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Sentiment Analysis of Review Data: A Deep Learning Approach Using User-Generated Content

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Abstract - **As information technology progresses rapidly, social media platforms are experiencing exponential growth, accompanied by a surge in online content. Sentiment analysis (SA) of online evaluations has piqued the interest of researchers from various organizations, including academia, government, and private industry. It has become an increasingly hot area of study in the fields of Machine Learning (ML) and natural language processing (NLP). Deep Learning (DL) algorithms are currently being utilized in the same field to achieve remarkable results. Much SA research has been conducted in different languages such as English, Chinese, and Spanish, as well as various Indian languages like Hindi, Malayalam, and Bengali. However, languages like Assamese have received very little attention in this field of research. Hence, this research work provides a novel approach to sentiment analysis by demonstrating the effectiveness of deep neural network models for the less explored and scarce resource language, Assamese. This paper introduces a hybrid model, combining Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM), termed LSTM-CNN, for Sentiment Analysis (SA). Keras word embeddings are employed for vectorization of the data. To achieve outcomes, our proposed models have employed dropout, max pooling, and batch normalization techniques. Experimental analysis is carried out on user-generated review content by translating the Bengali dataset into Assamese. Comparison and evaluation of the built models have been done with traditional machine learning models in predicting sentiment polarity. Comparative analysis shows that all the proposed models outperform with an accuracy of more than 98%.**
Keywords: **Sentiment Analysis, Assamese, Natural Language Processing, Convolution Neural Network, LSTM, Keras Word Embedding**

I. INTRODUCTION

This research attempts to determine if a certain review is positive or negative. In this context, a variety of approaches have been used to obtain the results. Many researchers have done investigations in this field. Deep learning has evolved into a powerful machine learning system that can learn several layers of data representations or features and produce cutting-edge prediction outcomes [1,2,3]. Deep learning has become widely used in sentiment analysis in recent years, following its success in a variety of other application domains [4]. Deep learning is a branch of artificial neural networks in which the objective is to learn data using networks with several layers. A signal is processed in neural networks in a similar manner it is done in the neurons in live organisms [5].

Sentiment analysis is a computational method used to identify and classify opinions expressed in text, usually to evaluate whether the writer's stance on a particular topic is positive, negative or neutral. [6]. Sentiment analysis, commonly referred to as opinion mining, is a computer method for analysing people's perceptions and attitudes regarding diverse things such as products, services, personalities, topics, events, and themes [7]. Taking into account the rapid growth in visitors and user preferences, an automated system is necessary to comprehend the contextual polarity of reviewer opinions shared on different online platforms. Assamese is an Indo Aryan language primarily spoken in the state of Assam in India, with approximately 23 million speakers in the country and 15.4 million speakers worldwide [8].

This makes it an important language to study and develop sentiment analysis techniques for the same. The unique cultural and linguistic characteristics of Assamese pose challenges in sentiment analysis that are not present in other languages. Additionally, the lack of standardized dataset, existing research in this area creates an opportunity for innovative and groundbreaking work. In this work, the main aim is to fill this gap by proposing a novel approach to sentiment analysis specifically tailored for the Assamese language using deep learning techniques. The complexity of sentiment classification in Assamese is compounded by the scarcity of benchmark datasets and the limited availability of textual content or reviews in the language. Many researchers are finding that the analysis of sentiment in qualitative content using opinion mining is an interesting field of study [9,10].

This article presents three different deep learning models to implement sentiment analysis on user created review contents.with the help of translator tool datset has been created from the existing ones in bengali language. Bengali being the most similar language to Assamese, authors proposed to use this language for creating own

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datset.Supervised learning approach has been used here in this work as, the reviews were alreadynlabelled and structured too. A comparative analysis has also been performed with the existing classical machine learning techniques proposed by many other authors with the similar type of labelled review datsets.

