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Novel Text Emotion Classification Model Using Long Short-Term Memory Network

Rubul Kumar Bania[1,*]

[1]*Department of Computer Science, Birangana Sati Sadhani Rajyik Vishwavidyalaya, India*

Abstract: Emotion has a great influence on human cognition, behavior, and communication. In last several years, there is a tremendous rise of users in social media platforms, due to which large amount of textual data got generated. Users continuously share their thoughts and sentiments, regardless of time or location. Furthermore, the growth of emotion detection mechanism for the social media platforms becomes truly remarkable. In this paper, one novel deep learning (DL)-based classification model is proposed which is underlined on the concepts of long short-term memory (LSTM) network for the classification of six different types of emotions such as sadness, anger, love, surprise, fear, and joy from English-based texts. The model is compared with nine distinctive state-of-the-art supervised learning models. Utilizing the 80%–20% train-test split, the proposed model has shown the higher classification accuracy of 90.28% in comparison to other compared models. Practically, this model can be used in chatbots, virtual assistants, and personalized applications during the interaction with users.

Keywords: emotion detection, LSTM, supervised models

1. Introduction

The escalation of Web 2.0 and Web 3.0 has led to an outpouring in user-generated content across the Internet. Given the wide-ranging volume of text generated across different online platforms such as Facebook, Twitter, Instagram etc., have realizing the underlying emotions and sentiments expressed in this content has gained heightened significance [1–3]. Consequently, analyzing these treasures of user-generated data is highly challenging due to diverse nature of users. Monitoring of public emotions and sentiments is proven to be demanding mechanism in various decision-making applications.

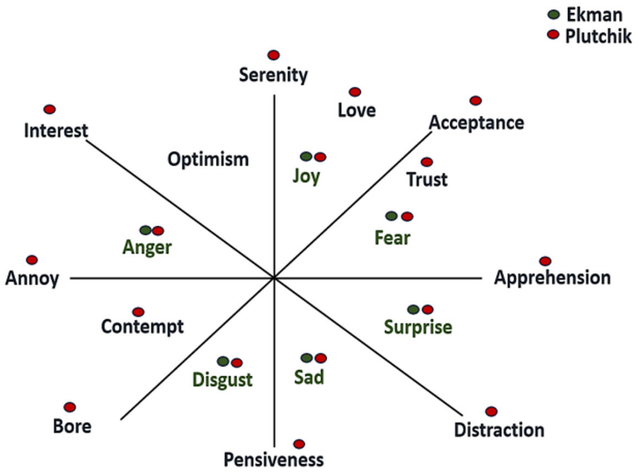
Emotions wield considerable influence over human cognition, behavior, and communication. Detecting and understanding these emotions from textual and even vocal expressions are crucial for enhancing man-machine interaction systems [4]. Exploring emotional signs within user-generated content not only reveals insights into people's hobbies, personality traits, and interests but also yields valuable clues about their mental health condition. Therefore, examining these emotional dimensions has the latent to make significant contributions across a range of fields [5, 6].

Experiencing emotions typically involves a deliberate activation of feelings through conscious awareness or external influences. As a result, emotions like happiness, sadness, fear, anger, surprise, and more are rooted in the subjective experiences of individuals, shaped by their personal encounters and interactions with the environment [4]. In the literature, the emotional models are normally categorized into two categories: dimensional and categorical [2, 7]. The dimensional model categorizes emotions using three key parameters: valence, arousal, and power. Valence refers to polarity, and arousal gauges the intensity or excitement of a feeling, where, for instance, "delighted" is considered more exhilarating than "happy." Power or dominance indicates the level of control or restriction exerted over an emotion. Conversely, emotions are delineated discretely, including states like anger, happiness, sadness, and fear. Figure 1 illustrates the multitude of emotional states given by the Ekman and Plutchik models [7].

Natural language processing (NLP) encompasses two primary facets: the comprehension of human language and the generation of human language. Nevertheless, language comprehension presents greater complexity due to their inherent ambiguities found in languages. Within the domain of NLP employing artificial intelligence (AI) techniques, emotion detection and sentiment analysis emerge as two pivotal application areas [8, 9]. Despite the interchangeable use of these terms, they possess nuanced distinctions. Sentiment analysis serves as a technique for ascertaining whether data conveys positivity, negativity, or neutrality [9–11]. Conversely, emotion detection is focused on the identification of a spectrum of human emotions. Emotion detection serves as a method for discerning people's emotions, attitudes, and sentiments in various contexts, including individuals, activities, organizations, services, products, and more. It represents a specialized evolution of sentiment analysis that goes beyond the mere categorization of text as positive, negative, or neutral; instead, its aim is to predict specific emotions [12, 13]. A diverse range of methods has been employed in the past to identify emotions within text, encompassing approaches like the keyword method, lexicon-based methods, and machine learning (ML) approaches [12, 14, 15]. However, it is important to note that keyword and lexicon-based methods have inherent limitations, as they predominantly revolve around the semantic relationships between words. AI, which includes ML and deep learning (DL)-based models, has been recognized to be more effective in classifying and detecting emotions within textual content.

*Corresponding author: Rubul Kumar Bania, Department of Computer Science, Birangana Sati Sadhani Rajyik Vishwavidyalaya, India. Email: drrubulkumarbania@bssrv.ac.in

Figure 1
Visualization of emotional models with their psychological states



By observing the requirements of emotion detection using the latest computational-based technologies, the main contribution of this study is the proposal of a DL-based prediction model underlined on the concepts of long short-term memory (LSTM) network for emotion detection and classification of English language-based text. The reasons behind proposing a DL-based prediction model for text classification problem are as follows: (i) Emotions in text are often subtle and context-dependent. DL models, especially the architectures like recurrent neural network (RNNs), LSTMs, can capture intricate linguistic patterns more effectively than traditional methods; (ii) DL models are useful to train on large-scale datasets and generalize better to diverse text inputs across different domains and languages.

