Spatio-Temporal Mechanism in Multilingual Sentiment Analysis

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Abstract

This study investigated the effectiveness of various models in deep learning in performing sentiment analysis on code-mixed Hinglish text, a hybrid language widely used in digital communication. Hinglish presents unique challenges due to its informal nature, frequent code-switching, and complex linguistic structure. This research leverages datasets from the HinGE, SemEval-2020 Task 9 & E-Commerce Reviews Datasets competition and employs models such as RNN (LSTM), BERT-LSTM, CNN, and a proposed BiLSTM model with Data Augmentation. The study's primary objective is to develop a robust sentiment analysis framework that accurately classifies sentiment in Hinglish text. The BiLSTM model demonstrated superior performance when trained and tested on 3 different datasets. This model outperformed existing approaches. The results highlight the proposed model's capability to handle the nuances of Hinglish in a more generalized manner, including its informal and code-mixed nature, more effectively than traditional models. The model also snags for future developments like data bias, interpretability of the model, scalability.

1 Introduction

During the last 10 years the worldwide expansion of social media with digital communication systems triggered an exceptional linguistic transformation leading to the emergence of multilingual hybrid expressions. Code-mixed languages have become prevalent markers of culture and globalization since they combine multiple languages in one communication context. Hinglish exists as the perfect example of a mixed language formed by combining Hindi and English that serves as a common communication method throughout India and throughout South Asia. However, Recurrent neural networks and their variant using long short-term memory units exhibit exceptional capability in identifying sequential dependencies in Hinglish text which enables them to process unstructured code-mixed sentences with diverse lengths. New opportunities for code-mixed language Sentiment Analysis emerged from the development of BERT (Bidirectional Encoder Representations from Transformers) and its transformer-based models & cross attention networks. The contextual embeddings produced by BERT-derived models like mBERT and IndicBERT obtain information from both local words and global linguistic patterns for the efficient disambiguation of polysemous words and hybrid phrases(He and Abisado, 2024; Hu et al., 2024; Li et al., 2024).However, the pathway faces multiple significant challenges that need to be resolved. The sociolinguistic diversity of Hinglish requires language frameworks to adapt through frameworks which understand continuous language development. The Hinglish language encompasses three levels of diversity that include geographical dialects together with differences between generational groups and technical jargon specific to platforms(Joshi et al., 2025). To counter this problem, this work presents Bidirectional LSTM(BiLSTM) model with Dense layers, with various data augmentation techniques. As a result, we get the features of LSTM, & various Dense layers help the model to get the most prominent features. As we know that text data can be uneven, which can lead to class imbalance. This work also showcases how data augmentation can be a technique which can tackle the problem of class imbalance on various datasets. This model is tested on 3 famous datasets - HinGE, E-Commerce Reviews & SemEval dataset. Comparing the results from previously implemented models, we get a descent result in general, and concluded that this model can be used on any kind of textual data.

The format of the paper is as follows: Section 2

Proceedings of the Workshop on Beyond English: NLP for all Languages in an Era of LLM from Texts associated with RANLP 2025, pages 82–89, Varna, Bulgaria, Sep 12, 2025.
https://doi.org/10.26615/978-954-452-105-9-010

emphasizes the relevant research which is done in this area, highlighting their methodologies & the dataset used. After that, Section 3 covers the proposed methodology along with the dataset used. Consequently, Section 4 showcases the comparative analysis and the proposed model's performance. Finally, Section 5 shows a brief conclusion & future work that can be done in this area.

2 Literature Review

Many researchers have developed various approaches in order to get the best performance of the model, using various machine learning techniques and deep learning architectures, or hybrid approaches. Let us look a few of them.

