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Article

HYBRID FUZZY LOGIC AND DEEP LEARNING FRAMEWORK FOR MOOD PREDICTION: A CROSS-DATASET STUDY

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Abstract: Mood is the representation of identifying and interpreting an individual's emotional state of mind. Changes in emotional states manifest through alterations in communication frequency, typing patterns, app usage duration, physical activity levels, social interaction preferences, and even subtle variations in gait or posture captured by wearable devices. In recent years, advances in technology have made it possible to infer moods accurately in real time, providing crucial insights that enhance human-machine interaction, healthcare, marketing, and social connectivity. By aggregating and analyzing these diverse data streams using machine learning algorithms and pattern recognition techniques, Internet of behavior (IoB) systems can identify mood states through the analysis of behavioral and physiological signals. To address this concerns, mood detection and IoB form a powerful synergy. IoB facilitates continuous monitoring and contextual analysis of behavior, enabling dynamic and precise mood detection. Mood are derived into different categories based on IoB parameter applied on E-DAIC and Reddit dataset. This classification is validated using PHQ-score and fuzzy logic. Random forest achieved 71.43% remarkable accuracy, 68.03% precision score and classified mood into depressed with 96% recall, 92.13% precision and 94.12% F1-score. These predictions give early signs of emotional and psychological issues. This combination has the ability to transform personalization efforts, psychological interventions, marketing campaigns, work environments, and other aspects through the development of an emotional system that can respond with empathy.
Keywords: Fuzzy logic, Machine learning, Mental health, Mood prediction, Behavioral analysis.

1. INTRODUCTION

Mood detection through IoB leverages the vast ecosystem of connected devices, sensors, and digital touchpoints that surround modern individuals to create a comprehensive behavioral profile. Unlike traditional mood assessment methods that rely on self-reporting or clinical observations, IoB-based mood detection operates passively and continuously, analyzing patterns in smartphone usage, social media interactions, movement patterns, sleep cycles, heart rate variability, voice tonality, and countless other behavioral signals that collectively form a digital fingerprint of emotional states [1]. The foundation of this approach rests on the understanding that human mood significantly influences behavioral patterns across multiple domains. Changes in emotional states manifest through alterations in communication frequency, typing patterns, app usage duration, physical activity levels, social interaction preferences, and even subtle variations in gait or posture captured by wearable devices. By aggregating and analyzing these diverse data streams using machine learning algorithms and pattern recognition techniques, IoB systems can identify mood states with remarkable accuracy and provide early warning signs of emotional distress or mental health concerns [2]. The mood is one of the key factors that significantly affect cognitive functions, social behaviors, and personal well-being. Traditional methods of mood assessment—such as self-reported questionnaires (e.g., PHQ-8, PANAS) and clinical interviews—are limited by their subjectivity, episodic nature, and reliance on human recall. These limitations hinder timely identification of mood fluctuations, especially in sensitive contexts such as early detection of depression, stress monitoring, or workplace well-being [3]. Different computational learning algorithms are used in IoB systems for the examining functional parameters of humans such as heart-rate variation, voice, face expression, and typing style to determine their actual moods including stress, happiness, and anxiety. These insights enable personalized interventions in diverse domains including mental health monitoring, customer experience management, and adaptive learning environments [4]. By contextualizing mood data within behavioral patterns, IoB allows organizations to not only predict emotional responses but also tailor their strategies to improve well-being, engagement, and decision-making, thereby transforming digital interactions into emotionally intelligent experiences. This intersection of behavioral analytics, emotional intelligence, and ubiquitous computing represents a frontier in human-computer interaction that promises to revolutionize how we understand, monitor, and respond to human emotional well-being in an increasingly connected world. All these strategies are evolved for recognizing the mental health problems. Therefore, the key elements of this paper considered as:

1. To integrate the behavioral and physiological data features for preprocessing.
2. To classify the mood categories based on IoB parametric values and validate using PHQ-score.
3. Classical machine learning and deep learning models are analyzed for mood prediction.
4. Estimate performance evaluation metrics for understanding the revolutionary approach in mental health domain.

2. LITERATURE REVIEW

Emotion and mood detection technologies have evolved significantly over the past decade, leveraging diverse modalities such as facial expressions, voice, physiological signals, textual data, and behavioral patterns. Different research work are presented in this section.

2.1 EMOTION RECOGNITION TECHNOLOGIES

Guo et al. [5] provided a comprehensive review of emotion recognition approaches, including those based on psychometric scales, speech signals, and facial expression analysis. They emphasized the role of biometric data from wearables (heart rate, skin conductance) and behavioral analytics combined with machine learning techniques like Support Vector Machines (SVM) and Deep Learning (DL) to effectively recognize moods with high accuracy. Speech-based emotion recognition, for instance, commonly used Mel Frequency Cepstral Coefficients (MFCC) for feature extraction, followed by classifiers like SVM and Convolutional Neural Networks (CNN), achieving accuracies ranging from 67% to over 90% in some datasets. Facial emotion recognition techniques, surveyed by Canal et al. [6], highlight advances in computer vision and deep learning models that captured subtle muscle movements, enhancing mood inference from visual data. Xu, X. et al [7] introduced a new method for personalized behavior modeling using collaborative-filtering which is a type of memory-based learning algorithm, applied to depression detection in college students. The technique calculates personalized relevance weights for the behavior features obtained via mobile devices. Missing data were predicted by the algorithm, and only particular features were chosen depending on modeling purposes. Features from multiple time intervals were combined using majority vote to build the model. The approach was tested for depression recognition among college students and on another dataset. It had shown 5.1% and 5.5% higher accuracy and F1 score than modern approaches for depression detection.