The structure of the remaining parts of the paper is outlined as follows. Section 2 explores into a review of prior studies related to emotion detection. Section 3 provides the background, while Section 4 summaries the methodology. Section 5 presents the experimental results, and Section 6 discusses the conclusions and future directions of this research work.

2. Literature Review

To understand emotions and how various text-based emotions are detected using AI, it is crucial to look at what other researchers have already done. This section aims to contextualize the current state of research and understanding surrounding emotions in written communication.

In Bhart and Varadhaganapathy [6], a pre-trained word vector is utilized to create the word embedding matrix, which is then incorporated into the DL model. The data for this study are sourced from three distinct datasets: International Survey on Emotion Antecedents and Reactions (ISEAR), WASSA, and Emotion-stimulus, each containing attributes for text and corresponding emotions. These datasets include three types of text: regular sentences, tweets, and dialogues, which are combined for analysis. This model integrates both DL and ML approaches, functioning as a text-based emotion recognition system. One key advantage of the proposed model is its ability to process multi-text formats, including sentences, tweets, dialogues, keywords, and lexicon words related to emotions, making it highly effective for emotion detection.

In Chopade [16], the effectiveness of different ML models is assessed by conducting experiments with the state-of-the-art ISEAR emotion dataset. Notably, among the classifiers, BPN exhibited the highest accuracy, achieving 71.27 percentage score. However, it is essential to concede several limitations of this study: (i) it focuses on just five emotion classes, (ii) relies solely on the ISEAR dataset, and (iii) utilizes traditional feature extraction mechanism only.

Authors have categorized the emotions within Indonesian texts in a latest study [17]. The study employs a range of ML algorithms, including Naïve Bayes (NB), support vector machine (SVM), K-Nearest Neighbor (K-NN), and a minimal optimization technique, while using text pre-processing tasks. The experimentation includes the use of 10-fold cross-validation, and the results indicate that the minimal optimization approach outperforms other methods. To extract variant tweets, the study leverages emotion-word hashtags, as well as data from the "Hashtag Emotion Corpus" collection.

In Guo [9], DL-assisted Semantic Text Analysis modeled with NLP was proposed for human emotion detection using big data. Their model shows excessive potential for emotion recognition, as it directly learns features from the given raw data. The qualitative findings indicate that the DLSTA approach notably attains the highest detection rate, achieving 97.22% and 98.02% classification accuracy across different emotional term embedding methods.

In Machová et al. [15], experiments were conducted using a lexicon approach and conventional ML methods, such as NB and SVMs, as well as DL techniques employing neural networks (NN). These approaches aimed to develop a text-based emotion detection model. The model was validated through tests conducted via a web application and in interactions with a Chatbot. Additionally, a web application was created based on the proposed detection model. This application enables users to input text, facilitating the analysis of emotions conveyed in posts or comments. Furthermore, the emotion detection model was utilized to enhance communication between some application and humans.

In a recent study, researchers aimed to classify human emotions from EEG signals [5]. It performs feature extraction through Deep Normalized Attention-based Residual Convolutional Neural Network to extract appropriate features and create a distinct representation of these features. The suggested NN also discovers appealing features using the proposed attention modules, resulting in reliable and steady performance. The performance and comparative analysis of the proposed study aim to identify the effectiveness of the system in detecting emotions from EEG signals [5].

In Ahmad [4], the study has developed a text-based emotion recognition and prediction system. The suggested investigation provides a pathway for addressing the prevalent challenges in accurate emotion analysis. By leveraging four ML algorithms-Multinomial NB, SVM, DT, K-NN tailored to Ekman's six fundamental emotions (anger, fear, disgust, joy, guilt, and sadness) and tries to enhance the understanding of emotion detection accuracy. The outcomes are anticipated to guide advancements in optimizing these algorithms, offering a more refined approach to emotion analysis with practical implications across diverse industries. The ISEAR dataset was used as a benchmark to evaluate all models. An English text-based emotion prediction system with a user-friendly graphical interface for predicting customer emotions from text has been successfully developed.

In summary, the reviewed studies present a diverse array of approaches and methodologies in the domain of emotion analysis. From hybrid models combining ML and DL to studies focusing on specific datasets and languages, each contributes unique insights.

3. Background

LSTM networks are a type of RNN specifically designed to address the vanishing gradient problem and effectively capture

Table 1
Symbols used in LSTM components

Symbol	Explanation
x_t	At time step of t this is the input
h_t	Hidden state at t
C_t	Cell state at t
X_f, X_i, X_C, X_O	Weight matrices for the forget, input, candidate, and output gates are used.
b_f, b_i, b_C, b_O	Biases for the forget, input, candidate, and output gates
σ	Sigmoid activation function
tanh	Hyperbolic tangent activation function

long-term dependencies [10, 18]. An LSTM cell comprises of several essential components such as the cell state C_t, the hidden state h_t the input gate i_t, the forget gate f_t, the output gate O_t, and the candidate cell state $\widetilde{C}_t$. In Table 1, all the symbols are explained.

The forget gate decides which information from the previous cell state, C_{t-1} should be discarded.

$$f_t = \sigma(X_f.[h_{t-1}, x_t] + b_f$$

The input gate controls which values will be updated. It is composed of two components: the input gate layer and the candidate cell state

$$i_t = \sigma(X_i.[h_{t-1}, x_t] + b_i$$

$$\widetilde{C}_t = tanh(X_C.[h_{t-1}, x_t] + b_C$$

The cell state is updated using the forget gate and the input gate.

