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Intelligent Techniques for Emotion Detection in Humans and Emotional States in Plants for Creating a Healthy Environment

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ABSTRACT

Emotion detection from text has gained significant attention in recent years due to its potential applications in various domains such as social media analysis, customer feedback analysis, and sentiment analysis. This research focuses on employing Natural Language Processing (NLP) techniques, including tokenizers and TF-IDF, along with different classifiers such as a hybrid model, LSTM model, and RF (Random Forest) model, for accurate emotion detection. The initial step involves data preprocessing, where tokenizers are utilized to break down the text into individual tokens or words, enabling further analysis. TF-IDF is then applied to assign weights to the tokens based on their frequency and importance in the document and across the corpus, respectively. This step helps identify the most significant words in the text data, allowing for a more focused analysis of emotions. Next, three different classifiers, namely a hybrid model, LSTM model, and RF model, are employed for emotion detection. The hybrid model combines the strengths of multiple ensemble models, including RF classifier, AdaBoost classifier, and Gradient Boosting classifier, using a voting classifier algorithm. The experimental findings provide strong evidence of the high accuracy achieved by both the hybrid model and LSTM model in detecting various emotions, such as happiness, sadness, fear, and anger. The hybrid model is also used to analyse psychological states in plants for creating a healthy environment. The hybrid model demonstrated exceptional performance, achieving an impressive testing accuracy rate of 94%, accompanied by precision and recall scores of 0.94 and 0.93, respectively. These results highlight the superior capability of these models in accurately classifying emotions from textual data. The robust performance of the hybrid model and LSTM model in emotion detection opens up numerous possibilities for their application in various fields. The ability to understand human emotions from text data can greatly inform decision-making processes in areas such as customer sentiment analysis, market research, social media monitoring, and psychological studies.

Keywords *- Natural Language Processing (NLP); Machine learning; Emotion detection; TF-IDF; LSTM.*

INTRODUCTION

Emotion detection from text using machine learning (ML) has emerged as a fascinating and valuable area of research in the field of natural language processing (NLP) [1]. With the increasing availability of vast amounts of textual data generated through social media, online platforms, and various digital sources, there is a growing need to understand and analyze the emotions expressed within the text [2, 3]. Emotion detection holds great potential for applications in sentiment analysis, customer feedback analysis, mental health monitoring, social media monitoring, and personalized content recommendation. The goal of emotion detection from text is to automatically identify and classify the emotions expressed in written text, such as happiness, sadness, anger, fear, and more [4]. Traditional rule-based approaches often struggle to capture the nuances and complexities of human emotions, making machine learning techniques an attractive alternative. By utilizing ML algorithms, such as support vector machines, random forests, or deep learning models like recurrent neural networks, it is possible to train models that can learn patterns and features from textual data to accurately predict and classify the underlying emotions [5]. To record data for analyzing plant responses resembling emotional states (stress, touch, sound and light), a combination of sensors and imaging systems is used to capture physiological and environmental signals. Electrical signals from the plant are measured using electrodes placed on leaves which are connected to amplifiers and microcontrollers to log voltage changes over time. Environmental factors such as temperature, humidity, light intensity, and soil moisture are monitored using appropriate sensors, while advanced techniques like thermal imaging and chlorophyll fluorescence capture subtle stress responses and photosynthetic activity. Volatile organic compounds (VOCs) released by plants under stress can also be detected using gas sensors [6].The process of emotion detection typically involves several steps, including data preprocessing, feature extraction, model training, and evaluation. Preprocessing techniques like tokenization, stemming, and stop-word removal are applied to transform the raw text into a suitable format for analysis [7]. Feature extraction techniques are then employed to capture relevant linguistic cues and contextual information from the text [8]. These features may include word embeddings, n-grams, syntactic features, or sentiment lexicons. ML models are trained using labeled datasets, where each text sample is associated with a specific emotion label. Emotion detection from text using ML has the potential to revolutionize various domains by providing valuable insights into the emotional states of individuals, groups, or communities [9]. It can enable organizations to gauge customer satisfaction, understand public sentiment towards products or services, identify emerging trends, and tailor communication strategies accordingly. Moreover, in mental health applications, emotion detection can assist in early detection of emotional distress or mood disorders, contributing to timely interventions and support [10]. As research in this field continues to advance, the development of accurate and robust models for emotion detection holds promise for a wide range of practical applications, enhancing our understanding of human emotions in the digital age.Emotion detection, with the aid of ML methods holds immense relevance for human beings in various applications. Understanding human emotions plays a vital role in fields such as healthcare, psychology, human-computer interaction, marketing, and in many other fields for decision making process. The ability to accurately detect and interpret emotions can lead to improved well-being, personalized experiences, and more effective communication. Numerous research studies have explored the application of ML methods in emotion detection. In [11], facial expression analysis was employed to detect and classify emotions in real-time. The researchers utilized deep learning techniques and achieved high accuracy in emotion recognition. Similarly, the work presented in [12] focused on using physiological signals such as heart rate variability and skin conductance to infer emotional states. Their findings demonstrated the potential of machine learning algorithms in detecting emotional responses based on physiological data. In addition to healthcare and psychology, emotion detection can also benefit other domains. For instance, in the field of human-computer interaction, the research work [13] proposed an emotion-aware system that utilizes machine learning to recognize and respond to user emotions for enhancing the user experience. In marketing and customer experience analysis [14], the authors explored the use of sentiment analysis and emotion detection to gain insights into customer preferences and sentiments which helps the businesses to tailor their products and services accordingly. The application of ML in emotion detection has far-reaching implications for various aspects of human life. The existing research studies highlight the diverse range of applications and methodologies employed in this field, demonstrating the potential of these technologies to improve well-being and for decision-making processes.

