International Journal of Computational and Experimental Science and ENgineering
(IJCESEN)
Vol. 11-No.2 (2025) pp. 2769-2783
http://www.ijcesen.com
ISSN: 2149-9144

Research Article

SentiNet: A Deep Learning-Based Architecture with Hyperparameter Optimization for Sentiment Analysis of Customer Feedback Reviews

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Article Info:

DOI: 10.22399/ijcesen.1810
Received : 25 Fenruary 2025
Accepted : 12 April 2025

Keywords :

Sentiment Analysis,
Opinion Mining,
Deep Learning,
Artificial Intelligence,
Online Review Analysis.

Abstract:

In the contemporary era, customers' opinions are paramount as they can help improve the quality of service that leads to business growth. People from all walks of life often voice their opinions about goods and services using social media. Modern businesses cannot ignore social media feedback. As technology advances, including big data, cloud computing, and distributed computing architectures, it is now possible to analyze large volumes of data to discover trends or patterns in customer behavior. Therefore, sentiment analysis has become an important research area that helps organizations promote their businesses. Artificial intelligence, of late, is widely used to discover sentiments from customer reviews. However, analyzing sentiments accurately is nontrivial due to the complexity of procedures involved in mining textual data. There is a need to leverage performance in sentiment analysis. This research aimed to achieve this goal by proposing a DL-based framework for analyzing the sentiments of given data. We proposed a novel DL architecture, SentiNet, to efficiently classify sentiments in customer reviews. We proposed an Efficient Learning-Based Sentiment Analyzer (LBSA) algorithm, which exploits novel vectorization, embeddings, and the novel architecture of the proposed SentiNet model. Our empirical study with a benchmark dataset of customer reviews on restaurants and food items revealed that the proposed SentiNet model outperformed many existing DLs with the most accurate simulations of 98.68%. Our framework can be incorporated into business applications for sentiment analysis and improving service quality.

1. Introduction

Nowadays, individual decisions are increasingly influenced by social media and reviews from various online platforms regarding services and products. Businesses globally have recognized the importance of analyzing customer sentiments on these virtual platforms beyond traditional feedback systems. If companies fail to consider social feedback, particularly consumer sentiment expressed in reviews, they risk becoming irrelevant in the contemporary setting. Thus, sentiment analysis of data from customer reviews is essential to comprehending customers' thought processes. This understanding can help businesses adapt their products and services to meet customer expectations. Many researchers have contributed to applying both DL and ML techniques to sentiment analysis. For instance, Wang et al. [1] introduced a Convolutional Recurrent Neural Network that combines LSTM networks with CNN to enhance text categorization accuracy. Said et al. [2] employed Bi-LSTM-CRF and AB-LSTM-PC models to analyze Arabic hotel reviews, aiming to improve sentiment detection with external lexicons and Gated Recurrent Units (GRU). Sulaiman et al. [3] emphasized the need for specialized techniques to analyze sentiment on Twitter, proposing a CNN model that integrates user behavior to improve classification on SemEval-2016 datasets. Jelodar et al. [4] achieved an accuracy of 81.15% in analyzing public sentiment related to COVID-19 using LSTM and Natural Language Processing (NLP). Basiri et al. [5] developed the ABCDM model, incorporating CNN layers and attention mechanisms, demonstrating solid results on tweets and reviews with potential for broader applications. It is clear from the literature research that artificial intelligence-enabled methods can significantly improve the identification of sentiments. However, there is a need to develop a hybrid methodology that combines the strengths of word embeddings, effectively processes time series data, and achieves accurate sentiment analysis within the given text corpus.

Here are the things we contributed to this paper. We propose a DL-based framework for analyzing sentiment in data. Specifically, we present an innovative DL architecture called SentiNet, designed to classify sentiments in customer reviews efficiently. Additionally, we present the Efficient Learning-Based Sentiment Analyzer (LBSA) algorithm, which utilizes new vectorization techniques, embeddings, and the unique architecture of the SentiNet model. Our empirical study, using a benchmark dataset of customer reviews about restaurants and food items, demonstrates that the SentiNet model achieves the greatest accuracy of 98.68%, outperforming several other deep learning models currently in use. This framework can be integrated into business applications for sentiment analysis and enhancing service quality. The rest of the paper is organized as follows: The literature on the several approaches that have used DL and ML for sentiment analysis is reviewed in Section 2. Section 3 details the proposed methodology and underlying algorithms alongside the framework aimed at improving performance in sentiment analysis. Section 4 outlines the experimental setup required for our study. Section 5 presents the empirical results and compares them with those of existing models. Finally, our research is concluded in Section 6, along with recommendations for further investigation.

2. Related Work

Many contributions are found in the literature on DL- Based on sentiment categorization. Wang *et al*. [1] focused heavily on text categorization, whereas conventional techniques rely on manually derived characteristics. This research offers a convolutional recurrent neural network that combines the memory of LSTM and may extract local features with the help of CNN to achieve better job classification accuracy. Smaid *et al*. [2] used two LSTM models—Bi-LSTM-CRF for aspect extraction and AB-LSTM-PC for sentiment—to deliver sophisticated Arabic hotel review sentiment analysis. Future work will examine external lexicons for sentiment enhancement and GRU for aspect extraction. Sulaiman *et al*. [3], because tweets have specific properties, social media sentiment analysis—like that on Twitter—requires special techniques. By combining user behavior into a CNN model, this work suggests improving sentiment categorization on SemEval-2016 datasets over conventional approaches. Jelodar *et al*. [4], for sentiment analysis, researchers employed LSTM and NLP, with an accuracy rate of 81.15%. To support policy decisions and public health initiatives, this study investigates public opinion and COVID-19-related issues. Basiri *et al*. [5] emphasized DNNs, such as GRU and LSTM. The ABCDM model uses CNN layers and attention to enhance sentiment categorization. Tests demonstrate cutting-edge outcomes on tweets and reviews. Other languages and sentiment analysis tasks can be added to the model.

Jianqiang and Xiaolin [6] used word embeddings and n-grams in a CNN model; Twitter sentiment analysis examines how people feel about particular products or events. Excels above baseline models. Social m*edia* and internet advancements produce substandard comment texts for Xu et al. [7]. This work provides an improved version of standard approaches for sentiment analysis: weighted word vectors and BiLSTM. Do *et al*. [8] focused on aspect-level sentiment in tweets and reviews. Without complicated characteristics, deep learning has potential. This review proposes enhanced combined aspect and sentiment analysis by comparing 40 models with CNNs, LSTMs, and GRUs. Bahad *et al*. [9], though false news undermines confidence, the media quickly disseminates information online. Fake news detection accuracy is increased by deep learning, particularly Bi-directional LSTM. Yang *et al*. [10] improved for particular targets via Sentiment analysis based on aspects. The accuracy of sentiment analysis is increased by attention processes, which enhance context and target concentration.

Jin *et al*. [11] analyzed, and EMD decomposition added to a deep learning stock prediction model decreases latency and increases accuracy. Rehman *et al*. [12] state that sentiment analysis techniques like the Hybrid CNN-LSTM Model are necessary because user opinions on social media are so abundant. Usama *et al*. [13] specialized in long-term dependencies, whereas CNN focuses on high-level characteristics. CNN and RNN are both good in NLP. A novel model that blends RNN with CNN-based attention exhibits better accuracy for sentiment analysis. Onan [14] focused on sentiment analysis. The suggested RCNNGWE model with group-wise augmentation improves the results of sentiment analysis. Ligthart *et al*. [15] examined sentiment analysis across various domains, emphasizing the trend in deep learning and issues such as domain dependence.