The authors in (Narang et al., 2024) operate to enhance misleading information detection powers by merging sentiment analysis techniques with text feature extractions. Their aim centers around building an effective method to detect false news within the current fast-paced digital era. The research draws from three different datasets including Covid-19.The proposed method delivers substantial performance gains that reach 20% accuracy betterment for detecting 2 classes in LIAR and 30% betterment when classifying 6 classes.TextGT in (Yin and Zhong, 2024) represents a new Aspect Based Sentiment Analysis(ABSA) approach which incorporates a double-view graph Transformer model according to the authors. The method implements specialized GNN layers for text graphs alongside Transformer layers for sequences while connecting them for resolving over-smoothing problems. The authors developed a new edge feature-enhanced graph convolution algorithm named TextGINConv for performance enhancement.The authors in (Alfreihat et al., 2024) create Emoji Sentiment Lexicon (Emo-SL) as part of their research to enhance sentiment analysis for Arabic tweets. The main goal focuses on managing the difficulties which arise from informal Arabic text specifically because of morphological complexity alongside language dialect variations. Combination of Emoji-based aspects with ML methods achieve enhanced sentiment classification because of their hybrid approach. A total of 58,000 Arabic tweets enter the dataset because they incorporate emojis. The collected dataset gathers tweets from the Arabic Sentiment Twitter database for achieving balanced positive/negative sentiment distribution. The model achieves an F1 score of 89% from sentiment classification and 26.7% in emoji feature extraction.
The authors in (Bilal et al., 2024) have set a goal to enhance sentiment classification accuracy through deep sequential feature combination with Random Forest (RF) technique application. The experimental results show that the proposed model detected 99.631% correct responses from the dataset which surpassed five baseline algorithms substantially. The research in (Li and Chen, 2024) investigates public discussions that focus on Virtual Humans together with their technological advancement and virtual idol and streamer applications and corporate investment along with policy strategies.The analysis tracked emotional tendencies as part of sentiment analysis procedures. Statistical analysis shows user discussions focus mainly on technological advancements of VHs and yield positive user reactions at 87.10%.This authors in (Mahmud et al., 2024) created a benchmark dataset dedicated to analyze sentiment in Cricket social media contents written in Bangla whereas the text comes from low-resource settings. The main purpose is to build better sentiment analysis tools for the Bangla language through an emphasis on cricket analysis since this content category stands as a major interest for Bangladesh. The research division established two parts for the dataset: training at 80% and testing at 20% which enabled a reliable assessment of model performance.Researchers in (Liu et al., 2024) work to resolve Multimodal Sentiment Analysis (MSA) difficulties which appear when uncertain missing modalities exist. The research introduces MTMSA which represents a novel modality translation-based Multi-Modal Sentiment Analysis model that improves sentiment classification outcomes through the proper use of text and audio and visual data. Gradual monologue videos in the CMU-MOSI dataset contain 2,199 instances that receive emotional score values between -3 & +3 and IEMOCAP presents extensive multimodal information for sentiment analysis. The authors in (Alsemaree et al., 2024) focus on sentiment analysis (SA) of Arabic social media texts, specifically targeting customer perceptions in the coffee industry. The text employs two methods of feature extraction for sentiment classification accuracy: Term Frequency-Inverse Document Frequency (TF-IDF) and Minimum Redundancy Maximum Relevance (MRMR). The researchers apply four supervised learning algorithms: KNN, support vector machine, decision tree and random forest for their analy-

sis. The newly proposed method reached an exceptional accuracy threshold of 95.95% using hard voting and 94.51% using soft voting. The authors in (Low et al., 2024) focus on creating a machine learning process which identifies and categorizes sexual harassment instances within literary documents while overcoming human interpretation shortcomings. Evaluation results demonstrated that the proposed LSTM-GRU deep learning model obtained 75.8% accuracy in sexual harassment type classification with superior performance compared to other five models. The same model design implemented for sentiment classification achieved an accuracy level of 84.5%. The authors in (Ramzy and Ibrahim, 2024) studied Arabic COVID-19 mobile health (mHealth) application user satisfaction by analyzing user review sentiments. The analysis used manual annotation of a representative 8,220 reviews to guarantee accurate sentiment identification. Six different machine learning systems consisting of Support Vector Machine (SVM), K-Nearest Neighbor (KNN), Naive Bayes (NB) and Logistic Regression (LR), Random Forest (RF) and Artificial Neural Network (ANN) were used to evaluate review sentiment. The ANN model revealed the best performance because it reached 89% accuracy and 89% F1 score. The study in (Lossio-Ventura et al., 2024) explores methods to assist healthcare providers and researchers with applying sentiment analysis tools to health-related free-text survey data when dealing with COVID-19. The authors used multiple human raters to establish gold-standard labels for a portion of their datasets that functioned as evaluation criteria for various sentiment analysis methods. The performed analysis demonstrated ChatGPT surpassing other sentiment analysis tools while also reaching superior accuracy values and F-scores. The accuracy scores from ChatGPT surpassed OPT by 6% and its F-measure results exceeded those of OPT by 4% to 7% across all datasets.