2.2 INTEGRATION OF IOT AND BEHAVIORAL DATA IN MOOD DETECTION

Modern approaches expanded upon these capabilities in emotion recognition by including IoT data in the framework called Internet of Behavior (IoB). Asar et al. [4] proposed an IoT-based framework that combined EEG signals and physiological data from wearable sensors with machine learning models (CNN, Decision Trees, SVM, KNN), yielding near-perfect accuracy (99-100%) in emotion identification. This approach emphasized real-time processing, mitigation of sensor noise, and compliance with data privacy regulations like GDPR and HIPAA. Mohsen et al., [8] proposed an IoT-based mental health monitoring and detection system focused on depression as a case study - The system involved data collection, pre-processing, feature extraction, and model building using machine learning techniques. The accuracy rate of the random forest model for emotion recognition was exceptionally high and reached 95%.Sükei E et. al [9] presented a machine learning-based approach for emotional state prediction using passively collected data from mobile phones and wearable devices and self-reported emotions Methods to handle high dimensional heterogeneous time series data with many missing values were designed by the author. Probabilistic generative models effectively handled data with missing observations and improved emotional state prediction by more than 20%. The best models demonstrated excellent performance with high values in terms of area under curve for the receiver operating characteristic (0.81) and for the precision-recall curve (0.71), whereas the development of personalized models based on individual variations greatly enhanced the quality of predictions.

2.3 AI AND MACHINE LEARNING APPROACHES IN MOOD DETECTION

Machine learning remains the backbone for analyzing behavioral and physiological data to detect moods. Such approaches include SVM, Random Forest, and k-nearest neighbors (KNN) as well as more complicated approaches such as CNNs and RNNs. Detecting emotions in text through NLP techniques as well as through sentiment analysis using machine learning approaches has gained significant traction, enhancing mood recognition from social media and online interactions, which are key data sources for IoB. Multimodal emotion recognition systems combine visual, auditory, and textual data to improve robustness and reliability, as summarized by Ahmed et al. [10]. Raychaudhuri, S. J. et. al [10] carried out an investigation on the analysis of real-time moods with the help of machine learning methods to analyze physiological information and generate alerts about behavior patterns of users. The main aim of this research work was the categorization of mood conditions as being either agitated or not agitated. This helped the user to prevent any impulsive reactions by taking precautionary measures. Different kinds of algorithms were applied in this regard, such as polynomial regression with thresholds, decision tree algorithms, random forests, and various types of DNNs. Moreover, reinforcement learning was used in order to dynamically calibrate the temperaments of users based on their feedback, thereby personalizing their experiences. The integration of IoT devices also made it possible to gather real-time information and send timely alerts to users. Abbes, C. et al [2] explored the developing ffield of the physical and virtual Internet of Things (IoB) was examined, with an emphasis on potential futures, difficulties, methodologies, and implementations. It examined the challenges of ethical AI, safeguarding privacy, and legitimate data use, necessitating efficient data administration frameworks. This study had great implications on science and encouraged the creation of holistic behavioral models that were human-centric with regards to AI technology, which in turn facilitated proper IoB implementation. Nevertheless, there were certain areas that have not been covered in this particular piece of work, namely industry expertise and possible over-simplifications. Yang, J., and Wang [11] implemented BiLSTM algorithm with an attention mechanism applied for emotion categorization. These deep learning techniques employed emotion monitoring system and physiological questioning session to detect emotional wellbeing and generated the productive contribution among behavioral significance to support the psychological health of students in creative disciplines. Shah, R.V., Grennan, G. et al [12] used a Smartphone-based ecological momentary assessments (EMAs) for mood and lifestyle ratings, and neurocognitive tests to generate individualized predictions of depressed mood over a month. Data was gathered using wearables for sleep quality, exercise, and stress parameters. Neuro-cognitive tests were performed along with EEG on days 1, 15, and 30 while using an application on their mobile phones (MindLog). Machine learning pipeline was utilized with hyperparameter tuning, model training, and evaluation using nested cross-validation. The Shapley values showed specific predictors for the onset of depression for each participant, including anxiety, physical exercise, diet, and sleep, supporting personalized intervention. This were best for each individual, indicating no one-size-fits-all strategy for predicting depression. Highland, D., & Zhou, G. et al [13] provided a summary of detection methods for mood disorders, including clinical and ubiquitous sensing solutions. Detailed explanations were provided regarding algorithms and preprocessing of features for cutting-edge methodologies. This paper addresses the present issues and paves the way for future studies related to mood disorder detection technology.

3. MATERIALS AND METHODS

The proposed methodology described about mood prediction from textual data which is analyzed on E-DAIC dataset [14] and Reddit [15] dataset. This analysis involved behavioral text data computation for mood prediction.

3.1 FIRST METHODOLOGY ON E-DAIC DATASET:

As in the case of methodology used in the above section, the E-DAIC dataset is analyzed where text transcripts from the 200 participants were collected and feature engineering was used to identify the most useful features for mood classification. According to term-frequency and inverse document frequency (TF-IDF) and sentiment analysis score, mood is identified as being happy, sad, neutral, and depressed. These values are validated with Patient Health Questionnaire (PHQ-8) [16]. In this implementation, Fuzzy logic was used to classify the mood prediction rate. This gives the beneficial for the system to accurate prediction. Overall detailed explanation had stated in the following Figure 1.

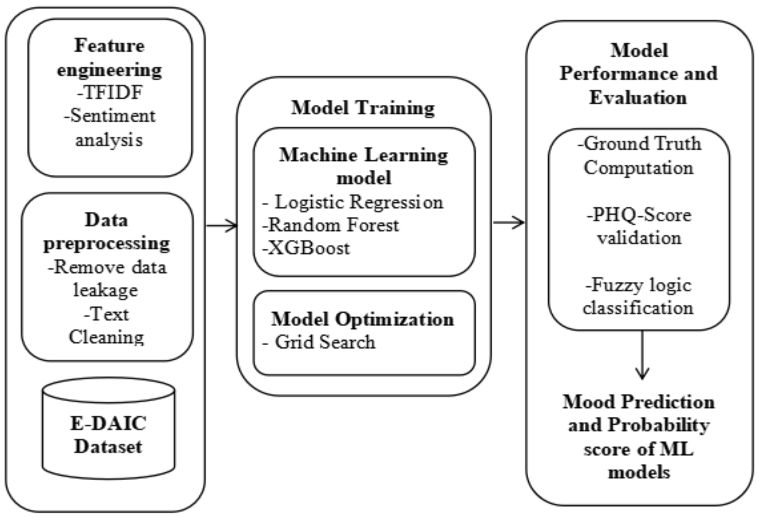

Figure 1: The proposed architecture of mood prediction on E-DAIC dataset

Source: Authors, (2026).