Muhammad *et al*. [16] used LSTM and Word2Vec to hotel reviews to classify sentiment. The optimal technique, utilizing a 300-dimensional vector, Hierarchical Softmax, and Skip-Gram for Word2Vec, achieves 85.96% accuracy. The LSTM employs the learning rate of 0.001, average pooling, and 0.2 dropout. Gupta *et al.* [17] presented the PERCY score, which assesses the spread of logic rules in sentiment categorization. Due to misleading accuracy measures, rule-mask mechanisms and attention processes are the subject of more investigation. Du *et al*. [18] presented a hybrid model for TABFSA that integrates lexical knowledge into pre-trained transformers by mixing symbolic and sub symbolic approaches. Future studies will look at transformer architecture and domain-specific lexicon coverage. Haque *et al*. [19] employed a CLSTM model to analyze sentiment in Bengali social media comments in multiple classes (SA). The results show a significant accuracy improvement of 85.8% and 0.86 F1 scores. Managing overlapping classes and investigating sophisticated models for additional accuracy improvement are tasks for the future. Fernandez *et al*. [20] presented a new physics-guided Bayesian RNN that combines RNNs and Bayesian techniques with physics-based models. The suggested approach produces reliable results, increases the accuracy of multistep forecasting, and accurately measures uncertainty. PHM systems for aircraft and seismic event prediction in buildings are examples of potential uses.

Mao *et al*. [21] used multimodal data from IoT; an LSTM model called IB-BiLSTM is built for sentiment analysis in animated online teaching. With 93.92% accuracy and 90.34% F1-score, it enhances students' emotional involvement in online learning. Kanwal *et al*. [22], with IoT data, the IB-BiLSTM model achieves 93.92% accuracy in sentiment analysis for online education. About movie review analysis, a hybrid model achieves 87% accuracy—plans for the future call for multiclass emotion categorization. Berrimi *et al*. [23] used Arabic sentiment analysis datasets, a hybrid BiGRU-BiLSTM model with attention layers achieves 98.6%, 96.19%, and 95.65% accuracy. Russian sentiment analysis, foul speech identification, and news classification all put generalization to the test. Park *et al.* [24] programs like LSTM and GRU are the primary research focus on bitcoin price prediction. A technique that uses sentiment analysis from Twitter to alter findings increases accuracy by 3%. The process improves investor action suggestions. Tan *et al*. [25], efficient sentiment analysis is necessary for comprehension and decision-making because social media is widely used. Sentiment analysis is a strong suit for a hybrid RoBERTa-LSTM model, which combines the advantages of recurrent and Transformer NNs with data augmentation.

Considering the expansion of mobile technologies, Tan et al. [26] say that social media has become essential for opinions. Combining ensemble methods and data augmentation, an ensemble model enhances sentiment Analysis by combining RoBERTa, LSTM, BiLSTM, and GRU. Song *et al*. [27] suggested an embedding technique for sentiment lexicon that enhances sentiment classification without outside assistance. The task-dependence of general-word embeddings is a hurdle to recent dl advances in natural language processing. Houdt *et al.* [28], by advanced Google's voice recognition and Alexa's answers, show that LSTM has transformed machine learning and neural computing. The uses of LSTM are reviewed, and hybrid models are suggested. Ma *et al*. [29] focused on certain elements and handled explicit knowledge with Sentic LSTM. Attention techniques improve sentiment analysis. Huang *et al*. [30], for the representation of sentences and documents, SR-LSTM employs two LSTM layers. By cleansing datasets for better input, SSR-LSTM achieves even more significant improvements.

Alayba *et al*. [31] enhanced by combining CNNs and LSTMs. On Arabic Health Services datasets, superior accuracy has been demonstrated by varying sentiment analysis levels and Ch5gram levels. Word representation models such as word2vec and GloVe that have already been trained will be incorporated into future development. Sohangir et al. [32] used CNNs, LSTM, and doc2vec, and StockTwits sentiment analysis was enhanced. Computer vision and speech recognition are areas where DL shines. Katic and Milicevic [33] argued that sentiment analysis is advantageous for commercial uses. LSTM performs better in document representation than bag-of-words. LSTM attained 95.55% accuracy in Amazon evaluations, demonstrating its potency with big datasets. Future studies will evaluate the Gated Recurrent Unit and the Bi-directional LSTM to improve performance. Deng *et al*. [34] suggested that the SSALSTM paradigm uses self-attention to weigh word relevance while effectively creating sentiment lexicons. Future research will focus on multi-class categorization and class imbalance and expand SSALSTM to other sectors, including e-commerce. Heikal *et al*. [35] examined the beliefs and feelings of individuals. With an F1-score of 64.46%, Arabic sentiment analysis utilizing CNN and LSTM ensemble performs better than previous models.

