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Emotions analysis from text using CNN, BiLSTM and hybrid models

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Abstract

Human emotion recognition using artificial intelligence has become a significant research area with applications in emotion analysis, opinion mining and affective computing for understanding users' emotional states. This study presents an emotion analysis framework based on machine learning and deep learning models trained on a Twitter-derived emotion dataset available on Kaggle. The dataset comprises 20,000 text–label pairs categorized into six emotion classes: Sadness, Joy, Love, Anger, Fear and Surprise. Data preprocessing includes stop-word removal, lowercasing, elimination of URLs and special characters, and TF-IDF–based feature extraction, followed by label encoding for model compatibility. To provide reliable analysis, the dataset is separated into subsets for training, validation and testing. Multiple models Convolutional Neural Networks (CNN), Bidirectional LSTM (BiLSTM), Logistic Regression and a Hybrid CNN–BiLSTM model with Multi-head attention are implemented and compared. According to experimental data, the CNN model outperformed the hybrid, BiLSTM and Logistic Regression models, with accuracy of 91.90%. The results show the effectiveness of deep and hybrid architectures in capturing fine emotional tone from informal textual data. The proposed framework provides an expandable and reliable solution for real-world applications in textual data analytics, human–computer interaction

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and intelligent emotion monitoring systems, with future scope for transformer-based and multilingual enhancements.

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Keywords: *Emotion recognition, Emotion analysis, NLP, TF-IDF, Text classification, Social media analytics.*

1. Introduction

Nowadays, when the use of digital and social media is rapidly growing, understanding emotion analysis too increased noticeably, as it plays vital role in forge ahead one's business. Emotions and analysis of emotions play an important part in the education sector also, for teachers and students both. A teacher's efficacy depends not just on his academic credentials, but also on his enthusiasm, talent and devotion. Taking prompt input from student is an extremely effective tool for a teacher to enhance their teaching methods [1]. In contrast, emotion classification is a way of recognizing unique human emotion tones such as angry, happy or sad. There are times when words like Emotion identification, Emotion detection, affective computing and Emotion analysis are used interchangeably [2].

Emotion analysis is a process through which one can analyze the feedback to see whether it is positive or negative. People also like to receive acceptance or rejection [3, 4]. Emotion analysis can be done in traditional and automated means involving the use of machine learning (ML) techniques. Various text analysis techniques have evolved through the years including ML, DL and NLP. NLP is a specific branch of AI that focuses on natural language: the natural language understanding between computer and human languages. At the same time, ML is an umbrella term encompassing different types of learning techniques and DL is a subset of ML which involves the use of advance technology for learning [5]. There are currently several NLP libraries that do text tokenization, named entity identification, emotion analysis, language modeling and part-of-speech tagging using ML and DL approaches [6]. Some of these tools are trained mainly on English language only and do not have pre-built support for other languages.

1.1 *Motivation and Contributions*

The fast emergence of digital communication platforms has necessitated automatic detection of emotion by text-based data in applications like emotion analysis, social media analytics and human computer interaction. Nevertheless, the issues, such as linguistic ambiguity, contextual variability, informality of short social media texts, still influence the accuracy of detection. In order to find a solution to these challenges, this study suggests a scalable multi-class emotion recognition system that takes advantage of some advanced preprocessing methods and deep neural networks. The offered method will enhance the performance of classifications and contribute to the creation of smarter emotional analysis system.

- Utilized a Twitter-based Kaggle Emotion dataset [7] of the six emotional categories sadness, joy, love, anger, fear, and surprise—are represented by 20,000 text-label pairings.
- Developed an improved preprocessing pipeline that involved stop-word elimination, lowercasing and removal of URLs and special characters, TF-IDF feature extractor and label encoder to feed structured models.
- Applied and compared various models CNN, BiLSTM [8, 9], Logistic Regression (LR), and a Hybrid CNN-BiLSTM with multi-head attention to make a thorough analysis of performance.
- Improved a highly scalable and powerful deep learning-based emotion recognition system that can be used in emotion analysis, opinion mining and human-computer interaction systems.

