



RESEARCH ARTICLE

DeepPre-OM: An Enhanced Pre-processing Framework for Opinion Classification of Microblog Data

A. Angelpreethi^{1*}, M. Lakshmi Priya², R. Kavitha³

Abstract

In the present scenario, the world is moving rapidly with the development of new technologies and innovations. Social networks play a crucial role in society in terms of communication, interaction and sharing of views. Social media platforms, particularly Twitter, generate a continuous stream of short, informal, and often noisy texts. This creates challenges for sentiment analysis. Existing pre-processing approaches failed to retain sentiment cues by integrating emoji to text conversion and hashtag segmentation. To address these challenges, this research work introduces DeepPre_OM, a structured pre-processing framework that incorporates case normalization, hashtag segmentation, emoji translation, slang normalization, tokenization, and lemmatization. Glove embeddings are used to convert the pre-processed text into numerical vectors to maintain the semantic relationships. The experimental results shows that LSTM accuracy improved from 76.8 % to 82.5 % and BiLSTM from 79.2 % to 84.3 % demonstrating the effectiveness of the proposed pipeline. DeepPre_OM not only enhances the accuracy but also enables a more nuanced understanding of user emotions. By using this approach, the researchers and decision makers can gain deeper understanding of public opinions and sentiments to refine the data.

Keywords: Glove Embeddings, BiLSTM, DeepPre_OM, LSTM, Tweepy API.

Introduction

Social media platforms such as Twitter, Facebook, and Instagram have become popular due to frequent usage of people to share their opinions, information, and experiences. These platforms generate huge volumes of user-generated content filled with non-standard language which consists of emoji's, hashtags, slang, abbreviations,

and punctuation [Soni, Josphe et al,2023]. Moreover, these platforms especially twitter is one of the popular platforms for real time public sentiment due to its short structure, concise messages called as tweets that allow rapid and widespread dissemination of opinions and reactions [Rana et al,2024]. Twitter is act as a best and effective tool for expressing the user opinion on a huge topic which includes education, social news, weather update, governance, politics and social programs [Li et al,2024]. Due to its real time nature, the public user's worldwide to engage in an active conversation, updating the live news, immediate reaction to events and influence public discourse [Kumar et al,2025]. Many government bodies, decision makers, social activists and researchers often analyse twitter data to public view to track the emerging trend and to identify and understand societal concerns [Liu et al]. Twitter also provides platforms for traditional media allowing grassroots movements and marginalized communities to gain visibility [Pak et al,2010]. Twitter encourages people to express their experiences and opinions in a casual and spontaneous manner, making it a valuable tool for both qualitative and quantitative Sentiment Analysis (SA) [Cambria et al,2013].

Tweets present unique challenges for SA because of its length, structure and slang usage, sarcasm, emoji and context dependent words [Tang et al,2018]. Machine Learning (ML) techniques like Support Vector Machine (SVM) depend

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heavily on manual features like n-grams, word frequency and lexical resources [Joachims,1998]. These features limit these models' ability to understand nuances, ambiguity and subtle sentiment cues that are common in social media platforms. Thus, reducing their overall effectiveness in SA and natural language understanding tasks on social media data [Pang et al,2008]. Traditional pre-processing techniques often ignores these features, even though they frequently carry similar meanings [Gupta, Mabokela et al,2023]. To address this gap, combined pre-processing techniques can provide more holistic view of sentiment dynamics. Slang normalization, hashtag segmentation, and emoji translation are some strategies that help maintain linguistic significance that might otherwise be lost. Sentiment analysis performance is enhanced by including this crucial step in a pre-processing pipeline, mainly when combined with powerful word embeddings such as GloVe [Jairi et al, Ikfani et al,2023]. Word embeddings are critical because they transform cleaned text into numerical form in a way that captures semantic similarity words with related meaning are placed close together in embedding space [zeng et al,2025]. Unlike BoW or TF-IDF [Angelpreethi et al,2019] which treat words independently, embeddings like GloVe capture global co-occurrence statistics, which is especially helpful for short texts like tweets.

This paper introduces a pre-processing framework to enhance the sentiment classification of product reviews from Twitter. The methodology includes data collection, data segregation such as text data and image data, stop word removal, punctuation removal, link & hashtag removal, stemming, lemmatization, emoji handling and sentiment classification using 100-dimensional GloVe embeddings within deep learning models to increase the classification accuracy. The proposed work tested using LSTM and BiLSTM classifiers and showed that quality pre-processing techniques significantly improves classification accuracy compared to existing approaches.