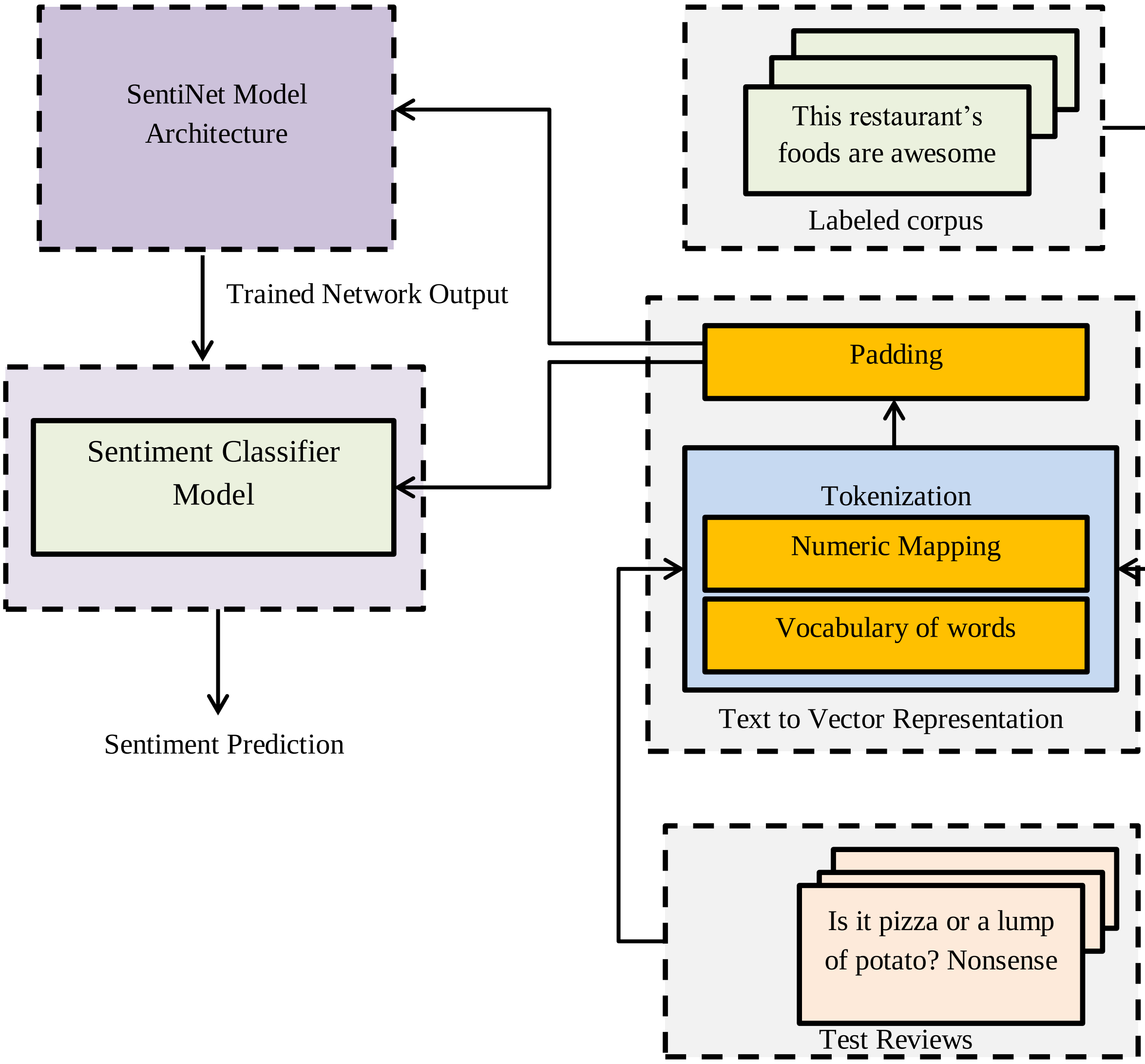

Figure 1. *Overview of the proposed framework for efficient sentiment classification*

Future research will examine other CNN architectures and remote training techniques.
Gandhi *et al*. [36] used DL models like CNN and LSTM; Twitter sentiment analysis analyses public tweets from various disciplines. Accuracy ratings are 87.74% and 88.02%. Upcoming projects will test on multiple Twitter datasets and improve CNN with intricate features—Shobana and Murali [37] established by sentiment analysis. Deep learning surpasses conventional techniques with greater accuracies when utilizing Skip-gram and LSTM with APSO optimization. Saha and Senapati [38], when it comes to unstructured data such as text and images, DNN is very good at machine learning. LSTM-based RNNs optimize parameters and architecture to address sentiment analysis problems. Qaisar *et al*. [39], with an accuracy of 89.9% in IMDb reviews, show that LSTM in RNNs shows promise for incorporation in sentiment analyzers. Governments, businesses, and consumers all gain from sentiment research, which is essential for insights. Afidah *et al*. [40], for evaluations from tourists in Indonesia, a new LSTM-CNN-Word2Vec model produced 97.17% accuracy, which helped with travel choices. Based on the literature review, artificial intelligence-enabled methods can enhance the learning-based identification of sentiments. However, there is a need to develop a hybrid methodology that leverages the advantages of word embeddings, processes time series data effectively, and achieves accurate sentiment analysis in the given text corpus.

3. Proposed Methodology

This section presents our methodology, including a novel DL architecture for efficient sentiment categorization in online reviews. It covers the problem and provides an overview of the proposed framework, the architecture of the proposed novel deep learning model, SentiN*et*, its underlying layers, the proposed algorithm, specifics about the dataset, and the assessment process.

3.1 Problem Definition

Provided a set of customer reviews in the form of textual corpora, developing a DL-based structure optimized for effective classification of sentiments towards leveraging state-of-the-art is the problem considered.

3.2 Overview of Our Framework

Our main objective is to develop SentiNet, a DL-based sentiment classifier that can divide restaurant evaluations into categories based on whether they are favorable or negative. The proposed framework is shown in abstract form in Figure 1. The suggested system has three main parts: a text-to-vector representation module, a model architecture module, and a sentiment prediction module.

The given textual corpora are subjected to many procedures for efficient sentiment classification. The given text is converted to vector representation with the novel approach described in Section 3.3. The proposed approach, supervised learning, is the foundation of sentiment analysis, which exploits labeled corpora. The vectorized data is given to the proposed novel deep learning architecture, SentiNet, which has mechanisms for sentiment classification, including embeddings and feature extraction. The following subsections provide more details about the mechanisms involved in the proposed framework.

3.3 Vectorization Method

Any deep learning algorithm's ability to perform well depends on the features used during training. $R[] = \{r_1, r_2, \dots, r_m\}$is the numerical mapping of the reviews that we must build because deep learning algorithms cannot learn from raw reviews. A vocabulary V of k unique words is established, $V = \{u_1, u_2, \dots, u_k\}$, to obtain this numerical mapping. Words (wi) in a review $r_j = [w_1, w_2, \dots, w_{l'}]$ are substituted with the words in V's index value (i). Thus, from a review (r_j),, we obtain the converted vector sequence $(s^{'})$, where $s^{'} = [i_1, i_2, \dots, i_{l'}]$. At this point, the sequences of variable lengths, $S = \{s_1, s_2, \dots, s_m\}$, are obtained and are unsuitable for training and feature extraction. $s^{'} = \{s_1^{'}, s_2^{'}, \dots, s_m^{'}\}$ is the fixed-length sequence created by using the pad sequence algorithm on $(s^{'})$. Every sequence (s_k) in S is a vector with a fixed length of size l. The best length of a series, l, is determined by examining the distribution of review lengths to minimize computing costs. It appears that the majority of the evaluations are less than 150 words. To preserve the necessary information and build the system with the most minor processing, l = 150 is selected as the ideal review length. Long reviews are eliminated by discarding extra words, which maintains the length l by padding a zero vector with brief reviews.

3.4 Deep Learning Model

The classification, BiLSTM, and embedding layers comprise the three main building components of the model architecture. We employed the word2vec [15] embedding approach in the embedding layer, which maps textual data's integer indices into a dense vector to extract the feature.