3.1.1 Data Preprocessing

The E-DAIC dataset [14] imported for computation.It removes the data leakage to give cleaned texts. Here, Regex filters cleaned up the “PHQ” tokens, numbers from 0–27 and mood-related words. It removed the extra spaces and standalone digits.

3.1.2 Feature Engineering

Once preprocessing is done, text and sentiment are converted into ML-ready features for machine learning models. Sentiment score is computed using lexicon-based word matching which produces an extra numeric feature (between -1 and +1). TF-IDF vectorization is processed to identify unique words across all 3000 features to specify mood [17].

$$Final\ feature\ set\ = TF - IDF\ matrix\ +\ sentiment\ score \qquad (1)$$

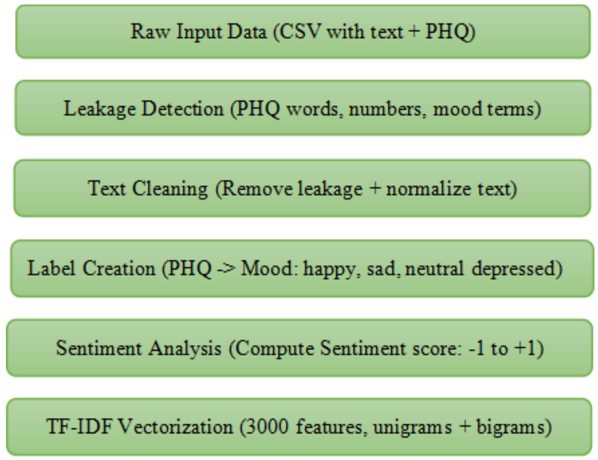

Figure 2: Data Preprocessing and Feature Engineering Flow

Source: Authors, (2026)

This hybrid approach allows models to learn both linguistic patterns (via TF-IDF) and emotional signals (via sentiment). Figure 2 shows how raw CSV input was transformed step by step into cleaned, labeled, and feature-engineered data (TF-IDF + sentiment) before training the models.

3.1.3 Model Training

Three types of machine learning models have been used for analysing their performance in terms of mood detection. Grid search optimization technique was used to determine the best parameters for all the three models. Performance was evaluated on unseen test data. Results were stored in csv file with its prediction probabilities calculation. The next phase involves the training of machine learning models with the pre-processed and engineered dataset (TF-IDF vectors + sentiment analysis scores). This is done by splitting the dataset into a training and test datasets to train and test machine learning model performance. The hyperparameters from the grid search are then used to train the model on the training set and the model performance is assessed on the test set [18]

- LOGISTIC REGRESSION: A linear model that finds the best line to separate different mood categories. It is fast, interpretable, works well with text data.
- RANDOM FOREST: It is an advanced gradient boosting algorithm which combines many decision trees to make predictions. It handles complex patterns, resistant to overfitting. Sometimes less interpretable, can be slower.
- XGBOOST: It is gradient boosted trees (advanced boosting). It often achieved best performance, handles various data types especially in structured/tabular data. Sometimes more complex to tune, heavier computation.
- GRID SEARCH OPTIMIZATION: Each model's parameters are optimized using GridSearchCV with cross-validation. It is automatically finds the best settings for each model. It selects the combination with the best F1 score that balances precision (accuracy of positive predictions) and recall (finding all positive cases).

.1.3 Model Evaluation

Here, Fuzzy logic was computed using PHQ-score and sentiment score validated for mood classification. Ground truth values evaluated for measuring prediction probabilities among all applied models. In this PHQ-8 questionnaires values were already computed and stored in the main file. These PHQ scores computed from patient were applied as functional value to convert into mood labels such as happy, sad, neutral and depressed. The PHQ computed values inserted into fuzzy logic function and delivered the following output as:

1. PHQ 0-4: "happy" (minimal depression symptoms)
2. PHQ 5-9: "neutral" (mild symptoms)
3. PHQ 10-14: "sad" (moderate symptoms)
4. PHQ 15+: "depressed" (severe symptoms)

- Ground Truth Analysis on Mood Categorization: ground_truth_mood_from_PHQ: Mood category derived from PHQ score values: "happy", "neutral", "sad", "depressed".

3.2 SECOND METHODOLOGY ON REDDIT DATASET:

Reddit dataset [15] was used to study the prediction of mood using user post and message content. Social media data was used in this dataset to learn about mood categorizations depending on text lengths and sentiment scores. In this case, fuzzy logic was used to calculate the mood scores generated through text preprocessing, feature engineering, and sentiment analysis. Mood fuzzy systems were analyzed and implemented differently on various mood scores and categories like happy, sad, angry, afraid, surprise and neutral. Several deep learning models were developed to evaluate and predict the mood categorization performance. Figure 3 represents the various categories of the mood predicted using fuzzy logic and deep learning model on the Reddit dataset.