$$C_t = f_t.\ C_{t-1}, i_t + \widetilde{C}_t$$

The output gate determines the next hidden state by using the updated cell state

$$O_t = \sigma(X_O.[h_{t-1}, x_t] + b_O$$

$$h_t = O_t \tanh(C_t)$$

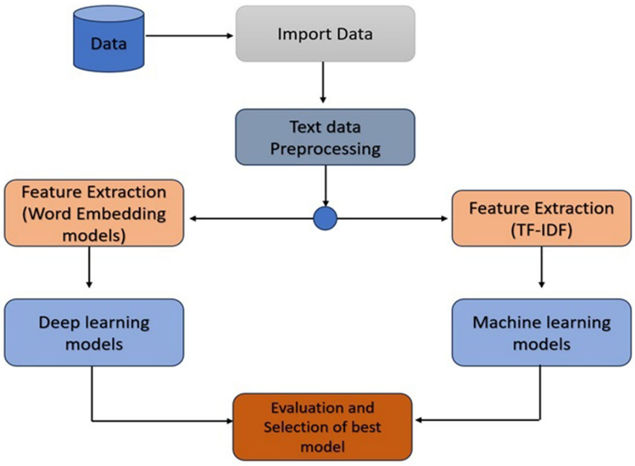
4. Methodology

The problem posed by text-based emotion detection involves the creation of computational models capable of precisely identifying and categorizing emotions conveyed through textual content. Specifically, when presented with a text segment, be it a sentence or a document, the aim is to discern the emotions being expressed within that text. The overarching objective of text-based emotion detection is to construct a dependable and precise automated system or model that can proficiently recognize and categorize emotions within text, all while taking into account the intricacies of language, context, and the multifaceted range of human sentiment.

As a block diagram, the methodology which is employed in this work for the text-based emotion detection mechanism is shown in Figure 2. There are several phases employed in the work. Before exploring the detailed descriptions of each phase, it is worth noting that the Natural Language Processing Toolkit, a Python-based platform, is used in this study.

During the initial phase, data collection and pre-processing tasks are performed. Six distinct emotions are analyzed: joy, sadness, anger, love, surprise, and fear. The dataset is sourced from the Kaggle repository [14, 17] and imported into the analysis environment.

Figure 2
Block diagram of proposed work



Extensive text pre-processing is applied to improve the quality of the textual data. Data pre-processing is crucial, as the dataset from Kaggle often comes in an unclean state. This includes basically the special characters, hashtags, and unnecessary symbols that are irrelevant for the task of analysis. Additionally, the data may contain punctuation, newline characters, mixed case text, and common stop words. Pre-processing involves applying various transformations to the data to prepare it for use in the prediction models or algorithms.

To expedite the machine understanding, the Term frequency-inverse document frequency (TF-IDF) [7, 19] and *word2vec* word embedding types of feature extraction art applied to convert words into numerical format. The vectorized data which are processed by the TF-IDF mechanism are passed to the ML-based models. The word embedding techniques are engaged on the DL-based models [18, 20]. After the text data have been vectorized or features extracted, the next step involves selecting appropriate learning models.

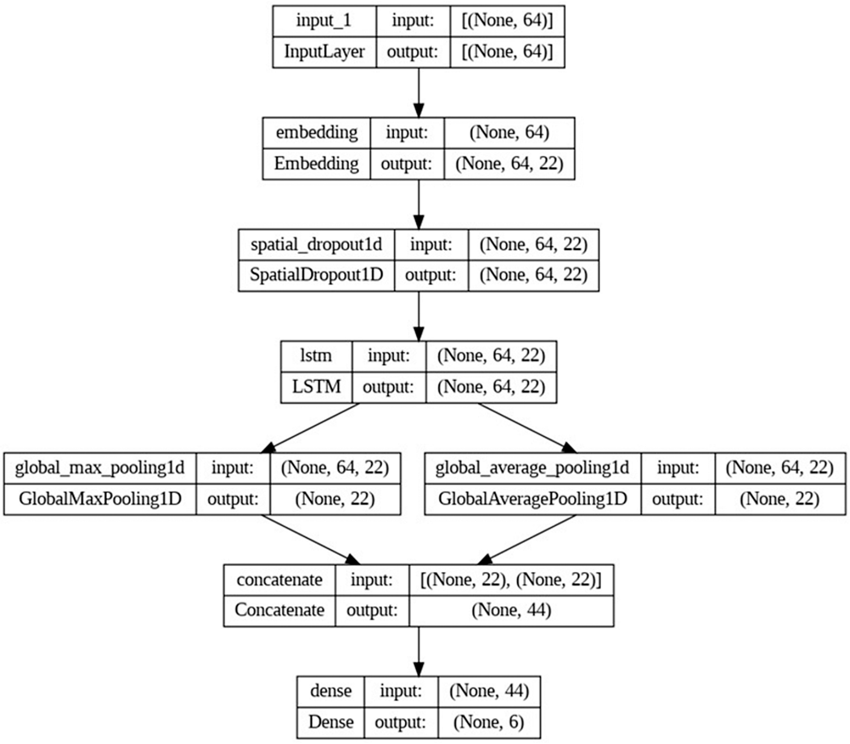
4.1. Proposed model

The graph-based architecture of the model is illustrated in Figure 3. It includes an input layer, an embedding layer, 1-D spatial dropout layer, which is followed by one LSTM layer. This is then trailed by a concatenation of the 1-D global maximum pooling layer and the 1-D global average pooling layer, terminating in a dense layer with a softmax activation function for the final text emotion classification task.

In the proposed model, the output from the embedding layer is passed to a spatial dropout layer that randomly drops certain features to enhance the system's generalizability during the process of training. The reduced feature set is then input into the LSTM network, which processes these features and returns appropriate facts as sequences of LSTM hidden states and final state values. These outputs are then passed in parallel into two separate layers namely the global max pooling layer and the global average pooling layer, which select the maximum and average of all state values, respectively. The outputs from both the layers are combined using a concatenate layer and then promoted to the final output layer, which is basically a fully connected dense layer with a softmax activation function, which produces an emotion class for the input text.

This work utilizes the word embedding technique, widely used in text-based applications for its ability to capture meaningful semantic properties and linguistic relationships between words.

Figure 3
Graph architecture of the proposed model



The rationale behind the spatial dropout layer is to ensure that the network does not become overly dependent on any single feature. This layer serves as a form of regularization to prevent overfitting during training. In the LSTM layer, each node in the network functions as a computational unit that consists of weighted input connections, an activation function, and an output connection.

