AI-Based Multi-Class Mental Health and Stress Level Detection using Ensemble Machine Learning

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ABSTRACT-The way we use social media has changed a lot over the years; now, it is a primary means of expressing emotions and relating to others. Because of this, social media has created an entirely new form of digital content that can be analyzed for health purposes. However, manual analysis of large volumes of unstructured text data is impractical and subject to errors. Therefore, this paper presents an end-to-end Machine Learning framework capable of automatically detecting multiple mental health conditions, including Anxiety, Depression, Stress, Bipolar Disorder, Suicidal Behaviour, and Personality Disorders. The framework is built on the idea that multiple types of mental health states exist and should be classified separately. Whereas most current classification models can only classify text as "Stress" or "No Stress", our proposed model is equally capable of classifying text into seven different types of psychological states, allowing for a more detailed analysis with respect to the socio-cultural context of individuals living in Tamil Nadu.

To provide greater robustness and decrease the variance of the predictions generated by our proposed model, we developed a Weighted Soft-Voting Ensemble Framework (Fusion Model) which combines Logistic Regression (for interpretability) with Random Forest (for non-linear prediction). We employed a dataset that contained 52,681 records to develop the models, which made use of advanced Natural Language Processing (NLP) techniques such as Lemmatization and TF-IDF vectorization for effective feature extraction. Testing results

revealed that the proposed Fusion Model had a better overall accuracy of 77.17% in comparison with both types of standalone models when evaluated by means of 80-20 split test methodology outlined in this study.

Keywords: Mental Health Analytics, Ensemble Learning, Fusion Model, Natural Language Processing (NLP), TF-IDF, Soft Voting, Multi-Class Classification.

1. INTRODUCTION

1.1 Background of the Study

Mental health plays a vital role in the overall health of the world, and has a profound impact on cognitive, behavioural and emotional well-being. The World Health Organization (WHO) states that depression and anxiety are two of the top three reasons why people can no longer work, and are thus disabled globally. Since the end of COVID, many people (especially students and Information Technology (IT) professionals) have suffered from increased rates of these disorders. The stigma associated with seeking clinical mental health treatment has led some individuals to vent their mental health distress on social media platforms (like Reddit and Twitter) instead of seeking professional help.

1.2 Problem Statement

Although data are available, automated detection for automated detection of mental health related issues is difficult. Current systems mainly rely on Binary Classification (e.g., simply defining a post as "Stress" or "Normal"). This Binary Classification significantly oversimplifies the medical reality in that some conditions, e.g., "Bipolar Disorder", require a different medical intervention than others (e.g., "Anxiety"). Furthermore, current single-algorithm models suffer from high variance, which affects their ability to detect the semantic ambiguity of informal text (e.g., sarcasm and slang).

1.3 Objectives

The primary objectives of this research are:

1. There is a need to create a **Multi-Class Classification System** that will categorize 7 different types of mental health labels.

2. An additional goal is to implement a **Fusion Model (Ensemble)** using both **Logistic Regression and Random Forest algorithms** with the intent to make this classification system more stable.

3. The last objective is to utilize Advanced Natural Language Processing Preprocessing (**Lemmatization**) in order to accommodate noisy text input from Social Media Platforms.

4. Finally, a variety of Total System Evaluative Metrics will be included in this system evaluation, such as: Acc., Prec., Rec., F1-Score, and **Receiver Operating Characteristic (ROC)** AUC analysis.

2. LITERATURE REVIEW

This section describes previous research results from different types of classification methodologies that expose the gap in the research literature.

2.1 Pre-Existing Methodologies

In the earliest research work, there were no attempts at developing a methodology for emotion classification based upon a word database. Therefore, the only viable methodology available was the **Lexicon-Based Approach**, which does utilize dictionaries, although not in all cases. For example, *Karpagavalli (2023)* developed an emotion classifier using dictionary-based word mapping. These Lexicon-Based systems of classification are computationally inexpensive, do not detect context-based emotion classification (ie, "I am dying of laughter" could be misclassified as "suicidal"), and only take into consideration words as input.