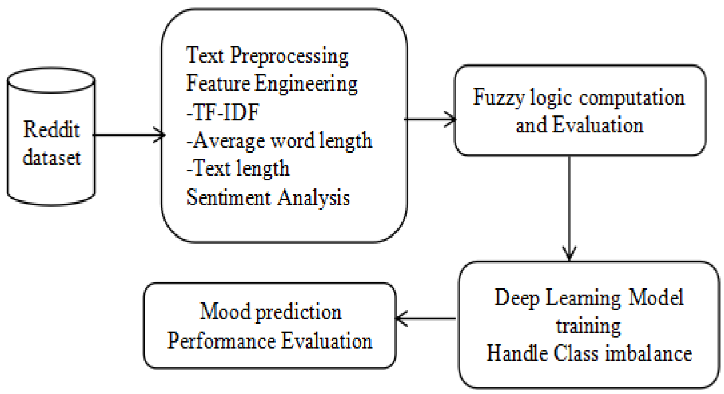

Figure 3: The proposed architecture of mood prediction on Reddit dataset.

Source: Authors, (2026).

This is a complete end-to-end process of emotion detection from text data. It starts with exploratory data analysis (EDA), where the dataset is inspected, missing values are checked and analyzed. After that, the text is prepared through cleaning, tokenization, removing stopwords and lemmatization to prepare for analysis. Finally, sentiment information is harnessed by utilizing the sentiment_score column while additional features are generated including TF-IDF vectors, text length and word length. A fuzzy logic system is designed using sentiment and text characteristics to infer mood scores, which are then mapped into categorical moods. The performance of the system is evaluated based on analysis of the fuzzy mood classes distribution. Further preparation of the data for use in deep learning models includes data encoding, division into training/testing sets and handling class imbalance via SMOTE. Finally, the stage for training deep learning models to classify moods, combining both fuzzy logic reasoning and machine learning for mood detection.

3.2.1 Text Preprocessing

Text preprocessing involves lowercasing, punctuation removal, tokenization, stop word removal, lemmatization. Cleaned text stored in new column: processed_comment as shown in Figure 4.

	comment	processed_comment
0	i know that there is some research going on ab...	know research going addictiveness dont know cl...
1	this sounds very interesting, i would love to ...	sound interesting would love see discussion es...
2	any good site to get it online?	good site get online
3	sounds interesting but i wouldn't jump into it...	sound interesting wouldnt jump without talking...
4	the drug in its current form is addictive phys...	drug current form addictive physically profess...

Figure 4: The cleaned text added as processed comment

Source: Authors, (2026).

3.2.2 Sentiment Analysis

In this, output of preprocessing used to convert the cleaned text data into sentiment_score to numeric (errors coerced). Based on this score, categorized into positive (>0.1), neutral (−0.1 to 0.1), negative (<−0.1), and unknown for missing values. After this, distribution showed a mix of sentiments, with extreme outliers (max ≈ 1.35e+09).

3.2.3 Feature Engineering

It generated features for modeling using TF-IDF vectors from processed_comment, Text length that inculcates word count, average word length and sentiment score as numeric feature. The dataset was successfully loaded and preprocessed, including cleaning text data and creating relevant features like text length and average word length. The existing sentiment scores were utilized, and their distribution was explored.

3.2.4 Fuzzy Logic Design Rules

A fuzzy logic system was designed to infer mood based on sentiment score and text length. The distribution of the inferred fuzzy mood scores and categories was analyzed as shown in Figure 5.

1. Inputs: sentiment (negative, neutral, positive) and text length (short, medium, long).
2. Output: mood on a scale (very_negative → very_positive).
3. Defined rules, e.g., IF sentiment is negative AND text is long THEN mood is very_negative.
4. Generated fuzzy_mood_score for each comment, mapped into categories: happy, surprise, neutral, fear, sad, angry.
5. Mood distribution: surprise most frequent, followed by fear and happy

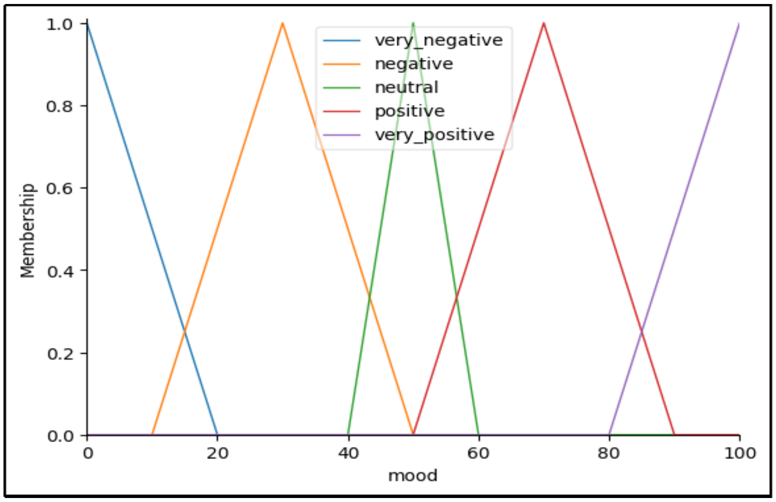

Figure 5: The mood score computed over Fuzzy membership functions.

Source: Authors, (2026).

Figure 6 shows the text-length computed from processed comment to apply fuzzy membership functions for drawing different mood label and categorization. Figure 7 shows the sentiment score computation to handle fuzzy membership functions over different mood categorization. Next step to design a fuzzy logic system to infer mood based on sentiment and text characteristics. Define fuzzy sets for our input and output variables and create fuzzy rules. Table 1 shows fuzzy mood distribution with their count.