1.2 *Organization of the paper*

The paper is ordered as follows: Next section explores relevant research in the field of emotion detection. Section 3 describes the suggested technique and dataset. Section 4 includes experimental data and model comparisons, while Section 5 ends the study with suggestions on future research areas.

2. Literature Review

In this section, the various machine learning algorithms, that are currently employed for emotion and emotion detection, are evaluated. Recent research works on the text-based emotion recognition using data-driven methods to enhance the accuracy. However, present-day models fail to generalize in various datasets with mixed emotions and lacking in contextual understanding.

Kesharwani et al. [10] initialized using 200-dimensional pre-trained GloVe embeddings, NetworkX is used to build graph topologies. To characterize relational context in talks, they assess three GNN architectures: GCN, GAT, and R-GCN. Models were evaluated against conventional classifiers like SVM, LR and Naive Bayes. Ouyang, Zhang, and Yang [11] demonstrated that the performance of the single modal model falls short of the multimodal data fusion model with reference to accuracy, precision, F1-score and other assessment indicators, particularly when the three modalities of text, audio and video are combined. The model's ultimate accuracy is 88.4%.

Yu and He [12] conducted the experiment and their experimental results show that, compared to the traditional use of methods based on distributed word vector representations, the best classification performance is achieved by using the model with SVM, with an accuracy of 90.61% and a precision of 91.11%. Wang [13] selected multiple sets of publicly available datasets to perform experiments to assess the performance of various algorithms. The experimental output proves that the text classification scheme based on Word2Vec and CNN has achieved more than 85% accuracy, precision, and recall may reach 87.6%.

Sharika et al. [14] aimed at discerning the underlying emotions and emotions embedded within written text. Deploying Bi-LSTM layers in conjunction with GloVe embedding, their approach endeavors to accurately detect and classify the prevailing emotions within textual data. Through rigorous experimentation, their proposed methodology has achieved a commendable accuracy rate of 70%. Malagi et al. [15] constructed a text-based emotion recognition and prediction model. Accuracy is the most important of the commercial obstacles that emotion analysis is facing. Consequently, supervised ML classification techniques DT, NB, SVM, LR, KNN and RF were investigated to achieve the results.

Huang and Jusoh [16] utilized a pre-trained model, ERNIE, and created a little DL model to identify emotions from sentences written in Chinese language and recognise the emotions using their defined rules. For example, feelings like 'happy' or 'like' are considered as positive emotions; where as feelings such as 'anger', 'disgust', 'sadness' or 'fear', on the other hand, indicate a negative mood. The experimental results show that positive and negative emotion had F1 scores of 93.00% and 90.14%, respectively, in Chinese music evaluations. Ahmadian et al. [17] used a hybrid technique, which combined the IndoBERT model's final hidden layer summation with a neural network model. The F1-score measure was used to analyze the effect of the generated model. Investigational findings reveal that the suggested model achieves an accuracy of 0.92 and 0.76 for emotion analysis and emotion classification, respectively.

Research Gap: Despite significant progress in emotions analysis, several research gaps remain. Existing studies have achieved high accuracy using ML and DL models, yet most focus on a restricted range of primary emotions and fail to capture complex or mixed emotional states [18]. While some models show improved performance through data augmentation and hybrid techniques, they often suffer from high computational complexity and limited real-world generalizability. These approaches based on the extensive use of feature engineering are less flexible to contextual variations and are not successful in coping with sarcasm, irony and cultural distinctions. Aside from this, models for machine learning are, while easy to implement, not able to learn deep semantic relationships between text. Overall, a more integrated and context-aware framework fusing linguistic knowledge with deep learning methods is needed for effective handling of various emotional expressions, necessary to be domain-independent, maintain scalability and be efficient in real-time while preserving accuracy.

3. Methodology

The proposed methodology involves the use of Twitter-derived emotion dataset [7] made available by Kaggle to identify a variety of emotions in six categories: Surprise, Joy, Love, Anger, Sadness and Fear. The textual data are pre-processed by removing of stop-words, lowercasing and deletion of URLs, punctuation marks and special characters. Numerical feature extraction is achieved through TF-IDF feature vectorization, which uses the n-gram features and then emotion classes are labelled. To conduct a thorough evaluation, the data is separated into three parts namely; training, validation and testing dataset.