3 Proposed Framework

This section presents the proposed method that has been implemented on 2 different datasets. We begin our discussion on the proposed method from data collection, then going towards data preprocessing. After that, we will delve into exploratory data analysis(EDA). Next discussion will be on data augmentation, and then going through data distribution. Finally, we will describe our proposed methodology.

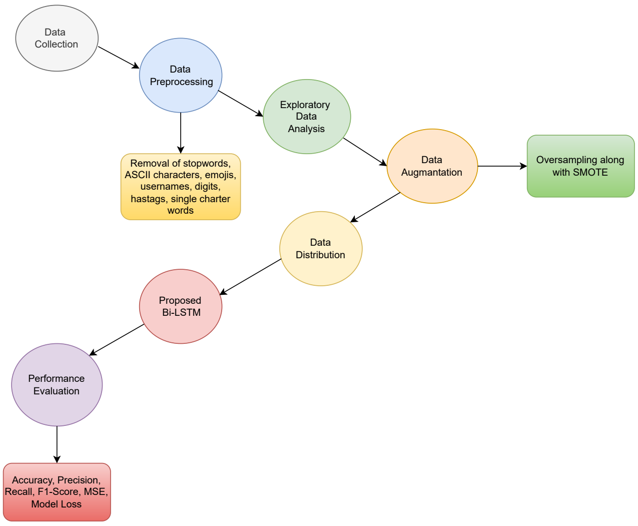


Figure 1: Proposed Workflow for the Sentiment Analysis using Bi-LSTM technique

3.1 Data Collection

We performed our experiment on the following datasets:

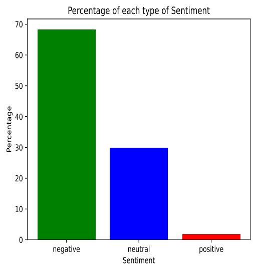
1. **HinGE Dataset:** The data originated from (Srivastava and Singh, 2021a), and futher used in (Jadon et al., 2024) provides 395, 2766, & 768 samples respectively for validation and training and testing purposes. The datasets present 3 sections namely "English," "Hindi" and "Hinglish" with synthetic Hinglish versions of Hindi & English.

2. **SemEval-2020 Task 9:** This dataset centers its analysis on the Twitter datasets of both Hinglish (Hindi–English) code-mixing along with Spanglish (Spanish–English). Comprising 19,000 tweets in Spanglish and 20,000 tweets in Hinglish contains sentiment classification and linguistic annotations for each tweet.

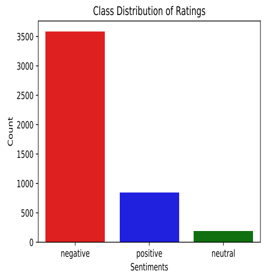
3. **E-Commerce Reviews Dataset:** This dataset has been generated by taking reviews from several E-Commerce platforms. It exhibits 10,000 reviews and their sentiment class distribution in "positive", "neutral" or "negative".

3.2 Data Preprocessing

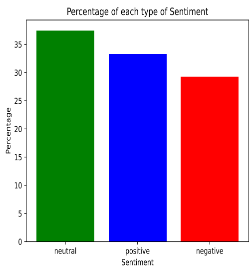
Initiating the process requires removing all additional symbols including #,,, %, and $.



(a) Dataset 1



(b) Dataset 2



(c) Dataset 3

Figure 2: Sentiment Class Distribution

Lowercase conversion of text represents one text cleaning operation while the removal of non-ASCII characters and numeric value stripping and punctuation mark elimination and hashtag symbol deletion and username blocking are additional procedures. Transaction tags ('RT') disappear while brief words and Hindi numerical digits are trimmed and URLs become indicated as "URL." The normalization process controls backslashes to improve consistency within the text data. Through their collective approach multiple cleaning techniques create a refined "processed text" column which ensures the Hinglish tweets undergo methodical cleaning procedures to become standardizable and free of noise until natural language processing can be employed.

3.3 Exploratory Data Analysis

The exploratory data analysis (EDA) approach serves as an advanced analytical stage to perform a complete evaluation of dataset quality together with its structural elements. Statistical and visual tools help researchers detect patterns and deviation points to determine suitable traits for future analysis during this method.

