INDIAN JOURNAL OF SCIENCE AND TECHNOLOGY

RESEARCH ARTICLE

OPEN ACCESS

Received: 02-10-2023

Accepted: 13-10-2023

Published: 17-10-2023

Citation: Parvin SA, Sumathi M, Barani R (2023) A Novel Approach to Classify Sentiments on Different Datasets Using Hybrid Approaches of Sentiment Analysis. Indian Journal of Science and Technology 16(44): 3962-3970. https://doi.org/10.17485/IJST/v16i44.2498

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Funding: None

Competing Interests: None

Published By Indian Society for Education and Environment (iSee)

ISSN
Print: 0974-6846
Electronic: 0974-5645

A Novel Approach to Classify Sentiments on Different Datasets Using Hybrid Approaches of Sentiment Analysis

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Abstract

Objectives: The objective of this study is to introduce an innovative hybrid approach that incorporates CNN and Bi-LSTM models to provide a solution to the sentiment analysis problem. The HCNN-BiLSTM Model is the acronym that we present for this methodology. **Methods:** Pre-processing, feature extraction, and sentiment classification are the three steps in this procedure. In the pre-processing stage, unneeded data gathered from the source text reviews is filtered out utilizing NLP systems. The prior studies presented an integrated strategy referred to as RBDT, which generates particular feature sets depending on the examination, for effectively extracting features. Next, sentiments are predicted using the proposed cutting-edge HCNN-BiLSTM model and grouped various sentimental phrases into five main groups: interest, sadness, anger, happiness, and disinterest. **Findings:** The findings showed that in terms of F-measure, accuracy, word count, and computational time, this suggested the HCNN-BiLSTM Model operates better than conventional deep learning (CNN) and machine learning techniques (SVM). **Novelty:** This proposed approach uses advanced methods on five review datasets, which include the Amazon dataset, Spotify app reviews, FIFA World Cup reviews, COVID-19 Vaccination reviews, and ChatGPT reviews, to produce competitive outcomes.

Keywords: Sentiment Analysis; Long ShortTerm Memory; Convolutional Neural Network; Natural Language Processing; Machine Learning; Deep Learning

1 Introduction

The process of examining the emotions, opinions, and sentiments conveyed in the text regarding a specific topic or entity is categorized as opinion mining and is additionally referred to as sentiment analysis. Word, phrase, sentence, and document counts can all be used for sentiment analysis[1]. Sentiment analysis identifies what a person thinks regarding a feature of a product or service at the word level[2]. The methods that are most commonly used for carrying out sentiment analysis are the lexicon-based method, the machine learning (ML) or deep learning (DL) approach, and the combination of both [3]. To ascertain a sentence's overall perspective, the lexicon-based approach utilizes an assortment of words with sentimental overtones [4]. Lexicon-based sentiment analysis techniques are considered to be limited because they do not take into account the sequential arrangement of words. Lexicon-based frameworks require regular servicing and fine-tuning, which increases the amount of work required for deployment.

In ML or DL-based methods, the dataset is split into datasets to be used for training and testing [5]. The former is used to teach the algorithm the way to associate a particular input text to an equivalent output when training. During the prediction phase, the testing dataset is employed, and a feature extractor is utilized to convert concealed textual inputs into feature vectors. Following the feeding of these vectors into the model, prediction tags are created for each of the related vectors. The hybrid strategy combines a Lexicon-based strategy with an ML-based method [6].

Each of the above methods demonstrated outstanding effectiveness in formal languages, text sources, and even in well-defined areas where pre-labeled information is readily available for training or the lexicon coverage contains the words that bear particular feelings inside a set of texts [7]. Such methods, however, are unable to cope with the unstructured material that is consistently provided online in terms of volume, diversity, and pace [8,9].

Machine learning and modern techniques for deep learning can be used to solve SA's parsing, labeling, and named entity recognition (NER) problems [10,11]. To the greatest extent of the author's understanding, this has been the first investigation that has successfully classified sentiment analysis utilizing an integrated methodology that includes deep learning, Lexicon-based approaches, and machine learning [12–16].

