neutral sentiment classes. The predicted sentiment is therefore

$$\hat{y} = \arg \max_{c \in \{1, \dots, C\}} P(y = c | X) \quad (33)$$

- 9) **Emotion Prediction:** In addition to sentiment classification, the proposed framework contains a separate emotion prediction branch. The emotion logits are computed as

$$z_e = W_e H_{\text{att}} + b_e \quad (34)$$

where W_e and b_e represent the emotion classification weights and bias. The probability of emotion class k is calculated as

$$P(e = k | X) = \exp(z_{(e,k)}) / \sum_{j=1}^K \exp(z_{(e,j)}) \quad (35)$$

where K denotes the total number of emotion classes. The predicted emotion is given by

$$\hat{e} = \arg \max_{k \in \{1, \dots, K\}} P(e = k | X) \quad (36)$$

For the proposed implementation, the emotion classes are Happiness, Sadness, Anger, and Surprise; therefore,

$$K = 4 \quad (37)$$

10) **Model Optimization:** The sentiment classification branch is optimized using categorical cross-entropy loss:

$$L_s = - \sum_{(c=1)}^C y_c \log(\hat{y}_c) \quad (38)$$

where y_c denotes the true probability or one-hot encoded label for sentiment class c , and $\hat{y}_c$ denotes the predicted probability for that class.

If the emotion branch is jointly optimized, its categorical cross-entropy loss is defined as

$$L_e = - \sum_{(k=1)}^K e_k \log(\hat{e}_k) \quad (39)$$

where e_k represents the true emotion label and $\hat{e}_k$ represents the predicted probability of emotion class k . The overall multi-

$$L_{total} = \lambda_s L_s + \lambda_e L_e \quad (40)$$

where λ_s and λ_e are weighting coefficients that control the relative contribution of sentiment and emotion losses.

If emotion prediction is implemented as a separate inference module rather than jointly trained with the sentiment classifier, only L_s is optimized during training and the emotion branch is evaluated independently.

Mathematical Comparison with the Previous Base Model

The mathematical distinction between the previous base formulation and the proposed formulation is primarily the introduction of the TextBlob lexical polarity representation and the explicit emotion prediction branch. The previous base model can be represented as

$$F_{base} = [F_{TFIDF} \parallel F_{BERT}] \quad (41)$$

whereas the proposed model uses

$$F_{proposed} = [F_{TFIDF} \parallel F_{TB} \parallel F_{BERT}] \quad (42)$$

Therefore, the additional information introduced by the proposed model can be expressed as

$$\Delta F = F_{proposed} - F_{base} \quad (43)$$

Conceptually, the proposed model adds the lexical polarity feature F_{TB} to the statistical and contextual representation spaces. Consequently, the model considers three complementary sources of information:

$$F = F_{Statistical} \parallel F_{Lexical\ Polarity} \parallel F_{Contextual} \quad (44)$$

The complete mathematical comparison is summarized in Table 3.

Table 3: Mathematical comparison between the previous base model and the proposed model

Component	Previous Base Model	Proposed Model
Input	$X = \{x_1, \dots, x_n\}$	$X = \{x_1, \dots, x_n\}$
Statistical feature	F_{TFIDF}	F_{TFIDF}
Lexical feature	Not included	$F_{TB} = p(X)$
Contextual feature	F_{BERT}	F_{BERT}
Feature fusion	$[F_{TFIDF} \parallel F_{BERT}]$	$[F_{TFIDF} \parallel F_{TB} \parallel F_{BERT}]$
CNN	Local feature extraction	Local feature extraction
BiLSTM	Bidirectional dependency modeling	Bidirectional dependency modeling
Attention	$A = \text{softmax}(QK^T / \sqrt{d_k})$	$H_{att} = \sum_{(t=1)}^n \alpha_t H_t$
Sentiment output	Positive, Negative, Neutral	Positive, Negative, Neutral
Emotion output	Not explicitly modeled	Happiness, Sadness, Anger, Surprise
Optimization	Sentiment loss	Sentiment and optional emotion loss
Overall objective	L_s	$L_{total} = \lambda_s L_s + \lambda_e L_e$

Discussion of the Mathematical Improvement

The proposed formulation extends the previous base model by introducing an additional lexical polarity feature and an explicit emotion prediction branch. The base model combines statistical TF-IDF features with contextual BERT representations and is formulated as

$$F_{base} = [F_{TFIDF} \parallel F_{BERT}]. \quad (45)$$

Although the base representation provides statistical term importance and contextual semantic information, it does not explicitly incorporate an independent lexical polarity feature. Therefore, the proposed model introduces the TextBlob polarity representation as

$$F_{TB} = p(X), \quad (46)$$

where $p(X)$ denotes the polarity score obtained from the input review X . The three representations are subsequently concatenated to form the proposed feature representation:

$$F_{proposed} = [F_{TFIDF} \parallel F_{TB} \parallel F_{BERT}]. \quad (47)$$

The fused representation is passed through CNN, BiLSTM, and attention layers. CNN extracts local feature patterns, BiLSTM captures bidirectional sequential dependencies, and the attention mechanism assigns higher weights to informative

features. The overall mathematical flow of the proposed framework is expressed as

$$X \rightarrow \{F_TFIDF, F_TB, F_BERT\} \rightarrow F_proposed \rightarrow C \rightarrow H \rightarrow H_att \rightarrow \{\hat{y}, \hat{e}\}. \quad (48)$$

Here, C denotes the CNN feature representation, H denotes the BiLSTM output, H_att denotes the attention-weighted representation, $\hat{y}$ denotes the predicted sentiment class, and $\hat{e}$ denotes the predicted emotion class.

The mathematical improvement is therefore achieved by adding TextBlob lexical polarity to the statistical and contextual feature spaces while retaining the CNN–BiLSTM classification backbone. Furthermore, the explicit emotion branch enables the framework to provide both sentiment polarity and emotion information from the input review.

IV. CONCLUSION

In this paper, a survey of context-aware research works for opinion mining was done, and a hybrid framework was proposed. It was found through the study that opinion mining research has shifted from traditional machine learning and feature engineering to the modern deep learning and contextual representation. Some of the research areas that need more exploration are negation, sarcasm, implicit sentiment, domain adaptation, and resource intensity [1], [4], [6], [9].

The paper proposed a Context-Aware Hybrid Model for opinion mining with a hybrid of traditional and modern methods. The framework was implemented using TF–IDF, TextBlob, BERT, CNN, BiLSTM, and Attention mechanisms for sentiment classification. TF–IDF and TextBlob were used for statistical and lexical features extraction, while BERT was used for contextual representation of words. For the implementation of the framework, CNN was used to model local features, BiLSTM was used to model sequential information in the text, and attention mechanisms were used to identify important features [3], [5], [7], [8], [16], [17].

The framework was designed with an emotion recognition module, storage, and visualization system for opinion mining. The framework was made hybrid and highly customizable by changing some of its components. The paper recommended further research on the framework for several languages and domains, exploring sarcasm, negation, and implicit sentiment, designing lightweight Transformers, interpreting results, analyzing multimodal data, and using large language models [6], [11], [12].

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