The remaining part of the paper has been divided into several sections. Literature review on previous works is presented in section 2. Section 3 introduces about theoretical background of the deep learning models used for the proposed work. In section 4 and subsequently in section 5, the discussion revolves around the methodology of the proposed work, the results obtained on proposed model and its comparison with existing counterparts. Finally, section 6 concludes with future directions for research and acknowledges the limitations of this study.

II. LİTERATURE REVIEW

Researchers have explored various computational models for sentiment analysis in academic literature, using text mining, qualitative information, natural language processing to identify emotions and opinions [11,12] However, the challenge remains in developing a precise model that improves sentiment and emotion classification performance. Sentiment analysis is currently the most popular approach for measuring consumer sentiment and viewpoints in text and serves as a foundation for developing innovative models. The field of sentiment analysis encompasses a diverse range of technical aspects and is an emerging area of research that merges knowledge fusion through machine learning. It holds substantial potential as a research topic in the realm of artificial intelligence [13, 14].

The study by authors in [15] investigates the function of emotions in online discourse, specifically for Bangladeshi users who communicate their feelings in Bangla. It offers four models that integrate various Word Embeddings using Convolutional Neural Networks (CNN) along with Long Short-Term Memory (LSTM) methodologies. The top-performing model enhances text-based interactions on social media platforms by incorporating Word2Vec embedding into a CNN-LSTM hybrid architecture. It achieves an amazing accuracy of 90.49% and an F1 score of 92.83%. Authors in [16] examines sentiment analysis of Bengali tweets, focusing on the classification of tweet sentiment polarity into positive, negative, or neutral. Various deep learning techniques, including LSTM, BILSTM, and CNN, are compared for their effectiveness in categorizing emotional tones. The study also compares traditional machine learning approaches with deep learning techniques to determine which method performs better in analyzing and classifying sentiments in Bengali tweets. Overall, the research seeks to improve the comprehension of sentiment analysis within the realm of Bengali text data on social media platforms.

In [17], the efficacy of machine learning methodologies, including the deep learning models and the hybrid models, is investigated for text classification tasks in both English and Bangla languages. The primary focus of the study is sentiment analysis, which is conducted by analysing feedback and comments from the popular Bengali e-commerce platform "DARAZ”. As part of the research methodology, seven machine learning models and various deep learning models, such as Long Short-Term Memory (LSTM), Bidirectional LSTM (Bi-LSTM), Convolutional 1D (Conv1D), and a combined Conv1D-LSTM, are implemented. The key findings demonstrate that Support Vector Machine (SVM) models, with the utilization of the Porter stemming algorithm, attain impressive accuracy levels: 82.56% for analysis of sentiments in English text and 86.43% for analysis of sentiments in Bangla text. This highlights the superior performance of SVM models compared to other methods in analysing sentiments in both English and Bangla texts. The efficiency of sentiment analysis models trained on a single language on multilingual tweets is investigated in [18].

The work makes use of a multilingual twitter dataset as well as experimental results from CNN, RNN, and combination CNN-RNN models. The CNN model achieves the highest performance, boasting an accuracy rate of 85.91% and an F1-score of 84.61%. Furthermore, it demonstrates robust performance when handling tweets in European languages not included in the original training data. In [19], researchers utilized a combination of techniques and technologies to analyze Bengali text. These included Glove word embedding and the Adam optimizer. Additionally, they utilized a deep learning classifier consisting of Convolutional Neural Networks (CNN) and Glove-BiLSTM. The study yielded impressive accuracy rate of 99.43% in evaluating Bengali texts.

In [20], the authors explore the use of Long Short-Term Memory (LSTM) model for sentiment analysis in Hindi text. It uses word embeddings and fine-tunes parameters to achieve accurate sentiment classification in Hindi. The study emphasizes the significance of analyzing sentiments in Hindi texts for organizations in India, providing valuable insights for product, service, and market presence enhancement.