The following are the key contributions to this study. (i) A GATE DictLemmatizer, a multilingual freeware lemmatizer that is currently available in English, German, Italian, French, Dutch, and Spanish and is simple to extend for additional languages, became available for the GATE NLP structure. The LGPL license allows for the software to be used without charge. The words from each dataset's reviews were manually divided into categories including interest, sadness, anger, happiness, and disinterest using the vocabulary that was employed in this work. (ii) Segmentation and Sentiment Word Extraction is our prior work, we proposed the RBDT unique feature extraction technique, which on the Amazon dataset outperformed all other existing features like TPF, POS, etc. (iii) To highlight the success rate of RBDT, it has been compared against N-Gram and Chi-Square on four more datasets, including the Spotify app, FIFA World Cup, COVID-19 Vaccination, and ChatGPT reviews. (iv) By using the CNN model for obtaining local features and the LSTM framework to capture long-distance dependencies, we combine all of these characteristics into a single suggested hybrid HCNN-BiLSTM model. Experimental findings demonstrated that our model produces effective outcomes.

2 Methodology

This part provides a summary regarding the proposed sentiment analysis approach for Amazon mobile phone feedback. The different phases of this particular task are depicted in Figure 1 , from data collection to model evaluation.

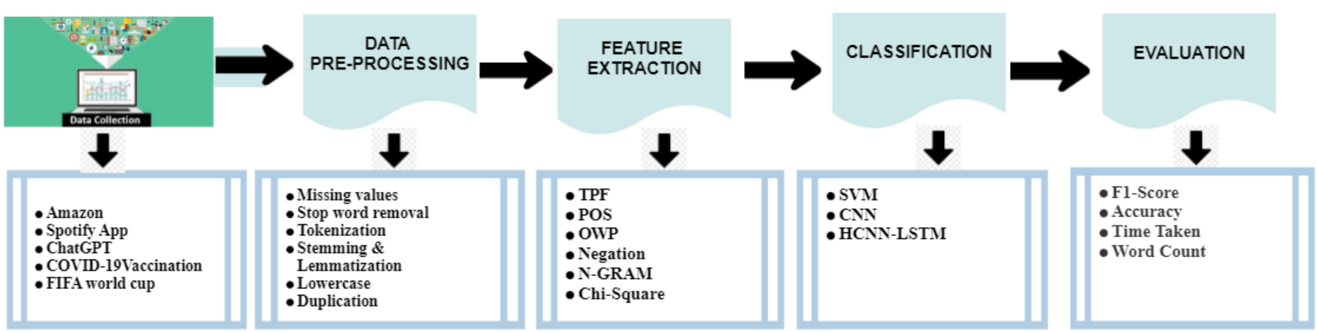

Fig 1. The overall methodology of sentiment analysis

2.1 Data Collection

2.1.1 Amazon Review Dataset

The data presented that supports the analysis's conclusions is freely accessible in Kaggle.

2.1.2 Spotify App Review Dataset

We used 64k Spotify App Reviews datasets that were gathered from the renowned Kaggle website to conduct our experiment.

2.1.3 ChatGPT Review Dataset

ChatGPT articulates information that is already widely known online in a concise paragraph that anybody can read. It was created by OpenAI specifically to produce text that sounds like human speech and is arranged conversationally.

2.1.4 COVID-19 Vaccination Review Dataset

In this study, we concentrate on examining the themes as well as sentiments expressed in Twitter conversations regarding the COVID-19 vaccine. There are 139 vaccine candidates as of August 23, 2021, 22 of which have received international approval, and 192 nations that have granted vaccine approval.

2.1.5 FIFA World Cup Review Dataset

The dataset was collected from Twitter during the 2022 World Cup football competition that took place in Brazil and is freely available on Kaggle. Around 2 million tweets with the game's hashtags are included in the dataset that is available for examination.