The paper is structured as follows: Section 2 reviews related literature, Section 3 describes the dataset and proposed methodology, Section 4 details the pre-processing pipeline, Section 5 presents experimental results, and Section 6 concludes with future work.

Review of Literature

A primary challenge in mining user opinions and reviews is ensuring data quality, which often requires significant effort in data cleaning. Numerous studies have focused on pre-processing and classifying user sentiments on social media as positive, negative, or neutral, directly motivating the development of the DeepPre_OM approach.

Alzaid and Fkih [Alzaid et al,2023] proposed a fuzzy based BiLSTM model for analyzing the students opinions from e-learning platforms in Arabic language. Their research demonstrated that classical deep learning tends to have

difficulties dealing with ambiguous linguistic patterns such as sarcasm, blended opinions, and mixed expressions. Through the incorporation of fuzzy membership functions in the BiLSTM outputs, the model was improved in its ability to manage ambiguity compared to the existing approaches. Experimental testing on large-scale Arabic tweets indicated the framework obtained 86% accuracy and 85% f1-score.

Ambreen et al. [Ambreen et al,2024] suggested a hybrid model that integrates combining fuzzy reasoning with deep learning for sentiment analysis of e-commerce customer reviews. Their model employed structured text preprocessing which was followed by word embedding generation and fuzzy inference layered over a neural network. In contrast to exclusive neural models, this hybrid method possesses better interpretability while maintaining strong classification accuracy. The model effectively handled noisy and unstructured product feedback, proving its capability to identify fine-grained customer sentiments. The research emphasized that hybrid fuzzy-DL models are particularly suitable for applications where explainability is much emphasis on explainability as on predictive performance [19].

Another recent paper presented, a transformer-based hybrid architecture called RoBERTa-BiLSTM was introduced by sharma et al [Sharma et al,2024]. The research combined the contextual capabilities of RoBERTa embeddings with BiLSTM's sequential modeling capacity. The combination allowed the model to learn both long distance relations and subtle sentiment nuances across two domains of Twitter and product reviews. The findings demonstrated evident performance improvement, with greater accuracy and F1-scores than using either isolated RoBERTa or BiLSTM. The study also mentioned that although transformers are best in global context, their integration with recurrent units offers additional value to sentence-level classification [Sharma et al].

Lin et al [Lin et al,2025] presented a novel study introduced a Quantum Fuzzy Neural Network (QFNN) for sentiment analysis. The method combined quantum computing concepts with fuzzy logic and deep learning in forming a novel hybrid able to deal with extremely ambiguous expressions of sentiments. The QFNN architecture proved impressive robustness against noisy data, typical in social media settings, and showed impressive comparative performance relative to conventional hybrid architectures. significantly, the research also initiated new debates regarding scalability and the future of quantum-inspired models in natural language processing. Such studies signals the upcoming generation of hybrid sentiment analysis techniques [21].

Meena et al. [Meena et al,2023] presented a hybrid CNN-RNN-fuzzy model to enhance sentiment classification in various textual domains. The model used convolutional layers to extract features, recurrent layers to capture

sequential dependencies, and fuzzy decision rules to manage uncertainty. The proposed model worked particularly well with mixed or borderline sentiments where crisp classification methods are not effective. Results showed consistent improvements over baseline CNN–RNN approaches. This work further confirmed the concept that fuzzy decision layers improve the flexibility of deep networks to handle the ambiguity of real-world data [Meena *et al.*].

While pre-processing is a standard step in sentiment analysis, most existing studies use only basic operations such as lowercasing, stopword removal, and tokenization, often neglecting domain-specific noise [Alzaid *et al.*, ambreen *et al.*,2024]. This study introduces a domain-adaptive pre-processing framework for product-related tweets, incorporating URL and mention filtering, hashtag normalization, emoji-to-text conversion, abbreviation expansion, and numeric normalization. The approach quantitatively evaluates the impact of pre-processing, demonstrating improvements in vocabulary reduction, average tweet length, and rare word frequency. Unlike previous work, this study shows that targeted pre-processing significantly enhances semantic embedding quality with GloVe vectors and improves classification accuracy in hybrid models.