The authors of [21] propose a sentiment classification system for tweets using deep learning techniques specifically Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM). The system categorizes positive emotions into subcategories like enthusiasm and happiness, while negative emotions are categorized into anger, boredom, and sadness. Through experimentation on three datasets, the LSTM model achieves high accuracy rate of 88.47% for positive/negative classification, while achieving accuracies of 89.13% for the positive subcategory and 91.3% for the negative subcategory. This research contributes to emotion recognition using deep learning techniques.

The researcher of [22] explores the challenges faced by under-resourced languages like Sinhala in utilizing deep learning methods for sentiment analysis in Natural Language Processing (NLP) applications. It uses old and new sequence models, a dataset of 15,059 Sinhala news comments, and a 9.48 million token corpus, making it the largest sentiment-annotated Sinhala dataset available.

The paper [23] presents a new method that integrates Convolutional Neural Networks (CNNs) with Recurrent Neural Networks (RNNs) for sentiment analysis of short texts. The model outperforms existing methods on benchmark datasets, achieving accuracy rates of 82.28%, 51.50%, and 89.95%, demonstrating its effectiveness in handling texts with limited contextual information. Latest research work in SA in different languages using various technology is listed in Table I.

TABLE I SENTIMENT ANALYSIS WITH ONLINE TEXT REVIEWS: RECENT LITERATURE

Sl. No.	Reference No	Domain	Language used	ML Techniques
1	[24]	Airline	English	Latent semantic analysis
2	[25]	Airline	English	Statistical analysis
3	[26]	Airline	English	SVM, ANN, CNN
4	[27]	Hotel	English	LR
5	[28]	Hotel	English	LSTM
6	[29]	Hotel	English	NB, KNN
7	[30]	Hotel	English	DT, NB, SVM
8	[31]	Hotel	English	Latent Dirichlet analysis
9	[32]	Airline	English	NB, SVM, NN
10	[33]	Airline	English	LR, DT, NB, SVM, LSTM, CNN, CNN-LSTM
11	[34]	Movie Review	Hindi	LSTM, GA-GRU
12	[35]	Cricket review	Bengali	LSTM
13	[36]	Movie review	Bengali	SVM, LSTM
14	[37]	Restaurant and movie reviews	Assamese	SVM, NB, LR, DT, KNN
15	Proposed study (2024)	Movie reviews	Assamese	LSTM, CNN, LSTM-CNN

III. THEORETİCAL BACKGROUND

A. LSTM

LSTM is a specific type of recurrent neural network (RNN) model that handles sequential data to produce longer-term dependencies more effectively than a typical RNN [38]. This model is well-suited for analysing time-series data and has a remarkable ability to retain numerous states. It is capable of being trained through supervised training and has a record for natural language text compression. As a recurrent neural network, LSTM can minimize errors by iteratively adjusting weights through feedback.

Memory units in LSTM deal with a period dependency. The core components of LSTM include the cell, input gate, output gate, and forget gate [39]. Typical architecture of LSTM is shown in fig.1. In the figure, it is seen that LSTM typically involves three inputs, with two inputs originating from the previous state. One input, ht-1, originates from the previous LSTM, while the other, Ct-1, serves as a memory retrieved from the previous time step.

The two gates, forget gate and the memory gates constitutes the key components of this model.

The general equation for LSTM can be outlined as follows.

$$i_t = \delta(w^i x_t + u^i h_{t-1})$$
$$f_t = \delta(w^f x_t + u^f h_{t-1})$$
$$O_t = \delta(w^o x_t + u^o h_{t-1})$$
$$C_t = tanh\,(w^c x_t + u^c h_{t-1})$$
$$C_t = i_t \odot \tilde{c}_t + f_t \odot \tilde{c}_{t-1}$$
$$h_t = O_t \odot \tanh(\tilde{c}_t)$$

Here, i_t denotes the input gate, f_t denotes forget gate, O_t denotes the output gate, δ denotes the sigmoid function, w^i, w^f, w^o, w^c and u^i, u^f, u^o, u^c used to represent the weight matrices, x_t is the input vector at timestep ‘t’, h_t is the previous hidden state, and C_t represents the memory cell state. The symbol ‘⊙’ denotes the element-wise multiplication. In this study, the LSTM model employs 128 units of neurons.