2.2 Data Pre-Processing

We initially removed the tweets that lacked information about their location, leaving the remaining 78,827 tweets[17]. The disruptive words were subsequently extracted out of the left tweets. The steps consist of: (1) Eliminating the hashtags, emojis, and URLs from Twitter; (2) Eliminating non-English phrases or commonly used phrases that are ineffective at illuminating a particular subject; (3) Case folding, which is the decreasing of phrase cases to facilitate the processing of words; (4) In addition, the reviews underwent a procedure known as tokenization; (5) Examining the pairing of two phrases (bigrams); and (6) Lemmatization helps eliminate imposed ends as well as restore a phrase to its base or lexicon style.

2.3 Feature Extraction

To carry out NLP, computer systems have to interpret human language. The models based on ML can be utilized with the text input after it is initially transformed into a number format.

2.3.1 Chi-square

In statistical analysis, the chi-square test is a technique to determine whether two incidences are separate. We can get the actual count O and the projected count E from measurements of two separate parameters. Chi-Square computes the variance between the projected count E and the actual count O. The formula used for determining Chi-Square is provided in equation (1).

$$X_G^2 = \frac{(O_i - E_i)^2}{E_i} \tag{1}$$

Where:

C= degree of freedom; O= actual value; and E= projected value.

We have to decide the link between the independent category feature (predictor) and the dependent category feature (response). The goal we have while selecting features is to select those that have a significant impact on the result. While the two features are independent, the actual count is relatively close to the projected count, so the Chi-Square coefficient tends to be smaller. A significant Chi-Square result thereby specifies that the independence assumption is untrue. In simple terms, features with higher Chi-Square values and greater response dependence may be selected for the training of models.

2.3.2 N-Gram

The substrings of the original text that are length n characters long make up the set of character n-grams in a document. The most frequent sizes for n are 2, 3, and 4 (bigrams, trigrams, and four-grams, respectively). Equations (2) and (3) represent the formula for uni-gram and bi-gram.

(a) For unigram:

$$p(w_1, w_2, \ldots w_n) \gg p_i p(w_i) \tag{2}$$

(b) For Bigram:

$$p(w_i \mid w_1, w_2, \ldots w_{i-1}) \gg p(w_i \mid w_{i-1}) \tag{3}$$

2.4 Classification Models

Classification is the process used to categorize data. Data is first categorized into two types: binary classification (such as "positive" and "negative") as well as ternary classification (such as "positive," "negative," and "neutral") in the field of sentiment analysis, while the sentiment analysis procedure concludes on the basis of those categories. To categorize the emotions, we use the Quinary model, which includes the categories of interest, sadness, rage, happiness, and disinterest. Customers' evaluations are typically classified according to their sentiment using two methods: lexicon-based and ML-based, as seen in Figure 2 . Depending on the words that have polarity or polarity scores marked, lexicon-based techniques can calculate the polarity of textual reviews. Nevertheless, two groups of ML methods include supervised and unsupervised learning. This present study combines supervised machine learning techniques (SVM), deep learning algorithms (CNN, BiLSTM), and a novel algorithm called the HCNN-BiLSTM model by integrating DicLemmatizer (Lexicon-based approach) to look up the meanings of the words, which is frequently employed in creating sentiment labels in sentiment analysis. Such algorithms create a training set initially and subsequently label the training data based on the sentiments. The classifier model is then fed with a group of features that were acquired from the training set.

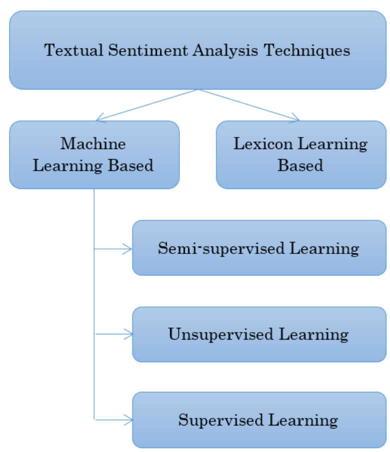

Fig 2. Sentiment Analysis Methodologies

2.4.1 Support Vector Machine (SVM

This is a supervised learning method used to generate a function that maps data using an initial training dataset that is accessible. In nonlinear regression, and this classifies each linear and nonlinear data, SVM is frequently used. The collection of labeled data may be classified using the mapping function as the classification function.