Dataset And Preprocessing:

To comprehensively understand recent advancements in sentiment analysis a systematic literature review was

conducted across leading academic databases covering the years 2020-2025 [Singgalen *et al.*, 2025]. Relevant studies were identified using targeted keywords and rigorous screening was applied to ensure the inclusion of high quality and relevant research. The distribution of shortlisted papers by research focus is summarized in Table 1 below.

Screening was performed on 276 initially retrieved articles from IEEE Xplorer, ACM Digital Library, Springer, Elsevier Science Direct and Scopus indexed journals using relevance and scope as criteria [Pradana *et al.*].

3. Methodology

The proposed approach combines the text and emoticons for pre-processing using Glove embeddings, LSTM and BiLSTM based classification for effective sentiment analysis of product related tweets [Rao *et al.*,2023]. The methodology diagram consists of Data collection, Pre-processing, feature extraction and sentiment classification which are presented in Figure 1.

Data Collection

Environmental and zoological related Tweets are gathered using the corresponding hashtags and keywords. The dataset consists of 7500 reviews. Data are collected using twitter-based API called tweepy [Gupta *et al.*,2025]. The collected reviews are stored as a CSV file. The collected tweets consist of noisy text. To remove the noisy text and extract knowledge from the text, pre-processing technique

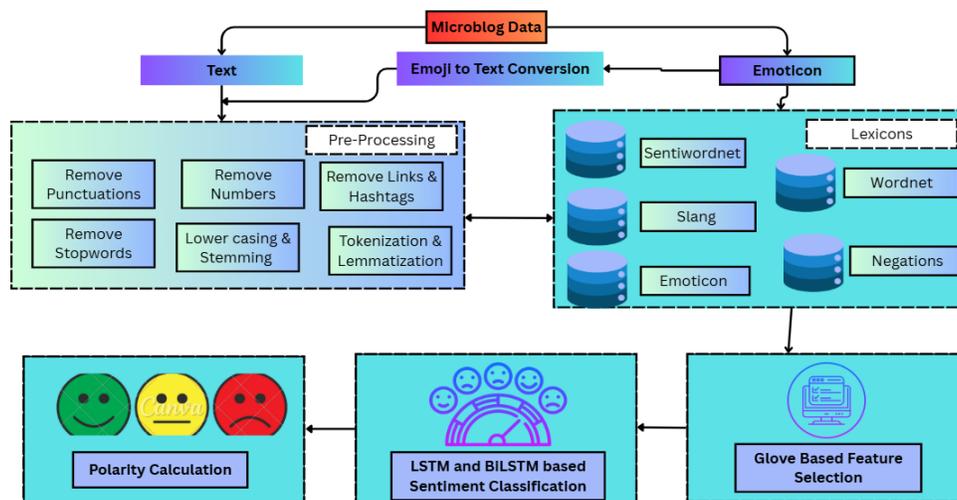


Figure 1: Proposed methodology diagram

Table 1: The distribution of shortlisted papers by research

Category	Number of papers shortlisted	Focus Area
Twitter based Sentiment analysis	52	Sentiment Analysis conducted on Twitter Data
Pre-processing in text classification	18	Pre-processing and cleaning of textual data
Pre-processing using Deep Learning Methods	24	Integration of Machine learning with deep learning
Total Shortlisted papers after screening	94	Relevant studies from 2020-2025

