Hybrid CNN LSTM Approach for Sentiment Analysis of Bengali Language Comment on Facebook

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***Abstract*—This study addresses the challenge of sentiment analysis in Bengali Facebook comments, where users express their opinions on various topics. Existing sentiment analysis techniques have difficulty achieving high accuracy in this situation, which has inspired the creation of a fresh methodology. To improve sentiment analysis of Bengali Facebook comments, we suggest a model that combines a hybrid convolutional neural network (CNN) and a long short-term memory network (LSTM). Our research adds to the expanding area of sentiment analysis, especially for languages with few resources, such as Bengali. The success of the Hybrid CNN LSTM model opens the door for more precise and context-aware sentiment analysis on social media platforms, allowing for a better understanding of user sentiments and boosting user experiences. Our study focused on dividing comments into five groups according to their emotional content: troll, not bully, sexual, religious, and threat. We carefully generated the handmade dataset and ensured the quality and relevance of a dataset of 50,000 Bengali comments before using it to train and test our algorithm. The Hybrid CNN LSTM model outperforms conventional approaches and achieves an outstanding accuracy rate of 92.09%, demonstrating amazing efficiency in sentiment recognition. This dramatic increase in precision indicates that machine learning techniques are successful in sentiment analysis of Bengali Facebook comments.**

***Index Terms*—NLP, Sentiment, CNN, Facebook, LSTM, Fully Connected Layer, Hybrid, Bengali Language, Comment, Predict.**

I. Introduction

Sentiment analysis on Facebook is an analysis of sentiments or emotions conveyed in the text data created by users on the platform. It is [1] a process that aims to understand how users perceive and express their feelings about different subjects. By analyzing user posts, comments, and interactions, Facebook can gain insight into whether the sentiment expressed is positive, negative, or neutral. Insights derived from sentiment analysis are valuable for Facebook in several ways. First, it helps [2] in enhancing the user experience by tailoring content and recommendations based on user sentiment. By understanding what users appreciate or dislike, Facebook can provide a more personalized and relevant experience for its users. Second, sentiment analysis [3] enables Facebook to personalize content and advertisements. By analyzing the sentiments associated with specific topics or brands, Facebook can deliver targeted content and ads that align with users' interests and preferences. This personalization enhances user engagement and improves the effectiveness of advertising campaigns. Thirdly, sentiment analysis [4] allows Facebook to monitor its brand reputation. By analyzing user sentiments towards brands or products, Facebook can assess the overall perception and reputation of these entities. This information [5] is valuable for businesses to understand public opinion and make informed decisions to effectively manage their brand image. Additionally, sentiment analysis helps Facebook to identify emerging trends. By tracking sentiments associated with certain keywords or topics, Facebook can detect shifts in public sentiment and identify emerging trends or discussions. This [6] info is crucial for users, marketers, and advertisers to stay informed and engage meaningfully. Sentiment analysis is vital for content moderation, aiding platforms like Facebook in identifying and addressing potentially harmful content to ensure a safe and positive user environment.

Our specialty is to create and manage the Bengali language We specialize in managing Bengali-language Facebook comments and enhancing client experiences. Bengali [7] spoken by over 245 million people worldwide, is the 7th most spoken language. While research in Bengali language processing is less extensive than in English or other major languages, it holds significant potential. Our primary focus is translating comments from Bengali Facebook users, contributing to the early development of this technology.

We combine Natural Language Processing and machine learning with human expertise to understand user sentiment on social media effectively. Our foundation is a carefully curated

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dataset of 50,000 Bengali comments sorted by sentiment. Using a Hybrid CNN LSTM Model, we've achieved an impressive 92.24% precision in sentiment detection, matching human interpretation accuracy.

Our focus was on sentiment analysis of Bengali-language Facebook comments, as most users in Bangladesh express their views in this manner. The availability of a meticulously curated dataset of 50,000 Bengali comments was crucial for this research. It allows us to analyze sentiment trends and patterns in the Bengali-speaking Facebook community effectively.

A. Contributions and Obligations

Our contributions and obligations are the following:

- Investigate methods to perform Sentiment Analysis in Bengali.
- Elaborate the importance and utility of Bengali sentiments and perform an analysis thereof.
- Apply many benchmark machine learning algorithms Sentiment Analysis.
- Apply a combination of the CNN-LSTM model to propose a hybrid approach for Sentiment Analysis.

