# A Hybrid Sentiment and Emotion Analysis Model for Marathi Text Using Horse Herd Optimization, Bidirectional RNN, and Affective Cognitive Computing

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**Abstract.** Marathi is the 13th most spoken language globally with around 90 million native speakers. Despite the growing use of this language, sentiment and emotion (SE) analysis research remains limited. This lack of extensive research poses a challenge to understanding the text's emotional and attitudinal content. The objective of this paper is to develop a hybrid model for SE analysis of low-resource languages like Marathi. The proposed hybrid model uses a combination of the Horse Herd Optimization algorithm (HHA), the Bidirectional Recurrent Neural Network (Bi-RNN), and the Ortony, Clore, and Collins (OCC) model to analyze opinions in Marathi texts. Our proposed model integrates OCC, which is an affective cognitive computing framework and serves as a foundation for emotion classification. Additionally, we use a version of HHA for hyperparameter optimization, followed by training a Bidirectional Long Short-Term Memory (Bi-LSTM) and Bidirectional Gated Recurrent Unit (Bi-GRU) model for final SE classification. Based on the results, the proposed model variants OCC+HHA+Bi-LSTM and OCC+HHA+Bi-GRU achieved remarkable performance scores in both SE classification tasks. For the sentiment analysis task, the model variants achieved F1 scores of 93.76% and 96.79% respectively for the testing set. For the emotion classification task, the model variants achieved F1 scores of 98.42% and 97.89% respectively. These variants outperformed other text-processing models in terms of classification metrics.

**Keywords:** Marathi text · Sentiment and Emotion analysis · Horse Herd Optimization algorithm · Bidirectional Recurrent Neural Network · OCC Model · Affective Cognitive Computing

## 1 Introduction

The study of sentiment categorization using online public opinion has gathered considerable attention due to the proliferation of online data and the escalating necessity for monitoring and regulating online public sentiment. SE analysis, a specific task within


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text classification, shares similarities with text classification but accentuates critical distinctions. While the latter focuses on objective content, SE analysis scrutinizes subjective aspects as its primary research subject. SE analysis, as a computational process, entails the systematic identification and classification of opinions expressed in textual data. This analytical task is fundamental for converting qualitative sentiments into quantifiable data points, enabling deeper insights and informed decision-making processes [1]. In delving into SE analysis, several considerations emerge. This endeavor encompasses extensive natural language processing (NLP) and comprises various stages for analyzing sentiment within source materials. Given the intricate nature of the problem, employing a robust algorithm is imperative for efficient analysis. A classifier serves as a vital component in categorizing provided text. The classifier mandates representing text as a feature vector and employing a feature selection strategy to identify optimal features is advisable. This technique finds utility across various textual information types, such as tweets, social media posts, customer reviews, surveys, news articles, and other sources [2, 3]. SE analysis finds widespread application across multiple domains, including analyzing consumer feedback, monitoring social media, conducting market research, student feedback, and facilitating financial analysis [3–5]. An essential application of subtitles involves categorizing the emotional tone of different scenes or segments. This can enhance the searchability and retrieval of content, simplifying the process for viewers to find content based on their mood [5].

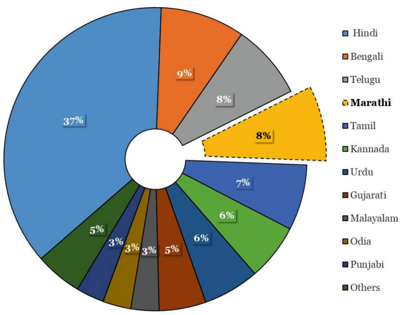


**Fig. 1.** Most spoken Native Indian Languages. Source: Chaudhari et al. [6]

Despite extensive research of SE analysis in languages with abundant resources like English [6], there is a notable gap in research for low-resource languages such as Marathi [7, 8]. Marathi, ranked as the 13th most spoken language globally among native speakers, boasts a significant presence with around 90 million native speakers, making it the third most widely spoken language in India [8], as depicted in Fig. 1. The quantity of Marathi content on the internet is steadily growing. Given the substantial Marathi-speaking population in India's online community, it is imperative to develop SE analysis models tailored to the specific characteristics of the Marathi language.

Emotions are manifestations of the core thoughts that individuals hold. The emotional tone conveyed by a piece of writing significantly influences its meaning and context. Hence, understanding the emotional content is quite important as it can aid in predicting the sentiment polarity of a particular text [9]. To improve the accuracy of emotion prediction in text-based emotion analysis techniques, we utilize emotion tags/objects extracted with the help of the OCC framework used in our model.