Related Work

In [1], the author presents the Aimens system, which aims to extract valuable information and identify user emotions from textual exchanges. The system utilizes the Long Short-Term Memory (LSTM) model, a deep learning method, and combines word2vec and doc2vec embeddings as the primary input. The trial results show that the Aimens system achieved a score of 0.7185, indicating significant improvements in F1-score compared to the baseline model. This approach proves effective in extracting emotions from contextual dialogues, particularly in social media chats, providing valuable insights into user sentiments within large amounts of text data. In [2], the author develops a framework for categorizing emotions in English phrases to enhance human-machine and human-human interaction. The framework focuses on understanding and identifying the emotions present in communication by creating an intermediate emotional data representation using the phrase's syntactic and semantic structure. The representation is generalized using ontologies, and an Emotion Recognition Rule (ERR) is generated. The ERR is compared to reference ERRs from a training set using various classifiers, resulting in an average F1-Score of 84%. This approach outperforms existing ML and rule-based classifiers, opening doors for improved communication, personalized suggestions, and enhanced user experiences. In [3], the author addresses the challenge of identifying emotions in Roman Urdu language, commonly used on social networking sites. Due to the lack of benchmark corpora in this area, the research annotates a complete corpus of 18k utterances with emotion classes. Fundamental algorithms such as KNN, Decision Tree, Support Vector Machine (SVM), and Random Forest are employed and evaluated. The SVM model demonstrates higher F1-measure scores, indicating the efficiency of this approach in analyzing emotional polarity in Roman Urdu phrases. In [4], the review article emphasizes the significance of sentiment analysis and emotion detection in processing the vast amount of unstructured data generated on social media platforms. The article explores different emotion models, levels of sentiment analysis, and methods for analyzing sentiment and identifying emotions in text. It highlights the challenges encountered in sentiment and emotion analysis. It also discusses the relevance and difficulties associated with understanding human psychology through textual material on social networking platforms.

In [5], the author investigates the automation of textual emotion recognition through transfer learning. Traditional deep learning models like LSTM, GRU, and BiLSTM often require large datasets, powerful computers, and extensive training time. To overcome these limitations, the author introduces Emotional-BERT, a pre-trained model built on BERT, which demonstrates improved contextual awareness and emotion detection. The performance of Emotional-BERT is compared with RNN-based models on benchmark datasets, with a focus on the impact of training data size on model performance. In [6], the author proposes a hybrid model for text emotion recognition that combines machine learning and deep learning approaches. By incorporating CNN, Bi-GRU, and SVM, this methodology addresses the limitations of keyword and lexicon-based approaches in capturing emotions. The effectiveness of the model is evaluated using various datasets comprising sentences, tweets, and dialogues, achieving an accuracy of 80.11%. The results demonstrate the efficacy of the hybrid strategy in recognizing emotions in text. In [7], the author explores the disparity between authors' intended emotions and readers' perceptions of textual information on social media. To detect readers' emotions in multi-target regression scenarios, a Bi-LSTM-based Attention model is proposed. The model is evaluated through two-phase experimental assessments using large datasets and benchmark datasets, outperforming several baselines in terms of performance. Additionally, attention maps are used to assess the interpretability of the model by visualizing relationships between emotions and specific words or named items. In [8], the author examines how emotion detection using brainwave EEG waves can revolutionize the diagnosis and treatment of medical illnesses. Different machine learning methods, including SVM, K-nearest neighbor, Linear Discriminant Analysis, Logistic Regression, and Decision Trees, are