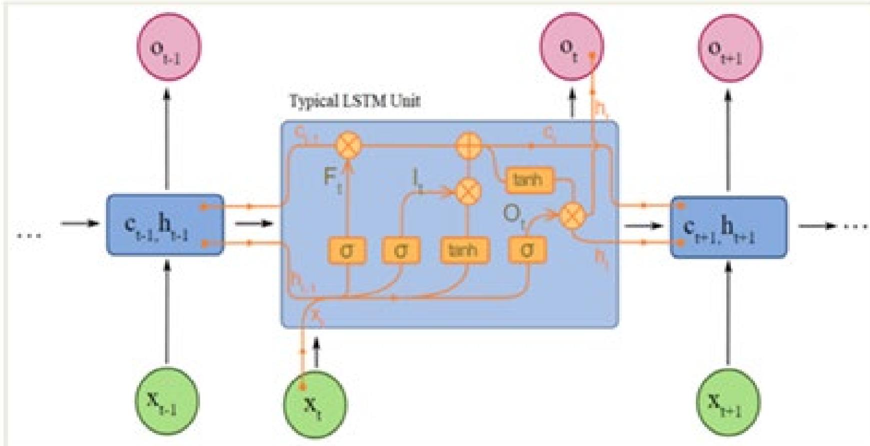

Fig. 1 Internal Structure of LSTM model

B. CNN

CNN, a type of neural network, specializes in processing spatial input, making it ideal for tasks such as classification and segmentation of video and image data.

In recent years, CNN has demonstrated significant effectiveness in Natural Language Processing (NLP) tasks. Early studies, such as [7], showcased impressive performance utilizing CNN for text classification across various tasks.

IV. METHODOLOGY

This research work study focuses on sentiment analysis of Assamese text review data acquired from multiple sources. A classification model that utilizes LSTM, CNN, and a hybrid LSTM-CNN strategy has been proposed here. By a detailed examination of the results obtained by the mentioned deep learning models, the efficacy of the suggested models in comparison to conventional machine learning models. The Python programming language serves as the primary tool. The overall model of the work is depicted in fig. 2 below.

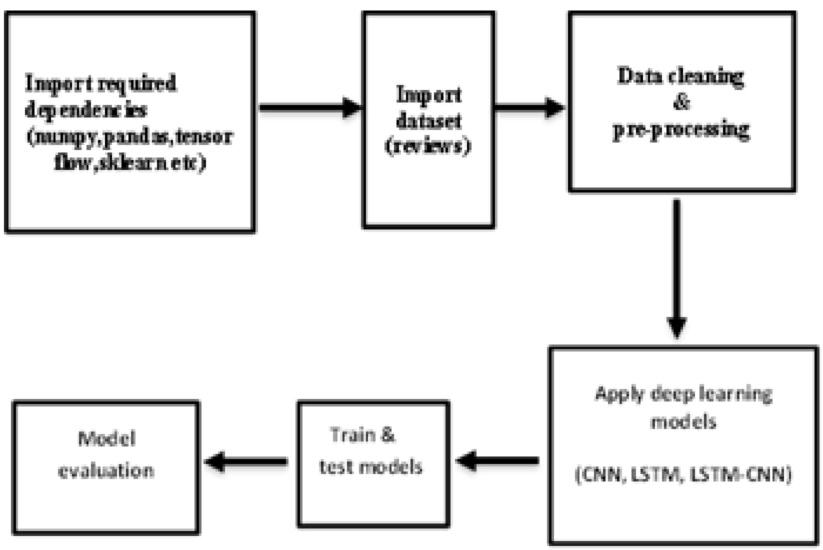

Fig. 2 Proposed Work Plan

A. Dataset Creation/Collection

Dataset creation as well as collection is the most crucial step for low resourced language like Assamese. This research work includes already built dataset by the same authors of this research article as mentioned in [37]. The existing dataset size was not enough to be used for deep learning approaches. Hence, additional reviews collected from various web sources have been included in the existing one. Thus, a total of around 4000 reviews in restaurant review and movie reviews have been used for this research work.