The rest of this essay is divided into the following sections Section II displays the related works. The methodologies are expressed in section III. The results of the analyses are rendered in section IV. Finally, section V wraps up the work.

II. Related Work

Machine learning has been used in various ways, such as in banking [8], [9], healthcare [**?**], [10]–[12], and sentiment analysis. Sentiment prediction [13]–[16] seeks to identify and classify the opinions of the general population as either positive, negative, or neutral. A Hybrid CNN LSTM Model is advised to increase sentiment prediction and overall accuracy. As a result, sentiment analysis becomes more accurate by addressing problems with outdated techniques and ineffective datasets.

The outcomes showed that the mixture of IG. Expressing the product rating sentiment, Xu et al. [17] implemented on a large-scale, multi-domain e-commerce platform. The parameter evaluation method was expanded to include NB for continuous learning mode as a result. Then, a variety of techniques were proposed to improve the learned distribution based on the three types of assumptions. The outcomes demonstrated that the suggested model had good accuracy for the movie and product review sentiment dataset on Amazon. Maqsood et al. [18] investigated the effects of several events that occurred between 2012 and 2016 on the stock market in 2020. The sentiment analysis for each of these occurrences was computed using the Twitter dataset in this case. Millions of tweets made up the dataset, which was used to gauge the event's emotional impact.

Some authors directly used the classification approach for predicting sentiment. They focused only on classification based on machine learning techniques. Afzar et al. [19] suggested aspect-based tuning as a novel method, with a focus on accurately identifying characteristics. A mobile application was developed to help users find the best hotels, and the model's performance was validated using real datasets. Results indicated that the model was successful in both detection and classification tasks. Arabic language sentiment analysis issues To enhance SA in Arabic, Belgacem et al. [20] created a technique that aims to extract subjective elements from document evaluations. They then offered a technique for extracting pertinent opinions, like review summaries and concluding opinions. To improve the outcomes of opinion classification, a hybrid strategy was suggested. Finally, based on the customer value model, they presented a way for assessing consumer opinions by identifying variables that affected their attitudes. Their categorization performance in F-Measure was 96%.

For addressing real-time data for in-depth emotion prediction, Kumar et al. [21] implemented ConVNetSVMBoVW, a combination of deep learning techniques and SVM. They had built a synthetic model to measure hybrid polarization. Additionally, the BoVW was trained using the SVM to anticipate the emotions of the visual content. In the end, it was found that the suggested ConvNet-SVMBoVW outperformed traditional models. Combining Deep learning and Machine learning, Ray et al. [22] addressed textual features and assessed user sentiment concerning those features. The characteristics were tagged with opportunistic phrases using a seven-layer Deep CNN. The performance of sentiment scoring and feature extraction models was enhanced by the authors using deep learning approaches with a collection of rule-based models. The suggested approach was found to have the highest accuracy in the end.

III. Research Methodology and Implementation

Here, we show how to predict sentiment utilizing the CNN Part, LSTM Part, and Fully Connected layers of our Hybrid CNN LSTM model. Additionally, word embedding, convolutional layers, pooling layers, sequential layers, etc. are all included in the architecture of our hybrid CNN LSTM model to predict sentiment. Figure 2 displays the overall Architecture of the Hybrid CNN LSTM Model and classification methodology for predicting sentiment.

A. Dataset Analysis

You have a dataset with 50,000 records that is divided into 80% training records and 20% testing records. There are 19,000 men and 31,000 women, all with different jobs. Troll (25.5%), not bully (36.5%), threat (4.17%), religious (15.7%), and sexual (18.2%) are all represented in the sentiment reactions distribution. There are 15,000 testing samples and 34,999 training samples available. Your training data is displayed as a "training_sentences" one-dimensional vector with a shape of (34999). The "train_labels" two-dimensional array contains the training labels, which have the shape (34999, 5), which denotes 34,999 rows and 5 columns.

B. Bengali Comment Processing and Feature extraction

In Figure 1, the Hybrid CNN-LSTM model captures both local and long-term text features and classifies them based on emotion labels using fully connected layers. This model is useful for a variety of natural language processing applications, including sentiment analysis and opinion mining in Bengali text. It was trained using a loss function and optimization approaches. It can handle word-to-vector translation using programs like Bangla Glove and Word2Vec, evaluate word significance using TF-IDF, and classify sentiment in machine learning models using Bag of Words (BOW).