explored using epoch data from EEG sensor channels. Principal Component Analysis (PCA) is applied for dimensionality reduction, and hyper-parameter tuning is performed using grid search. The DEAP Dataset, which records participant judgments of musical snippets based on emotional states, is utilized. The results reveal that certain categorization methods are more effective for different emotional states, with PCA and SVM achieving the highest accuracy (84.73%) and recall (98.01%) in certain time intervals.
In [9], the author introduces a DL assisted semantic text analysis (DLSTA) approach for human emotion detection using big data. By merging NLP methods with word embeddings, the approach achieves a high human emotion detection rate of 97.22% and a classification accuracy rate of 98.02%. These results surpass previous state-of-the-art techniques and suggest the potential for further advancements with additional emotive word embeddings. In [10], an overview of emotion detection (ED) within the context of sentiment analysis is provided. The article emphasizes the extraction and analysis of emotions from text data and discusses the significance of text mining and analysis in the Web 2.0 era. Various methods for creating text-based ED systems are surveyed, including recent state-of-the-art ideas, their contributions, techniques, datasets, outcomes, strengths, and limitations. The research offers emotion-labeled data sources to assist newcomers in selecting appropriate text datasets for ED and explores unresolved issues while suggesting future research directions. In [11], the author explores the use of different recurrent neural network (RNN) models for EEG-based emotion detection in Brain-Computer Interfaces (BCIs). Three architectures, namely RNN, LSTM, and GRU, are employed to classify emotions using EEG inputs. Experimental data from the EEG Brain Wave Dataset: Feeling Emotions demonstrate the effectiveness of these networks, achieving average detection accuracies of 95% for RNN, 97% for LSTM, and 96% for GRU. These findings highlight the potential of deep learning techniques to enhance BCI systems' ability to recognize emotions. In [12], the author presents a comprehensive overview of various emotion detection methods utilized over the past decade. The research investigates four main approaches: text semantics, voice signal variation, physiological signal recognition, and face expression recognition. Several common and self-created databases are utilized for analysis. The study identifies effective methods for detecting the seven most common emotions by comparing different methodologies. Notably, biogeography-based optimization techniques with PSO support achieve the highest accuracy of 99.47% on the BES dataset.

Major Contributions

This research makes several major contributions to the field of emotion detection using NLP methods such as tokenizers and TF-IDF, along with classifiers including a hybrid model, LSTM model, and RF model. Firstly, it demonstrates the effectiveness of tokenizers and TF-IDF in preprocessing text data and identifying important words for emotion analysis. Secondly, it introduces a hybrid model that combines the strengths of multiple ensemble classifiers, resulting in improved accuracy in emotion detection. Thirdly, the research showcases the potential of LSTM models in capturing sequential information and contextual dependencies for better understanding of emotions in text. Lastly, it validates the efficacy of the RF model in accurately classifying emotions.

PROPOSED METHODOLOGY

A detailed explanation of each step involved in data analysis for textual datasets:
a. Identification of important texts: In this step, we analyze the textual dataset to identify important texts that contributes to understanding the data. This involves examining the content of the texts and identifying keywords that are relevant to the research objectives to identify the emotions from the text.

b. Patterns identification: After identifying important words, we explore patterns that may exist across the dataset. Patterns can reveal common categories within the data, providing insights into the underlying sentiment of an individual.
c. Proportion of positive and negative emotions: In emotion detection tasks, it is important to determine the proportion of positive and negative texts within the dataset. This involves counting the number of texts/documents that express positive or negative sentiment.
d. Frequency of words: The frequency of words is an essential metric in textual data analysis. It involves counting how often specific words appear within the dataset. By calculating the frequency of words, we identify the most common terms within the texts. This information is used to assess the relevance of certain words and their impact on the overall analysis.
e. Data distribution among the target variable: It is important to check the data distribution among the target variables. The sentiment labels in our research are happiness, sadness, anger and fear to understand the emotions of people.
These steps in textual data analysis provide insights into the dataset, help in identifying important words or texts, reveal patterns and provide a foundational understanding of the data distribution.

Use of Tokenizers

The tokenizers play a crucial role in identifying emotions from text by breaking down the text into individual tokens, such as words or sub-words. Tokenization is the process of segmenting a sequence of characters into meaningful units, which are easier to analyze and process.
1. Tokenizers splits text into individual words, allowing for analysis at the word level. Emotions are often associated with specific words [21]. By tokenizing the text, we can identify emotion-indicative words and their frequency of occurrence. For example, words like "happy," "sad," "angry," or "excited" may provide valuable insights into the emotional content of the text.
2. Tokenizers also take into account the context in which words appear. This contextual understanding is crucial in identifying emotions, as the meaning of a word can vary depending on the context.
3. Tokenizers are used as a preprocessing step for sentiment analysis, which involves determining the overall sentiment expressed in a piece of text, such as happy, sad, or anxiety [22]. Sentiment analysis models often rely on tokenization to break down the text into smaller units for analysis.
4. Tokenizers also handle emoticons and emojis, which are commonly used to express emotions in text [23]. By preserving these symbols as separate tokens during tokenization, their presence provides additional insights into the emotions conveyed by the text.
5. In our proposed research, the tokenizers are used in conjunction with machine learning methods for emotion detection. By tokenizing the text and representing it as a sequence of tokens, ML models can be trained to recognize patterns and relationships between tokens and associated emotions [24]. The tokenizer helps in creating a structured input representation for the model, facilitating the learning process.