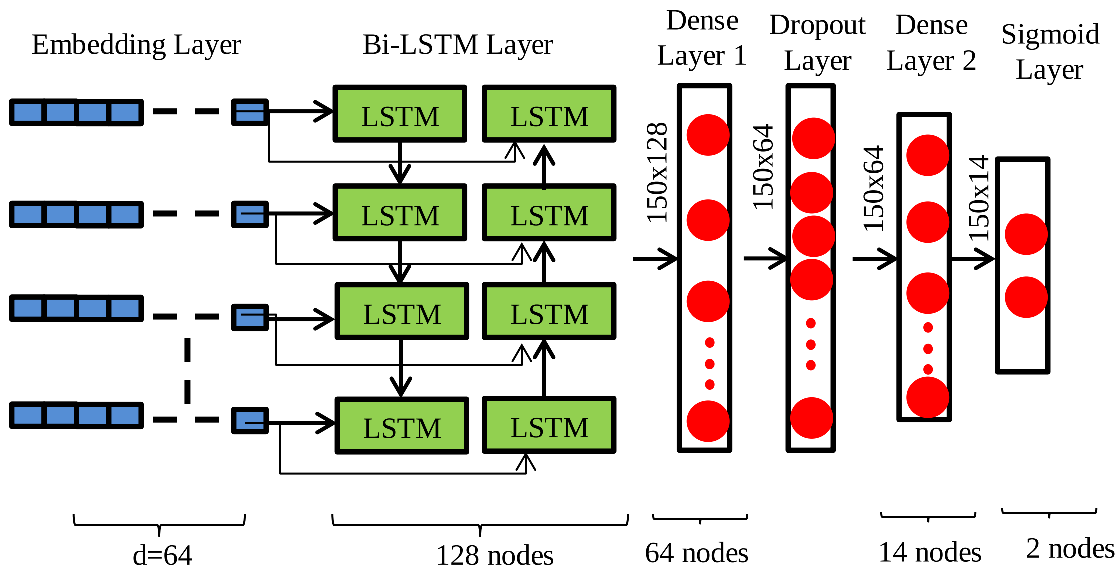

Figure 2. *Architecture of the proposed deep learning model SentiNet*

Using the Keras embedding layer, we trained word2vec using the whole BRRC. The three inputs (V_k,d,l) that the embedding layer requires are V_k (vocabulary size), d (embedding dimension), and l (length of review). The length of a word's vector representation is determined by a hyper-parameter called embedding dimension (d). The embedding layer transformed a review into a 2D vector with dimension l×d. We therefore produced a feature vector of dimension F = R×l×d for the R number of reviews

Figure 2 Regarding the LSTM layer, one popular version of the RNN used to solve the exploding and vanishing gradient problem is the LSTM network. In particular, it has been demonstrated [28] that LSTM helps record enduring dependence in a text. To preserve contextual information from both the previous and next words, we used bidirectional LSTM (BiLSTM) [12,8]. Each LSTM of hidden units of size h receives values for the embedding layer's word embedding. For BiLSTM, we acquired a two-h vector representation by concatenating each LSTM output. An input sequence of an embedding vector as a pair $(e^{<i>}, y^{<i>})$ *is processed by an LSTM. A local support vector machine (LSTM) maintains a hidden vector* $h^{<t>}$ *and a remember vector* $m^{<t>}$ *for every pair* $(e^{<i>}, y^{<i>})$ *and time step t. These vectors control the state's updates and results, aiding in producing the desired output.* $y^{<i>}$ *depending on the input* $x^{<i>}$*'s previous states. The processing stages that the Eqs. 1-6 carry out at time t.*

$$u_g = \sigma(W_u * h^{<t-1>} + I_u) \qquad (1)$$

$$f_g = \sigma(W_f * h^{<t-1>} + I_f) \qquad (2)$$

$$o_g = \sigma(W_o * h^{<t-1>} + I_o) \qquad (3)$$

$$c_g = tanh(W_c * h^{<t-1>} + I_c) \qquad (4)$$

$$m^{<t>} = f_g \odot m^{<t-1>} + u_g \odot c_g \qquad (5)$$

$$h^{<t>} = tanh\left(o_g \odot m^{<t>}\right) \qquad (6)$$

In this case, σ stands for the sigmoid activation function, and the weight, together with the recurrent units' projection matrices, are W_u,W_f, W_o and W, respectively. By storing in the memory vector m^() for as long as necessary, the calculated gates u_g,f_g,o_g, and c_g of LSTM cells play a crucial role in obtaining essential properties from the computed vector. The update gate $c_g$uses input gate u_g, and the previously remembered vector $m^{<i-1>}$, to write the updated information in the new remember vector $m^{<i>}$, whilst the forget gate f_g determines how much information should be dumped from the previous remember vector $m^{<i-1>}$. Lastly, the output gate $\left(o_g \odot m^{<t>}\right)$ keeps track of the data that is transferred from the hidden vector $h^{<i>}$ to the new memory vector $m^{<i>}$.

The next layer is the classification layer. In this stage, a sigmoid layer comes after two thick layers. The BiLSTM layer converts the input of size (l×d) for the r^{th} input sequence into an output vector of size (l ×2h). After passing through the first dense layer, this vector is propagated through the ReLU activation function, which creates a new vector with the shape $(l \times dl_1)$. A 26% dropout ratio dropout layer was inserted between two thick layers to prevent over-fitting [9]. A new vector of size $(l \times dl_2)$ is further generated at each iteration when 74% of neurons are randomly selected to transfer their output from the first dense layer to the second dense layer. It should be noted that the first and second dense layers' dl_1 and dl_2 represent the number of hidden neurons, respectively. The output vector of the second dense layer was flattened, resulting in a one-dimensional vector of size. f_v. The output vector from the last layer finally entered a sigmoid [9] layer.

$$\sigma(f_v) = \frac{1}{1 + e^{-f_v}} \qquad (7)$$

$$y_{pred} = \begin{cases} 1\ (positive)\ if\ \sigma(f_v) > Threshold \\ 0\ (negative)\ if\ \sigma(f_v) < Threshold \end{cases} \qquad (8)$$

The cross-entropy loss function [9], which we employed to train the model, is represented by equation 9. In this case, the r^{th} input review is denoted by the subscript r and the actual emotion class of the r^{th} review is denoted by t_r.

$$Loss\left(y, y_{pred}\right) = -\frac{1}{R}\sum_{r=1}^{R} \left((t_r\ log(y_{pred})\right) \qquad (9)$$

The text-to-vector representation module receives an unlabeled review for categorization, which is then processed via the tokenization and padding stages. This converted vector is then sent into the trained sentiment classifier model, which uses it to forecast the review's sentiment.

3.5 Hyperparameter Optimization

The parameters that directly control a model's training process are called model hyperparameters. These variables control the network's design, including its number of layers, hidden units, and training process, including learning rate and batch size. Two layers contain 64 and 14 hidden units, respectively. Table 1 lists the hyperparameter values for the suggested model, including the batch size, learning rate, optimizer, dropout rate, embedding dimension, and epoch count. We randomly pick a starting value for each hyperparameter except for the embedding dimension. We go over the hyperparameter space to determine a hyperparameter's ideal value. With these perfect hyperparameter configurations, the suggested model is trained

3.6 Proposed Algorithm

We proposed a novel DL architecture, SentiNet, to efficiently classify sentiments in customer reviews. We proposed an Efficient Learning-Based Sentiment Analyzer (LBSA) algorithm, which exploits novel vectorization, embeddings, and the novel architecture of the proposed SentiNet model.