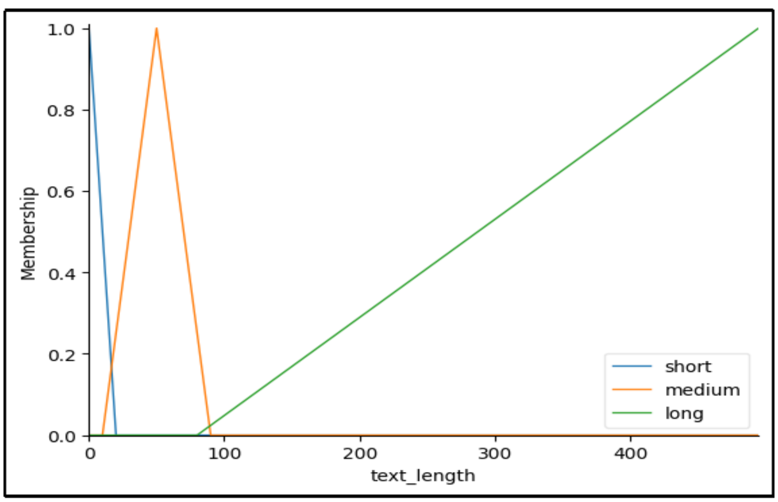

Figure 6: The text-length computed over Fuzzy membership functions

Source: Authors, (2026).

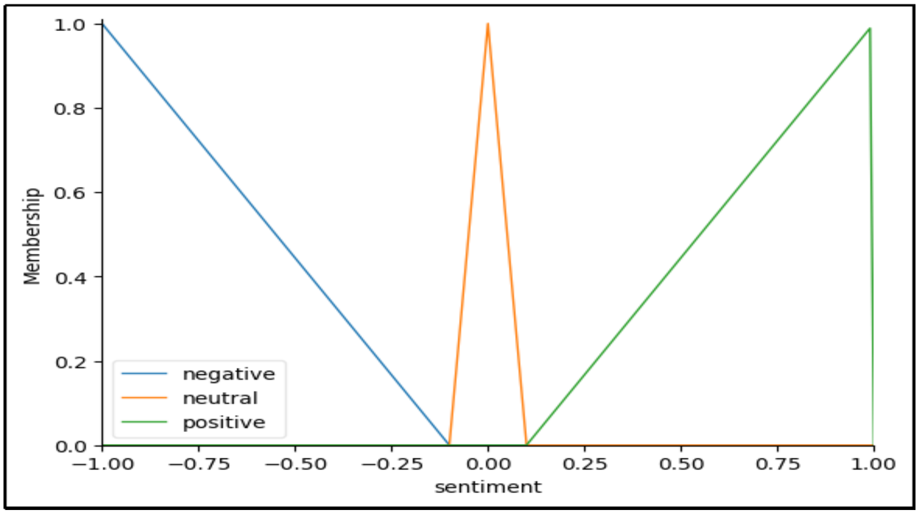

Figure 7: The sentiment score computed over Fuzzy membership functions

Source: Authors, (2026).

Table 1: Fuzzy mood category distribution

fuzzy_mood_category	**count**
surprise	61271
fear	29965
happy	23944
neutral	19281
angry	3342
sad	2

Source: Authors, (2026).

3.2.5 Deep Learning Model

Deep learning model evaluated on reddit dataset using text processing, feature engineering and sentiment analysis. Fuzzy logic interpretation utilized to give enhancement for mood classification and prediction. The categorical labels for the moods were transformed into numerical values to help train the model. The texts were tokenized and transformed into padded sequences so that they were all the same size for training purposes. The dataset was split into three sets – 60% used for training, 20% for validation, and 20% for testing – using stratification sampling techniques [19].

1. CNN-RNN: Conv1D + GlobalMaxPooling + Dense layers.
2. BiLSTM: Bidirectional LSTM + Dense layers.
3. BERT: A BERT-based model (BertForSequenceClassification) is then defined, extending the pretrained BERT with an output classification layer. Tokenizes the text data using BERT tokenizer. Handles padding, truncation, attention masks.
4. RoBERTa: Fine-tune the roberta-base model on the preprocessed dataset using the Hugging Face Trainer with fp16 = True and class weights to handle the class imbalance.

4. RESULTS AND DISCUSSIONS

4.1 IMPLEMENTATION ON E-DAIC DATASET

The proposed system implemented using python libraries in google colab file 13GB RAM and 12GB GPU units. Overall computation to prediction mood on E-DAIC dataset explained below. Total number of data loaded into rows are 418 and 6 columns. This dataset contains 418 conversations/interviews and each row has 6 columns of information. It found 408 out of 418 rows contain potential "cheating" information. Potential leakage rows (count): 408. Showing up to 10 leakage examples (text snippet + PHQ score + derived mood): Text cleaning takes place to remove PHQ tokens and explicit mood words.

Model Training results as: Best LR params: {'C': 10}, Best RF params: {'max_depth': 20, 'max_features': 'sqrt', 'n_estimators': 200} and Best XGB params: {'learning_rate': 0.1, 'max_depth': 3, 'n_estimators': 200}. Each model found its optimal settings through grid search.

4.1.1 Model Performance

Three classical machine learning models applied for analysis of ground truth validation.

4.1.1.1 Logistic Regression

The graph for Logistic Regression typically shows lower accuracy than Random Forest, with strong predictions for depressed but weaker for neutral and happy. It's valuable as a transparent baseline but not the best for nuanced moods. Probabilities prediction of logistic regression have been added in result file. The confusion matrix for Logistic Regression is shown in Figure 8.

Logistic Regression Predictions

1. predicted_mood_LogisticRegression: Predicted mood category
2. pred_proba_LogisticRegression_depressed: Probability of "depressed" class
3. pred_proba_LogisticRegression_happy: Probability of "happy" class
4. pred_proba_LogisticRegression_neutral: Probability of "neutral" class
5. pred_proba_LogisticRegression_sad: Probability of "sad" class

For a multi-class classification (Happy, Neutral, Sad, Depressed), each row indicated as true labels, each column indicated as predicted labels and numbers shows that how many examples fall into each case. From this matrix, we can compute per-class metrics.