This research work focuses on developing a hybrid model that integrates the OCC model, providing a structured framework for SE analysis classification. This model serves as a reference point for standardizing emotion labeling across diverse opinions. Enhancements include integrating the HHA, a metaheuristic algorithm known for effectively addressing complex optimization problems. HHA utilizes a range of control parameters inspired by the behavior of horses across different age groups [10]. Subsequently, a Bi-RNN model is trained for the final SE classification. We utilize two variants of the Bi-RNN model (Bi-LSTM and Bi-GRU) to carry out the classification task. Comparative evaluation against different established text processing models demonstrates that the proposed hybrid OCC+HHA+Bi-RNN model outperforms the other models in terms of precision and accuracy, especially for addressing high-dimensional optimization problems.

The following are the major contributions of this work:

1) Development and implementation of a cognitive OCC model delineating 6 main emotion categories, serving as the foundational framework for our investigation.
2) Integration of the Horse Herd Optimization Algorithm (HHA), tailored for optimizing SE analysis on the Marathi Text dataset.
3) Deployment of a Bi-RNN classifier for conclusive SE classification.
4) Conducting an empirical comparative analysis contrasting various state-of-the-art algorithms with the proposed architecture.

## 2 Literature Survey

The analysis of social media posts has predominantly centered on global languages, with comparatively less attention given to regional languages that have experienced significant usage growth in recent times. This section outlines the progress achieved in the domain of low-resource languages thus far. Despite the predominance of English in online content, native languages hold considerable significance. With the internet's global reach, individuals can now share information in a plethora of languages, including their mother tongues. However, restricting sentiment analysis to specific languages risks losing crucial information, as observed in China, where Mandarin predominates online content. Similarly, India's linguistic diversity, with around 1600 spoken languages, underscores the necessity for multilingual SE analysis [11].

In the study [12], the authors focus on enhancing tweet sentiment analysis for Hindi-English code-mixed text through a clustering-based classification approach. Employing pre-processing techniques and diverse feature extraction methods, including Count Vectors, MTF-IDF, and word embeddings, the research introduces a Sentiment Word Embedding-based Agglomerative clustering and a Hybrid BLSTM-CNN model. Modified horse herd optimization is utilized for weight optimization in the Hybrid BLSTM-CNN, resulting in improved accuracy, precision, recall, and F1 score compared to existing approaches. The study contributes to the advancement of sentiment analysis in multilingual and code-mixed contexts.

Marathi, being classified as a low-resource language due to limited training data for developing accurate Natural Language Processing (NLP) models, faces challenges in

SE analysis. Recognizing this, L3Cube-Pune compiled the L3CubeMahaSent dataset [12], comprising labeled Marathi tweets. The L3cube-mahanlp project [13] elaborates on the study's objectives and the resources allocated, harnessing the linguistic content within this dataset. The models are purpose-built for the Marathi language, meticulously optimized to achieve state-of-the-art performance in multiclass (two or three) sentiment classification tasks, solely leveraging textual data.

Various models are available for conducting sentiment analysis across multiple languages. One widely adopted example is XLM-RoBERTa-base, a model that is based on RoBERTa (Robustly Optimized BERT Pre-training Approach) [13]. It has been trained in 100 diverse languages, including prominent national languages like Spanish, Russian, and Arabic, this model offers extensive linguistic coverage. MuRIL, short for Multilingual Representations for Indian Languages, is another notable model tailored specifically for Indic languages [14]. It was built on the BERT model and trained on datasets such as PMINDIA, common crawl, Wikipedia, and the Dakshina corpus, MuRIL is proficient in 17 Indian languages, including Hindi, Marathi, and Tamil, among others. Leveraging both monolingual and parallel data, which encompasses translated and transliterated versions of monolingual input data, MuRIL addresses the complexities of multilingual contexts.

The analysis of emotions is essential for industries that rely on consumer input and evaluations, as understanding the emotions expressed in reviews may be used as valuable resources for categorization and analysis. Emotions and feelings are interconnected, although they are not quite synonymous. This fact can be utilized to enhance the precision of SE analysis for a given input. Emotion recognition has been studied using different methodologies, such as the neural network based deep learning approach, heuristic and rule based approach, Keyword-based approach, Hybrid concatenated approach, and others. In [15], the authors introduce an affective emotion model-based approach to extracting emotions from online reviews, addressing a gap in traditional methods by incorporating emotion theories. A highly popular model is the one established by Chung-Hsien Wu in [16]. The model is based on rules, and it describes the input by using semantic labels and characteristics based on the Emotion Generation Rules (EGRs). In [17], the authors demonstrate the efficacy of customized recurrent neural networks in enhancing emotion recognition within decision support systems. Emotion and sentiment recognition have also been accomplished using multimodal techniques [18]. There have been minimal efforts made thus far to add emotions to enhance sentiment prediction of social media posts and text in languages with limited resources like Marathi [19].