A NN can efficiently learn the complex relationship between input and output data by properly setting hyperparameters during training. In Table 2, settings of the values which are used during the experiments are shown. The number of nodes in the LSTM network is critical, with the LSTM layer containing 22 nodes. The Global Max Pooling layer selects the maximum value for each feature from the LSTM output, while the Global Average Pooling layer calculates the average value for each feature. Both outputs are then passed to the next layer, which is the concatenate layer. This layer merges the outputs from the Global Max Pooling and Global Average Pooling layers into a single feature frame and forwards it to the final output layer.

Table 2
Settings of hyperparameters

Hyperparameters	Values
Optimizer	Adaptive Moment Estimation
Learning Rate	0.001
Loss Function	Sparse Categorical Cross-entropy
Embedding Layer	10
LSTM nodes	22
Number of Epochs	50
Patience	5
Dropout	0.5
Spatial Dropout	0.5

5. Experimental Setup and Data Used

For reliability in the investigated experimental results, all the models which are considered in this study are developed in Python environment. The experiments were conducted on a computer system having an Intel Core i5 8300H @ 2.30GHz processor, 8 GB of RAM, running on operating system Windows 11. The development environment included Jupyter Notebook and various useful Python packages.

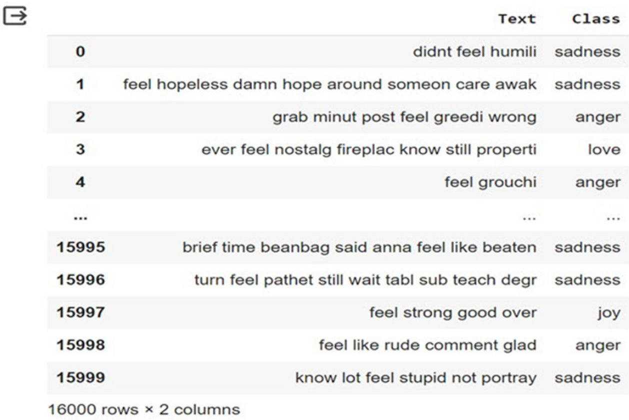
The dataset is built on both emotional stimuli and statements. The dataset is grouped into 6 types of emotions (sadness, anger, love, surprise, fear, and joy). During the evaluation time, datasets are split into training (80%) and testing set (20%). In previous studies [7, 21], authors have used this dataset. Sample of the dataset is shown as an image in Figure 4. The pie chart shown in Figure 5 represents the distribution of emotions in a dataset extracted from Twitter posts. Each slice of the pie corresponds to a specific emotion, and the size of the slice indicates the proportion of tweets associated with that emotion. Joy (33.5%) is the most prevalent emotion in the dataset, representing a significant portion of Twitter posts. This suggests that a substantial number of tweets convey positive sentiments or experiences. Anger (13.5%), fear (12.1%), love (8.1%), and surprise (3.6%) collectively represent the less frequent emotions in the dataset. These emotions are less commonly expressed on Twitter based on the analyzed data.

5.1. Evaluation measures

The following four main metrics were used to evaluate a classification model [10].

a) **Accuracy:** It is a simple metric that gauges the overall accuracy of a model. It represents the ratio of correctly predicted instances,

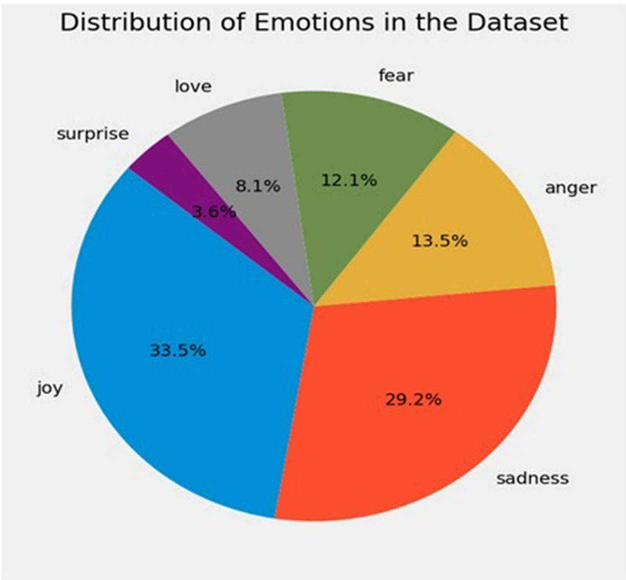
Figure 4
Sample of the Twitter emotion data



	Text	Class
0	didnt feel humili	sadness
1	feel hopeless damn hope around someon care awak	sadness
2	grab minut post feel greedi wrong	anger
3	ever feel nostalg fireplac know still properti	love
4	feel grouchi	anger
...	...	...
15995	brief time beanbag said anna feel like beaten	sadness
15996	turn feel pathet still wait tabl sub teach degr	sadness
15997	feel strong good over	joy
15998	feel like rude comment glad	anger
15999	know lot feel stupid not portray	sadness

16000 rows × 2 columns

Figure 5
Distribution of each class of the dataset



comprising both true positives (TP) and true negatives (TN), to the total number of instances.

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

b) **Precision**: It refers to the proportion of relevant instances among all the instances that were predicted to be part of a specific class. It is a metric that focuses on the accuracy of positive predictions. It can be expressed as:

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

c) **Recall**: It denotes the ratio of instances predicted to belong to a class relative to all the instances actually belonging to that class. It is also known as sensitivity or true positive rate (TPR) and measures the coverage of positive instances.