Use of TF-IDF (Term Frequency-Inverse Document Frequency)

TF-IDF is a numerical representation technique used in information retrieval and text mining. It is designed to evaluate the importance of a term within a document in a collection. The TF component of TF-IDF measures the frequency of a term within a specific document [25]. It assigns a weight to each term based on how often it appears in the document. The rationale is that frequently occurring terms within a document are likely to be more important or indicative of its content. The IDF component calculates the rarity of a term by considering how many documents contain that term. Terms that appear in many documents have lower

IDF scores, while terms that appear in fewer documents have higher IDF scores. The idea behind IDF is that rare terms tend to carry more discriminative power and contribute more to the understanding of the emotions from document's content. To calculate the TF-IDF score for a term within a document, the TF and IDF values are multiplied together. The resulting score represents the importance of the term within the document relative to the entire corpus. High TF-IDF scores indicate that a term is both frequent within the document. The formula for calculating TF-IDF for a term (t) in a document (d) within a corpus is as follows:

*TF-IDF (t, d) = TF (t, d) * IDF (t)*

Where:

TF (t, d) is the term frequency of term *(t)* in document *(d).*

IDF (t) is the inverse document frequency of term *(t)* across the document or text.

Tokenizer and TF-IDF

Tokenizer and TF-IDF are both essential NLP tools that are used together to aid in identifying emotions from text.

The first step is to tokenize the text using a tokenizer, which breaks down the text into individual words or subwords (tokens). This process helps in structuring the text and separating meaningful units for further analysis. Tokenization allows for better understanding and representation of the emotional content present in the text. After tokenization, various preprocessing steps are applied to the tokens, such as removing stopwords, stemming, or lemmatization. These steps help in reducing noise and normalizing the text, enabling more accurate emotion analysis. Once the text is tokenized and preprocessed, TF-IDF values can be calculated for each term (token). TF-IDF assigns higher scores to terms that are both frequent within the document and rare across the corpus, indicating their potential importance in characterizing the document's content. The TF-IDF scores for each token are used to represent the document's emotional content as a feature vector. Each dimension of the feature vector corresponds to a unique token, and its TF-IDF score reflects the token's relevance to the document. This representation captures the relative importance of different terms in terms of their emotional significance.

By combining tokenization and TF-IDF, NLP tools can effectively identify emotions from text. Tokenization breaks down the text into meaningful units, allowing for more focused analysis, while TF-IDF provides a quantitative measure of term importance within the document.

USE OF MACHINE LEARNING FOR CLASSIFICATION

Random Forest (RF) classifier

RF is an ensemble learning method that combines the predictions of multiple decision trees to make robust predictions. It is then used for emotion detection from text. Decision trees are the building blocks of RF algorithm. A decision tree is a flowchart-like structure where each internal node represents a feature or attribute, each branch represents a decision rule, and each leaf node represents the outcome or prediction. The decision tree splits the data based on different features and their corresponding thresholds to classify or predict the target variable, which in this case is the emotion label. Random Forest combines the predictions of multiple decision trees to obtain a final prediction. Each decision tree in the ensemble independently predicts the emotion label for a given input. The final prediction is determined by majority voting or averaging the predictions from all the individual trees. In classification tasks, the majority class prediction is chosen as the final prediction.

Let's consider a training dataset consisting of *N* samples, where each sample is represented as a feature vector X_i and has a corresponding emotion label Y_i.
Random Forest creates a forest of *T* decision trees, each denoted as DT_t, where t ranges from 1 to *T*.
For each decision tree DT_t, a random subset of the training samples is selected with replacement, forming a bootstrap sample. The size of the bootstrap sample is typically the same as the original dataset *(N)*, but some samples are repeated, while others may be omitted. Additionally, a random subset of features *(m)* is selected at each node of the decision tree, where *m* is typically a square root or logarithm of the total number of features. At each node of a decision tree, a feature and threshold are selected to split the data into two child nodes, based on entropy criterion. The process of recursively splitting the nodes continues until a stopping criterion is met. To predict the emotion label for a new input X, each decision tree in the Random Forest traverses the tree, and the majority class prediction across all trees is considered as the final prediction. Hyperparameters of the RF model are tuned to optimize performance. These hyperparameters include the number of decision trees (T), the maximum depth of each tree, the criterion for splitting, and the number of features to consider at each split (m). By aggregating the predictions of multiple decision trees, RF can effectively detect emotions from text.