## 3 Overview of the Models

### 3.1 Horse Herd Optimization Algorithm

The HHA replicates the behavior shown by horse herds at different phases of development. Horses exhibit consistent behavioral characteristics that can be classified into six broad categories: Grazing, Hierarchy, Sociability, Imitation, Defense Mechanism, and Roaming [19].

The horse's position and velocity are updated using the following Eq. (1):

$$X_i^{\{iter\},AGE} = V_i^{iter,AGE} + X_I^{(iter-1),AGE}, AGE = \alpha, \beta, \gamma, \delta \quad (1)$$

$X_i^{\{iter\}}$ represents the position of the *ith* horse during iteration, $V_i^{\{iter\}}$ represents the velocity vector of the *ith* horse during iteration, and *AGE* represents the age range of the horses. Horses exhibit distinct behavioral patterns at various stages of their life cycle. About that matter, we categorize them into the subsequent four groups, namely alpha (α), beta (β), gamma (γ), and delta (δ), according to their age ranges. The term δ is used to denote horses aged 0 to 5, γ symbolizes horses aged 5 to 10, β designates horses aged 10 to 15, and α refers to horses older than 15.

A thorough matrix of responses should be developed for each iteration to determine the age of the horses. Consequently, the matrix should be arranged based on the correct answers. Subsequently, the $\alpha$ horses are selected from the uppermost 10% of horses in the ordered matrix. The subsequent 20% of horses are classified under the $\beta$ group, while the remaining horses are distributed around 30% and 40% among the $\gamma$ and δ horses, respectively. The velocity vector is determined by statistically simulating six horse behaviors.

Equation (2, 3, 4, 5) represents the motion vector in the algorithm for horses of varying ages, considering the behavioral tendencies.

$$V_i^{iter,\alpha} = G_i^{iter,\alpha} + D_i^{iter,\alpha} \tag{2}$$

$$V_i^{iter,\beta} = G_i^{iter,\beta} + H_i^{iter,\beta} + S_i^{iter,\beta} + D_i^{iter,\beta} \tag{3}$$

$$V_i^{iter,\gamma} = G_i^{iter,\gamma} + H_i^{iter,\gamma} + S_i^{iter,\gamma} + I_i^{iter,\gamma} + D_i^{iter,\gamma} + R_i^{iter,\gamma} \tag{4}$$

$$V_i^{iter,\delta} = G_i^{iter,\delta} + I_i^{iter,\delta} + R_i^{iter,\delta} \tag{5}$$

Below, we present a comprehensive explanation of the functioning of social and individual intelligence in horses.

**1. Grazing**

Grazing is a prevalent activity pattern observed in horses. Horses engage in grazing behavior throughout their entire lifespan. Equation (6) establishes the mathematical framework for describing grazing.

$$\begin{gathered} G_i^{iter,AGE} = g_{iter}\left(\breve{u} + p\breve{I}\right)\left[X_i^{(iter-1)}\right], \quad AGE = \alpha,\beta,\gamma,\delta \\ g_i^{iter,AGE} = g_i^{((iter-1))} \times \omega_g \end{gathered} \tag{6}$$

$G_i^{iter,AGE}$ represents the locomotion of the *ith* horse and showcases their inclination to feed on grass.

**2. Hierarchy**

Wild horses form social groups known as bands to enhance their collective protection against predators. Horses exhibit hierarchical behavior when they are in a herd. The law of hierarchy stipulates that a herd of wild horses must be led by an adult stallion. Hence, *h* is defined as the inclination of all equines in a group to trail behind the dominant and most aged horse. Horses in the middle ages had a hierarchical structure between the ages of 5 and 15, which can be described by the following Eq. (7).

$$H_i^{iter,AGE} = h_i^{iter,AGE}\left[X_*^{(iter-1)} - X_i^{(iter-1)}\right], AGE = \alpha, \beta, \gamma, \delta \quad h_i^{iter,AGE} = h_i^{(iter-1),AGE} \times \omega_h \tag{7}$$

The variable $X_i^{(iter-1)}$ depicts the location of the best horse, whereas $h_i^{iter,AGE}$ indicates the impact of the best horse's position on the velocity vector.