C. Hybrid CNN LSTM Model Implementation

A hybrid CNN LSTM model processes sequential text data by combining CNNs and LSTMs. CNNs focus on local patterns, while LSTMs address long-range dependencies. This architecture is useful for projects like sentiment analysis, text categorization, and natural language sequence modeling. Our proposed model architecture for the Hybrid CNN LSTM is outlined in Figure 2.

1) Word Embedding: A CNN LSTM hybrid model uses word embeddings to represent words as continuous vectors, understanding their meanings and relationships to classify text sentiment as positive, negative, or neutral.

- Word Embedding Layer:

$$w1, w2, w3, ..., w\_n \tag{1}$$

  Each word ‘wi‘ is represented by a vector ”E(wi)” obtained from a pre-trained word embedding matrix. The embedding function maps words to their respective embeddings:
- CNN Part: The CNN part processes word embeddings, treating them as spatial features. The output of the CNN operations applied to the word embeddings is represented as ”CNN_output”:

$$CNN\_output = CNN(E(w1), E(w2), E(w3), ..., E(wn)) \tag{2}$$

$$E(wi) = WordEmbedding(wi) \tag{3}$$

- LSTM Part: The LSTM network processes ”CNN_output” sequentially, capturing temporal dependencies in word embeddings. LSTM hidden states evolve steps, enabling context understanding.

$$LSTM\_output = LSTM(CNN\_output) \tag{4}$$

- Fully Connected Layers: The final LSTM hidden state or a combination of its states can be fed into the fully connected layers for sentiment classification. The output of these layers can be interpreted as sentiment probabilities:

$$sentiment\_probabilities = FullyConnected(LSTM\_output) \tag{5}$$

2) Convolutional layer: A Hybrid CNN LSTM model for sentiment analysis combines CNN to extract word-level patterns and LSTM to capture context and temporal dependencies.

- Word Embedding Layer: As previously mentioned, the input sentence is represented as a sequence of word embedding:

$$E(w1), E(w2), E(w3), ..., E(wn) \tag{6}$$

  Each ”E(wi)” is a continuous vector representation of the corresponding word ”wi”.
- Convolutional Layer: The Convolutional layer applies small filter kernels to word embeddings, detecting local patterns, similar to CNNs in image data. However, it convolves along the sequence of word embeddings.
  Let us denote the convolutional operation as ”Conv()”, and the filter/kernel as ”F”. The output of the convolution operation, or the ”feature map,” is denoted as ”C”:

$$C = Conv(E(w1), E(w2), E(w3), ..., E(wn), F) \tag{7}$$

  The filter ”F” is learned during the training process and is used to extract relevant features from word embeddings.

- Pooling Layer: Following the convolutional operation, max pooling is often applied to downsample the feature map and to retain the most important information. Max pooling involves the selection of the maximum value within each pooling window. The output of max pooling is denoted as ”P”:

$$P = MaxPooling(C) \tag{8}$$

  Max pooling helps reduce the spatial dimensionality while preserving the most salient features.

- Flattening and Transition to LSTM: After max pooling, the feature map is typically flattened to be compatible with the input requirements of the subsequent LSTM layers. The flattened features are then fed into the LSTM network to capture the temporal dependencies and context.

3) Pooling layer: In a Hybrid CNN LSTM model for sentiment analysis, a pooling layer follows the convolutional layer to reduce feature map dimensions and preserve vital information. Max pooling is often employed for this purpose, improving computational efficiency and feature extraction.

- Convolutional Layer Output: After the convolutional layer processes the input word embeddings, it generates a feature map. This feature map consists of a grid of values that represent the extracted features.

$$FeatureMap : C = [c1, c2, c3, ..., cn] \tag{9}$$

- Max Pooling Layer: it divides a feature map into windows and selects the maximum value in each window, emphasizing local features and producing a downsized grid of maximum values. The working logic is equation 8.
  P = MaxPool(C) The operation involves selecting the maximum value within each pooling window, resulting in a reduced dimensionality of the feature map.