LSTM classifier for emotion detection

LSTM is a powerful neural network architecture used for emotion detection from text. It excels at capturing the sequential and temporal dependencies within text data. The LSTM model consists of multiple layers, each equipped with memory cells that can store and update information over long sequences. This ability to retain and propagate relevant information throughout the sequence is crucial for understanding the context and emotional nuances in text. Mathematically, an LSTM unit operates through a set of equations. Given an input sequence of words, each word is transformed into a numerical representation, such as a word embedding. These numerical representations are then fed into the LSTM layers. At each time step, the LSTM layer updates its hidden state and cell state based on the current input, the previous hidden state, and the previous cell state. The update is performed through a set of mathematical operations involving gates that control the flow of information. These gates determine how much information should be forgotten, stored, and outputted, respectively.
The LSTM layers learn to capture important patterns and dependencies in the text through the training process. The parameters of the LSTM, including the weights and biases, are adjusted to minimize a suitable loss function, such as categorical cross-entropy, by comparing the predicted emotion labels with the ground truth labels. Once the LSTM layers have processed the input sequence, the final hidden state is passed through dense layers. The output layer produces the predicted emotion label, with the number of nodes in the output layer corresponding to the number of emotion classes. Activation functions, such as softmax, are used to normalize the output probabilities across the emotion classes.
The LSTM-based model for emotion detection from text offers several advantages. Its architecture enables the model to capture long-term dependencies, understand the contextual meaning of words, and consider the emotional implications of previous words in the sequence. This makes it well-suited for capturing the subtle emotional nuances within text data. By training the model on labeled data, accurate emotion detection can be achieved. The sensor system will provide real-time data on air quality parameters, offering high spatial resolution mapping of pollution levels in urban areas. The AI algorithms will enable the system to generate actionable insights and alerts for authorities and individuals, facilitating prompt interventions and decision-

making. By providing accurate and timely information about air pollution, the system will contribute to the development of effective pollution control strategies, urban planning, and public health management.
The research will involve designing and optimizing the optical sensor hardware, developing AI algorithms for data analysis and pattern recognition, and conducting field testing and validation in urban environments. The results of the research will contribute to advancing air quality monitoring technologies and supporting sustainable urban development practices. Ultimately, the AI-enhanced optical sensor system will play a crucial role in improving air quality, protecting public health, and creating healthier and more livable cities.

A novel hybrid model for emotion detection

The hybrid model for emotion classification from text combines three powerful ensemble models: RF Classifier, AdaBoost, and Gradient Boosting. Each of these models brings its own strengths and capabilities to the classification task. By integrating these models using a voting classifier algorithm, we aim to utilize their collective intelligence and improve the overall accuracy of emotion classification.
In the first step of the methodology, we preprocess the text data by removing irrelevant elements such as stop words, punctuation, and special characters. This ensures that we focus on the essential content of the text. We then tokenize the preprocessed text, converting it into a sequence of words. Additionally, we apply techniques such as stemming to normalize the words and reduce their variations.
Next, we extract features from the preprocessed text using TF-IDF technique. TF-IDF assigns weights to words based on their frequency in the document. These features capture the importance and contextual information of words, enabling the models to understand the emotional content of the text. Moving on to the ensemble model training, we train the classifiers individually. Each model is trained on the preprocessed text data with the corresponding set of features. The ensemble models learn to identify patterns and relationships between the features and the emotion labels through an iterative process.
To obtain the final prediction from the combination of the ensemble models, we employ a voting classifier algorithm. The voting classifier aggregates the predictions from the individual models and selects the final predicted emotion label based on majority voting. This way, we benefit from the diverse perspectives and decision-making approaches of the ensemble models. After training the hybrid model, we evaluate its performance on a separate test sets. Finally, the trained hybrid model is used for emotion classification on unseen text data. The results of all classifiers are evaluated on trained and unseen data.

RESULTS & ANALYSIS

Experimental Set-up

The experimental set-up for hardware and software for testing the results of the mentioned methods for emotion classification from text is demonstrated below

Hardware Setup

A desktop with a multi-core processor (Intel Core i5) and sufficient RAM (16GB) to handle data processing and model training efficiently. Adequate storage of capacity (512 gigabytes) to store the datasets, trained models, and any intermediate files generated during testing has been used.

Software Setup

The operating system such as Windows 10 is used. Jupytor Notebook is installed as suitable IDE (integrated development environment). The necessary Python libraries and packages are installed. The NLTK library is used for text preprocessing and tokenization. Scikit-learn is employed for implementing ensemble models and the voting classifier. Keras is used to incorporate LSTM-based models into our testing. Pandas are installed for data manipulation and analysis.

EVALUATION OF HYBRID MODEL

When evaluating the performance of a hybrid model for emotion classification, several metrics are used to assess its effectiveness. The confusion matrix is shown in Figure 1. The hybrid model achieved a testing accuracy of 94.67%, which indicates the percentage of correctly predicted emotion labels out of the total test instances. Additionally, the F1-score is 0.95, indicating a good balance between precision and recall as shown in Table 1. The hybrid model achieved a precision of 0.94, indicating that it accurately classified a high proportion of positive instances. A recall score of 0.93 means that the hybrid model successfully identified and classified 93% of the positive instances correctly. These evaluation metrics collectively indicate that the hybrid model performed well in classifying emotions from text. It achieved a relatively high accuracy, demonstrating its ability to predict the correct emotion labels for the majority of the instances.