Table 3
Comparative result analysis of various methods

Models	Precision	Recall	$F1$-score	Accuracy (%)
RF	0.832	0.829	0.839	83.34
BNB	0.761	0.770	0.766	77.56
LR	0.761	0.781	0.790	80.70
MJV	0.841	0.832	0.840	84.28
SVM	0.708	0.712	0.718	71.53
CNN-LSTM	0.756	0.747	0.755	77.59
Bi-LSTM	0.833	0.844	0.814	86.00
[14]	0.798	0.787	0.803	80.69
[22]	0.811	0.795	0.795	81.69
Proposed Model	**0.867**	**0.855**	**0.864**	**90.28**

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

d) ***F*1-score**: The $F1$-score merges the precision and recall of a classifier into a single metric by calculating their harmonic mean. It offers a balanced assessment that takes into account both false positives (FP) and false negatives (FN).

$$F1\ Score = 2 * \frac{Precision\ \ \mathrm{x}\ \ Recall}{Precision + \ Recall}$$

In summary, evaluation measures like accuracy provides an overall view of the model performance, precision, recall, and $F1$-score offer nuanced insights, particularly in situations where there is class imbalance or where the costs of FP and FN are unequal.

5.2. Comparison and analysis of results

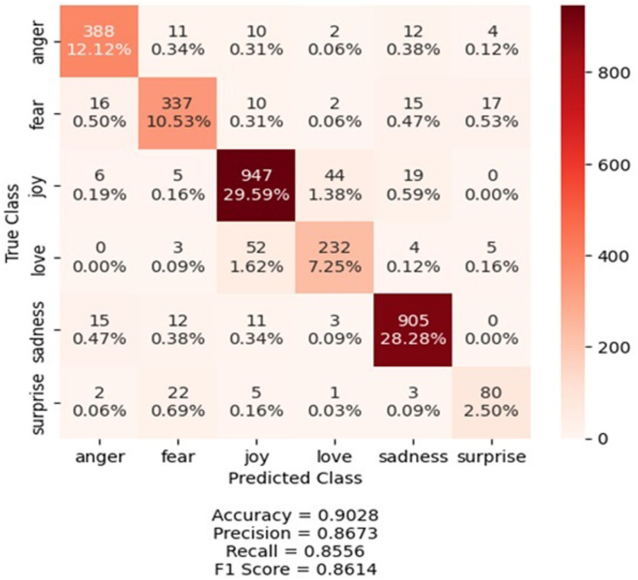
To classify the tweets into six distinct categories, extensive experiments are conducted using both the training and test set splits of the dataset. These experiments are applied to the proposed model as well as the comparison prediction models. For the utilization of supervised ML models as the baseline classifiers, five different ML models are developed in this study.

Those models are RF, which is an ensemble method combining multiple decision trees, LR, which is a linear model suitable for binary and multiclass classification tasks, third one is BNB, which is a probabilistic model for binary and multiclass classification. Leveraging the enriched ensemble learning mechanism, these three supervised models have been curated to form a diverse ensemble classifier based on Majority Voting mechanism.

In this study, along with the five ML-based models, four different DL-based models including- Bidirectional LSTM (Bi-LSTM), CNN-LSTM, Chowanda et al. (COMP-1) [14] and Tanwar et al. (COMP-2) [22] are also compared. The reason behind choosing all these above-mentioned supervised models is that all of the models are very popular and robust in various application domains. Also, Tanwar [22] has developed a convolutional neural network model and applied that model on the dataset which is considered in this study. This study assesses the performance of all these models for the task of emotion detection. Finally, the models are tested and evaluated and then compared with the proposed model.

Broad summary of the experimental results obtained by the various models on the emotion dataset is shown in Table 3. From the tabulated results, it can be observed that the proposed model has obtained suitable results in comparison to the other methods. All the evaluation measures such as accuracy, precision, recall, and $F1$-score

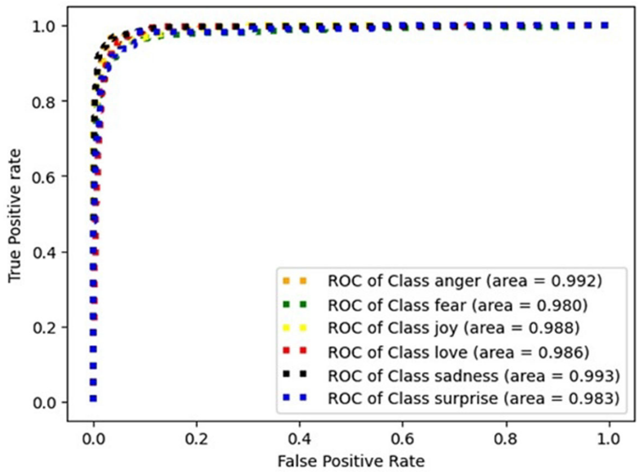
Figure 6
(a) Model loss curve and (b) model accuracy curve



have better performance. However, the Bi-LSTM, CNN-LSTM, COMP-1 and COMP-2 have also achieved near about good results. It is noticeable that traditional ML-based model viz., RF performs reasonably well but it is not comparable to the performance of the NN-based models. Proposed model has shown higher values for all the evaluation metrics (precision, recall, *F*1-Score, and accuracy), reflecting their ability to correctly identify positive instances (emotion) while minimizing false positive results.

A commonly used plot for debugging a network is the cross-entropy (loss) curve during training, which offers insights into the training process and how the network is learning. Another essential

Figure 8
Confusion matrix for the proposed model



plot is the accuracy curve, which tracks both training and validation accuracy to monitor the network's performance. Figure 6(a)–(b) displays these two graph plots for the proposed model.

In Figure 7, receiver operating characteristic (ROC) curves for the proposed model using the One-vs-Rest scheme, which compares each class against all others, are shown. Typically, ROC curves are employed in binary classification, where the TPR and false positive rate (FPR) can be clearly defined. In this study, addressing multiclass classification, so the concepts of TPR and FPR are derived only after binarizing the output.