  Flattening: The pooled features are typically flattened into a one-dimensional vector to be compatible with

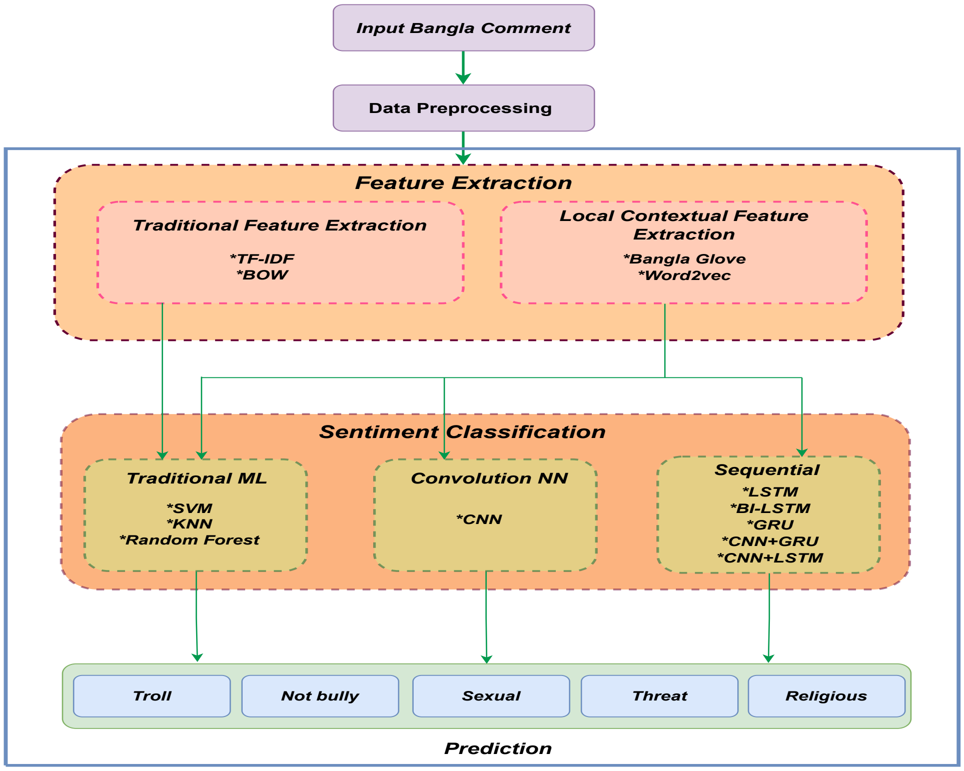

Fig. 1. Sentiment Predict with feature extraction and Language processing

subsequent LSTM layers. Flattening essentially converts a grid of pooled values into a linear sequence.

$$FlattenedFeatures : F = [f1, f2, f3, ..., fn] \quad (10)$$

The mathematical expression for a max pooling layer in a hybrid CNN LSTM model is as follows:

$$y = max(x) \quad (11)$$

The max pooling layer takes the maximum value in each subregion of the input feature map. This results in a feature map with a smaller size, but which still contains the most important features.
The mathematical expression for an average pooling layer in a hybrid CNN-LSTM model is as follows:

$$y = mean(x) \quad (12)$$

Average pooling calculates the average value within each subregion of the input feature map, reducing its size while preserving the average feature values.
4) Sequential layer: The sequential layer consists of Input Text Representation, CNN Layers, Max Pooling, Flattening, LSTM Layers, Fully Connected Layers, and Output Layer. Mathematically, the sequential layer (LSTM) part of the hybrid CNN LSTM model can be represented as follows:
Let's assume:

- Input sequence of word embeddings: X = [x, x, ..., x_T], where T is the sequence length.
- LSTM hidden state at time step t: h_t
- LSTM cell state at time step t: c_t

The LSTM equations are given by:

Forget Gate: f_t = (W_f * [h_t-1, x_t] + b_f)
Input Gate: i_t = (W_i * [h_t-1, x_t] + b_i)
Candidate Cell State: ĉ_t = tanh(W_c * [h_t-1, x_t] + b_c)
Updated Cell State: c_t = f_t * c_t-1 + i_t * ĉ_t
Output Gate: o_t = (W_o * [h_t-1, x_t] + b_o)
Hidden State: h_t = o_t * tanh(c_t)

D. Finding Sentiment or output

The output of the LSTM layers, h_T, is fed into a dense layer:

$$z = W\_dense * h\_T + b\_dense \quad (13)$$

Softmax Activation: The output of the dense layer, z, is then passed through the softmax activation function to obtain the predicted sentiment probabilities for each class.

$$Y\_pred = softmax(z) \quad (14)$$

In mathematical terms, the softmax function applied element-wise to the vector z is defined as:

$$softmax(z)\_i = exp(z\_i)/sum(exp(z\_j)jall\_classes) \quad (15)$$

where exp is the exponential function and i ranges over all sentiment classes.