**3. Imitation**

Horses are highly sociable animals capable of observing and imitating the behaviors of their peers, including the ability to identify and find a suitable grazing area. Juvenile equines are more prone to display this conduct. This can be delineated in Eq. (8).

$$I_i^{iter,AGE} = i_i^{iter,AGE}\left[\left(\frac{1}{pN}\sum_{j=1}^{pN}\hat{X}_j^{(iter-1)}\right) - X^{(iter-1)}\right], AGE = \gamma \quad i_i^{iter,AGE} = i_i^{(iter-1),AGE} \times \omega_i \tag{8}$$

The variable $I_i^{iter,AGE}$ represents the directional movement of the ith horse towards the mean or average position of the best horses, denoted as $\hat{X}$. The variable $pN$ denotes the number of horses that occupy the best location. There has been a proposal to designate 10% of the horses as $p$.

**4. Sociability**

Behaving in groups has become an essential need for survival in social mammals. Due to the presence of predators, the horses' safety is assured by living in a herd. The survival rates in herd life are higher because of the presence of pluralism, which facilitates easier escape. Horses' sociability can be defined as their inclination to engage in social interactions and form social bonds with other horses (9).

$$S_i^{iter,AGE} = s_i^{iter,AGE}\left[\left(\frac{1}{N}\sum_{j=1}^{N}X_j^{(iter-1)}\right) - X_i^{(iter-1)}\right], AGE = \beta, \gamma \quad s_i^{iter,AGE} = s_i^{(iter-1),AGE} \times \omega_s \tag{9}$$

The variable $S_i^{iter,AGE}$ represents the social movement vector of the ith horse, which decreases by the fraction $\omega_s$ with each iteration. N is the total number of horses. Sociability is more prevalent among individuals within the age range $\beta$ and $\gamma$.

**5. Defense Mechanism**

When faced with danger or the perception of danger, most horses rely on flight as their main means of defense. They engage in combat as a supplementary means of protection. Horses exhibit an immediate instinct to flee when confronted with peril. The horses exhibit their protection mechanism by actively avoiding unsuitable and less-than-ideal reactions. Equation (10) formulates the defense mechanism employed by horses to avoid unfavorable postures, characterized by negative coefficients.

$$D_i^{iter,AGE} = -d_i^{iter,AGE}\left[\left(\frac{1}{qN}\sum_{j=1}^{qN}\widehat{X}_j^{(iter-1)}\right) - X^{(iter-1)}\right], AGE = \alpha, \beta, \gamma \quad d_i^{iter,AGE} = d_i^{(iter-1),AGE} \times \omega_d \tag{10}$$

$D_i^{iter,AGE}$ is the vector that represents the escape route of the *ith* horse. It is determined by calculating the average of the worst location of the *ith* horse, which is indicated by the $\hat{X}$ vector. Furthermore, $qN$ denotes the horses positioned in the most unfavorable spot. There is a hypothesis that $q$ corresponds to 20% of the total count of horses.

**6. Roam**

The horse exhibits a strong inclination towards exploration, frequently venturing into various locations in search of fresh grazing grounds and acquainting itself with its surroundings. A factor r is employed to replicate this behavior by introducing a random motion. During their early years, it is nearly inevitable for horses to wander, but this behavior gradually diminishes as they mature.

$$\begin{aligned} R_i^{iter,AGE} &= r_i^{iter,AGE} pX^{(iter-1)},\ AGE = \gamma, \delta \\ r_i^{iter,AGE} &= r_i^{(iter-1),AGE} \times \omega_r \end{aligned} \quad (11)$$

The concept of roaming is defined in (11) as the utilization of $R_i^{iter,AGE}$ as a random velocity vector for conducting local searches and preventing the occurrence of local minima.

### 3.2 OCC Model

The OCC emotion model, coined after the initials of its originators Ortony, Clore, and Collins, is a cognitive framework for understanding emotions. It classifies and explains emotional states by taking into account three primary factors: the triggering event, the target of the feeling, and the behaviors of other individuals involved [20]. The OCC emotion model, in contrast to typical emotion models, distinguishes 22 emotion categories that are determined based on the assessments of these factors. This enables a more comprehensive examination of the text, taking into account not only the sentiment but also the specific emotion expressed, providing a valuable understanding of the intricate nature of human emotions. Additionally, it reveals not only the polarity of opinions but also the intensity and characteristics of the emotions involved. The integration of the OCC emotion model into SE analysis algorithms signifies notable progress compared to conventional approaches. By providing a well-organized system for evaluating emotions, it improves the level of detail, precision, and ability to understand emotions within SE analysis.