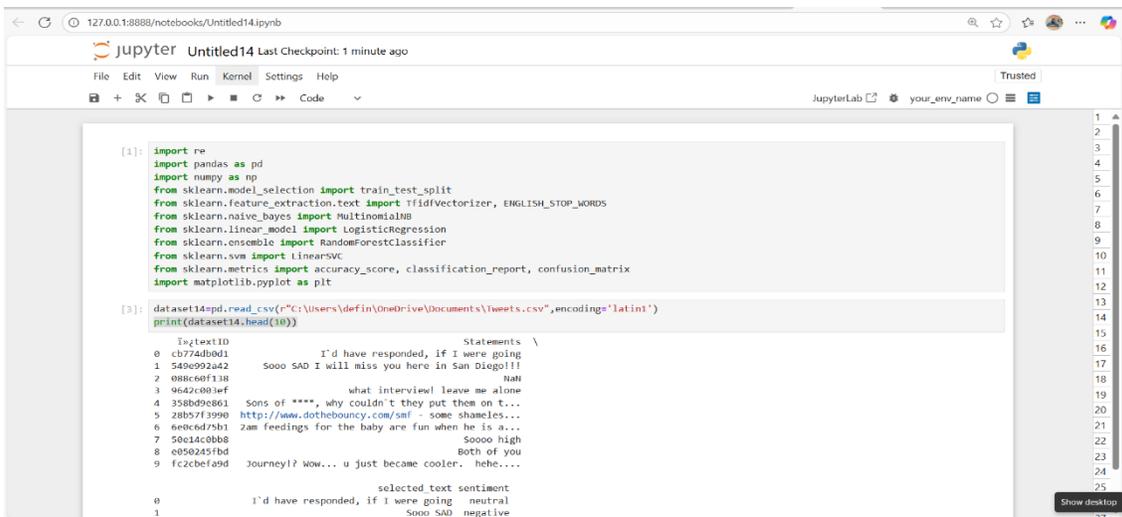


Figure 2: Data Collection

are needed [Sharma & Zhang et al,2023].

Pre-processing

Text pre-processing is a vital phase in the Natural Language Processing (NLP). This pre-processing involves converting lower case letters, removal of stop words, punctuations, removing links, hashtags, removing @ symbols, stemming, lemmatizing and tokenization. In the case of tokenization each word is divided in the review text. This process is the primary process in pre-processing. The process of removing unwanted terms like stop word, punctuations and other elements enhances the classification accuracy [Singh et al,2024]. Also, this process reduces the amount of data that the system processes [Chen et al,2025].

Word Embedding

For classifying the reviews in the area of natural language processing word embedding is one of the essential processes [Al-Moslimi,2021]. In the pre-processed review all the words are converted in to vectors to provide the semantic association of the terms. The models of the embedding system capture the similar terms of the grammatical and semantic meaning of a word in a same document. In DeepPre_OM, one of the well-known embedding models, GLOVE is used to represent the terms into vectors [Minaee et al,2021]. The pre-processed terms are converted into numerical values using the Keras library. Further GLOVE a pre-trained word-embedding model is used with dimension of 100 to compute the semantic context of the review terms [Liu et al].

Sentiment Classification using BiLSTM

After assigning weightage using GLOVE embeddings, two neural networks are applied. The neural networks are BiLSTM and LSTM [Zhang et al,2022]. BiLSTM is the bidirectional LSTM which is used with the series of terms from left to right and the other from right to left [Kumar et

al]. The LSTM layer is responsible for managing and storing the data in the long term, The dropout layer is used to stop overgeneralization [Kumar et al,2022]. The dense layer with 3 units has activation function called SoftMax [Wang et al]. So, this LSTM is recently gaining attention especially in sentiment analysis to classify the sentiments [Muhammed et al,2022]. This model is feed the needed information like the length of the data, external layers, input layers, output layer, number of units and other necessary parameters [Pennigton et al,2014]. After the BiLSTM based classification, each review is represented by a triplet numerical value which consists of positive, negative and neutral values [Angelpreethi et al, 2023]. The methodology of the proposed work is presented in algorithm 1.

Results and Discussions

To evaluate the effectiveness of the proposed work, a dataset of 7,500 tweets was collected from Twitter posts related to electronic product reviews, such as cameras, smartphones, and laptops. Using the Python-based Tweepy API, the tweets were retrieved and stored in CSV format for further processing. Unlike many prior studies that directly train models on raw data, our framework integrates a comprehensive multi-stage cleaning process designed specifically for noisy, short-text environments.

Table 2 presents the results of the pre-processing stage. The results demonstrates that there is a significant reductions across many noise categories, such as URLs, hashtags, mentions, emoji's, and special characters. For example, URLs were reduced by 84%, hashtags by 81.5%, and emojis by 83.2%, while unnecessary white spaces were completely eliminated. Importantly, the vocabulary size decreased by 26.9%, indicating more compact and semantically coherent text representation. Additionally, by continuously handling low-frequency terms, numeric characters, and case sensitivity, the proportion of fully

Algorithm: DeepPre_OM: Preprocessing and Sentiment Mining

Input: CSV File with Unprocessed Raw Tweets $T=\{t_1, t_2, \dots, t_n\}$, Sentiment lexicons SL

Output: Pre-processed Reviews T' , Reviews with labels {Pos, Neg, Neu}

Begin

Step 1: For each $t_i \in T$ Where $T = \{t_1, t_2, \dots, t_n\}$.