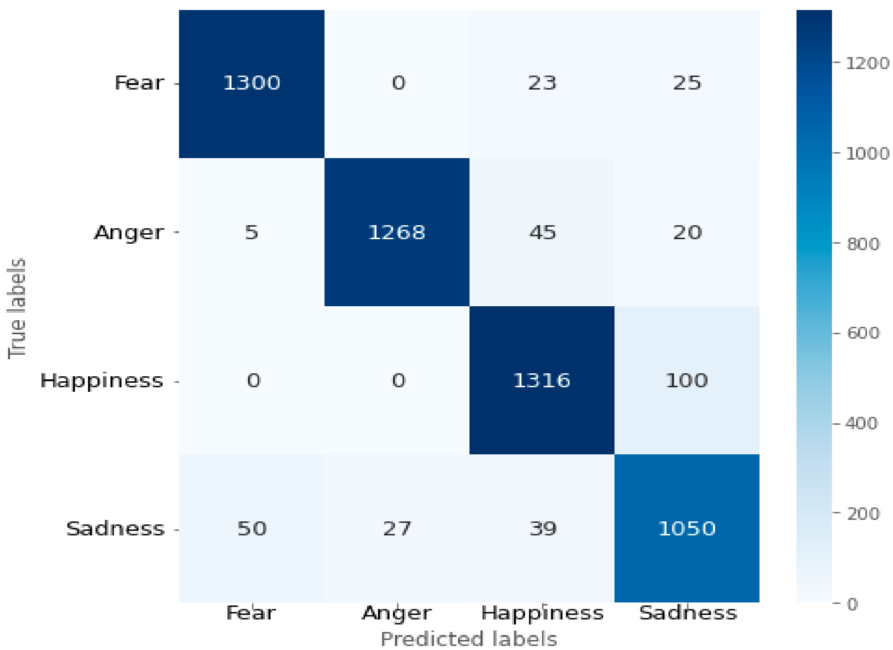

Figure 1.Confusion matrix for hybrid model

Algorithm	Precision	Recall	F1-Score	Testing Accuracy
RF model	0.94	0.93	0.95	94.67%

Table 1. Performance evaluation values for hybrid model

Performance of RF based Model

The Random Forest (RF) model was evaluated for emotion classification using several performance metrics: The RF model achieved a precision of 0.88, indicating that when it predicted an instance, it was correct 88% of the time. In other words, the RF model had a relatively low rate of false positives as shown in Table 2.

The RF model achieved a recall of 0.78, indicating that it correctly classified 78% of the actual positive instances. The F1-Score is 0.82, indicating a reasonable balance between precision and recall. The testing accuracy is approximately 75.65% of the instances in the test dataset as presented in confusion matrix (Figure 2) and in Table 2.

The performance of the RF model suggests that it has a reasonably good ability to classify emotions from the given dataset. The relatively high precision indicates a low rate of false positives, and the decent recall suggests the model's capability to capture a significant portion of the positive instances.

Algorithm	Precision	Recall	F1-Score	Testing Accuracy
RF model	0.88	0.78	0.82	75.65%