B. Data Pre-Processing

This step involves data cleaning. Here dataset is cleaned using various NLP tasks such as tokenization, stop words removal, punctuation removal etc. Data preprocessing is done with the purpose of utilizing the standard form of dataset to be analyzed by deep learning models. This step helps in removing unnecessary words, phrases which holds no meaning in relevant to sentiment analysis. For example, words like ‘i’, ‘she’, ‘you’, ‘for’ , ‘from’ etc in Assamese ‘মই’, ‘তুমি’, ‘বাবে’, ‘পৰা’ etc holds no sentiment in any sentence.

C. Deep Learning Model Application

Three different set of deep learning models have been used here in this proposed study. They are LSTM, CNN and a hybrid model by combining CNN-LSTM. Model details are discussed below in results and discussion section.

D. Train and Test Data

The proposed models were trained and tested using a splitting ratio of 80:20, where 80% of the data was allocated for training, and the remaining 20% was reserved for testing the model’s performance.

E. Model Evaluation

For evaluation purpose a set of hyperparameter settings has been considered as mentioned in Table II. Training and testing loss vs accuracy has also been observed with these settings as shown in figure 3,4 and 5 for the proposed three models.

V. RESULTS AND DISCUSSION

TABLE II HYPERPARAMETER SETTINGS FOR THE PROPOSED MODELS

No of epochs	10
Batch size	128
Activation Function	Sigmoid
Train test splitting ratio	80:20
Loss function	Binary Cross entropy
Optimizer	Adam
Dropout	0.2

Using movie reviews datasets of Assamese language, the performance of the suggested models was assessed using conventional parameters. To examine the proposed models with keras embedding method, following considerations has been taken into account as mentioned in Table II.

When it comes to assessing sentiment in Assamese movie reviews, all three of the suggested models perform admirably when used with the hyperparameter settings indicated above in table II. The CNN and LSTM-CNN models are more accurate, with a 99% accuracy rate; the LSTM model is very close behind, at 98%.

A. Proposed LSTM Model

```
Model: "LSTM"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 embedding (Embedding)       (None, 86, 128)           128000

 spatial_dropout1d (Spatial  (None, 86, 128)           0
 Dropout1D)

 lstm (LSTM)                 (None, 128)               131584

 dense (Dense)               (None, 2)                 258

=================================================================
Total params: 259842 (1015.01 KB)
Trainable params: 259842 (1015.01 KB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

Fig. 3 Summary of the Proposed LSTM model

```
history=model.fit(X_train, Y_train, validation_data=(X_test, Y_test), epochs=10,batch_size=128,validation_split=0.2 )