### 3.3 Bi-RNN Model

Bi-RNN is a neural network architecture that processes input data in both forward and backward directions. Traditional Recurrent Neural Network (RNN) processes sequences in one direction, from the beginning to the end, making them sensitive to the order of input data. Bi-RNN overcomes this limitation by processing the input sequence in both forward and backward directions simultaneously. This enables them to capture information in the text from both past and future contexts, making them more effective in capturing long-range dependencies in sequential data. There are two specific variants of Bi-RNN: Bi-LSTM and Bi-GRU.

**Bi-LSTM:** Bi-LSTM is an RNN architecture that is commonly used for processing sequential data, particularly for NLP tasks. It is an advanced version of the traditional LSTM network, with the key difference being that it processes input sequences in both forward and backward directions. The input sequence is processed from the beginning to the end, just like in a regular LSTM. At each time step, the forward LSTM cell computes its hidden state and cell state based on the current input and the previous hidden state and cell state. During the backward pass, the input sequence is processed in reverse, from the end to the beginning. At each time step, the backward LSTM cell computes its hidden state and cell state based on the current input and the previous hidden state and cell state. The final output for each time step is obtained by concatenating the forward and backward hidden states.

**Bi-GRU:** Bi-GRU is another variant of the Bi-RNN architecture, specifically designed for processing sequential data. Bi-GRU processes the input text sequence in both the forward and backward directions. This is achieved by using two separate GRU layers – one for processing the input sequence from the beginning to the end, and the other for processing it in reverse direction. During the forward pass, the forward GRU cell computes its hidden state based on the current input and the previous hidden state. Similarly, during the backward pass, the backward GRU cell computes its hidden state based on the current input and the previous hidden state. Concatenating the forward and backward hidden states yields the final output for each time step like that of Bi-LSTM.

## 4 Proposed OCC+HHA+Bi-RNN Model

The proposed model in Fig. 2 follows a HHA and Bi-RNN architecture for SE analysis of Marathi text data. SE analysis on Marathi text is approached through a multi-faceted methodology, incorporating the OCC affective computing model, the HHA algorithm for hyperparameter optimization, and the Bi-RNN model. Each step is designed to enhance the accuracy and comprehensiveness of SE classification.

First, basic preprocessing steps were applied to the dataset, including stop word removal, data imputation for missing values, data transformation for model training, sampling, and randomization.

We followed the emotion annotation method based on OCC described in the work [20]. The emotion extraction process begins by processing the Marathi text unlabeled dataset as the primary input data. The subsequent Emotion-Dimension Dictionary Construction phase involves a multi-step approach. Initially, a small set of seed words representing various emotional dimensions is manually selected. This seed set serves as the foundation for the emotion-dimension dictionary. The dictionary is then expanded using WordNet, a lexical database, and syntactic templates based on the syntactic structure of sentences. A scoring mechanism, based on co-occurrence, filters out unreliable emotion word which ensures the dictionary's quality. The process iterates to refine and update the dictionary with newly discovered emotion words. The Dictionary Refinement step addresses inconsistencies and conflicts within the emotion-dimension dictionary, utilizing WordNet for synonyms and antonyms to determine word polarity. A scoring function is applied to compute polarities and maintain balance. The OCC Model for