BiLSTM with multi-head attention are trained and evaluated on standard metrics like Accuracy, Precision, Recall, and F1-Score to identify the most efficient classifier. Figure 1 illustrates the general sequence of actions in the proposed framework.

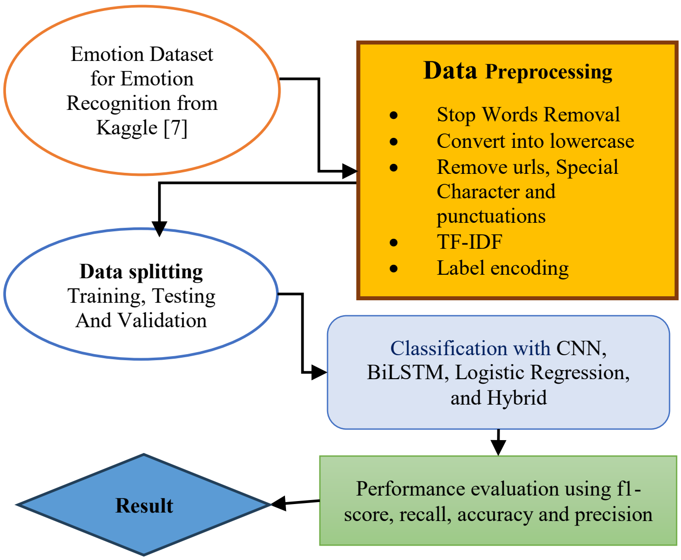

Figure 1
Flowchart of the Proposed Framework Emotions Recognition

3.1 *Dataset and Analysis*

This study uses a Twitter-based emotion recognition dataset obtained with the help of emotion-related hashtags using Twitter API and located on Kaggle [7]. It comprises brief textual tweets that are labeled using discrete categories of emotions, and thus it is applicable to the natural language processing and emotion classification. The dataset includes labeled textual data of the emotions used in social media communication.

Each tweet is annotated with one of six emotion classes:

Table 1
Emotions Label Mapping

Label	Emotion	No_of_Tweets
0	Sadness	4666
1	Joy	5362
2	Love	1304
3	Anger	2159
4	Fear	1937
5	Surprise	572

The dataset includes the following primary fields: (Described in Table 2)

- Text
- Emotion Label
- Emotion

Table 2
Emotion Dataset Fields with Description

Field	Description
Text	Raw tweet text collected from Twitter
Label	Numeric emotion class identifier (0–5)
Emotion	Mapped emotion category (Sadness, Joy, Love, Anger, Fear, Surprise)

It is a dataset format in which all the emotional expressions are explicitly labelled based on the interactions in the real social media. The informal and brief format of tweet brings linguistic variation, short forms, and situational context, so the data is very convenient to test advanced NLP, ML and DL emotion detection models.

Figure 2 presents the correlation heatmap of text length, word count, char count, avg word length and label. Text length exhibits a strong positive correlation with the word count and the characters in the text (0.98-1.00) and the avg word length gives a weak correlation and slight negative correlation with the word count and the character count respectively. The label variable demonstrates a close relationship with the text features, indicating a low correlation value with all these aspects of text alone.