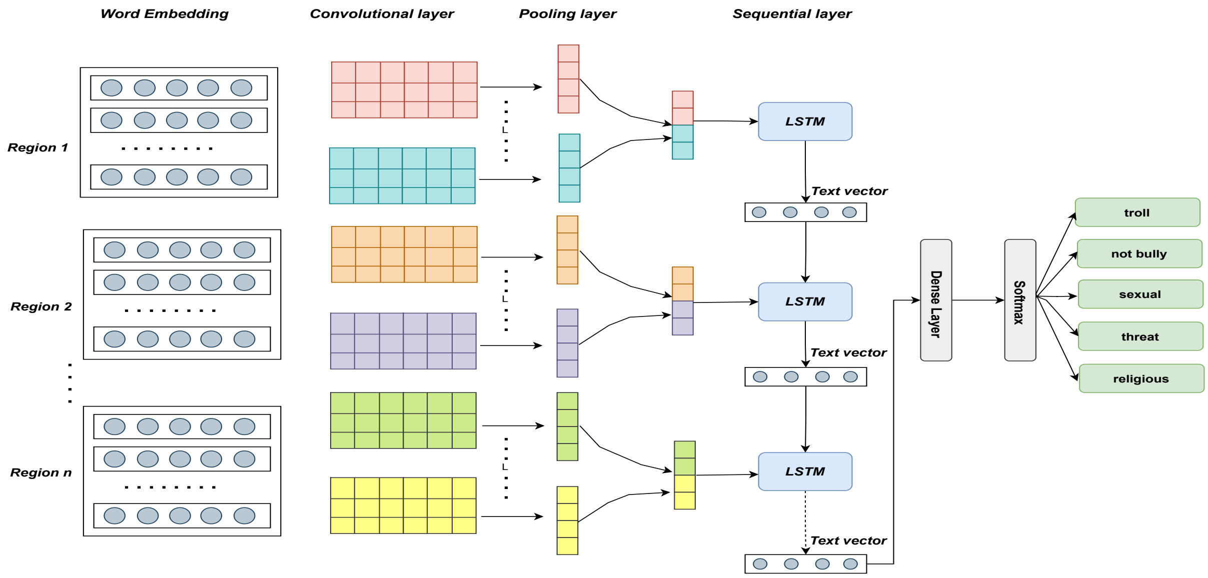

Fig. 2. Sentiment Prediction with Hybrid CNN LSTM Model Architecture

IV. Implement Result

We analyze the performance of our sentiment analysis system during training and testing in detail in the results section. Using criteria like accuracy, precision, recall, F1 score, and support, we analyze the distribution of commenters and categorize them. To provide a clear and thorough evaluation of our sentiment analysis method, we also analyze training loss, offer a confusion matrix, and summarise sentiment prediction outcomes using several methods.

A. System Performance Measurement

We evaluate our sentiment classification model's accuracy using essential metrics: True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN). These metrics offer insights into the model's performance in sentiment categorization. Figure 3 visually presents the accuracy across epochs.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{16}$$

Table I displaying precision, recall, and F1 score provides a clear visual representation of a machine learning or classification model's performance.

TABLE I
Precision, Recall, F1 score and Support for five sentiment

Sentiment	Precision	Recall	F1 Score	Support
Not Bully	0.70	0.81	0.75	3620
Troll	0.65	0.57	0.61	2582
Sexual	0.68	0.64	0.66	1836
Religious	0.85	0.79	0.82	1540
Threat	0.64	0.48	0.55	422

Precision: Precision in machine learning assesses the accuracy of positive predictions by calculating the ratio of true positive instances to all instances labeled as positive, indicating the model's ability to correctly identify positive cases.

$$Precision = \frac{TP}{TP + FP} \tag{17}$$

Recall: Recall, or sensitivity, is a critical metric in machine learning and statistics that gauges the model's ability to accurately identify all actual positive instances among the total positive instances in the dataset.

$$Recall = \frac{TP}{TP + FN} \tag{18}$$

F1-score: The F1-score is a common metric in machine learning and statistics that provides a balanced evaluation of a model's performance, especially when precision and recall need to be balanced.

$$f1\ score = 2 * \frac{Precision * Recall}{Precision + Recall} \tag{19}$$

Support: Support in classification evaluations tallies instances for a class, revealing its importance and data distribution for metrics like precision, recall, and F1-score.