Algorithm: Efficient Learning-Based Sentiment Analyzer (LBSA)
Input: Zomato Restaurants dataset D
Output: Sentiment classification results R, performance statistics P

1. Begin
2. (T1, T2)←SplitCorpora(D)
   Vectorization
3. V1←Vectorization(T1)
4. V2←Vectorization(T2)
   Train SentiNet Model
5. Configure SentiNet model m (as in Figure 2)
6. Compile m
7. m'←TrainSentiNet(V1)
8. Persist m'
   Sentiment Classification
9. Load m'
10. R←ClassifySentiments(m', V2)
11. P←EvaluateSentiNet(R, ground truth)
12. Display R
13. Display P
14. End

Algorithm 1: *Efficient Learning-Based Sentiment Analyzer (LBSA)*

Algorithm 1 is designed to process the Zomato Restaurants dataset (D) and produce sentiment R and P. The algorithm begins by splitting the dataset D into two parts, T1 and T2, for training and testing, respectively, using the SplitCorpora function. The Vectorization function is then applied to both parts, T1 and T2, to create vector representations V1 and V2, respectively. The algorithm proceeds to train the SentiNet model, which involves configuring and compiling the model (m) and then teaching it with the vectorized data V1, resulting in a trained model m'. This trained model will persist for future use. For sentiment classification, the trained model m' is loaded, and the ClassifySentiments function is used to process the vectorized data V2, producing the sentiment classification results R. The model's effectiveness is then assessed using the EvaluateSentiNet function, which compares the classification results R against the ground truth data. Finally, the algorithm displays both the sentiment classification results R and the performance statistics P.
The algorithm is depicted in a step-by-step process that includes dataset splitting, vectorization, model configuration, training, persistence, classification, evaluation, and results display. The process suggests a supervised learning approach, where the model is trained on labeled data and then evaluated for accuracy. The output includes the sentiment classification results and the model's performance metrics, which would help understand public opinion regarding restaurant reviews on a platform like Zomato.

3.7 Dataset Details

The dataset used for this empirical study is the Zoomato Bangalore Restaurants dataset collected from [41]. This dataset includes customer reviews on food items from about 12,000 restaurants located in Bangalore. By analyzing customer reviews, it is possible to discover various trends in customer behavior and learn their sentiments towards different foods or service providers.

Table 1. *Hyperparameter settings*

Hyperparameters	Initial value	Hyperparameter space	Optimal value
Embedding Dimension	-	8, 16, 32, 64, 100, 128, 200, 256, 400, 512, 600, 700, 800, 1024	128
Batch Size	32	4,8,16, 32, 64, 128, 256, 512	64
Dropout	0.1	0.1, 0.15, 0.2, 0.23, 0.27, 0.3, 0.33, 0.36, 0.4, 0.43, 0.46, 0.5, 0.54, 0.57, 0.6, 0.63, 0.66, 0.69, 0.72, 0.75	0.46
Optimizer	*Adam*	*SGD, RMSprop, Adam, Nadam*	*RMSprop*
Learning Rate	0.01	0.9, 0.6, 0.3, 0.1, 0.09, 0.06, 0.03, 0.01, 0.009, 0.006, 0.003, 0.001, 0.0009, 0.0006, 0.0003, 0.0001, 0.00001, 0.000001	0.0001
Number of Epochs	20	4, 6, 8, 10, 12,14,16, 18, 20, 25, 30, 35, 40, 45, 50	10

3.8 Performance Evaluation Methodology

Since we used a learning-based approach, metrics derived from the matrix of misunderstanding, shown in Figure 3, are used for evaluating our methodology.

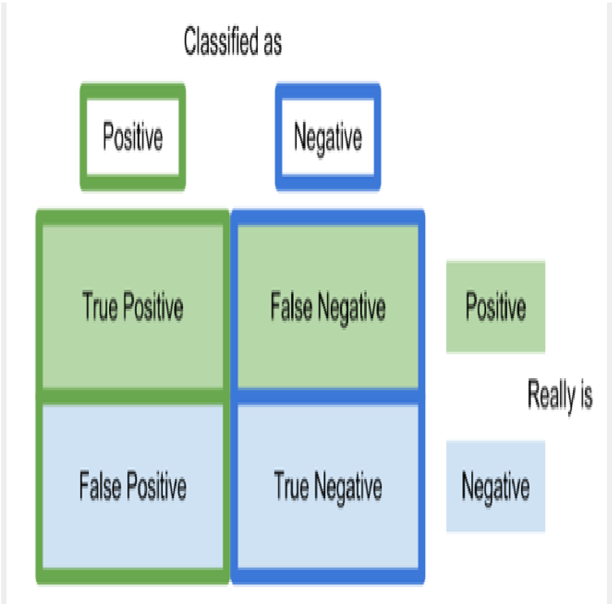

Figure 3. *Confusion matrix*

Performance statistics are obtained by comparing our technique's predicted labels with the ground truth based on a confusion matrix. Equations 1 through 4 express the measures utilized in the performance evaluation.

$$Precision\ (p) = \frac{TP}{TP+FP} \qquad (10)$$

$$Recall\ (r) = \frac{TP}{TP+FN} \qquad (11)$$

$$F1\text{-}score = 2 * \frac{(p*r)}{(p+r)} \qquad (12)$$

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \qquad (13)$$

The outcome of the performance evaluation metrics is a number between 0 and 1. These measures are often utilized in machine learning research.

4. Experimental Setup

This experiment aims to determine the optimal hyperparameter combination and evaluate the suggested model's performance compared to alternative ML techniques. We conducted tests using Google Colaboratory, a popular platform for developing DL applications. Pandas == 1.0.5 is the data preparation framework. A deep learning model was created using the TensorFlow 2.2.0 and Keras 2.3.0 frameworks. 72% (6072 reviews), 18% (1519 reviews), and 10% (844 reviews) of the total reviews are comprised of sets of training, validation, and tests. The model is trained with the training set, and validation samples are used to modify its hyper-parameters (learning rate, batch size, etc.). Finally, a trained model was evaluated on the test set.

5. Experimental Results

This part presents our empirical study's findings and the suggested sentiment analysis paradigm. The proposed DL model, SentiNet, was evaluated with the benchmark data set and provided superior performance compared to state-of-the-art models. The experimental results in this section include exploratory data analysis, essential data analytics, and sentiment analysis results in terms of the proposed DL model's performance compared with some existing models.

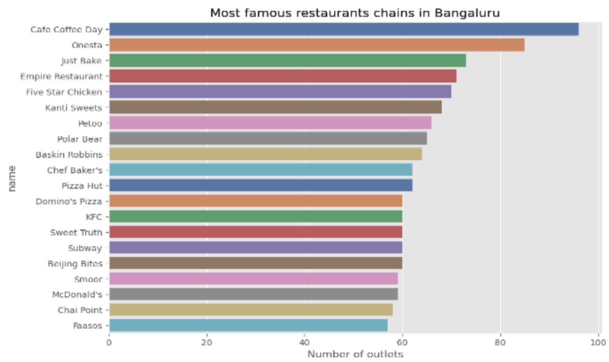

Figure 4. *Restaurants in Bangalore with their order of expansion*

From the data analytics shown in Figure 4, it is understood that there were several famous restaurants with many outlets in Bengaluru. The visualization of restaurants is provided in terms of their number of outlets in descending order.

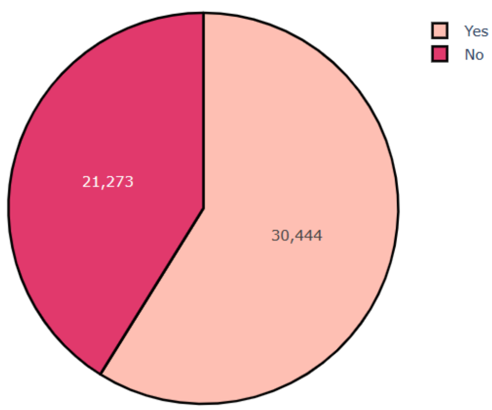

Figure 5. *Online order acceptance dynamics*

Figure 5 shows the dynamics of restaurants in Bengaluru accepting orders through online platforms.