A confusion matrix is a mechanism for measuring the performance of a classification algorithm or model. It basically offers a thorough breakdown of the model's performance for each emotion class, including anger, fear, love, joy, sadness, and surprise. The figures given in Figures 8 and 9 show the confusion

Figure 7
ROC curves of the proposed model

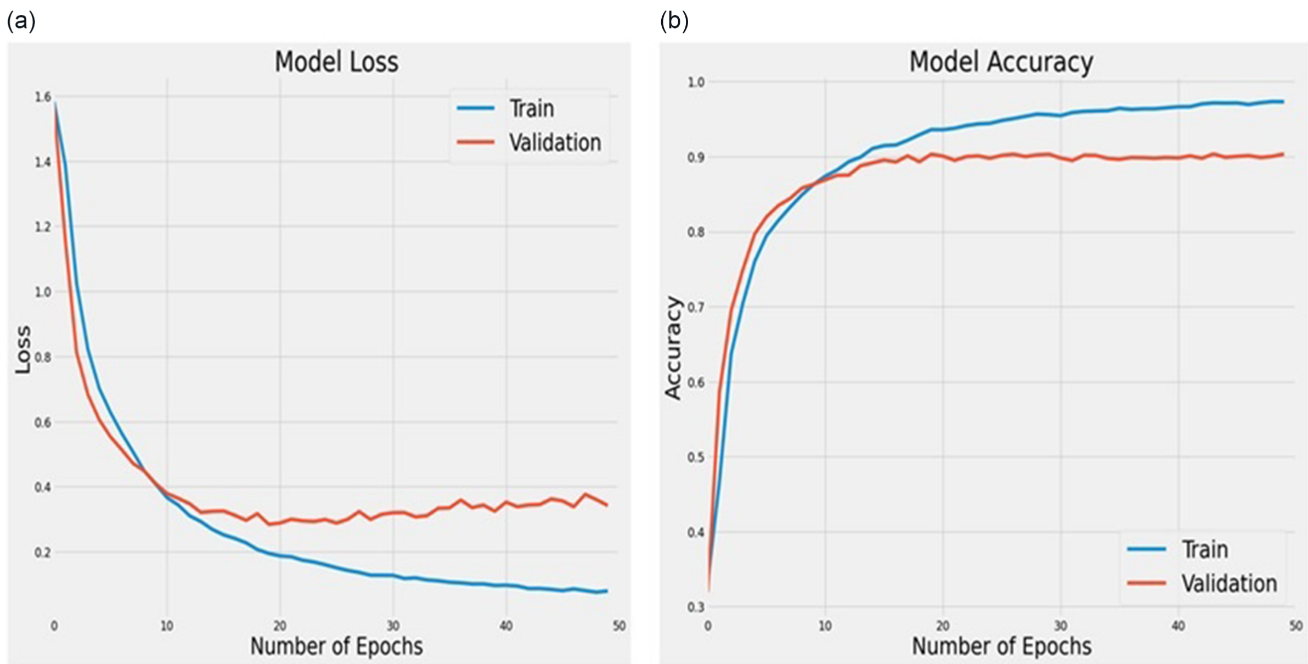
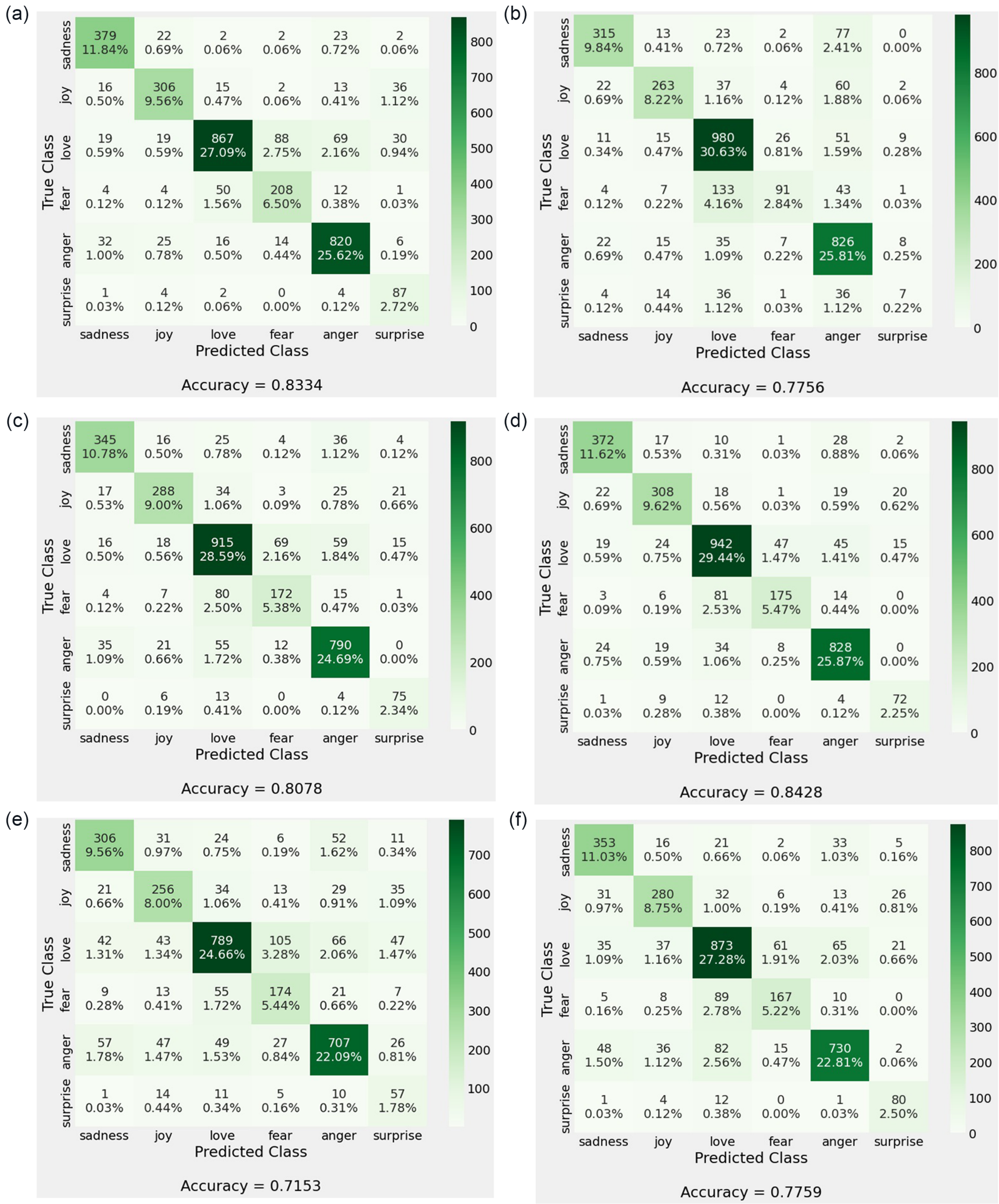
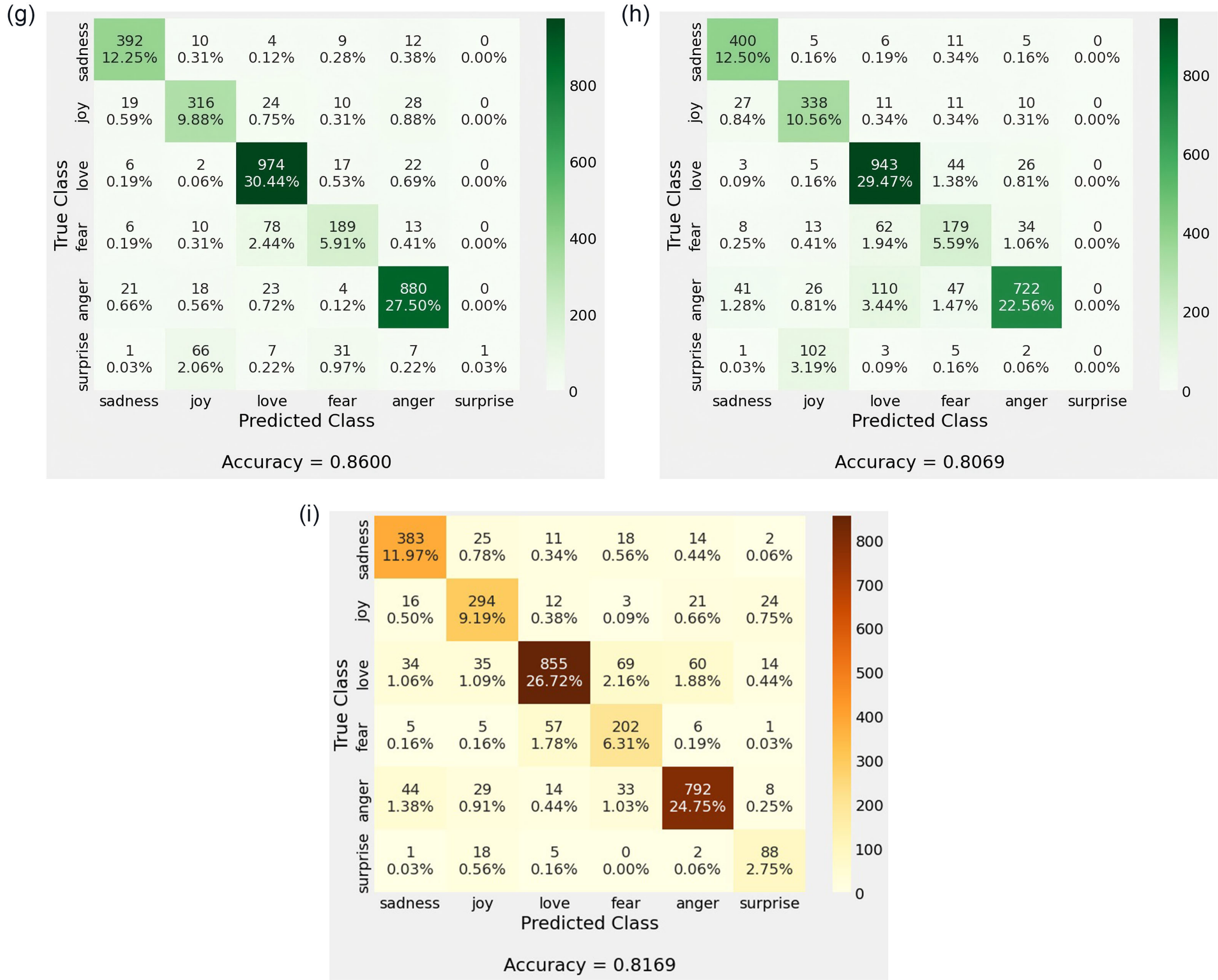