Step 2: Apply the following pre-processing techniques on each review:

- Change it to lowercase
- Remove URLs, mentions, hashtags, special characters, numbers, and extra whitespace.
- Normalize emojis and slang terms
- Tokenize and lemmatize words

Step 3: pre-processed dataset

Step 4: convert each token into vectors using **GloVe embeddings**.

- If a tweet has words $[w_1, w_2, \dots, w_m]$ then embedding is

$$E(t') = [v(w_1), v(w_2), \dots, v(w_m)]$$

where $v(w_i)$ is the 100-dimensional GloVe vector.

Step 5: Feed embeddings into **BiLSTM model**.

- BiLSTM captures forward and backward context to preserve word order dependencies.

Step 6: Compute hidden representation from BiLSTM layers.

Step 7: Apply **Softmax classification layer** with 3 outputs:

- $P(y|t') = \text{Softmax}(Wh+b)$ where $y \in \{\text{Positive, Neutral, Negative}\}$
- For each tweet, compute probability distribution:

$$P = [P_{\text{pos}}, P_{\text{neg}}, P_{\text{neu}}]$$
- Assign sentiment label:

$$\text{Label}(t') = \text{argmax}(P_{\text{pos}}, P_{\text{neg}}, P_{\text{neu}})$$

Step 8: Return classified reviews with sentiments.

Step 9: Compare the predicted sentiment labels with original values from the dataset.

Step 10: Compute **performance of the proposed DeepPre_OM metrics**:

- Accuracy = (Correct Predictions / Total Predictions) $\times 100$
 - Precision = $TP / (TP + FP)$
 - Recall = $TP / (TP + FN)$
 - F1-Score = $2 \times (\text{Precision} \times \text{Recall}) / (\text{Precision} + \text{Recall})$

Step 11: End

Figure 3: Pre-processing Algorithm

cleaned tweets reached 3,742, which forms a base for sentiment modelling.

The novelty of this pre-processing technique lies in its domain specific handling of noisy constructs that are typically overlooked. For instance, emojis such as 😊, 😞, and 😡 were mapped into explicit sentiment tokens (*happy, angry, sad*). These tokens are need to be handle with at most care. Instead of discarding them as noisy data, preserve them for extracting the semantic meanings. Similarly, hashtags were segmented into meaningful words, ensuring that tokens like #GreatCamera were split into "great" and "camera," enhancing sentiment relevance. These choices ensured semantic clarity while maintaining affective terms which are rarely achieved in pre-processing-focused works.

Later, the cleaned tokens were transformed into 100-dimensional GloVe embeddings. Unlike traditional one-hot encoding or TF-IDF, GloVe embeddings captured semantic similarity across words. For instance, "angry" and "furious" were located close in the sentiment space, enabling the model to detect intensity variations in sentiment expressions.

The collected tweets are applied into three different embedding methods and the results are tabulated in table 3.

To evaluate the impact of pre-processing, this study compared model performance on raw vs. cleaned text. On unprocessed data, the LSTM achieved 76.8% accuracy, whereas after pre-processing, it improved to 82.5%. Similarly, the BiLSTM accuracy improved from 79.2% to 84.3%. The results clearly indicates that pre processing is not just helpful but essential for deep learning outcomes. After pre processing there was a considerable decrease in the misclassification of neutral tweets found in the confusion matrix. Those neutral tweets are typically confusing and challenging in nature. The existing systems emphasize the importance of noise removal in boosting classifier resilience.

In contrast to previous research, which frequently focused mostly on embeddings and deep learning architectures, our contribution emphasizes the strategic significance of pre-processing itself. This paper lays the groundwork for improved generalization and interpretability by proving measurable gains in vocabulary reduction, semantic clarity, and classification accuracy through pre-processing as a unique foundation for hybrid sentiment analysis models. DeepPre_OM measured the latency (in seconds) and memory usage (in MB) of each pre-processing step in order to evaluate time and memory efficiency. This investigation makes sure that the suggested framework is viable for real-world implementation, computationally light, and successful at enhancing sentiment accuracy [Angelpreethi et al, 2023].