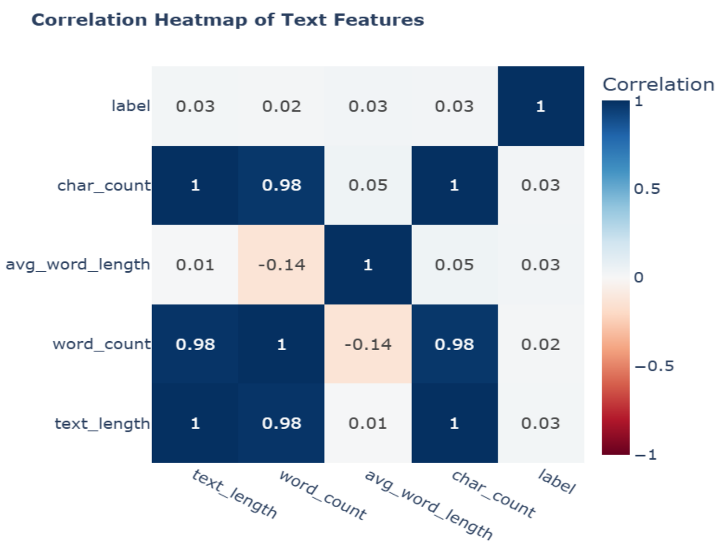

Figure 2
Correlation Heatmap of Text Features

In figure 3, boxplots of the text length of Sadness, Anger, Love, Surprise, Fear and Joy are presented. The median lengths of most categories are close to each other, but Love, Joy and Surprise appear to have a bit longer texts and are more varied. All the emotions have outliers, which means that there are some very long entries. In general, the variations of text length are not highly emotional and are rather moderate.

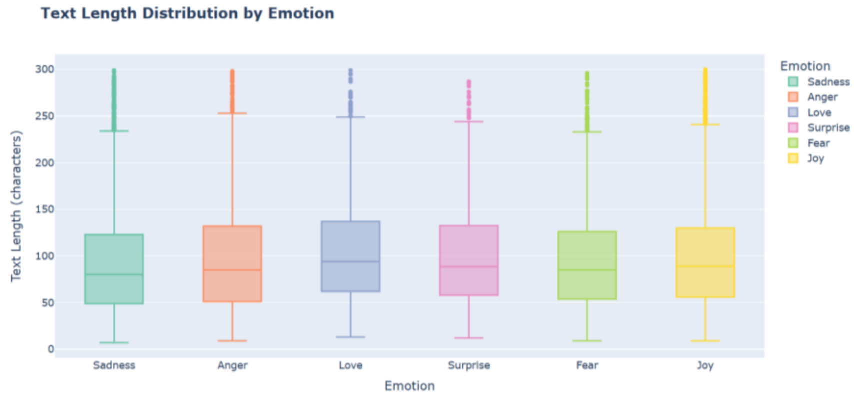

Figure 3
Text Length Distribution by Emotions

3.2 *Data Preprocessing and Splitting*

One important step in emotion analysis is preprocessing of the selected data. It is also essential to convert the unstructured data into a structured one. It represents the input data in a consistent way that can be efficiently processed by the ML techniques. The preprocessing steps implemented on the proposed system are to groom the raw text and eliminate any information item that can have a bad impact on the emotion analysis output. The key steps of data pre-processing include stop-words removal, converting text into lower case, removal of urls, special characters and punctuations.

Then after TF-IDF is used to extract features from the baseline models and compared to the proposed models, it performed better on all of the criteria. It is calculated as shown in (1).

$$IDF_{i,j} = log\frac{|D|}{|d_j \in D : t_j \in d_j|} \quad (1)$$

The lemmatized text information is transformed by means of TF-IDF to numerical feature matrices to model training. This setting of the vectorizer assumes a maximum of 5000 features and includes representations of unigrams, bigrams and trigrams whereby very frequent and very rare words are filtered out. It is trained on the training dataset and applied to transform the validation and test datasets so as to ensure feature consistency. Each split is then extracted as the corresponding labels and the resulting TF-IDF matrix shapes are visualized, ensuring that the data being processed yields the intended dimensionality.

In machine learning, label encoding is used to get numerical representation from categorical data. It converts the data into a format that algorithms can handle by giving each category in a column an individual integer value [19]. However, label encoding can pose a number of possible concerns that should be taken into consideration when working with a large number of categories in a column.

After processing the dataset is classified into training dataset, validation dataset and test dataset, as indicated in Table 3. This categorical separation of the datasets allows useful training of the model and facilitates stable testing in the emotion and emotion classification.

Table 3

Dataset Split Summary

Dataset Split	No_of_Samples	No_of_Features
Training dataset	16,000	2
Validation dataset	2,000	2
Test dataet	2,000	2

3.3 *Emotions Analysis using Deep Learning and Hybrid Models*

Deep learning and hybrid models are employed to perform emotion analysis to classify textual emotion. In this paper, CNN, BiLSTM, Logistic Regression and a CNN-BiLSTM with multi-head attention model are tested. The hybrid model yields better results because it integrates both convolutional and sequential mechanisms to predict emotions more accurately.