Figure 9
Confusion matrix of (a) RF (b) BNB (c) LR (d) MJV (e) SVM (f) CNN-LSTM (g) Bi-LSTM (h) COMP-1 (i) COMP-2





matrix generated by various classification models. It can be seen from the confusion matrix that the proposed model appears to have robust enactment across all the classes, as indicated by high numbers of TP and TN. It is also notable that Bi-LSTM also shows somewhat strong performance, aligning with the high numbers of TP and TN in its confusion matrix. From these summarized experimental results shown in Table 3 and confusion matrix (Figures 8 and 9), the proposed model has performed better in terms of accuracy, precision, recall, and $F1$-Score across all the emotion classes (anger, fear, love, joy, sadness, and surprise).

6. Conclusion and Future Work

The advancement of web and Internet technologies has created an accessible environment for individuals to easily share content on online platforms, including comments on news articles, blogs, and more. By utilizing text analysis techniques, it is possible to identify the emotions and viewpoints of specific target demographics. In this research endeavor, meticulously examined and scrutinized eight distinct supervised learning models such as RF, BNB, LR, one Majority Voting-based Classifier, SVM, Bi-LSTM, CNN-LSTM, Chowanda et al. [14] and Tanwar [22]. A new model based on the architecture of LSTM network is proposed. All models are designed to analyze textual data from tweets. Significantly, the proposed classification model has shown superior performance compared to the other nine classifiers. The confusion matrices offer detailed insights into each model's performance across various emotion classes.

The LSTM-based proposed model is capable of accurately detecting six distinct emotions from English texts. This kind of model can be useful in the applications of various fields, including sentiment analysis and affective computing. In future research, this study shall be applied on bulk text datasets. Also, different latest word embedding techniques will be used.