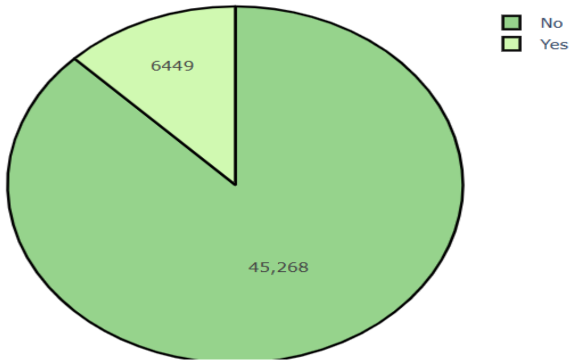

Figure 6. *Table booking dynamics of restaurants in Bengaluru*

As presented in Figure 6, the dynamics of table bookings among the restaurants located in Bengaluru.

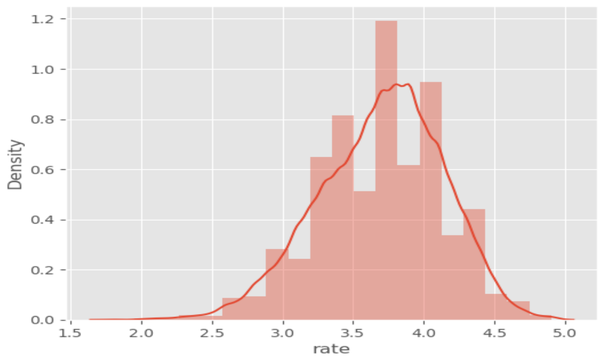

Figure 7. *Rating distribution dynamics against density*

The rating distribution dynamics against density are visible in Figure 7, reflecting how the ratings are given to various restaurants in Bengaluru.

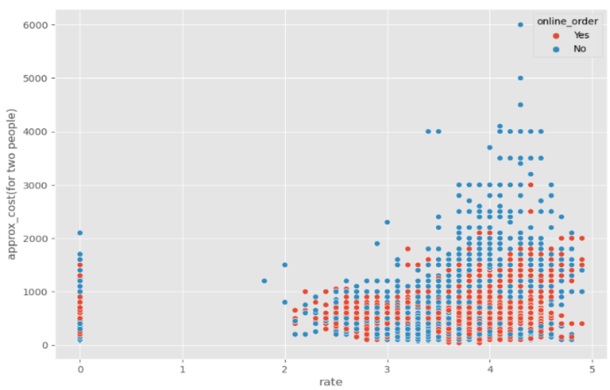

Figure 8. *The pricing dynamics against rating in restaurants in Bengaluru*

As presented in Figure 8 the cost of restaurants for two individuals is compared against the rate or rating given to restaurants in Bengaluru.

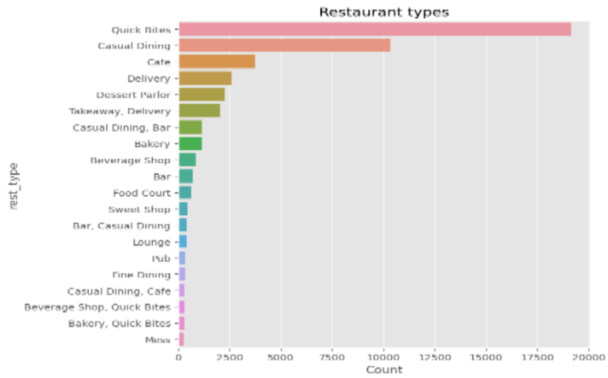

Figure 9. *Different types of restaurants in Bengaluru*

characterize the needs of different types of customers, and the count of restaurants for each category is shown in Figure 9.

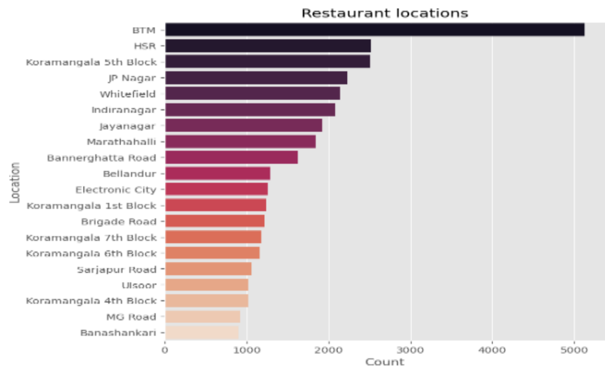

Figure 10. *Restaurants located in different parts of Bengaluru*

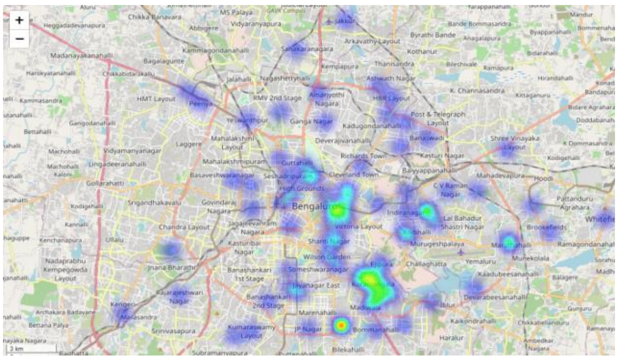

Figure 11. *Visualization of the count of restaurants*

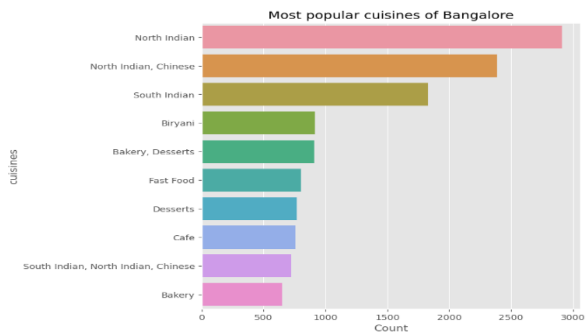

Figure 12. *Cuisines and their popularity reflecting the number of restaurants offering such cuisines.*

Figure 10 shows the number of restaurants in various parts of Bengaluru that serve different food items to people. Figure 11 presents the restaurants in various places and their density in terms of the number of restaurants or outlets visualized.

Figure 12 presents the most popular food items served in Bengaluru and shows the number of restaurants serving them.

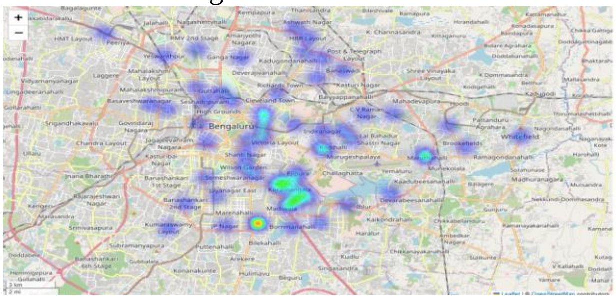

Figure 13. *The dynamics of restaurants serving North Indian cuisines*

As presented in Figure 13, the details of restaurants located in Bengaluru serving North Indian cosines are provided. As presented in Figure 14, the details of restaurants in Bengaluru serving North Indian cosines are provided.