Table 2. Performance evaluation values for RF model

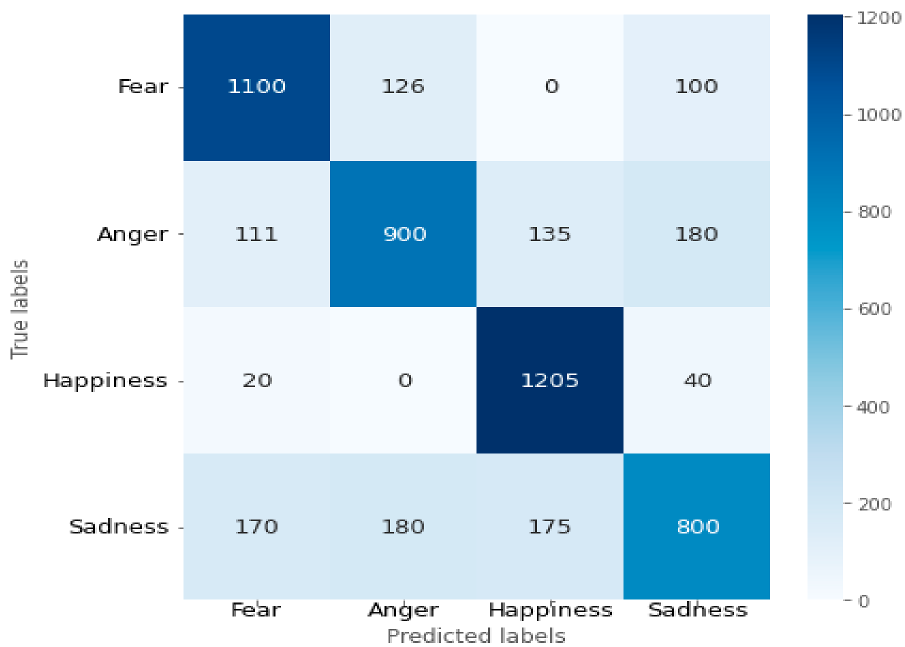

Figure 2. Confusion matrix for RF based emotion classification

Performance of LSTM based Model

The LSTM-based emotion detection classifier exhibited exceptional performance, achieving a high level of accuracy. The testing accuracy of 85.63% indicates that the model accurately predicted the emotions for the majority of instances in the test dataset as shown in Table 3 and respective confusion matrix is shown in Figure 3. The F1-score of 0.85 reflects a balanced measure of precision and recall, indicating the model's ability to accurately classify emotions while minimizing false positives and false negatives. The precision score of 0.85 suggests that a high proportion of instances predicted correctly. Similarly, the recall score of 0.85 demonstrates the model's capability to capture a significant portion of actual positive instances. Overall, these evaluation metrics showcase the LSTM-based emotion detection classifier's high accuracy and its effectiveness in accurately classifying emotions from text data.

Algorithm	Precision	Recall	F1-Score	Testing Accuracy
LSTM model	0.857	0.856	0.85	85.63%

Table 3. Performance evaluation values for LSTM model

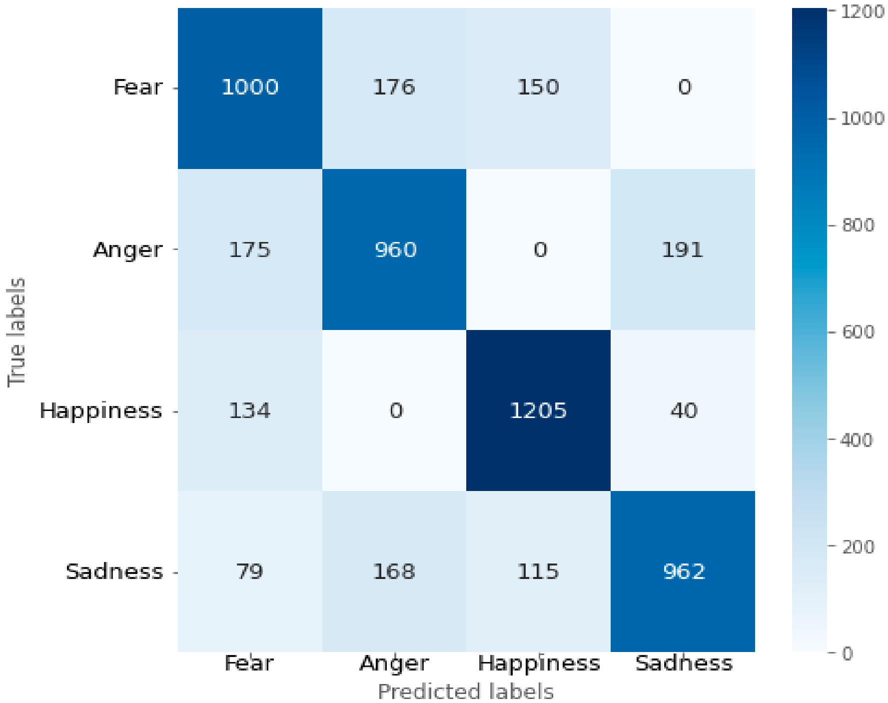

Figure 3. Confusion matrix for LSTM based emotion classification

The overall performance of three algorithms is shown in Figure 4. These performance metrics indicate that the Hybrid model outperforms both the RF and LSTM models in terms of precision, recall, and F1-Score for emotion detection and followed by Hybrid model which also shows 94% accuracy in detection of emotions.