1) Convolutional Neural Networks (CNNs)

The CNNs are known to be skilled in image processing and computer vision applications [1]. They have also proven useful in cloud computing

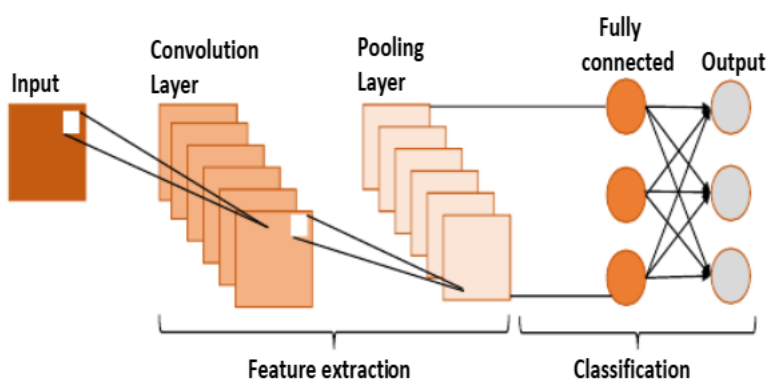

Figure 4
The structure of CNN [21]

through the capability of analyzing historical data on resource usage. Use of CNN is beneficial in exploring data especially when presented in time series or in multi-dimensional data because they identify patterns. They can also be successfully used in cloud environments to identify the repetitive patterns of resource usage, as shown in figure 4 to perform automatic feature extraction and detect anomalies. CNNs therefore becomes very important to derive useful knowledge regarding historical resource data, in CNN data transfer is described by (2). thus, leading to future resource prediction.

$$Y = \text{FC}(\text{Pool }(\text{Re LU}(\text{Conv }(\text{X})))) \text{ [20]} \tag{2}$$

2) Bi-directional LSTM

Bi-LSTM is used to train a model that takes past and future sequences of input data. Two associated layers are used and predicts the sequence of individual elements with the help of finite sequence based on the past and the future context of the elements. This is because two LSTMs are operating in parallel one left-right and the other right-left [2]. The prediction of a target signal is referred to as composite output. The technique has been rather useful. Bidirectional LSTM with H number of hidden units and L units as input results in the forward operation obtained by (3) and (4). Figure 5 displays a bidirectional LSTM model. The hidden layer of the bi-directional LSTM network stores 2 values. A is used in the forward calculation and A transpose is used in the reverse calculation. The end result is a value of y which relies on the A transpose:

$$a_h^t = \sum_{l=1}^{L} x_l^t \; w_{lh} + \sum_{h',t>0}^{H} b_{h'}^{t-1} \; w_{h'h} \tag{3}$$

$$a_h^t = \theta_h(a_h^t) \tag{4}$$

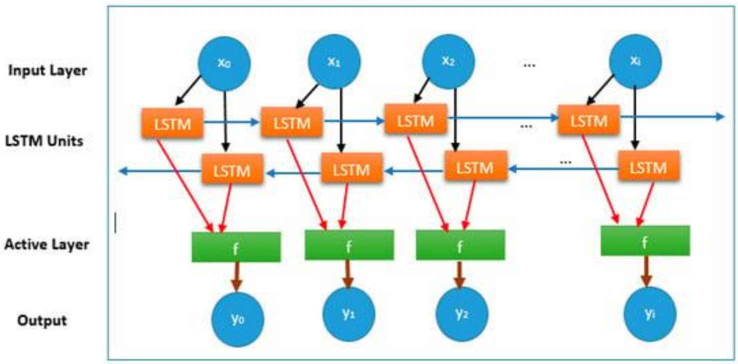

Figure 5
The Bi-directional LSTM (Bi-LSTM) algorithm's structure [22]

3) Logistic regression (LR)

LR is applied to determine the likelihood of the inputs belonging to the various classes with the help of the logistic or the sigmoid function [3].