Our analysis shows a low model loss of 0.23 and a higher validation loss of 1.58. These losses were calculated during a 40-epoch training process. Figure 4 displays graphically the loss of the model over the number of epochs.

B. Determining Confusion Matrix

In Figure 5 we show the confusion matrix of five sentiments. it summarizes a classification model's performance by comparing predicted and actual class labels in a table format.

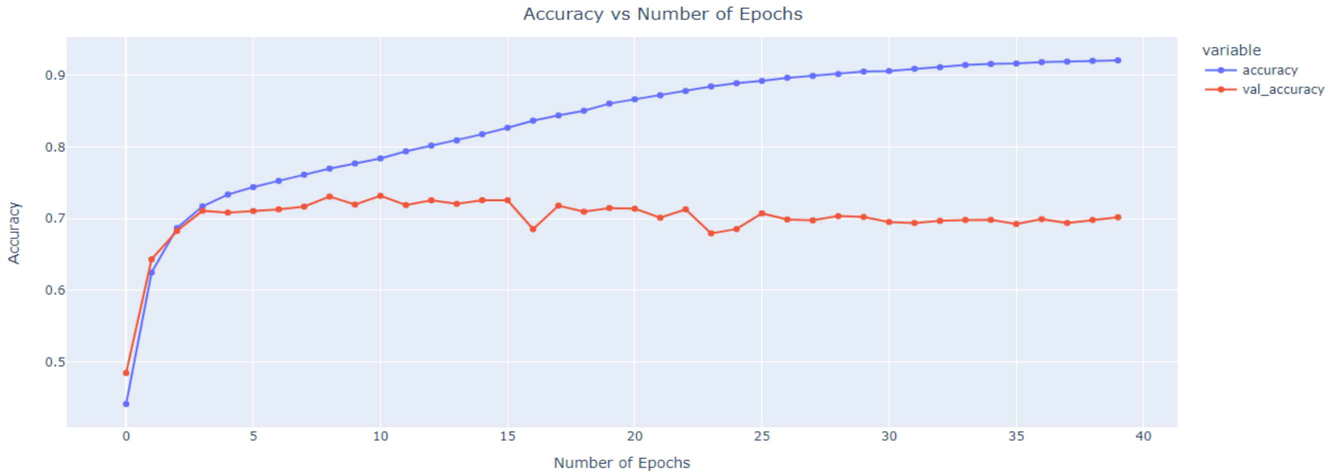

Fig. 3. Accuracy of Model With number of Epochs

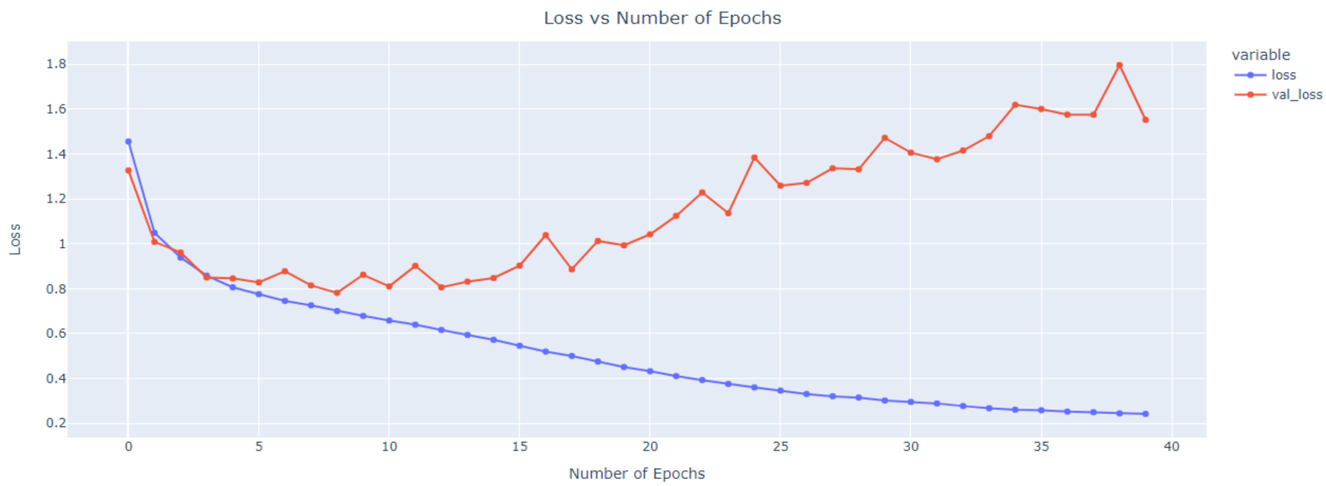

Fig. 4. Loss Counting With a Number of Epochs

C. Performance ratings of Different model what we Examined

We focused on accuracy and validation accuracy metrics. We also explored Random Forest and KNN for comparison. In deep learning, we evaluated LSTM, GRU, and Bi-LSTM, considering both past and future data. Our analysis guided us in selecting the most suitable models. Table II summarizes the model performances, with the hybrid CNN LSTM model emerging as the top performer, delivering the best results.

TABLE II
DIFFERENT MODEL'S ACCURACY AND VALID ACCURACY WHAT WE IMPLEMENT FOR OUR SYSTEM

Model/Classifier	Accuracy	Valid Accuracy
SVM	76.72%	54.98%
Random Forest	61.95%	48.29%
KNN	64.51%	52.32%
LSTM	85.89%	69.67%
GRU	88.84%	69.72%
Bi-LSTM	85.21%	68.59%
CNN+GRU	87.36%	70.17%
CNN+LSTM(Proposed)	**92.09%**	**74.77%**

D. Comparison of Existing and Proposed Model Result

In Table III we shows some novel model result what contain Facebook platform sentiment analysis

V. CONCLUSION AND FUTURE RESEARCH