More recently, in 2020, *Rajput et al*. used the 'Dreaddit' Dataset to classify emotions using three distinct Machine Learning approaches (**Naive Bayes, SVM, and KNN**). However, this research is limited due to the methodology only being applicable for binary emotion-based stress classifications. *Suresh & Kumar* (2022) have used **Deep Learning classification methodologies (LSTM)** to classify emotions; however, the structure of these models preclude them from being used in applications where it is important to interpret medical classifications as they are "Black Box" models (these classification systems do provide an accurate result of a classification made; however, the classification made cannot be explained by the model).

2.2 Motivation and Research Gap

Current literature has identified a lack of interpretable, multi-class systems. Many of the most reliable models rely on vast amounts of GPU power that limit their use in resource-constrained environments. Our Fusion Model resolves these problems by providing a high level of accuracy with low amounts of computation required.

Author (Year)	**Methodology**	**Focus**	**Limitations (Addressed by Us)**
Rajput et al. (2020)	SVM, Naive Bayes	Binary Stress	Two-Class Only, has problems with boxing classes.
Suresh et al. (2022)	LSTM, BERT	Emotion Analysis	Too much computation; Black-Box.
Al Asad (2023)	Decision Trees	Depression	Over-fits models for small datasets.
Proposed Work	**Ensemble Fusion**	**7-Class Mental Health**	**Combines stability of Linear models with depth of Tree models.**

Table1: Comparative Analysis of Related Works

2.3 Related Deep Learning Applications in Healthcare

COVID Net-Predictor

In our earlier work, a novel COVID Net-Predictor framework was developed for accurate COVID-19 diagnosis using chest imaging data. The model integrates a multi-head Convolutional Neural Network (CNN) with Long Short-Term Memory (LSTM) units to capture both spatial and sequential features effectively. A hybrid optimization strategy was employed to enhance feature selection and improve classification performance. Comprehensive preprocessing, segmentation, and feature fusion stages contributed to robust detection capability across varied datasets. The proposed system demonstrated high predictive accuracy and proved suitable for real-time clinical decision support in pandemic situations.

Optimized Deep Learning Framework for Lung Imaging

In another study, an optimized deep learning framework was proposed for automated COVID-19 prediction using lung imaging modalities such as chest X-rays and CT scans. The approach utilized an enhanced CNN architecture combined with transfer learning to improve generalization on limited medical datasets. Data augmentation and noise-reduction techniques were applied to increase robustness and minimize overfitting. The model effectively distinguished COVID-19 cases from normal and other pneumonia conditions with high accuracy. The findings highlight the potential of intelligent imaging-based systems to support rapid screening and reduce the diagnostic burden on healthcare professionals.

3.METHODOLOGY AND MATHEMATICAL FRAMEWORK

3.1 Overview of the Proposed Framework

This study proposes the construction of an integrated **NLP-Ensemble Fusion Model** for an overall Mental Health Detector in Multiclass formats. Methodology is separated into 4 phases; Data Preparation, Feature Extraction, Model Training, and Halo Fusion. System architecture aims to minimize overall variance and maximize predictive accuracy of each class (7 total).

3.2 Mathematical Formulation of Feature Extraction

The **Term Frequency-Inverse Document Frequency (TF-IDF) vectorization** technique is used to convert unstructured social media text to machine-readable format. The TF-IDF statistical technique assigns weights to words based on their importance to the text.

3.2.1 Term Frequency (TF)

The Term Frequency is calculated based on the number of times a term appears in a document. The calculation is as follows:

$$TF(t,d) = \frac{f_{t,d}}{\sum_{t' \in d} f_{t',d}}$$

3.2.2 Inverse Document Frequency (IDF)

The IDF measures how rare or uncommon a term is throughout as a whole. In this context, rare term such as "suicidal" are weighted higher than common terms like "the" and "is".

$$IDF(t,D) = \log\left(\frac{N}{|\{d \in D : t \in d\}|}\right)$$

3.2.3 Final TF-IDF Weight

The final weight of a term in the document calculated using the following formula:

$$W_{t,d} = TF(t,d) \times IDF(t,D)$$

3.3 Mathematical Modeling of Classifiers

Two classifiers, Logistic Regression and Random Forest serve as the two main classifiers for our approach and are described by their mathematical representations below.