3.4 Data Augmentation

The data augmentation technique transforms training datasets to improve their overall quality together with their range of content while also making them more resistant to errors. The techniques create expanded datasets through processed variations of available data which maintain its original meaning or structural elements. We used 2 such techniques in our dataset - Oversampling along with SMOTE.

- **Oversampling:** Oversampling is conceptually simple: it duplicates existing samples from the minority class. Mathematically, this process involves selecting a sample x_i from the minority class dataset X_{minority} and adding it multiple times to the dataset. Let $X_{\text{minority}} = \{x_1, x_2, \ldots, x_m\}$ represent the minority class samples & X_{new} represent the augmented dataset after oversampling. The procedure of oversampling can be expressed as:

$$X_{\text{new}} = X_{\text{minority}} \cup \bigcup_{j=1}^{k} \{x_i \mid x_i \in X_{\text{minority}}\}$$

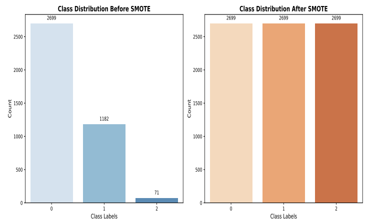
  Here k is the number of times each sample x_i is duplicated & the union operation ($\cup$) indicates that the original minority samples are combined with their duplicates. For example, if $X_{\text{minority}} = \{[1,2],[3,4]\}$ and $k = 2$, then:

$$X_{\text{new}} = \{[1,2],[3,4],[1,2],[3,4],[1,2],[3,4]\}$$

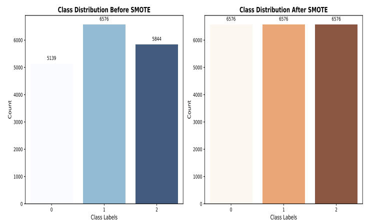
- **Synthetic Minority Over-sampling Technique(SMOTE):** SMOTE generates synthetic samples by interpolating between existing minority-class samples. It calculates new points along the line segment connecting a sample x_i and one of its k-nearest neighbors x_j. Suppose $X_{\text{minority}} = \{x_1, x_2, \ldots, x_m\}$ represent the minority class samples, $\text{NN}_k(x_i)$ denote the set of k-nearest neighbors of x_i in feature space & $\lambda \in [0,1]$ represent a random interpolation factor. Then For each sample $x_i \in X_{\text{minority}}$ will randomly select a neighbor $x_j \in \text{NN}_k(x_i)$ and generate a synthetic sample x_{synth} as:

$$x_{\text{synth}} = x_i + \lambda(x_j - x_i)$$

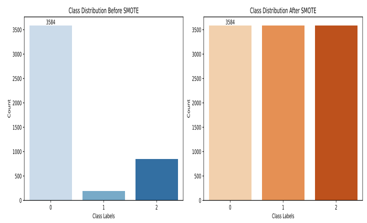
  where x_i is the original sample, x_j is the selected neighbor & λ controls the position of the synthetic point along the line segment between x_i and x_j. The augmented dataset X_{new}



(a) Dataset 1



(b) Dataset 2



(c) Dataset 3

Figure 3: EDA before and after Data Augmentation in all 3 datasets

is described as:

$$X_{\text{new}} = X_{\text{minority}} \cup \{x_{\text{synth}} \mid x_{\text{synth}} \text{ generated using the above formula}\}$$

3.5 Data Distribution

The application of an 70:20:10 data splitting ratio stands as a vital process step when dealing with sentiment analysis for Hinglish textual information ratio. The data was arranged into three subsets where validation data represents 20% of total data and test data comprises 10% of total data supplementary to training data containing the remaining 70%.

3.6 Proposed Model

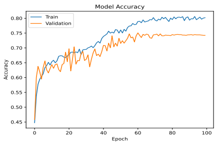
The implemented model utilizes a Bidirectional LSTM architecture that analyzes sequential data from forward and backward time sequences. The bidirectional method delivers the model access to contextual information flowing from past and future time points which boosts its ability to spot complex dependencies between sequence inputs. LSTMs enable strong performance in sentiment analysis and other applications with complex linguistic structures specifically in Hinglish language. The updation process governing the LSTM cell is shown in algorithm 1.