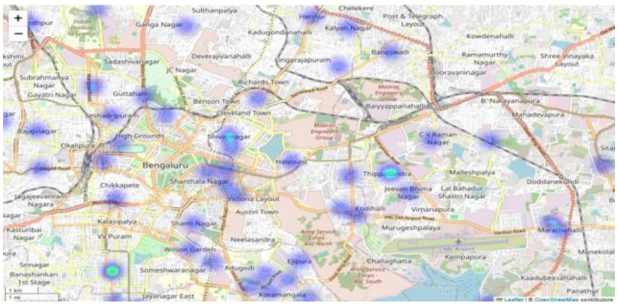

Figure 14. *The dynamics of restaurants serving North Indian cuisines*

Figure 15. *Word cloud reflecting cuisines popular in various kinds of restaurants*

Figure 16. *Word cloud reflecting customer feedback for various kinds of restaurants*

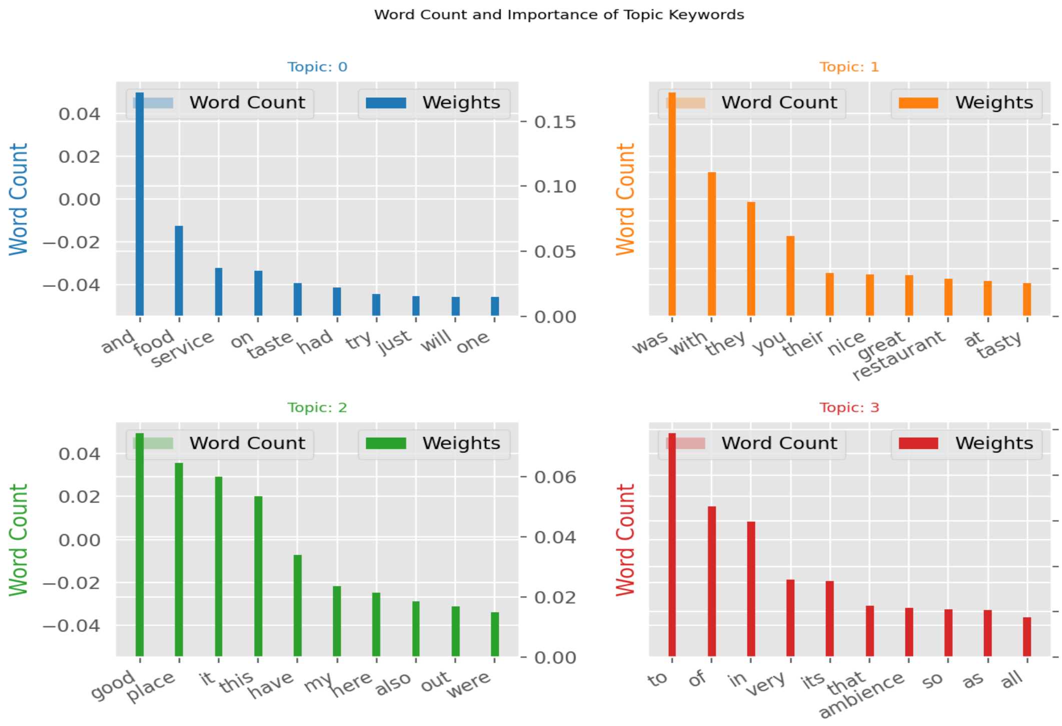

Figure 17. *Results of topic modeling for positive comments*

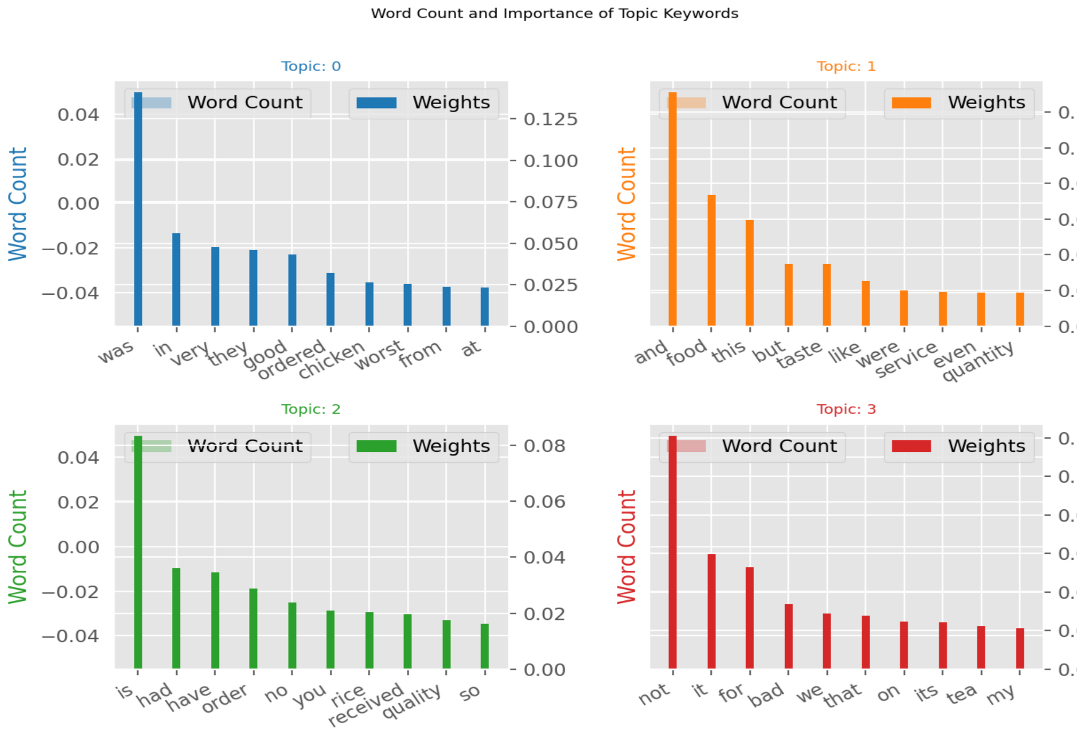

Figure 18. *Results of topic modeling for negative comments*

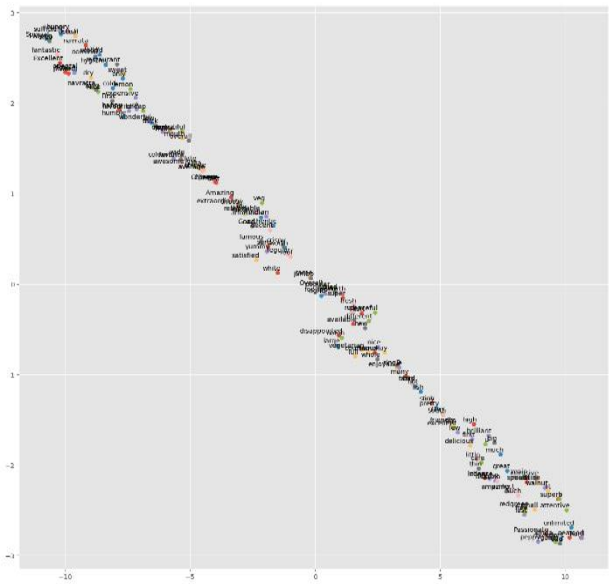

Figure 19. *T-SNE of adjectives used in positive reviews*

Figure 15 shows the word cloud visualization, which reflects the dynamics of popular food items served in different kinds of restaurants in Bengaluru.