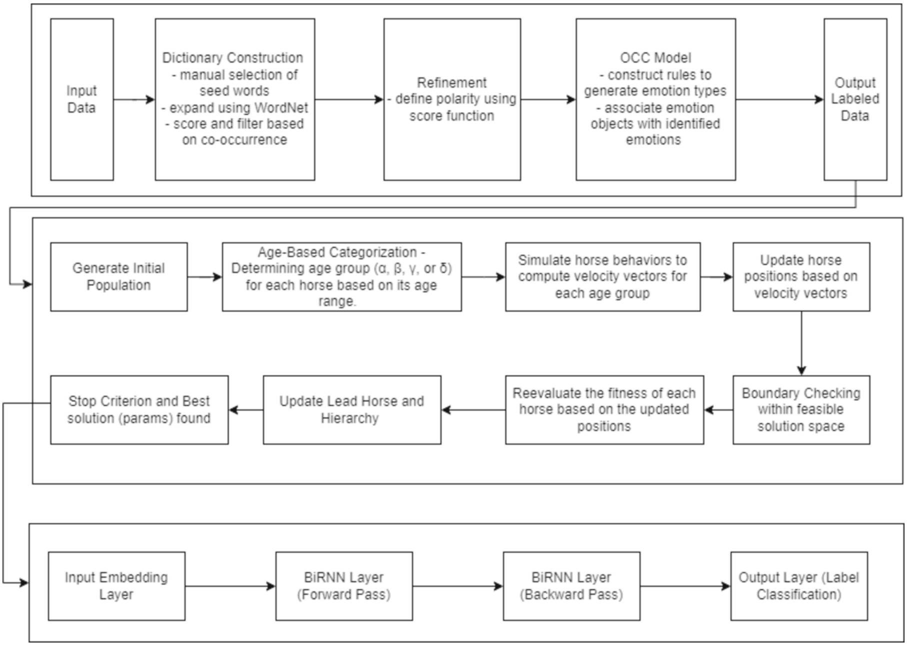


**Fig. 2.** OCC+HHA+Bi-RNN model

Emotion Extraction employs OCC rules to generate emotion types based on the refined dictionary. These rules identify different emotion types such as 'Distress', 'Neutral', 'Joy', 'Anger', 'Admiration', and 'Hate'. The emotion objects are then determined using an opinion object recognition method. Finally, the output includes emotion types linked to Marathi text records and the corresponding emotion objects/labels identified within the records, providing a comprehensive understanding of the emotional context.

The HHA algorithm is then utilized for hyperparameter optimization and feature selection [19, 20]. The outlined HHA algorithm for SE analysis initiates with the generation of an initial set of solutions, mirroring potential configurations for SE classification models. Each solution, metaphorically termed a "horse," is categorized into age groups (α, β, γ, or δ) based on its characteristics found through text embeddings. Behavioral simulations such as Grazing, Hierarchy, Imitation, Sociability, Defense Mechanism, and Roaming guide the update of solution positions, analogous to adjusting model features in the sentiment analysis context. Boundary checking ensures that the configurations remain within feasible solution space, and fitness evaluation assesses the performance of sentiment classification models with updated features. The algorithm iteratively updates the lead "horse" and hierarchy based on positions, incorporating a stopping criterion to determine when optimization is sufficient. Ultimately, the best solution, corresponding to the SE classification model with optimal performance, is returned. This tailored HHA algorithm streamlines the optimization process for SE analysis model configurations, enhancing their effectiveness in discerning sentiments from textual data.

In the SE dataset classification using Bi-RNN, the process involves four main layers. Firstly, the input layer utilizes embeddings to transform the raw textual data into a continuous vector space where semantic relationships among words are captured. Following this, the Bi-RNN is employed with two distinct layers: the Bi-RNN forward layer processes the input sequence from the start to the end, capturing sequential information, while the Bi-RNN backward layer processes the input sequence in reverse, capturing contextual information. These two layers effectively capture both past and future dependencies in the text. Subsequently, the information from both forward and backward passes is concatenated to form a comprehensive representation of the input sequence. Lastly, the output classification layer employs this concatenated representation to make SE predictions, mapping the learned features to SE labels, thereby providing a comprehensive and context-aware outcome.

With the Bi-RNN model, we also compare its performance with other text generation and processing models as described below –

**LSTM:** LSTMs are a type of artificial neural network (ANN) used in the domain of artificial intelligence (AI) and deep learning (DL). Unlike conventional feed-forward neural networks, which are also referred to as RNNs, these networks possess feedback connections.

**GRU:** GRU is a variant of RNN architecture that shares similarities with LSTM. Similar to LSTM, GRU is specifically designed to represent sequential data by enabling the selective retention or omission of information across time.

**1D-CNN:** A Convolutional Neural Network (CNN) is a prevalent neural model design in Deep Learning that is employed in the field of Computer Vision.