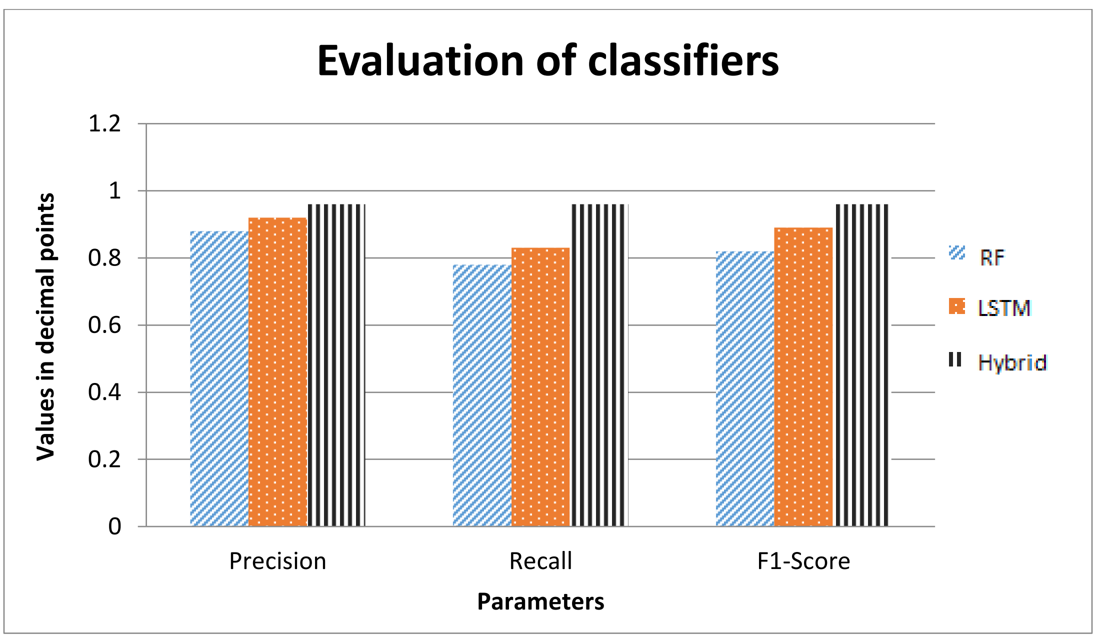

Figure 4. Comparative results of the algorithms for identification of the emotions

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Performance of hybrid model for emotion detection in plants

The hybrid model is also applied to identify emotions in plants for creating a healthy environment. The comparison is made with the existing ML methods. To record data for analyzing plant responses resembling emotional states, we have used a combination of sensors like gas sensors and electric sensors. Environmental factors such as temperature, humidity, light intensity, and soil moisture are monitored using appropriate sensors. Volatile organic compounds (VOCs) is taken as one target variable which is released by plants under stress. This comprehensive dataset (available at Kaggle) is then be used to train hybrid machine learning model which is mentioned in proposed methodology to classify plant states such as stress, health, and recovery which is serving as a proxy for emotion-like behavior. **The Hybrid Model** combines features of DL and ML algorithms for identifying emotions in plants. The results are stated in Figure 5.

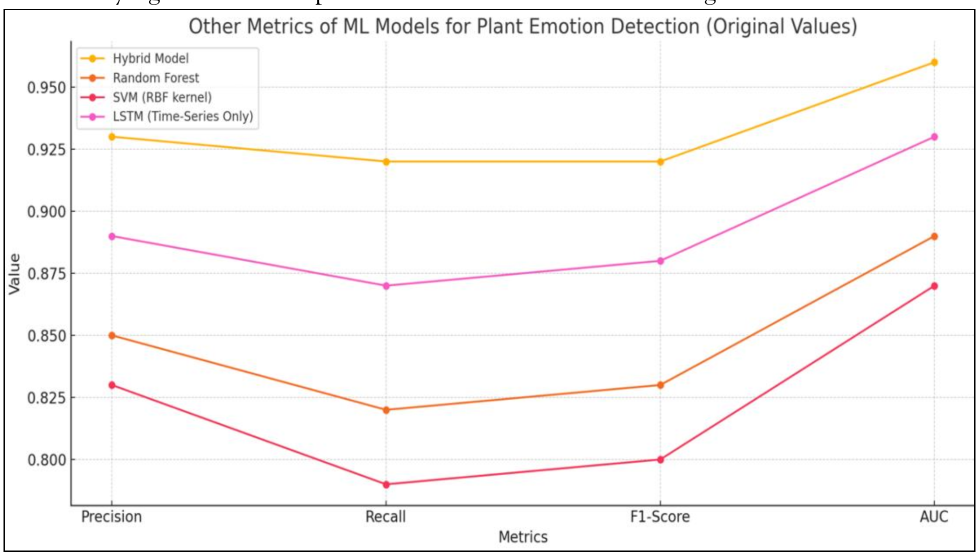

Figure 5: Presenting performance of hybrid model and other algorithms

The results (Figure 5.) show that the proposed hybrid model can predict the emotions in plants with high accuracy as precision, recall, AUC and F1-score obtained by the hybrid model have promising scores to identify emotions in plants accurately.

CONCLUSION

In conclusion, this research has made significant strides in the field of emotion detection from text by employing NLP methods, tokenizers, and TF-IDF, along with classifiers including a hybrid model, LSTM model, and RF model. These results underscore the potential of NLP techniques and classifiers in advancing emotion detection capabilities for better understanding of textual emotions. The findings from this research provide valuable insights for the development of more robust and accurate emotion classification systems. This research contributes to the growing field of emotion detection, paving the way for advancements in analyzing emotions from text. The findings demonstrate the effectiveness of these approaches in accurately identifying emotions. The hybrid model has shown a remarkable accuracy rate of 94%, utilizing the strengths of multiple ensemble classifiers to achieve improved performance. Additionally, the LSTM model, with its ability to capture sequential information and contextual dependencies, achieved an impressive accuracy rate of 85%. Although slightly lower, the RF model still demonstrated commendable accuracy, achieving a rate of 75%. These results highlight the potential of NLP techniques and classifiers in enhancing emotion detection and understanding textual emotions. The outcomes of this research provide valuable insights for developing more robust and accurate emotion classification systems, opening doors for various applications in sentiment analysis, social media analysis, and customer feedback analysis.

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