2.4.2 Convolutional neural network model

A unique category of neural network utilized in image processing is the CNN. However, text classification has successfully used the CNN model. In CNN, layers are referred to as feature maps since a portion of the input to their previous levels is joined by a convolutional layer in the model. The polling layer in the CNN model is used to lessen the computational complexity. The CNN polling methods minimize the output dimension from one stack layer to the next while preserving critical information. Although other polling methods exist, max-polling is most often employed when the pooling window has the max value element. The flattened layer gets fed into the polling layer's output. The output of the polling layer is given to the flattened layer, which then maps it to the next layers.

2.4.3 Recurring Networks Model

The Recurrent Neural Network (RNN) form called BiLSTM is utilized in the model that we propose. A directed cycle connects the neurons within an RNN with each other. The model of an RNN processes data systematically since it utilizes internal memory for handling a series of words. Any component of an RNN finishes a single task given that output depends on all inputs of preceding nodes while remembering data for further analysis. Equation (4), in which x_t signifies the input vector at time t, h_t represents the current state at time t, f_w indicates a coefficient with w parameter, and h_t-1 denotes the previous state, represents the generalized RNN framework.

$$h_t = f_w\left(h_t - 1, x_t\right) \tag{4}$$

We move the weighting equation from Eq. 4 to Eq. 5.

$$h_t = \tanh\left(W_{hh} h_l + W_{xh} x_t\right) \tag{5}$$

In Eq. 5, wh represents the hidden state's weight, xt is the given input vector, and tanh is the activation function. While learning of the gradient technique is back propagated by the network, the exploding gradient or vanishing problem develops. The problem of vanishing gradients is solved using a particular kind of RNN model known as Long Short-Term Memory (LSTM). RNN and LSTM both have chain-like structures, but LSTM utilizes three gates to control as well as safeguard the data within each node state. Eqs. 6 to 9 offer a description of LSTM gates and cells.

$$\text{Input Gate } \mathrm{In}_t = s\left(W_{\mathrm{in}} \cdot \left[hs_t - 1\right] x_t + b_{\mathrm{in}}\right) \tag{6}$$

$$\text{Memory Cell } C_t = \tanh\left(W_c \cdot \left[hs_t - 1\right] x_t + b_c\right) \tag{7}$$

$$\text{Forget Gate } f_t = s\left(W_f \cdot \left[hs_t - 1\right] x_t + b_f\right) \tag{8}$$

$$\text{Output Gate } f = s\left(W_0 \cdot \left[hs_t - 1\right], x_t + b\right) \tag{9}$$

2.4.4 HCNN-BiLSTM Classification Model

We display the primary design of the suggested hybrid HCNN-BiLSTM framework in Figure 3. As part of the pre-processing stage, it executes operations such as sentence segmentation, tokenization, stop word elimination, and stemming upon receiving a sentence as input. The Lemmatized word is then discovered using DicLemmatizer. The resulting word is then fed into the Feature Extraction algorithms to find the high-level features. High-level features are extracted by the Feature Extraction layer, while the resulting values are then used as inputs by the Classification model[18]. The outcomes from the suggested hybrid HCNN-BiLSTM model have been compared with those from DL (CNN) and traditional ML (SVM), and these are covered in more detail in the performance evaluation part. Figure 4 shows the workflow of the proposed model.

Pseudo code for sentiment Analysis

Input: DS ← Dataset,
Output: SW ← Sentiment word categories
Step 1: Initialization: F = DS{ f 1 , f 2 , …, f n }
Step 2: A ← Stopwords Removal (F).
Step 3: B ← Tokenization (A).
Step 4: C ← Stemming and Lemmatization (B).
Step 5: D ← Change Lowercase (C).
Step 6: PP ← Remove Duplication values (D). // Preprocessed Data from Dataset
Step 7: F1 ← Feature Extraction from (PP).
// Feature set (TPF, POS, OWP, Negations, N-Gram, Chi-Square and Proposed)
Step 8: SW ← Sentiment word Categories are classified from Feature set F1.
//Sentiment word Categories (Interest, Happy, Not Interested, Sad and Anger)