## 5 Results and Discussion

### 5.1 Dataset

We conducted SE analysis experiments using a recently introduced Marathi sentiment analysis dataset called L3CubeMahaSent. This dataset was curated by Kulkarni et al. [2] and consists of about 16,000 unique tweets. It is annotated into three classes: positive, neutral, and negative. The tweets were carefully selected from various Maharashtrian personalities' Twitter accounts to ensure diversity and relevance. We divided the dataset into a training set (12,114 tweets), and a testing set (3,750 tweets) with each set having a balanced distribution across the three sentiment classes. The emotion annotations for emotion classification were done algorithmically following a comprehensive policy to maintain consistency and eliminate biases. We used the OCC model to identify six main types of emotions: 'Distress', 'Neutral', 'Joy', 'Anger', 'Admiration', and 'Hate'. Each text record in the new dataset is now labeled with both SE label for classification. This dataset is significant as it addresses the lack of resources for SE analysis for Marathi text, and provides a valuable benchmark for future research on performance evaluation in this domain.

## 5.2 Performance

The OCC+HHA+Bi-RNN model is validated using standard classification metrics such as accuracy, recall, precision, and F1 score. Different combinations of HHA using models such as 1D-CNN, LSTM, and GRU are also assessed.

**Table 1.** Performance analysis on the training set for sentiment classification.

| Model | Accuracy | Precision | Recall | F1 Score |
|---|---|---|---|---|
| HHA+Bi-LSTM | 0.9527 | 0.9670 | 0.9789 | 0.9729 |
| HHA+1D-CNN | 0.8731 | 0.8672 | 0.8610 | 0.8641 |
| HHA+LSTM | 0.8562 | 0.8769 | 0.8309 | 0.8533 |
| HHA+GRU | 0.8890 | 0.8230 | 0.8473 | 0.8350 |
| HHA+Bi-GRU | 0.9780 | 0.9952 | 0.9789 | 0.9870 |

**Table 2.** Performance analysis on the testing set for sentiment classification.

| Model | Accuracy | Precision | Recall | F1 Score |
|---|---|---|---|---|
| HHA+Bi-LSTM | 0.9422 | 0.9298 | 0.9456 | 0.9376 |
| HHA+1D-CNN | 0.8742 | 0.8677 | 0.8520 | 0.8597 |
| HHA+LSTM | 0.8311 | 0.8702 | 0.8297 | 0.8494 |
| HHA+GRU | 0.8670 | 0.8500 | 0.8310 | 0.8403 |
| HHA+Bi-GRU | 0.9500 | 0.9681 | 0.9678 | 0.9679 |

**Table 3.** Performance analysis on the training set for emotion classification.

| Model | Accuracy | Precision | Recall | F1 Score |
|---|---|---|---|---|
| HHA+Bi-LSTM | 0.9673 | 0.9878 | 0.9778 | 0.9828 |
| HHA+1D-CNN | 0.8700 | 0.8938 | 0.8380 | 0.8650 |
| HHA+LSTM | 0.8321 | 0.8319 | 0.8534 | 0.8425 |
| HHA+GRU | 0.8227 | 0.8296 | 0.8367 | 0.8331 |
| HHA+Bi-GRU | 0.9658 | 0.9764 | 0.9902 | 0.9833 |

Table 1, Table 2, Table 3, and Table 4 show that the proposed OCC+HHA+Bi-RNN models outperform the remaining models in terms of the defined performance metrics. The proposed variants HHA+Bi-LSTM and HHA+Bi-GRU emerge as the standout performers across both the given tasks. Their ability to balance high precision with effective recall makes them well-suited for SE classification tasks. The consistent outperformance

**Table 4.** Performance analysis on the testing set for emotion classification.

| Model | Accuracy | Precision | Recall | F1 Score |
|---|---|---|---|---|
| HHA+Bi-LSTM | 0.9612 | 0.9850 | 0.9835 | 0.9842 |
| HHA+1D-CNN | 0.8673 | 0.8235 | 0.8675 | 0.8449 |
| HHA+LSTM | 0.8111 | 0.8256 | 0.8353 | 0.8304 |
| HHA+GRU | 0.8364 | 0.8235 | 0.8364 | 0.8299 |
| HHA+Bi-GRU | 0.9739 | 0.9702 | 0.9878 | 0.9789 |

of the proposed model suggests its robustness in capturing nuanced patterns within SE data. Additionally, we saw that compared to the sentiment analysis task, which had only three classes, there was performance improvement in the emotion analysis task with more classes.

Figure 3 and Fig. 4 demonstrate that the hybrid Bi-RNN models (Bi-LSTM and Bi-GRU) perform better than the other models, maintaining a high Area Under the Curve (AUC) score of 0.94 and 0.99 respectively for sentiment analysis. Similarly, the emotion analysis task shows excellent performance with scores of 0.98 for both respectively.