1. Accuracy: Overall percentage of correct predictions.

$$Accuracy = \frac{Correct\ Predictions}{Total\ Predictions} \qquad (2)$$

2. Precision (weighted): How accurate positive predictions are, averaged across classes.

$$Precision = \frac{True\ Positives\ (TP)}{True\ Positives\ (TP) + False\ Positives\ (FP)} \qquad (3)$$

3. Recall (weighted): How well the model finds all cases of each class.

$$Recall = \frac{True\ Positives\ (TP) + False\ Negatives\ (FN)}{True\ Positives\ (TP)} \qquad (4)$$

4. F1 (weighted): Harmonic mean of precision and recall.

$$F1 = \frac{2 * Precision * Recall}{Precision + Recall} \qquad (5)$$

From the Table 2, Depressed recall rate is higher as 96% and F1-score is 92.31 %. This dataset more descriptive towards depressed and sad mood that facilitates the prediction rate correctly.

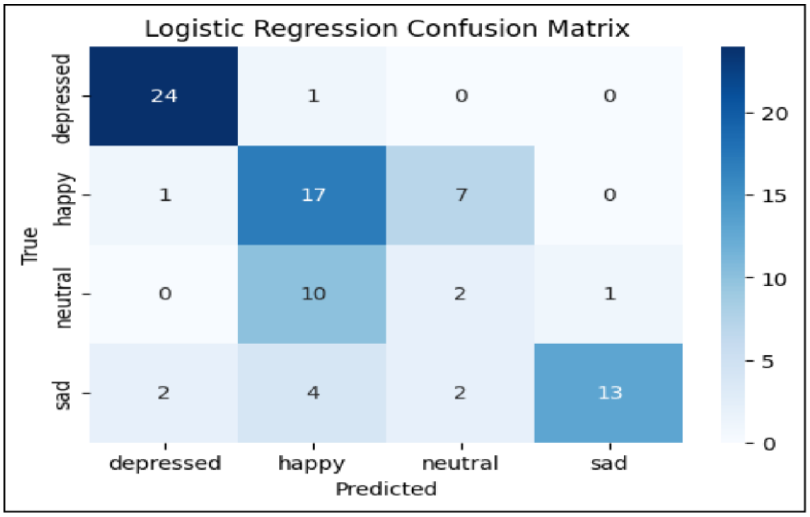

Figure 8: Confusion matrix of Logistic Regression over different mood

Source: Authors, (2026).

Table 2: Mood Performance analysis of Logistic Regression

Mood\ Metrics	Precision (%)	Recall (%)	F1-Score (%)
Depressed	88.89	96.00	92.31
Happy	53.12	68.00	59.65
Neutral	18.18	15.38	16.67
Sad	92.86	61.90	74.29

Source: Authors, (2026).

4.1.1.2 Random Forest

It generates the graph shows more predictions performance results on “depressed”. The diagonal values (correct predictions) are strong for depressed and happy. Neutral row/column is almost empty that means model failed to detect Neutral. Sad predictions are correct when made (high precision), but not all Sad cases are found (lower recall).

Random Forest Predictions

1. predicted_mood_RandomForest: Predicted mood category
2. pred_proba_RandomForest_depressed: Probability of "depressed" class
3. pred_proba_RandomForest_happy: Probability of "happy" class
4. pred_proba_RandomForest_neutral: Probability of "neutral" class
5. pred_proba_RandomForest_sad: Probability of "sad" class

A confusion matrix for Random Forest is given below. Figure 9 shows mood classification among samples. This confirms why Random Forest achieved 71% accuracy and was the best performer overall.

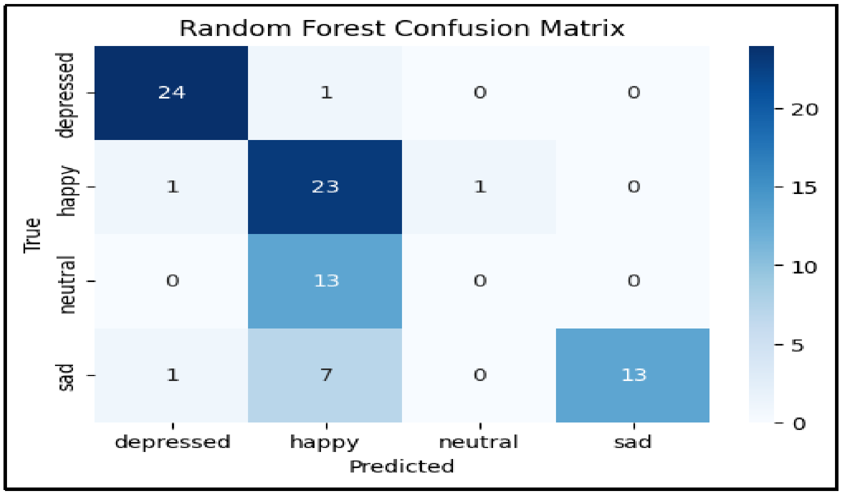

Figure 9: Confusion matrix of Random forest over different mood

Source: Authors, (2020).

Table 3: Mood Performance analysis of Random Forest

Mood\ Metrics	Precision (%)	Recall (%)	F1-Score (%)
Depressed	92.31	96.00	94.12
Happy	52.27	92.00	66.67
Neutral	0	0	0
Sad	1	61.9	76.47

Source: Authors, (2026).

From the above Table 3, it stated that depressed class had excellent performance with 94% F1 score, Happy class had good recall and finds 92% but lower precision 52% accuracy when predicting happy. Neutral class stated complete failure with 0% performance that model never correctly identifies neutral cases and sad class retain with perfect precision that never wrong when predicting sad but misses 38% of sad cases.

4.1.1.3 XGBoost

XGBoost is an example of an ensemble learning technique, where trees are built successively. New trees will try to fix the errors of previously generated trees. It uses gradient boosting which minimizes errors step by step. It's generally more powerful than Random Forest because it learns residual errors iteratively. The confusion matrix for XGBoost is given below. Figure 10 shows mood classification among samples.