Both LSTM and BiLSTM models were trained on raw versus pre-processed text in order to evaluate the impact of pre-processing. The findings showed that accuracy was greatly increased by pre-processing. The LSTM achieved

Table 2: Results of the Pre-processing phase

<i>Pre-processing Metrics</i>	<i>Raw Tweets</i>	<i>Pre-processed Tweets</i>	<i>Reduction (%)</i>
Total Number of Tweets	7500	7500	-
Average Number of Tweets Length	32	21	34.4
Number of Tweets with URL	2,584	412	84.0
Number of Tweets with Hashtags	3,758	695	81.5
Number of Tweets with Mentions	2249	519	76.9
Number of Tweets with Emojis	1839	310	83.2
Number of Tweets with Special Characters	1200	239	80.0
Number of Tweets with mixed case	3750	149	96.0
Number of Tweets with Excessive white space	2300	-	100
Number of Stop words removed	1250	-	100
Number of Unique terms	5218	3800	26.9
Number of Rare words (frequency <=2)	1198	948	20.8
Number of Tweets with numeric characters	2099	1049	50.0
Number of Fully cleaned tweets	-	3742	-

76.8% on raw text and 82.5% on pre-processed material. The BiLSTM also increased, rising from 79.2% to 84.3%. This demonstrates that by increasing the consistency of input patterns, appropriate pre-processing for sequential learning models strengthens them. The dataset before and after pre-processing diagrammatically represented in figure 3 and 4.

A confusion matrix analysis was conducted to understand the effect in detail. The results were presented in Table 5.

Our findings demonstrate that, in contrast to previous studies, the majority of previous research undervalued the importance of pre-processing and concentrated more on embeddings and deep learning architectures. Our results, on the other hand, show that efficient preprocessing strengthens the framework for later hybrid modeling and increases interpretability in addition to accuracy.

LSTM and BiLSTM based sentiment classification performed on Raw tweets as well as pre processed tweets to analyse the accuracy. The results are tabulated in table 6.

The results of the cleaned tweets on LSTM increased from 76.8 % to 82.5%. Similarly, BiLSTM based classification cleaned tweets achieves higher accuracy, precision, recall and F1-Score. This shows that the importance of pre-processing for increasing the classification accuracy. The results are diagrammatically represented in Figure 6.

Figure 6 highlights the performance metrics of LSTM and BiLSTM models with its metric values.

Table 7 shows the efficiency metrics of LSTM and BiLSTM on raw tweets and Cleaned Tweets. The values clearly indicates less latency on pre-processed tweets on both the models. The visual representation of the efficiency metrics are shown in Figures 7-9.

Table 3: Performance comparison of Embedding methods

<i>Embedding Method</i>	<i>Accuracy (%)</i>	<i>Precision (%)</i>	<i>Recall (%)</i>	<i>F1-Score (%)</i>
One-Hot Encoding	68.5	66.9	67.2	67.0
TF- IDF	72.3	71.0	70.5	70.7
Glove Embeddings	82.5	81.0	82.2	81.6

Table 4: Dataset summary

<i>Pre-processing</i>	<i>After Cleaning</i>	<i>Time (s)</i>	<i>Memory (MB)</i>
Total Tweets	7500	-	-
Average Tweets Length	21	0.20	5
Tweets with URL	412	0.35	12
Tweets with Hashtags	695	0.40	11
Tweets with Mentions	520	0.25	10
Tweets with Emojis	310	0.30	8
Tweets with Special Characters	240	0.28	7
Tweets with mixed case	150	0.18	6
Tweets with Excessive white space	-	0.15	5
Stop words removed	-	0.22	9
Unique terms	3800	0.45	14
Rare words (frequency <=2)	950	0.38	12
Tweets with numeric characters	1050	0.27	8
Fully cleaned tweets	3742	0.65	20