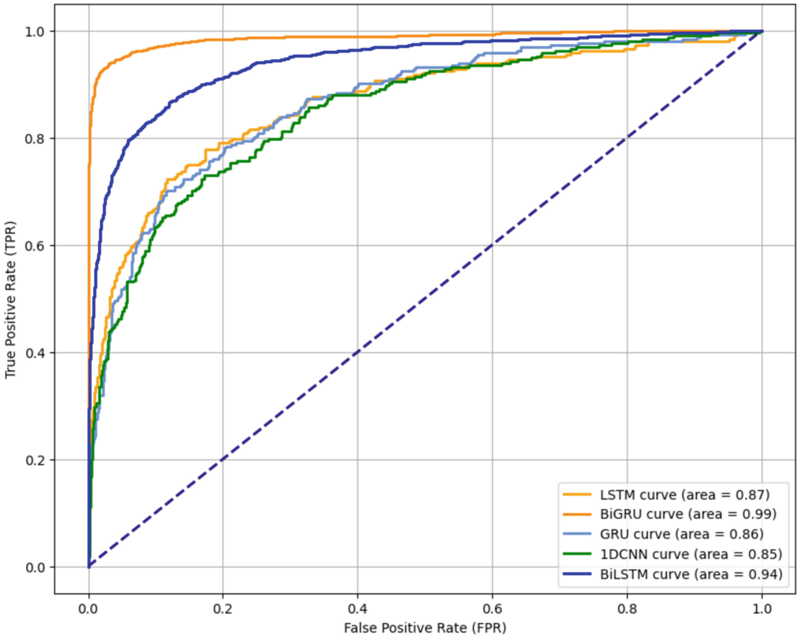


**Fig. 3.** AUC-ROC curves for all the models used for sentiment analysis task.

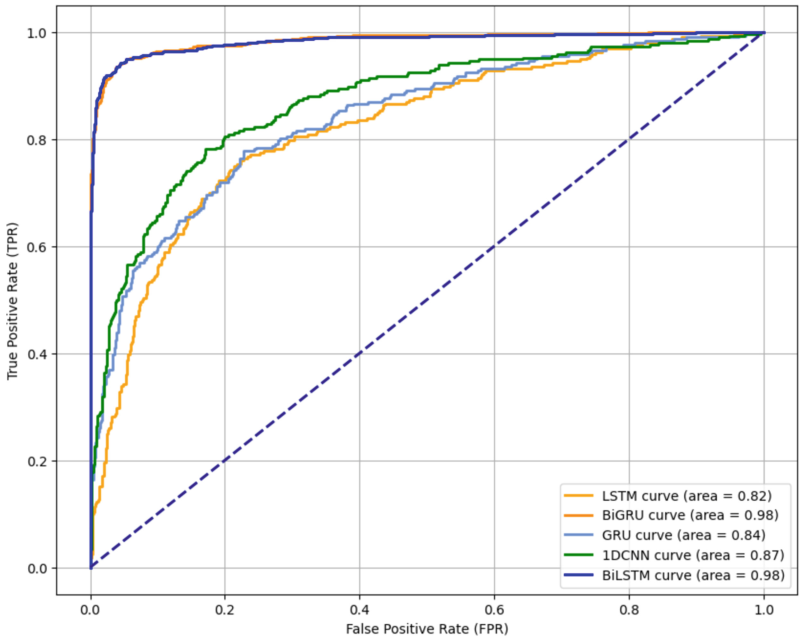


**Fig. 4.** AUC-ROC curves for all the models used for emotion analysis task.

## 6 Conclusion

This research work makes significant contributions in the domain of SE analysis for the Marathi text. The developed hybrid model, combining the OCC model, HHA algorithm, and Bi-RNN classifier, demonstrates superior performance compared to other language processing algorithms. The study addresses the gap in sentiment analysis research for low-resource languages like Marathi, with a focus on understanding the sentimental and emotional tone expressed in textual data. The model's accuracy and efficiency are trained, tested, and validated using a Marathi sentiment analysis dataset, L3CubeMahaSent, which comprises 16,000 unique tweets annotated into positive, negative, and neutral categories. We also annotate the emotions of the text records using the OCC model. The results show that the hybrid model consistently outperforms other models, achieving high accuracy, precision, recall, and F1 scores on both SE data. This research not only contributes to the advancement of SE analysis techniques for low-resource languages but also introduces a novel hybrid approach that combines cognitive computing, optimization algorithms, and deep learning. Overall, the study provides a comprehensive framework for SE analysis in the Marathi text, paving the way for further research and development in this area.

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