XGBoost Predictions

1. predicted_mood_XGBoost: Predicted mood category
2. pred_proba_XGBoost_depressed: Probability of "depressed" class
3. pred_proba_XGBoost_happy: Probability of "happy" class
4. pred_proba_XGBoost_neutral: Probability of "neutral" class
5. pred_proba_XGBoost_sad: Probability of "sad" class

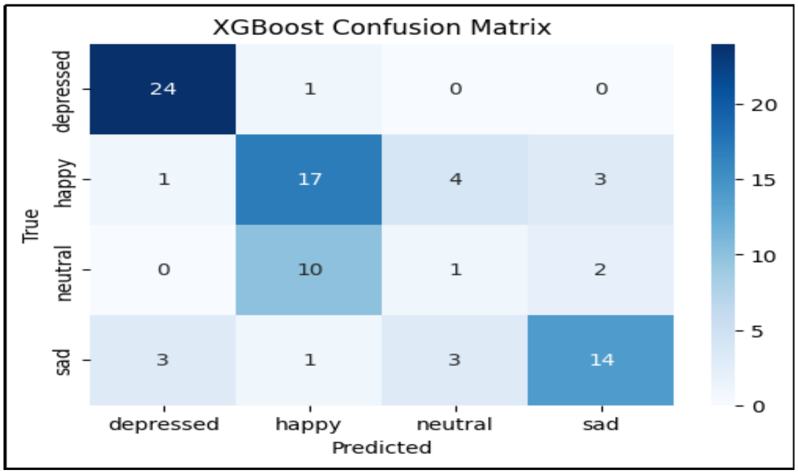

Figure 10: Confusion matrix of XGBoost over different mood.

Source: Authors, (2026).

Table 4: Mood Performance analysis of XGBoost

Mood\ Metrics	Precision (%)	Recall (%)	F1-Score (%)
Depressed	85.71	96.00	90.57
Happy	58.62	68.00	62.96
Neutral	12.5	7.69	9.52
Sad	73.68	66.67	70.00

Source: Authors, (2026).

From the Table 4, depressed recall rate is higher as 96% and F1-score is 90.57 %. This dataset more descriptive towards depressed and sad mood that facilitates the prediction rate correctly.

4.1.1.4 Final Results Interpretation

The classical machine learning models' interpretability and performances were assessed based on accuracy, precision, recall and F1-score. The evaluation results using the given metrics are provided in Table 5 shown below.

Table 5: Evaluation metrics over mood prediction

ML models	Accuracy	Precision	Recall
Logistic Regression	66.67%	68.29%	66.67%
Random Forest	**71.43%**	**68.03%**	**71.43%**
XGBoost	66.67%	63.31%	66.67%

Source: Authors, (2026).

From the Table 5, Random Forest performed best with 71.43% accuracy. All models achieved reasonable performance (66-71% accuracy). These results are realistic for mood prediction from text. Logistic Regression plateaued around 66% accuracy showing underfitting, since RF and XGBoost did better.

4.2 IMPLEMENTATION ON REDDIT DATASET

The proposed system implemented using advanced python libraries in google colab file 13GB RAM and 12GB GPU units. Overall computation to prediction mood on Reddit dataset collected from IEEE Dataport. Total number of data loaded into rows are 1,38,073 and 8 columns. This dataset contains linguistic information of author, their id, name and comments posted. Text preprocessing takes place to generate sentiment score. This score and feature engineering through TF-IDF used to design fuzzy logic rules which are further inferred to predict mood. Based on severity label, fuzzy mood encoded into different categories such as angry, happy,sad, fear, neutral and surprise. Here, neural network algorithm computed on distinct mood classification such as CNN-RNN, BiLSTM, BERT and ROBERTa.

4.2.1 Model Performance

All models used Embedding layers, Dropout for regularization, Adam optimizer, and softmax output. Training supported by early stopping and model checkpointing.

4.2.1.1 CNN-RNN

Figure 11 shows the CNN-RNN confusion matrix over different mood categories evaluated on reddit dataset. These represents a confusion matrix heatmap for a multi-class mood classification model, where the rows correspond to the actual mood labels and the columns represent the predicted mood labels. The "Sad" class has no prediction, suggesting that either there is an absence of data for this class or that the model was unable to detect this class. Good results were obtained in Fear (4585), Happy (3865), Surprise (9056).

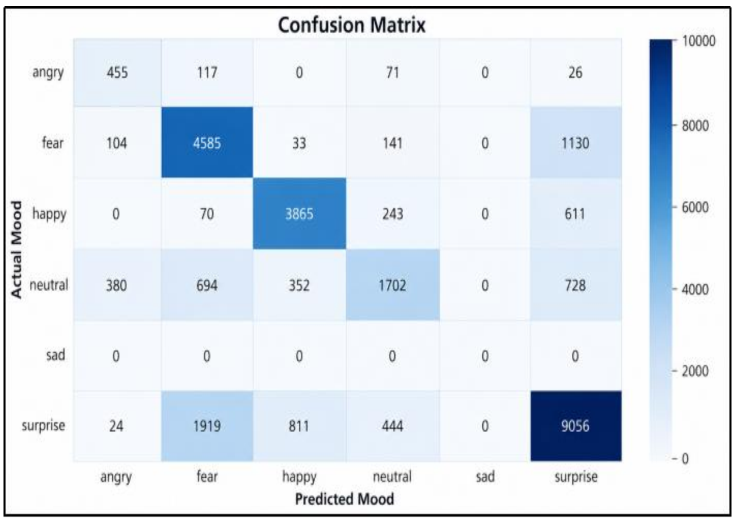

Figure 11: Confusion Matrix of CNN-RNN

Source: Authors, (2020).