This approach can be generalized to SoftMax regression or the multinomial logistic regression by using the SoftMax function instead of the sigmoid function. Logistic and SoftMax regression offer simple and easy to understand methods of addressing classification issues which can be used to make accurate and predictive results. The flow diagram of the entire logistic regression model is presented in figure 6. The likelihood of the input in a certain classification with the help of the logistic, sigmoid, function is determined through (5).

$$h_\theta\left(x^{(i)}\right) = \frac{1}{1+e^{-(\theta_0+\theta_1 x_1+\cdots+\theta_n x_n)}} \tag{5}$$

where input features are represented by x_0, x_1, …, x_n and the associated parameters updated during the learning process are represented as θ_0, θ_1 …, θ_n. The output is in the range of 0 to 1.

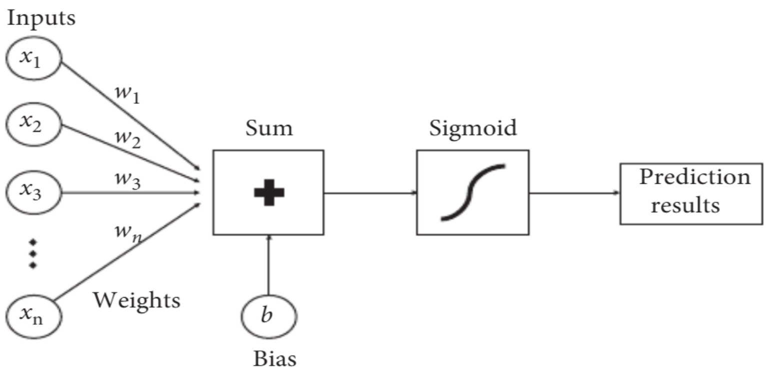

Figure 6
Flowchart of logistic regression [23]

4) Hybrid

It is a combination or integration of various DL models or methods to enhance the overall conduct of the model and to solve difficult learning problems. The hybrid approaches can extract features better, understand context and predict more accurately than the standalone architectures using the complementary advantages of the different models. This research employs Hybrid CNN-BiLSTM with multi-head attention as the emotion classification model, using convolutional, sequential and attention networks to learn better text representations.

The hybrid model suggested has an input sequence layer followed by an embedding layer which converts tokens to dense vectors. The architecture is composed of two parallel sections: CNN with 128 filters (kernel size 5) and 64 filters (kernel size 3) to extract the local features and Bidirectional LSTM with 64 units and dropout 0.3 to learn the contextual dependencies. Their outputs are then concatenated and sent to a multi-head attention layer consisting of 4 heads with key dimension 64, then layer normalization and global average pooling is done. The combined features undergo dense 128 and 64-neuron dropout rates of 0.5 and 0.3 respectively. The input is classified into one of six emotion classes by the final SoftMax layer.

3.4 *Model Evaluation*

When evaluating a classification model's performance on a set of test data for which the real values are known, the confusion matrix, a tabular representation of the model's performance is used. By comparing the model's predicted values with the actual target values, the matrix illustrates how accurate the classifications are. The confusion matrix makes use of the following metrics, which are characterized in terms of true positive, true negative, false positive and false negative [24]:

Accuracy: Accuracy is the overall predictive accuracy of the model measured by the proportion of observations that were accurately predicted to all observations. In the case of detection, it is expressed as in (6):

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{6}$$

Precision: It determines the effectiveness of the classifier in identifying the correct number of true positive cases from all the predicted number of positive cases. This is especially important and is represented as (7):

$$Precision = \frac{TP}{TP+FP} \tag{7}$$

Recall: Sometimes also referred to as sensitivity, it is defined as the proportion of observations of the positive set that is correctly estimated as positive to the total number of correctly estimated positive and incorrectly predicted negative observations in the actual class. The recall is written as shown in (8):

$$Recall = \frac{TP}{TP+FN} \tag{8}$$

F1-score: The balance of precision and recall, weighted by their inverse. The F1 score can be formulated as follows (9):

$$F1 = \frac{2*(Precision*Recall)}{Precision+Recall} \tag{9}$$

These metrics are used to compare models' performance.

4. Result Analysis and Discussion

The paper is concerned with emotion analysis with machine learning models. Experiments is done on Windows 11 using an Intel(R) core i7-7200U CPU (2.5-3.1GHZ) with Pandas, NumPy and Scikit-learn libraries in Jupyter Notebook. Table 4 indicates that CNN model had the highest accuracy of 91.90 as compared to Hybrid Model (90.90), BiLSTM (89.75) and Logistic Regression (88.35). In addition, CNN has also had the highest Precision (92.01%), Recall (91.90%), and F1 Score (91.94%), which are the highest values among the other tested models in terms of emotion classification.