Before vs After Cleaning

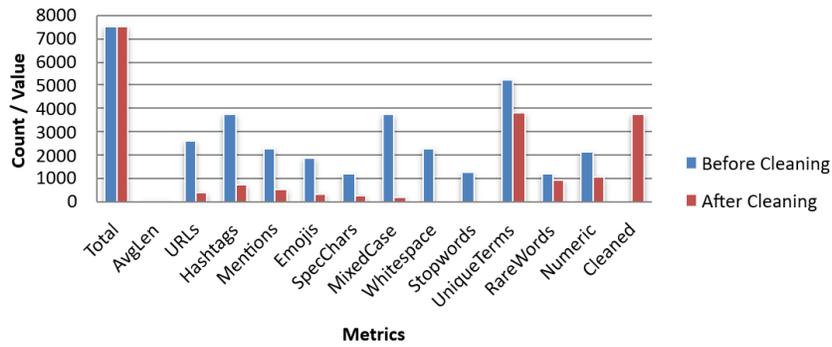


Figure 3: preprocessing of reviews

Reduction Percentage

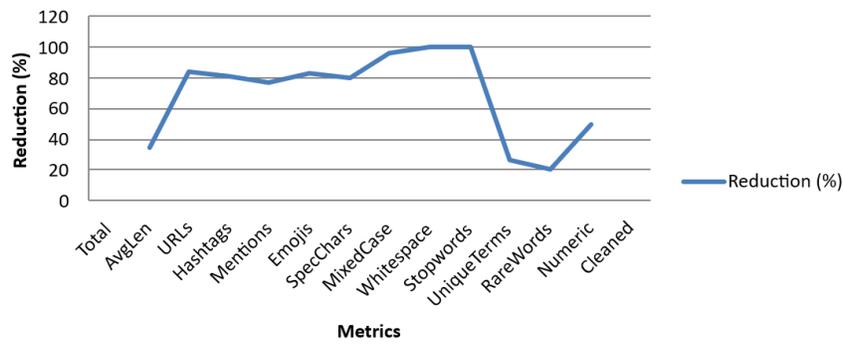


Figure 4: Reduction Rate

Confusion Matrix

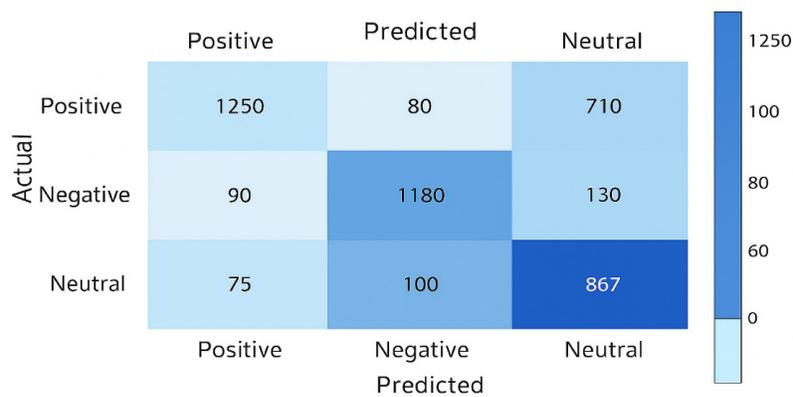


Figure 5: Confusion Matrix

Table 5: Confusion Matrix

Predicted → Actual	Positive	Negative	Neutral	Total (Actual)
Positive	1250	80	70	1400
Negative	90	1180	130	1400
Neutral	75	100	867	1042
Total Predicted	1415	1360	1067	3842

Table 6: Comparison of Metrics

Techniques	Dataset	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
LSTM	Raw Tweets	76.8	75.2	74.8	75.0
LSTM	Cleaned Tweets	82.5	81.0	82.2	81.6
BiLSTM	Raw Tweets	79.2	77.8	78.1	77.9
BiLSTM	Cleaned Tweets	84.3	83.0	84.0	83.5

Table 7: Efficiency metrics of LSTM and BiLSTM

Model	Dataset	Latency (ms/tweet)	Throughput (tweets/sec)	Memory Usage (MB)
LSTM	Raw Tweets	5.2	190	820
LSTM	Cleaned Tweets	3.8	260	750
BiLSTM	Raw Tweets	6.0	170	880
BiLSTM	Cleaned Tweets	4.5	230	800