Epoch 1/10
14/14 [==============================] - 8s 546ms/step - loss: 0.0317 - acc: 0.9899 - val_loss: 0.1953 - val_acc: 0.9310
Epoch 2/10
14/14 [==============================] - 5s 361ms/step - loss: 0.0287 - acc: 0.9887 - val_loss: 0.2162 - val_acc: 0.9238
Epoch 3/10
14/14 [==============================] - 13s 958ms/step - loss: 0.0265 - acc: 0.9893 - val_loss: 0.2219 - val_acc: 0.9333
Epoch 4/10
14/14 [==============================] - 15s 1s/step - loss: 0.0236 - acc: 0.9911 - val_loss: 0.2171 - val_acc: 0.9262
Epoch 5/10
14/14 [==============================] - 8s 496ms/step - loss: 0.0200 - acc: 0.9970 - val_loss: 0.2060 - val_acc: 0.9262
Epoch 6/10
14/14 [==============================] - 5s 351ms/step - loss: 0.0194 - acc: 0.9935 - val_loss: 0.2150 - val_acc: 0.9262
Epoch 7/10
14/14 [==============================] - 7s 517ms/step - loss: 0.0190 - acc: 0.9946 - val_loss: 0.2459 - val_acc: 0.9190
Epoch 8/10
14/14 [==============================] - 5s 340ms/step - loss: 0.0157 - acc: 0.9958 - val_loss: 0.2079 - val_acc: 0.9381
Epoch 9/10
14/14 [==============================] - 7s 543ms/step - loss: 0.0152 - acc: 0.9940 - val_loss: 0.2590 - val_acc: 0.9238
Epoch 10/10
14/14 [==============================] - 5s 386ms/step - loss: 0.0168 - acc: 0.9946 - val_loss: 0.2482 - val_acc: 0.9214
```

Fig. 4 Results of Proposed LSTM model

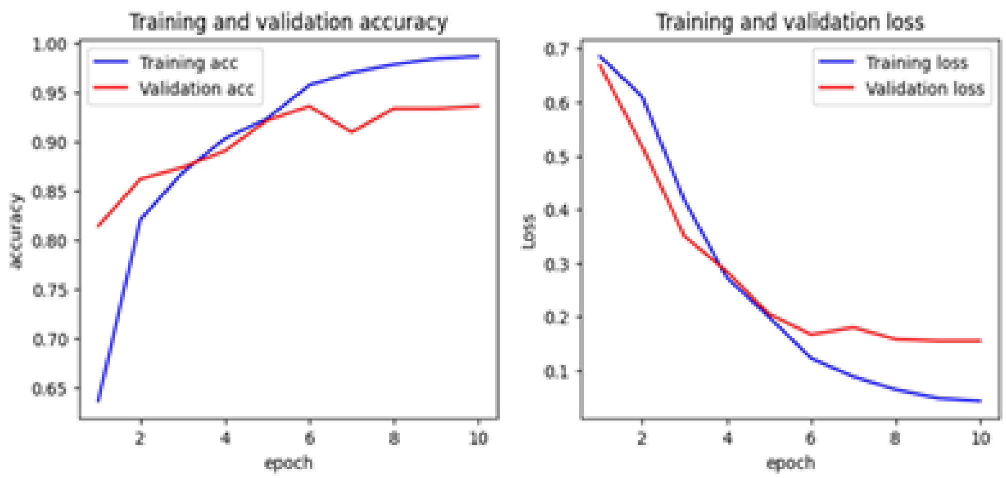

Fig. 5 Accuracy results and validation accuracy of the proposed LSTM model

B. Proposed CNN

```
Model: "CNN"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 embedding_5 (Embedding)     (None, 100, 128)          1280000

 conv1d_5 (Conv1D)           (None, 96, 128)           82048

 global_max_pooling1d_5 (Gl  (None, 128)               0
 obalMaxPooling1D)

 dense_5 (Dense)             (None, 1)                 129

=================================================================
Total params: 1362177 (5.20 MB)
Trainable params: 1362177 (5.20 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