Table 4
Model Performance for Emotions Analysis

Metrics/Model	CNN	Hybrid Model	BiLSTM	LR
Accuracy	91.90	90.90	89.75	88.35
Precision	92.01	91.73	89.85	88.38
Recall	91.90	90.90	89.75	88.35
F1 Score	91.94	90.99	89.77	87.92

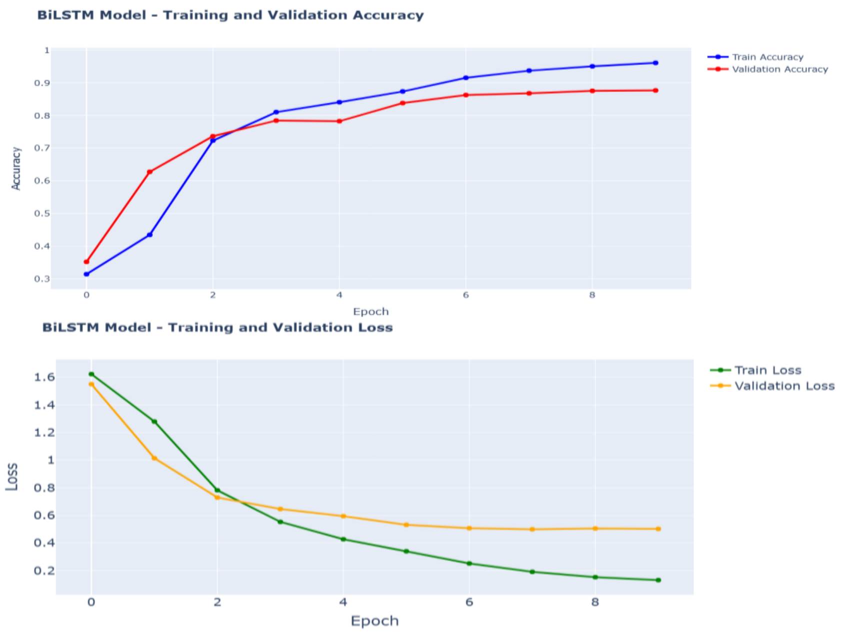

Figure 7
BiLSTM Model Training and Validation Performance

BiLSTM model's training and validation performance by epoch are displayed in figure 7. The training accuracy grows gradually with an initial epoch of around 0.50 to the final epoch of around 0.98 and the validation accuracy also grows with a starting value around 0.68 to the final epoch of about 0.91 which means that there is indeed good learning with a small generalization gap. The loss curves show that the training loss decreases rapidly between about 1.10 and lower than 0.10, which shows effective model optimization. The loss of validation reduces at first up to approximately 0.90 and then reaches approximately 0.38, with few variations, indicating slight overfitting during mid-epochs. In general, the figure indicates that the BiLSTM model reaches high accuracy with converged training and fairly constant validation performance.

Figure 8 draws comparisons of the confusion matrices of four models, including CNN, BiLSTM, Logistic Regression, and the Hybrid (CNN+BiLSTM+Attention) model, in emotion classification. The diagonal numbers show the accurate prediction, with the hybrid model displaying the greatest number of accurate predictions in most of the emotions like Joy (640), Fear (212), Anger (232) and Sadness (550) implying the best classification. BiLSTM and CNN are also good at performing but have higher rates of false identifications within the similarity of emotion such as Love-joy and Fear-surprise. Logistic Regression attributes relatively few correct predictions and more confusion between classes. In general, the figure proves that the Hybrid model can accomplish the most accurate and balanced emotion recognition compared to all the approaches considered.