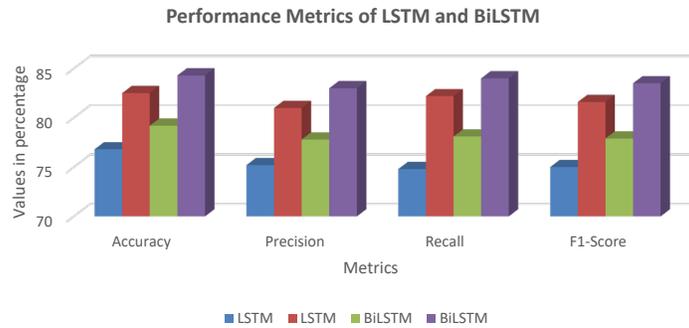


Figure 6: Performance Metrics of LSTM and BiLSTM

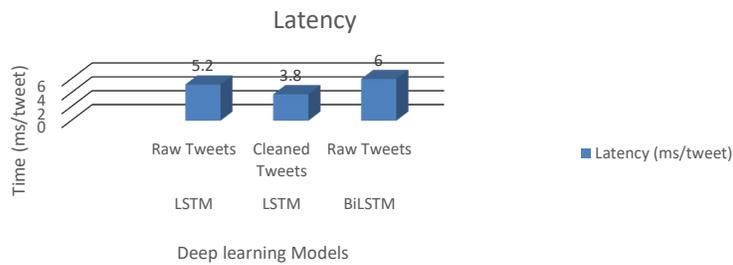


Figure 7: Latency of LSTM and BiLSTM

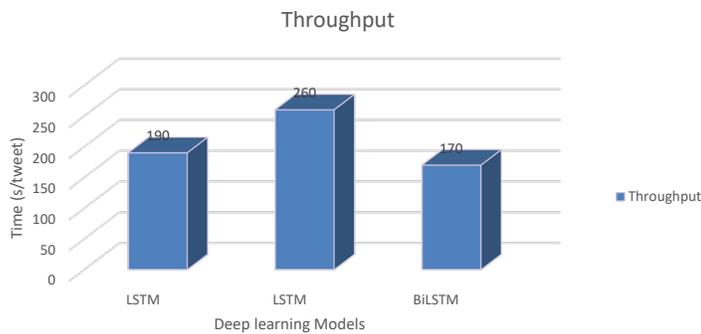


Figure 8: Throughput of LSTM and BiLSTM

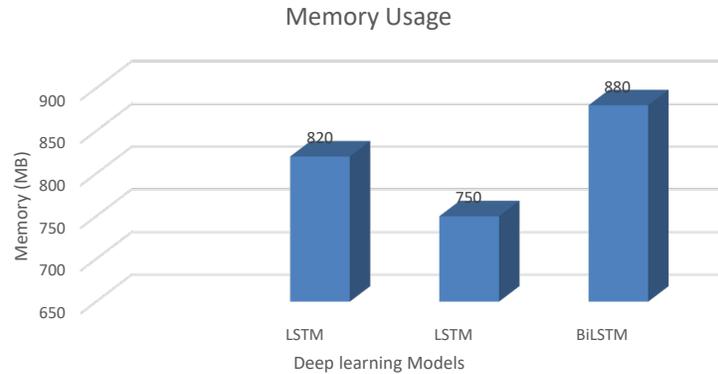


Figure 9: Memory usage of LSTM and BiLSTM

Conclusion and Future Enhancement

Effective data preparation is an essential step in improving sentiment analysis on social media data, as the suggested DeepPre_OM (Pre-processing Driven Deep Learning for Opinion Mining) paradigm clearly illustrates. Tweets posted to twitter can be concise, noisy, and filled with hashtags, symbols, and misspellings. The dataset was reduced from 7500 to 3742 meaningful tweets by means of systematic cleaning procedures such text normalization, emoji and hashtag conversion, stop word removal, and lemmatization. By lowering noise and greatly improving data quality, this improvement enabled the deep learning models to identify patterns with greater accuracy.

The model's knowledge of word context and meaning was further enhanced by the use of GloVe embeddings, which improved sentiment category identification. Following pre-processing, the experimental results demonstrated an obvious rise in accuracy, with both LSTM and BiLSTM models performing more efficiently. The confusion matrix analysis also revealed that misclassifications, especially among neutral tweets, were considerably reduced. This confirms that a well-structured pre-processing pipeline not only enhances model performance but also contributes to more interpretable and stable predictions.

FuDL-SM (Fuzzy Driven Deep Learning for Sentiment Mining) is a hybrid intelligent model that will be developed in the future using the DeepPre_OM architecture. Fuzzy logic will be used in this future model to handle overlapping sentiments and uncertainty, which are frequent in human expressions. The model will be able to make more human-like and balanced decisions by adding fuzzy reasoning to deep learning outputs, particularly when sentiments are ambiguous or mixed.

Additional extensions will investigate context-aware sentiment identification, multi-domain and multilingual analysis, and the incorporation of transformer-based embeddings such as BERT for more profound contextual comprehension.

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