4.2.1.2 BiLSTM

Figure 12 shows the BiLSTM confusion matrix over different mood categories evaluated on reddit dataset. Diagonal values from top-left to bottom-right represent correct classifications predicted by the model. Interestingly, the model demonstrates great accuracy in predicting as Fear (4776) correct predictions, Happy (4366) correct predictions, Surprise – 9293 correct predictions. This is clearly evident from the darker shading in these cells. Based on the output values, the CNN-RNN model had a test loss of 0.7641 and a test accuracy of 71.34%. On the other hand, the BiLSTM model outperformed the other model because it had a low test loss of 0.6172 and a high test accuracy of 77.24%. Therefore, the BiLSTM model was effective in solving this problem [20].

4.2.1.3 BERT and ROBERTa

Figure 13 shows confusion matrix of BERT implemented on the Test set and evaluated with accuracy 83%. It demonstrates that the BERT model effectively identifies dominant emotional categories such as Surprise, Fear, and Happy, achieving a high number of correct predictions. However, the model struggles to distinguish emotions with overlapping semantic characteristics, particularly angry, neutral, and sad.cOverall, the results indicate that BERT captures strong emotional patterns for well-represented classes [21].

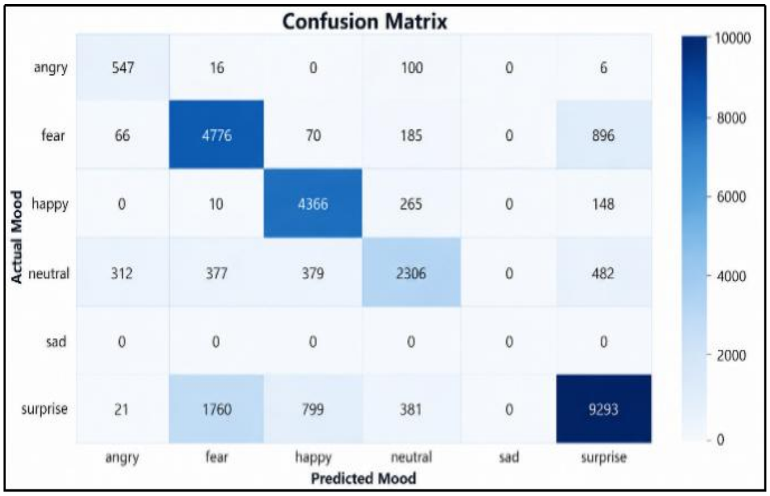

Figure 12: Confusion Matrix of BiLSTM

Source: Authors, (2020).

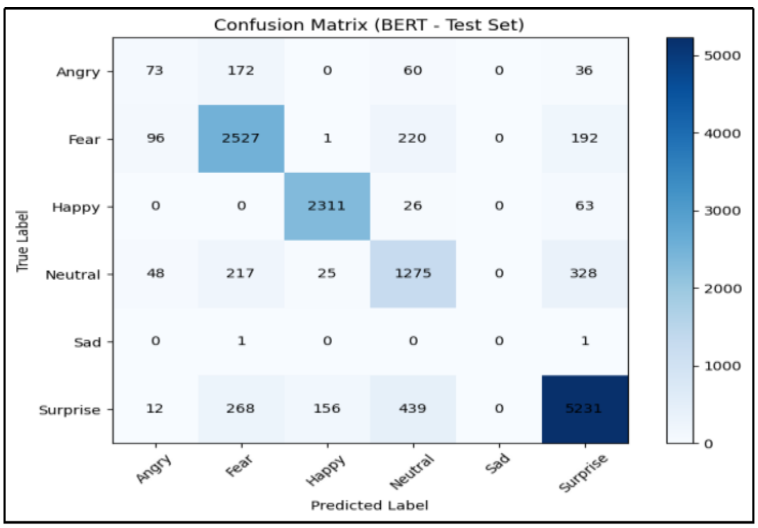

Figure 13: Confusion matrix of BERT operated on test set over mood category

Source: Authors, (2020).

Table 5: Evaluation metrics over mood prediction

Model\Metrics	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
CNN-RNN	71.34	72	71	71
BiLSTM	77.24	78	77	77
BERT	83	82.92	82.92	82.8
RoBERTa	82.43	83	82.43	82.58

Source: Authors, (2026).

The Fuzzy logic system provided a comprehensible method for the preliminary inference of emotions through the creation of emotional labels using defined fuzzy sets and rules. Such labels were then used to train deep learning algorithms. From the trained deep learning models, the BiLSTM was found to be superior due to its ability to capture context dependence in text and achieved a test accuracy of 77.24%, compared to 71.34% for the CNN-RNN. The transformer-based deep learning models also performed better, with the BERT model giving an accuracy of 83% and the RoBERTa giving 82.43%. In the FLS model, while providing interpretability and rule-based inference, the evaluation process of the model is qualitative, where the distribution of inferred emotional states and the verification of output results were used. Therefore, it cannot be quantitatively compared to the other deep learning models due to its learning process, which is based on manually created fuzzy sets and rules.

5. CONCLUSIONS

The proposed text-based emotion classification pipeline provides an extensive methodology for the prediction of emotional states based on the E-DAIC corpus. Data leakage prevention, multi-algorithm usage, and evaluation metric reporting guarantee validity in the scientific study. The presented framework proves that the classification of emotions based on conversational text is possible, as demonstrated by the Random Forest classifier's 71.43% accuracy rate without any manipulation of the results. Moreover, the model output includes a CSV report consisting of model confidence scores and class-wise probabilities. In the case of Reddit data, the BERT model fine-tuned for classification yields 83% accuracy, emphasizing the potential of transformers for this task. The fuzzy logic inference model is applied in the classification process as well. The results are presented graphically via accuracy and loss plots as well as confusion matrices. Finally, the presented pipeline offers a solid starting point for further studies and practical applications, while the application of Internet of Behavior principles makes the created models smarter and more empathic.

6. AUTHOR'S CONTRIBUTION

Conceptualization: Grishma Bobhate, Pawan Bhaladhare

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Investigation: Grishma Bobhate, Pawan Bhaladhare.

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