Fig. 6 Model Summary of Proposed CNN

```
Epoch 1/10
14/14 [==============================] - 4s 188ms/step - loss: 0.6733 - accuracy: 0.6815 - val_loss: 0.6443 - val_accuracy: 0.7286
Epoch 2/10
14/14 [==============================] - 4s 261ms/step - loss: 0.5698 - accuracy: 0.8696 - val_loss: 0.5222 - val_accuracy: 0.8619
Epoch 3/10
14/14 [==============================] - 2s 166ms/step - loss: 0.3845 - accuracy: 0.9250 - val_loss: 0.3517 - val_accuracy: 0.9024
Epoch 4/10
14/14 [==============================] - 3s 188ms/step - loss: 0.2025 - accuracy: 0.9565 - val_loss: 0.2319 - val_accuracy: 0.9286
Epoch 5/10
14/14 [==============================] - 2s 155ms/step - loss: 0.0951 - accuracy: 0.9857 - val_loss: 0.1814 - val_accuracy: 0.9357
Epoch 6/10
14/14 [==============================] - 2s 155ms/step - loss: 0.0471 - accuracy: 0.9935 - val_loss: 0.1663 - val_accuracy: 0.9429
Epoch 7/10
14/14 [==============================] - 5s 372ms/step - loss: 0.0271 - accuracy: 0.9970 - val_loss: 0.1641 - val_accuracy: 0.9357
Epoch 8/10
14/14 [==============================] - 3s 186ms/step - loss: 0.0176 - accuracy: 0.9982 - val_loss: 0.1638 - val_accuracy: 0.9333
Epoch 9/10
14/14 [==============================] - 2s 154ms/step - loss: 0.0136 - accuracy: 0.9982 - val_loss: 0.1617 - val_accuracy: 0.9333
Epoch 10/10
14/14 [==============================] - 2s 152ms/step - loss: 0.0095 - accuracy: 0.9994 - val_loss: 0.1620 - val_accuracy: 0.9405
```

Fig. 7 Result of Proposed CNN model

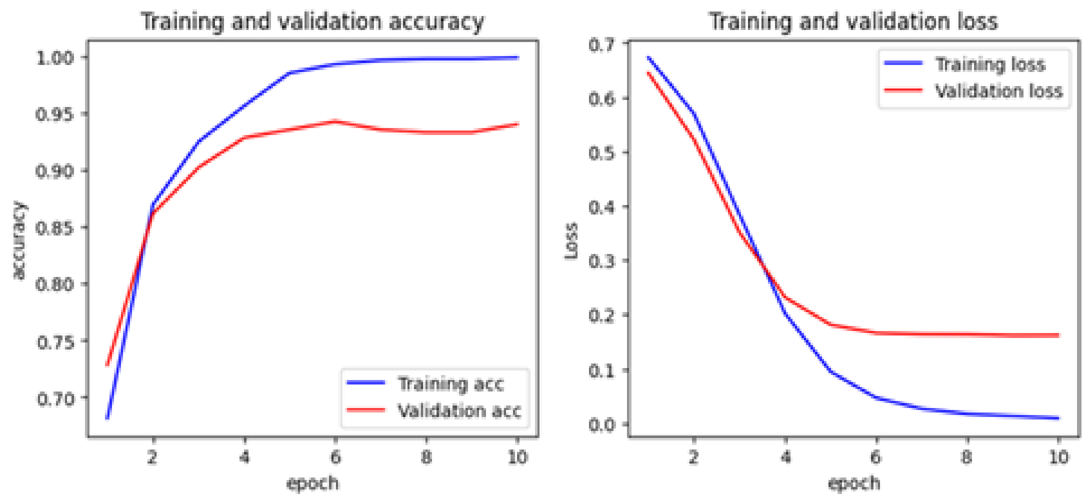

Fig. 8 Findings regarding the accuracy and validation accuracy of the proposed CNN model

C. Proposed LSTM-CNN

```
Model: "LSTM-CNN"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 embedding_5 (Embedding)     (None, 165, 128)          128000

 bidirectional_5 (Bidirecti  (None, 165, 256)          263168
 onal)

 conv1d_4 (Conv1D)           (None, 165, 100)          128100

 conv1d_5 (Conv1D)           (None, 165, 64)           19264

 global_max_pooling1d_1 (Gl  (None, 64)                0
 obalMaxPooling1D)

 dense_5 (Dense)             (None, 1)                 65

=================================================================
```