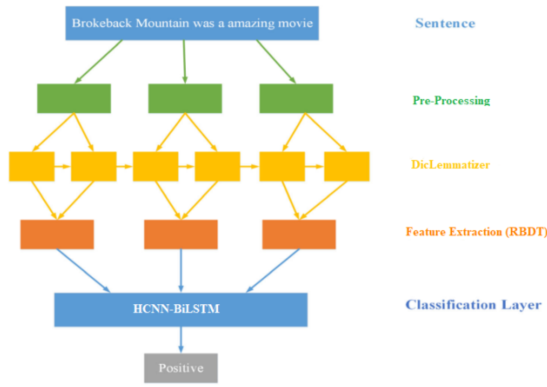

Fig 3. HCNN-BiLSTM's fundamental architecture for a review

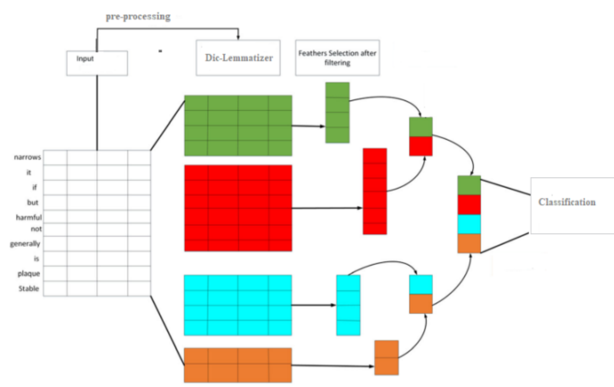

Fig 4. Workflow of the Proposed Model

3 Results and Discussion

For the evaluation of our suggested Hybrid HCNN-BiLSTM Model, we employed five common datasets. On all of the datasets, several tests are carried out using the suggested model. With regard to the metrics of high f-measure, accuracy, typical processing time, and word count, the approach we employed accomplished better than commonly used ML methods like I Base, Support Vector Machine, etc.

3.1 Evaluation Metrics

3.1.1 Confusion Matrix

The confusion matrix represents a table that displays the classification model's precision in categorizing events into different categories. The confusion matrix can be utilized to assess the extent to which each model has predicted true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN) while assessing various models. If an algorithm outperformed the others in terms of predicting TP and TN, we used it as the foundation for our model[19–22].

3.1.2 F1-Score

The F1 score is an average weighting of recall and precision. F1-score is an ML model effectiveness statistics that is utilized as a complement to accuracy metrics by fairly weighting Precision and Recall while determining the degree to which the model is accurate. The f1-score is calculated as follows:

$$\text{F1 Score} = 2' \frac{\text{Recall' Precision}}{\text{Recall} + \text{Precision}} \tag{10}$$

3.1.3 Accuracy

Accuracy, whose definition is simply the ratio of observations that are correctly predicted compared to all observations, is the easiest measurement of performance to comprehend. If the model has a high accuracy rate, it is thought to have been satisfactory.

$$\text{Accuracy} = \frac{TP+TN}{TP+FP+FN+TN} \tag{11}$$

The primary challenge of NLP is to create an approach that can comprehend the hierarchal arrangement of a sentence in a text. It is thought of as a combined assignment for obtaining successive data from hierarchical input using classification and feature extraction. The objective of this study is to decrease the execution time while increasing accuracy and the F-Score measure of the recommended approach HCNN-BiLSTM. It has additionally been contrasted with additional experiments. Figure 5 a illustrates the confusion matrix as well as estimates of the SVM classifier's predictive accuracy for categorizing sentiment analysis for tweets on multiple datasets with an 80:20 training-to-testing ratio. 10,157 tweets with sentiment labels have been properly categorized, while 14,178 tweets with sentiment labels are categorized incorrectly, yielding an accuracy of 55.974% and F-score measure of 0.560. From Figure 5 b, we can understand that our novel feature extraction algorithm RBDT has outperformed all the other baseline algorithms with an accuracy of 65%. We don't consider the categories but we take into account only the number of features that have been retrieved by various algorithms for SVM, which, within all classifiers, is the most primitive. It demonstrates that SVM cannot accurately categorize the tweets.