Figure 16 shows the word cloud visualization, which reflects the customer feedback for different kinds of restaurants in Bengaluru

The topic modeling dynamics is presented in Figure 17, where different positive topics are visualized along with word count and weights associated with a given topic.

The topic modeling dynamics is presented in Figure 18, where different negative topics are visualized along with word count and weights associated with a given topic.

As presented in Figure 19, the T-SNE of adjectives used in positive comments is visualized to understand customer sentiments about the restaurants located in Bengaluru.

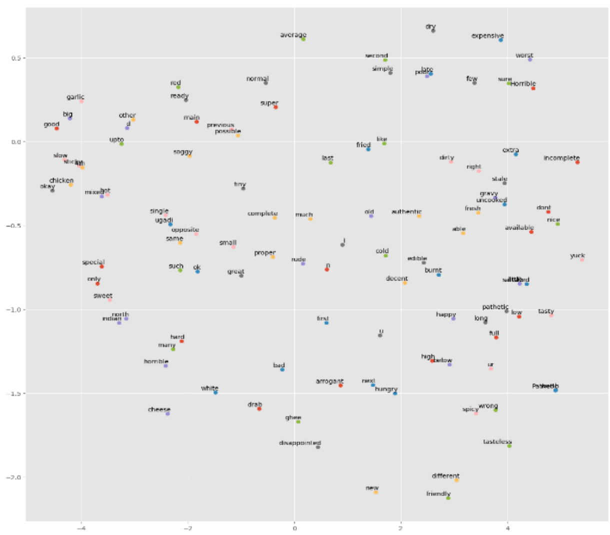

Figure 20. *T-SNE of adjectives used in negative reviews*

As presented in Figure 20, the T-SNE of adjectives used in negative comments is visualized to understand customer sentiments about the restaurants located in Bengaluru.

Table 2 compares the models' respective performances in sentiment analysis in terms of different performance metrics that help understand the capability of different models.

Table 2. *Performance comparison among models in sentiment analysis*

Model	Precision	Recall	F1-score	Accuracy
Baseline CNN	89.74	89.23	89.48	89.52
Baseline LSTM	90.89	90.54	90.71	90.21
Bi-LSTM	94.56	94.56	94.56	94.13
SentiNet (Proposed)	96.93	98.04	97.48	98.68

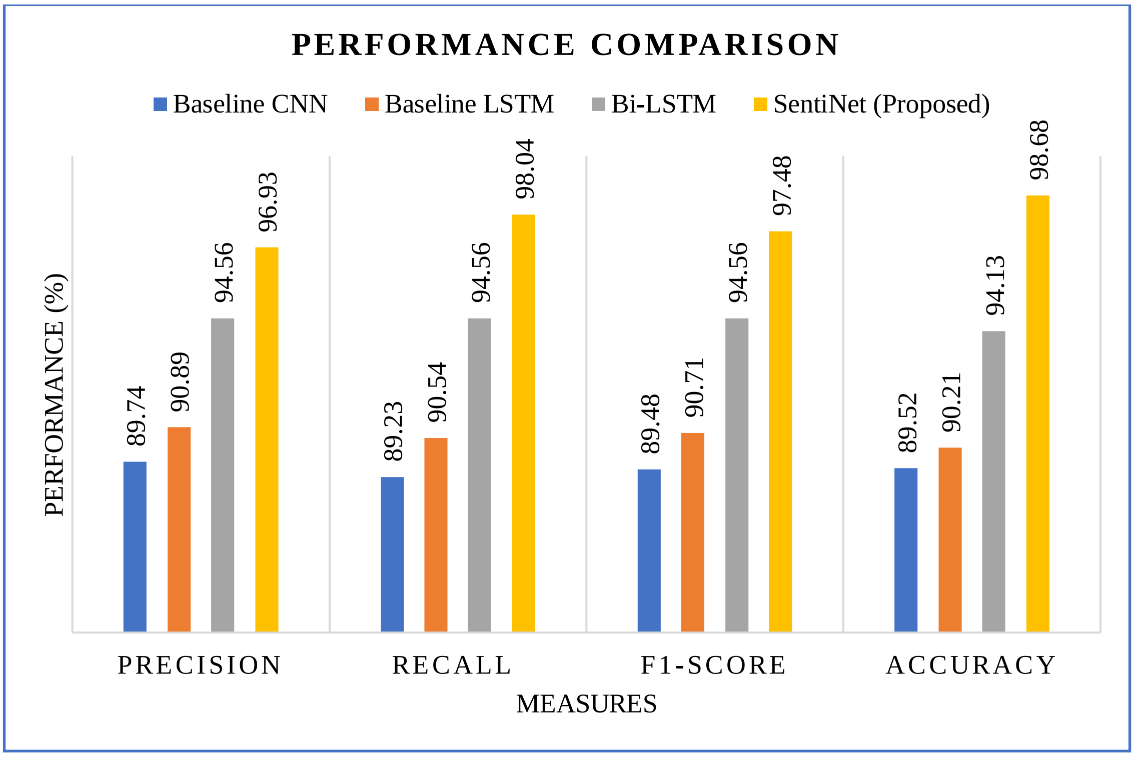

Figure 21. *Performance comparison among different models for sentiment analysis*

As presented in Figure 21, different models could provide various performance levels in sentiment analysis. However, the proposed model could outperform other models due to its hybrid approach to leveraging performance. The precision of the baseline CNN model is 89.74%, the baseline LSTM model is 90.89%, the Bi-LSTM model is 94.56%, and the proposed SentiNet model is 96.93%. The recall of the baseline CNN model is 89.23%, the baseline LSTM model is 90.54%, the Bi-LSTM model is 94.56%, and the proposed SentiNet model is 98.04%. The F1 score of the baseline CNN model is 89.48%, the baseline LSTM model is 90.71%, the Bi-LSTM model is 94.56%, and the proposed SentiNet model is 97.48%. The accuracy of the baseline CNN model is 89.52%, the baseline LSTM model is 90.21%, the Bi-LSTM model is 94.13%, and the proposed SentiNet model is 98.68%.

6. Conclusion and Future Work

We proposed a DL-based framework for analyzing the sentiments of given data. We proposed a novel DL architecture, SentiNet, to efficiently classify sentiments in customer reviews. We proposed an Efficient Learning-Based Sentiment Analyzer (LBSA) algorithm, which exploits novel vectorization, embeddings, and the novel architecture of the proposed SentiNet model. The given text is converted to a vector representation using the novel approach. Our empirical study with a benchmark dataset of customer reviews on restaurants and food items revealed that the proposed SentiNet model outperformed many existing deep-learning models with a maximum accuracy of 98.68%. Our framework can be incorporated into business applications for sentiment analysis and improving service quality. In the future, we intend to strengthen our deep learning system using the generative adversarial network architecture. This enhancement is expected to improve performance in sentiment classification by leveraging text corpora.

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.

- **Conflict of interest:** The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper
- **Acknowledgement:** The authors declare that they have nobody or no-company to acknowledge.
- **Author contributions:** The authors declare that they have equal right on this paper.
- **Funding information:** The authors declare that there is no funding to be acknowledged.

- **Data availability statement:** The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

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