The study developed a state-of-the-art Hybrid CNN LSTM model for sentiment analysis of Bengali Facebook comments, successfully predicting sentiment in five categories with a remarkable accuracy rate of 92.09%. The study carefully collected the data, evaluated it using a variety of representations, emphasized the value of Bengali sentiment analysis on social media, and demonstrated the model's potential for content control and user safety. Overall, it raises the bar in this industry.

We're dedicated to quality and pushing research to pro-

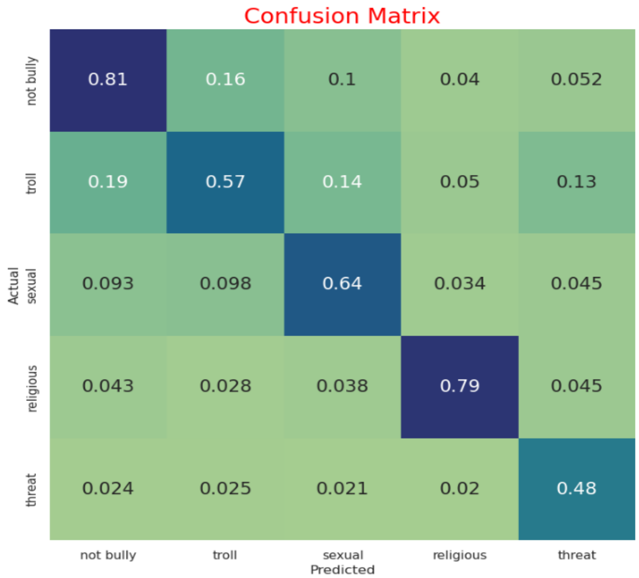

Fig. 5. Confusion Matrix of Five Sentiments

TABLE III
COMPARING THE PERFORMANCE AND LIMITATIONS OF EXISTING APPROACHES

Ref.	Dataset Type	Model	Accuracy
[23]	FB Message	SentBuk	83.27%
[24]	FB Status	MaxEnt	85%
[25]	Arabic Comments	Gaussian SVM	86.86%
[26]	FB Comment	ML Prediction	83.78%
[27]	Turkish FB Comment	RNN	91.60%
[28]	FB Comment	Lexicon	98%
[29]	FB comments	Lexicon and ML	90%
[30]	Bengali FB Comment	LSTM	96.95%
[Proposed]	**Bengali FB Comment**	**H.B CNN LSTM**	**92.09%**

vide superior results. Our main objective is to achieve unmatched accuracy in sentiment analysis, hence our focus is on modernizing and expanding our data integration to improve performance. We're leading the way in enhancing text production and sentiment analysis by utilizing cutting-edge technology like Generative Adversarial Networks (GANs). We are steadfast in our commitment to pushing limits and remaining at the cutting edge of technological innovation.

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