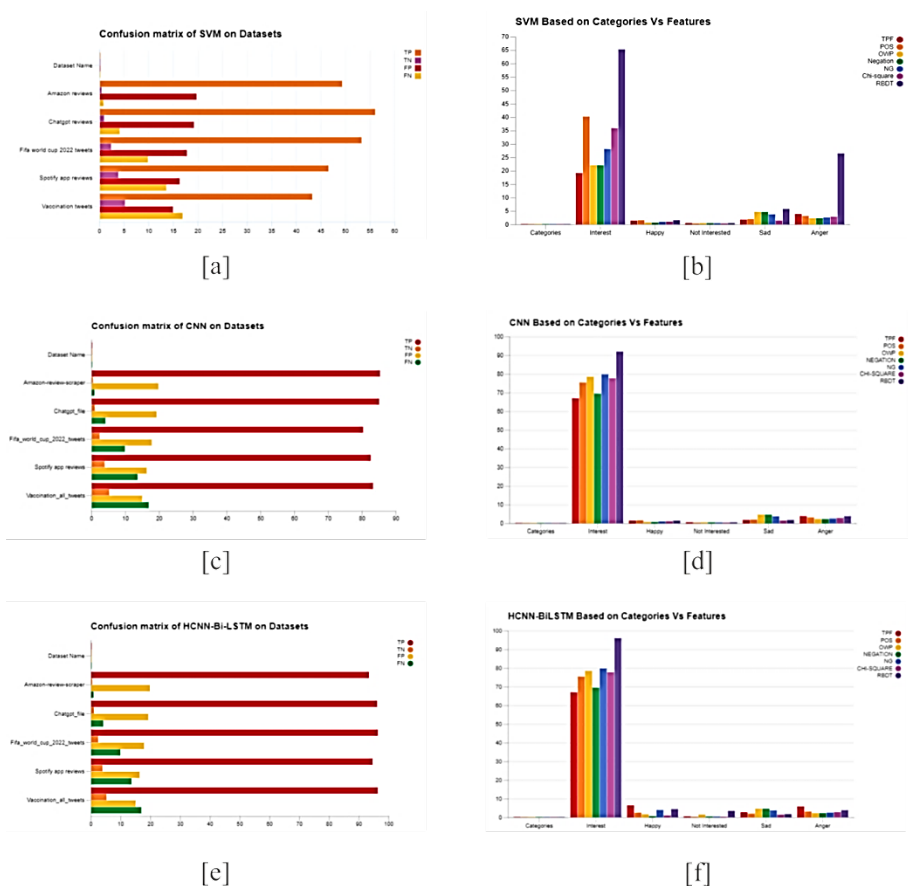

Fig 5. [a] Confusion matrix of SVM on various datasets, [b] SVM on various categories and features, [c] Confusion matrix of SVM on various datasets, [d] CNN on various categories and features, [e] Confusion matrix of HCNN-BiLSTM on various datasets, [f] CNN on various categories and features

For a training-to-testing proportion of 80:20, resulting in improved results when categorizing sentiment analysis for tweets, Figure 5 c displays the confusion matrix for an estimate of predictive accuracy by the CNN classifier. With 21,290 sentiment-labeled tweets appropriately categorized and 3045 sentiment-labeled tweets erroneously categorized, an accuracy of 87.839%

and F1-score measure of 0.889 were accomplished. From Figure 5 d, we can understand that our novel feature extraction algorithm RBDT has outperformed all the other baseline algorithms with an accuracy of 92% which shows that CNN is performing better when compared to SVM. The confusion matrix as well as estimation of the HCNN-Bi classifier's predictive accuracy for a training-to-testing ratio of 80:20 when categorizing sentiment analysis for tweets on different datasets are shown in Figure 5 e. With 51,690 sentiment-labeled tweets appropriately categorized and 3135 sentiment-labeled tweets erroneously categorized, an accuracy of 96% and an F-Score measure of 0.964 were attained. From Figure 5 f, we can understand that our novel feature extraction algorithm RBDT has outperformed all the other baseline algorithms with an accuracy of 96%.