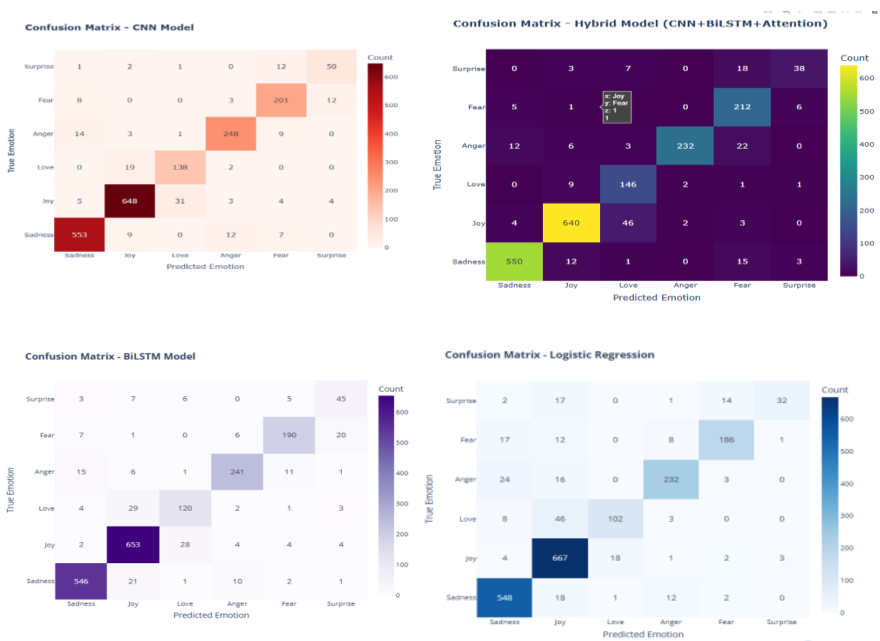

Figure 8
Confusion Matrices for Emotions Classification Models

In figure 9, there are sample text inputs and actual emotion and confidence scores as well as prediction status. The examples indicate proper classifications of various emotions. Sadness, Joy and Fear with extremely large confidence levels between 0.9987 to 1.0000. An example of this is with emotionally descriptive sentences concerning insecurity and distress, they would be correctly predicted as Fear or Sadness whereas positive and friendly statements are predicted correctly as Joy.

```
Text: i either have to feel submissive and as such agree to taking pain for someone or there has to not be an option presented
True Emotion: Sadness
Predicted Emotion: Sadness
Confidence: 0.9999
Status: Correct
--------------------------------------------------------------------------------------------------------------------

Text: i was feeling fairly keen
True Emotion: Joy
Predicted Emotion: Joy
Confidence: 1.0000
Status: Correct
--------------------------------------------------------------------------------------------------------------------

Text: i can feel that they are kind friendly and can understand my feelings
True Emotion: Joy
Predicted Emotion: Joy
Confidence: 1.0000
Status: Correct
--------------------------------------------------------------------------------------------------------------------

Text: i feel somewhat safe to give hosting a try
True Emotion: Joy
Predicted Emotion: Joy
Confidence: 0.9999
Status: Correct
--------------------------------------------------------------------------------------------------------------------

Text: i was feeling very unsure of myself and at near breaking point
True Emotion: Fear
Predicted Emotion: Fear
Confidence: 0.9847
Status: Correct
```

Figure 9
Sample Emotions Prediction Outputs

The high confidence and correct position of the results in the samples is a sign of a high level of reliability of the model in real-life situations with emotion prediction.

5. Conclusion

Emotion analysis is the technique of recognizing and classifying the emotional overture or mood conveyed in a textual information. It is important in realizing consumer opinion, feedback and social media interactions so that organizations can make sure decisions and increase the satisfaction of users. In this work, a DL and ML-based emotion recognition model is established and trained on a Twitter-derived dataset of emotions. The data comprises brief written tweets that are assigned to six emotional categories. Various models CNN, BiLSTM, Logistic Regression and a Hybrid model with Multi-Head attention are developed and tested on the basis of performance indicators. According to experimental results, CNN model has the highest overall accuracy of 91.90 and is better than the Hybrid model, BiLSTM, and Logistic Regression models. The findings emphasize the usefulness of DL models in extracting intricate emotional patterns of informal social media text. Future research will emphasize incorporating transformer-based architectures, including multilingual datasets, and using real-time streams of social media to facilitate a better understanding of context, scaling and general emotion classification across various application settings.

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