Algorithm 1 LSTM Cell Updation

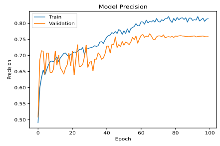
Step 1: Data Preparation and Splitting
for each sample $(x_i, y_i) \in \mathcal{D}$ **do**
  $x_i \leftarrow \texttt{LOAD}(x_i)$
  $x_i \leftarrow \texttt{PREPROCESS}(x_i)$
  $\mathcal{D} \leftarrow \mathcal{D} \cup \{(x_i, y_i)\}$
end for
$(\mathcal{D}_{\text{train}}, \mathcal{D}_{\text{test}}) \leftarrow \texttt{SPLIT}(\mathcal{D}, r = 0.2)$
Step 2: Model Definition and Training
Define model architecture: $\Phi \leftarrow \texttt{Sequential}(\text{FC}, \text{BN}, \text{Dropout}, \texttt{BiLSTM}, \text{FC})$
Initialize parameters θ, optimizer Adam$(\eta = 0.001)$, and regularizers
for epoch = 1 to max_epochs **do**
  for each batch $B = \{x_j\}_{j=1}^{b} \in \mathcal{D}_{\text{train}}$ **do**
    $\hat{y}_j = \Phi(x_j)$
    $\mathcal{L} = \texttt{CrossEntropy}(\hat{y}, y) + \lambda \|\theta\|_2^2$
    $\nabla_\theta \mathcal{L} \leftarrow \texttt{BACKWARD}()$
    $\theta \leftarrow \texttt{OPTIMIZE}(\theta, \nabla_\theta \mathcal{L})$
  end for
  Evaluate validation loss $\mathcal{L}_{\text{val}}$
  if $\mathcal{L}_{\text{val}}$ not improving for `patience` epochs **then**
    `EarlyStopping` $\rightarrow$ break
  else if reduce_on_plateau condition met **then**
    $\eta \leftarrow \max(\eta \cdot 0.5, 10^{-6})$
  end if
end for
Step 3: Save and Deploy Model
$\theta^* \leftarrow \texttt{SAVE\_MODEL}(\theta)$
$\Phi^* \leftarrow \texttt{LOAD\_MODEL}(\theta^*)$

4 Results & Discussion

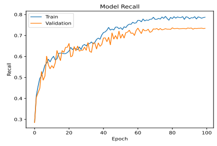
The use of Bidirectional LSTMs enhances the model's ability to capture both short-term and long-term dependencies in sequential data. This capability is crucial for analyzing the nuanced structure of Hinglish text, where context plays a vital role in determining sentiment. Additionally, the incorporation of regularization techniques such as dropout and L2 regularization ensures robust feature extraction and prevents overfitting, further improving the model's generalization capabilities. The model is compared on the basis



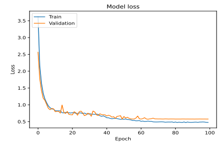
(a) Accuracy



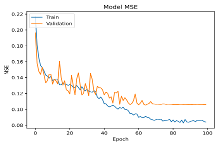
(b) Precision



(c) Recall

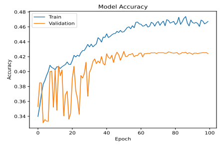


(d) Loss

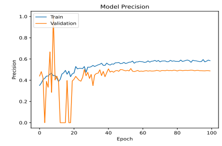


(e) MSE

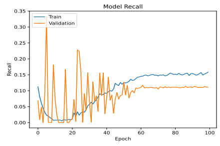
Figure 4: Learning Curve Analysis for the proposed Bi-LSTM model against Dataset 1(HinGE)



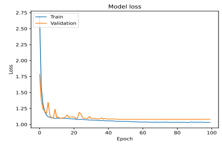
(a) Accuracy



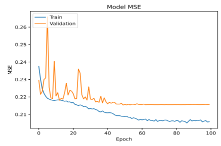
(b) Precision



(c) Recall



(d) Loss



(e) MSE

Figure 5: Learning Curve Analysis for the proposed Bi-LSTM model against Dataset 2(SemEval)

of the following metrics(Bala Das et al., 2023; Das et al., 2025):