Table 1. Assessment of Suggested Hybrid HCNN-BiLSTM using SVM and CNN

Datasets-based Overall Performance						
Datasets	**Accuracy**			**F-Score**		
	SVM	**CNN**	**HCNN-BiLSTM**	**SVM**	**CNN**	**HCNN-BiLSTM**
Amazon-review-scraper	39.834	**87. 839**	95. 739	0.363	0.859	**0.964**
Chatgpt_file	41.560	84.114	**96.114**	0.432	**0.889**	0.932
FIFA world cup tweets	**55.378**	87.335	95.835	0.458	0.824	0.958
Spotify app reviews	34.673	83.209	93.209	**0.560**	0.846	0.960
Vaccination_all_tweets	36.789	80.257	0.244	0.057	0.431	0.946

From five databases, we applied two widely used deep learning models (CNN and BiLSTM) and suggested a hybrid HCNN-BiLSTM model. In an effort to make an honest contrast between rival methods, we ran a number of investigations upon datasets for sentiment analysis. We followed the investigative procedures outlined earlier in the research we conducted. A single assessment appears in each dataset with numerous sentences. On all of them, the suggested hybrid HCNN-BiLSTM system was used. We initialized the words as sentiment words using the DicLemmatizer method and then obtained a confined feature set using feature extraction techniques. On each of the datasets in Table 1 , we demonstrate the precision and f-measure associated with our suggested hybrid HCNN-BiLSTM system and various other approaches. The very first emphasis of our analysis on the Amazon review dataset is that, while compared to both CNN and LSTM separately, our suggested hybrid approach improves the f-measure score by 4-8%. Comparing our hybrid approach to the systems suggested earlier, it is more effective at extracting local information. We found that the accuracy of our suggested Hybrid HCNN-BiLSTM system was higher than that of the baseline methods proposed earlier. Results show that our proposed method has achieved less execution time of 0.06252 milliseconds.

3.2 Comparison with State-of-the-art approaches

Table 2 displays the assessment of the suggested Hybrid HCNN-BiLSTM model with the other research studies in terms of achieved accuracy on various review datasets in classifying sentiments.

Table 2. Assessment of the suggested Hybrid HCNN-BiLSTM

S.No.	**Datasets**	**Accuracy(%)**
1.	Stanford Large Movie Review	93.3
2.	Publicly available dataset – corpus of movie review	45.4
3.	3 physically collected datasets; 2 were taken from Amazon and one from IMDB movie reviews	91.3%
4.	Amazon and IMDB movie reviews	91
5	FIFA World Cup soccer tournament tweets	88.17
6	movie reviews	93.80
7	SemEval-2014 data set and Sentiment140 data set	90 and 92
8	Amazon dataset, Spotify app reviews, FIFA World Cup reviews, COVID-19 Vaccination reviews, and ChatGPT reviews	**96 (Proposed)**

4 Conclusion

Learning the manner in which to obtain features from data with the aid of CNN. To detect dependence over time, a neural network additionally requires several convolution layers, and the difficulty of doing so increases when the size of its input sequence rises. In essence, it results in a convolution neural network layer that is exceptionally deep. The long-term dependence among word sequences has the capability of being captured by the BiLSTM framework. We proposed a Hybrid HCNN-BiLSTM system for sentiment analysis in this research. About accuracy, the recommended hybrid CNN-BiLSTM design outperformed the single CNN and LSTM frameworks on all benchmark review datasets. Comparing the suggested Hybrid HCNN-BiLSTM system to conventional ML as well as DL models, it attained 96% accuracy. The combination of lexicon-based machine learning approaches with DL algorithms for sentiment analysis has the goal of demonstrating how natural language processing approaches can accurately categorize semantic databases. In the future, additional machine learning methods will be analyzed for sentiment analysis concerning natural language processing approaches for effective categorization.

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