Fig. 9 Model summary of Proposed LSTM-CNN

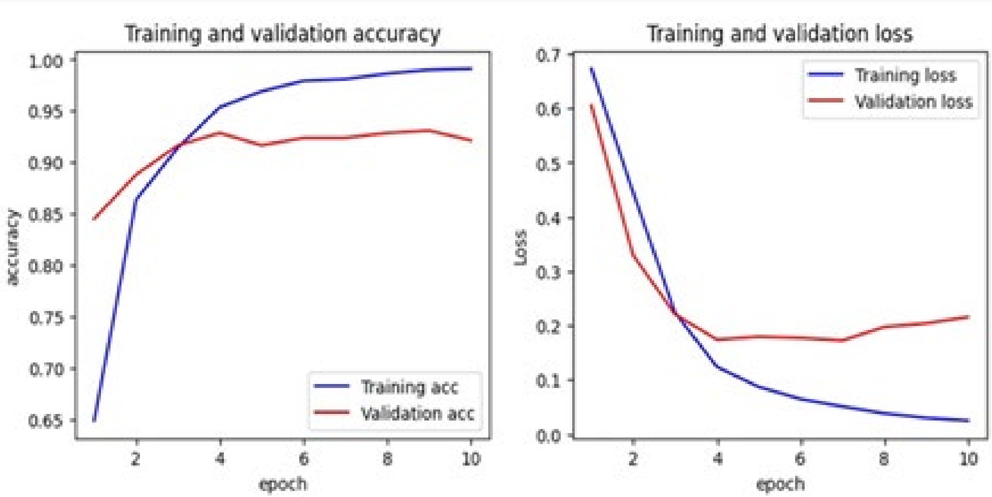

Fig. 10 Results of the accuracy and validating accuracy of proposed LSTM-CNN model movie data

TABLE III COMPARİSON OF PROPOSED MODEL WİTH EXİSTİNG MODELS WİTH DİFFERENT DATASETS AND LANGUAGES

Classifier	Accuracy	Dataset used	Language used
CNN [28]	85%	Airline sentiment	English
LSTM [28]	85.2%	Airline sentiment	English
CNN-LSTM [28]	90.2%	Airline sentiment	English
CNN [28]	87.1%	Twitter Airline sentiment	English
LSTM [28]	88.2%	Twitter Airline sentiment	English
CNN-LSTM [28]	91.3%	Twitter Airline sentiment	English
LSTM [36]	72.1%	Cricket review	Bengali
SVM [37]	88.9%	Movie review	Bengali
LSTM [37]	82.42%	Movie review	Bengali
SVM [38]	82%	Restaurant Reviews	Assamese
MNB [38]	89%	Restaurant Reviews	Assamese
SVM [38]	81%	Movie review	Assamese
MNB [38]	93%	Movie review	Assamese
Proposed LSTM	98%	Movie Reviews	Assamese
Proposed CNN	99%	Movie Reviews	Assamese
Proposed LSTM-CNN	99%	Movie Reviews	Assamese

VI. CONCLUSION AND FUTURE SCOPE

The research conducted here proposes three different deep learning models for sentiment analysis that are LSTM, CNN and combination of LSTM-CNN. To achieve this, Keras embedding was used to convert text reviews into vectors of numbers. The input vectors were then utilized for feeding into the models. Following this, the output from each model was employed as input for the subsequent LSTM model. Results obtained from the experimental investigation showed high accuracy compared to other classical machine learning models. This study suggests numerous pathways for future research, as it only focuses on the sentiment analysis of text reviews from restaurant and movie domain. There are still several areas within the food and entertainment industry that can be explored for disentangling consumer's sentiment. It should be noted that this study only considers data obtained from an online platform that has been translated to Assamese sentences. Therefore, consumer reviews written in other indigenous and low resourced languages are not included in sentiment analysis. Future research could involve the analysis of text reviews in such languages or a mixture of multiple languages. While this research introduces three separate classifiers for classification of sentiments, there is a possibility for other hybrid models to provide improved solutions, especially when dealing with larger datasets. Finally, different optimization techniques could be applied to machine learning models in future studies to enhance sentiment analysis performance. There exists extensive scope of study in the same area using multiple deep learning hybrid network models. The findings presented in this paper can serve as the foundation for further research in sentiment analysis for Assamese text.

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