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

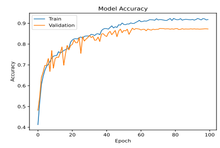
$$\text{Precision} = \frac{TP}{TP + FP}$$

$$\text{Recall} = \frac{TP}{TP + FN}$$

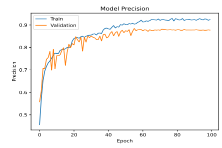
$$\text{F1-Score} = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$$

$$\text{MSE} = \frac{1}{N} \sum_{i=1}^{N} (y_i - \hat{y}_i)^2$$

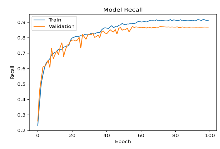
When we compared our model with the previously implemented models, the model was able to achieve the performance of the models on different datasets. As shown in Table 1, it gives us the 2nd highest performance in dataset 1. If we refer to Table 2, it again perfroms 2nd best performance in dataset 2. If we look at Table 3, it comes out to be the 5th best model among all the algorithms, which is in dataset 3.
In generalization, we can say that the model will perform as same as the previously implemented models, but it will generation of Model loss as shown in fig 4, 5, 6 respectively, and MSE will be low as compared to other models. In some cases, it will also outperform other models.



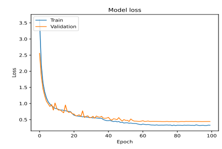
(a) Accuracy



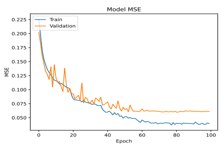
(b) Precision



(c) Recall



(d) Loss



(e) MSE

Figure 6: Learning Curve Analysis for the proposed Bi-LSTM model against Dataset 3(E-Commerce reviews)

5 Conclusion & Future Work

This paper implements a Bidirectional LSTM (BiLSTM) network as an efficient approach to resolve linguistic challenges existing in the combined Hindi & English language. The model stands out in detecting sentiment properly because it processes contextual information together with word relations. The proposed model the BiLSTM architecture features its optimization capabilities for feature extraction while speeding up training time to reach accurate results. The model delivers exceptional

Model	F1-Score	MSE
Classifier Neural Network + Multilingual BERT (Furniturewala et al., 2022)	0.234	3.000
Bi-LSTM (Guha et al., 2022)	0.098	6.000
M-BERT (Srivastava and Singh, 2021b)	0.202	2.797
Proposed BiLSTM with SMOTE	**0.742**	**0.106**

Table 1: Quantitative Analysis of Dataset 1

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score
HF-CSA (Raza et al., 2023)	76.18	81.61	73.86	0.234
CNN (Angel et al., 2020)		51.00	49.60	0.458
GRU (Angel et al., 2020)		35.80	37.30	0.290
Proposed BiLSTM with SMOTE	**42.41**	**48.78**	**11.10**	**0.390**

Table 2: Quantitative Analysis of Dataset 2

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score
SVC (Ahmed and Ahmed, 2024)	91.71	91.81	91.76	0.916
KN (Ahmed and Ahmed, 2024)	72.05	75.13	71.93	0.715
NB (Ahmed and Ahmed, 2024)	79.14	79.18	79.19	0.791
DT (Ahmed and Ahmed, 2024)	87.14	87.80	87.25	0.868
LR (Ahmed and Ahmed, 2024)	88.62	88.74	88.64	0.885
RF (Ahmed and Ahmed, 2024)	92.13	92.15	92.14	0.920
AdaBoost (Ahmed and Ahmed, 2024)	67.90	68.41	67.78	0.676
BgC (Ahmed and Ahmed, 2024)	88.41	88.85	88.51	0.881
ETC (Ahmed and Ahmed, 2024)	92.97	93.06	92.92	0.929
GBDT (Ahmed and Ahmed, 2024)	72.40	73.32	72.28	0.721
XGB (Ahmed and Ahmed, 2024)	86.58	86.92	86.59	0.864
Proposed BiLSTM with SMOTE	**87.29**	**87.73**	**86.86**	**0.870**

Table 3: Quantitative Analysis of Dataset 3

performance with accuracy of 74.24%, precision of 75.85% with recall value of 73.42% , F1-Score of 0.742 & MSE of 0.106 for dataset 1. For dataset 2, the values are 42.41%, 48.78%, 11.10%, 0.390 & 0.215 respectively. If we look at dataset 3, the values vary from 87.29%, 87.73%, 86.86%, 0.870 & 0.215 respectively.

Future studies should focus their research on enhancing model generalization and robustness through specific improvement areas which these current constraints have identified. The model needs domain adaptation strategies or transfer learning approaches to achieve better generalization between different Hinglish usage patterns.

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