Ethical Statement

This study does not contain any studies with human or animal subjects performed by any of the authors.

Conflicts of Interest

The author declares that he has no conflicts of interest to this work.

Data Availability Statement

The data that support the findings of this study are openly available in Kaggle at https://www.kaggle.com/datasets/praveengovi/emotions-dataset-for-nlp.

Author Contribution Statement

Rubul Kumar Bania: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Writing – original draft, Writing – review & editing, Visualization.

References

[1] Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes*, *50*(2), 179–211. https://doi.org/10.1016/0749-5978(91)90020-T

[2] Ajzen, I., & Fishbein, M. (1980). *Understanding attitudes and predicting social behavior*. New Jersey: Prentice-Hall.

[3] Acheampong, F. A., Wenyu, C., & Nunoo-Mensah, H. (2020). Text-based emotion detection: Advances, challenges, and opportunities. *Engineering Reports*, *2*(7), 1–24. https://doi.org/10.1002/eng2.12189

[4] Nasir, A. F. A., Nee, E. S., Choong, C. S., Ghani, A. S. A., Majeed, A. P. P. A., Adam, A., & Furqan, M. (2020). Text-based emotion prediction system using machine learning approach. *IOP Conference Series: Materials Science and Engineering*, *769*, 012022. https://doi.org/10.1088/1757-899X/769/1/012022

[5] Alsubai, S. (2023). Emotion detection using deep normalized attention-based neural network and modified-random forest. *Sensors*, *23*(1), 225. https://doi.org/10.3390/s23010225

[6] Bharti, S. K., Varadhaganapathy, S., Gupta, R. K., Shukla, P. K., Bouye, M., Hingaa, S. K., & Mahmoud, A. (2022). Text-based emotion recognition using deep learning approach. *Computational Intelligence and Neuroscience*, *2022*, 1–8. https://doi.org/10.1155/2022/2645381

[7] Nandwani P., & Verma, R. (2021). A review on sentiment analysis and emotion detection from text. *Social Network Analysis and Mining*, *11*(81), 1–18. https://doi.org/10.1007/s13278-021-00776-6

[8] Bhavya, A. V., Dhanush, R. H., Sangeetha, J., & Jose, A. C. (2024). Personalised emotion detection from text using machine learning. In J. A. Marmolejo-Saucedo, R. Rodríguez-Aguilar, P. Vasant, I. Litvinchev, & B.M. Retana-Blanco (Eds.) (pp. 169–180). Springer.

[9] Guo, J. (2022) Deep learning approach to text analysis for human emotion detection from big data. *Journal of Intelligent Systems*, *31*, 113–126. https://doi.org/10.1515/jisys-2022-0001

[10] Bania, K. R. (2024). CovDLCNet: LSTM based deep learning network for multiclass sentiment analysis on COVID-19 public tweets. *Multimedia Tools & Applications*, *83*, 67535–67567. https://doi.org/10.1007/s11042-023-18042-6

[11] Samuel, J., Ali, G. G. M. N., Rahman, M. M., Esawi, E., & Samuel, Y. (2020). Covid-19 public sentiment insights and machine learning for tweets classification. *Information*, *22*(4), 1–21. https://doi.org/10.3390/info11060314

[12] Mauryaa, C. G., & Jha, K. S. (2024). Sentiment analysis: A hybrid approach on Twitter data. *International Conference on Machine Learning and Data Engineering: Procedia Computer Science*, *235*, 990–999. https://doi.org/10.1016/j.procs.2024.04.094

[13] Abdelhady, N., Elsemman, I. E., & Soliman, T. H. A. (2024). A real-time predicting online tool for detection of people's emotions from Arabic tweets based on big data platforms. *Journal of Big Data*, *11*, 171. https://doi.org/10.1186/s40537-024-01035-z

[14] Chowanda, A., Sutoyo, R., Meiliana, & Tanachutiwat, S. (2021). Exploring text-based emotions recognition machine learning techniques on social media conversation. *Procedia Computer Science*, *179*, 821–828. https://doi.org/10.1016/j.procs.2021.01.099

[15] Machová, K., Szabóova, M., Paralič, J., & Mičko, J. (2023). Detection of emotion by text analysis using machine learning. *Frontiers in Psychology*, *14*, 1190326. https://doi.org/10.3389/fpsyg.2023.1190326

[16] Chopade, C. R. (2015). Text based emotion recognition: A survey. *International Journal of Science and Research*, *4*(6), 409–414.

[17] Hasan, M., Rundensteiner, E., & Agu, E. (2019). Automatic emotion detection in text streams by analyzing twitter data. *International Journal of Data Science and Analytics*, *7*(1), 35–51 https://doi.org/10.1007/s41060-018-0096-z

[18] Dar, M. N., Akram, M. U., Khawaja, S. G., & Pujari, A. N. (2020). CNN and LSTM-based emotion charting using physiological signals. *Sensors*, *20*(16), 4551. https://doi.org/10.3390/s20164551

[19] Bania, K. R. (2021). Heterogeneous ensemble learning framework for sentiment analysis on COVID-19 tweets. *INFOCOMP Journal of Computer Science*, *20*(2), 1–14. https://www.researchgate.net/publication/356714785

[20] Mozhdehi, M. H., & Moghadam, A. E. (2023). Textual emotion detection utilizing a transfer learning approach. *Journal of Supercomputing*, *79*, 13075–13089. https://doi.org/10.1007/s11227-023-05168-5

[21] Li, Z., Xie, H., Cheng, G., & Li, Q. (2021). Word-level emotion distribution with two schemas for short text emotion classification. *Knowledge-Based System*, *227*, 107163. https://doi.org/10.1016/j.knosys.2021.107163

[22] Tanwar, V. (2024). Deep learning-based emotion detection on Twitter: A study of six primary emotions. In *IEEE Second International Conference on Intelligent Cyber Physical Systems and Internet of Things*. https://doi.org/10.1109/ICoICI62503.2024.10696512

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