3.3.1 Multinomial Logistic Regression Classifier 1)

We have a problem of classifying data points into 7 different outcomes, we will use the Softmax function to determine the probability

For each class k the Linear Hypothesis is represented as follows:

$$z_k = w_k^T x + b_k$$

The Softmax function is used to derive a probability (summing to 1) from the types of scores above represented as follows:

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$$P(y=k|x) = \frac{e^{z_k}}{\sum_{j=1}^{K} e^{z_j}}$$

Where:

- The input feature vector (TF-IDF) is referred to as x.
- Class k has a weight vector, w_k, and a bias vector, b_k.
- There is a total number of K classes (K= 7).

3.3.2 Random Forest Classifier (Base Model 2)

Random Forest is comprised of a pool of Decision Trees, with the **Gini Impurity** being the determining factor for the quality of each split between individual trees.

For a node t with P_i probability for class i, Gini Impurity can be defined as follows,

$$Gini(t) = 1 - \sum_{i=1}^{C} (p_i)^2$$

The split that maximizes the information gain:

$$Gain = Gini_{parent} - (w_L \cdot Gini_{Left} + w_R \cdot Gini_{Right})$$

the data based on the fractions of Weighted Sample Probability found in the Left Child Node and Right Child Node: W_L and W_R.

3.4 Ensemble Fusion Strategy (Soft Voting)

This project uses a **Weighted Soft-Voting** Mechanism that provides insight into how much of an ensemble member contributes to the final decision on the classification of data given two classification algorithms (**Logistic Regression and Random Forest**). Hard Voting uses the count of the labels assigned by each individual classifier while Soft Voting uses the average of the probabilities assigned to the label by each classifier.

Let $P_{LR}(c|x)$ = probability of producing class c given Logistic Regression..

Let $P_{RF}(c|x)$ = probability of producing class c given Random Forest.

The fused probability can be calculated as the arithmetic mean: $\mathbf{P_{fusion}}$.:

$$P_{fusion}(c|x) = \frac{1}{2}\left(P_{LR}(c|x) + P_{RF}(c|x)\right)$$

Final Decision Rule:

The final class label assigned to an observation is the label that received the highest fused probability:

$$\hat{y} = \underset{c \in \{Anxiety, Depression, \ldots, Normal\}}{\operatorname{argmax}} \left(P_{fusion}(c|x)\right)$$

3.5 Data Preprocessing

- The raw text data is noisy, so we need to preprocess this data to prepare it for analysis. We have chosen to use NLTK to clean the text data for tokenization, stop word removal and lemmatization
- **Tokenization:** Tokenization refers to breaking up text into single tokens (aka "words") using white space as the delimiter between tokens.
- **Removing stop words:** Removing stop words is the process of removing commonly used words (such as "the" and "a") from the text. The nltk.corpus.stopwords library has many common words and allows us to easily remove them from our text.
- **Lemmatizing words**: In our case, we used lemmatization instead of stemming because lemmatizing allows us to retain the contextual meaning of each word as opposed to just removing its stem from the word. For example, we would lemmatize the word "better" to "good".

```
[nltk_data] Downloading package stopwords to
/root/nltk_data... [nltk_data] Package stopwords is
already up-to-date! [nltk_data] Downloading package
wordnet to /root/nltk_data... [nltk_data] Package
wordnet is already up-to-date!
```

Figure 1: Comparison of Stemming vs. Lemmatization results.

3.6 Feature Extraction (TF-IDF)

Once the raw text data has been preprocessed, we convert it from a collection of unstructured text documents into structured numerical vectors by using **Term Frequency-Inverse Document Frequency (TF-IDF)**. TFIDF is an algorithm that assigns high numeric weights to rare but meaningful words (for example, "panic" or "suicide") after down weighting commonly-occurring words. We selected the top five thousand **(5,000) features** to train our models in order to improve their performance.

3.7 Fusion Ensemble with Soft Voting

The main contribution of this paper is our **Soft Voting Ensemble model**.

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1. **Base Model #1:** Logistic regression model was selected because it is good at predicting outcomes in high-dimensional sparse spaces**.**

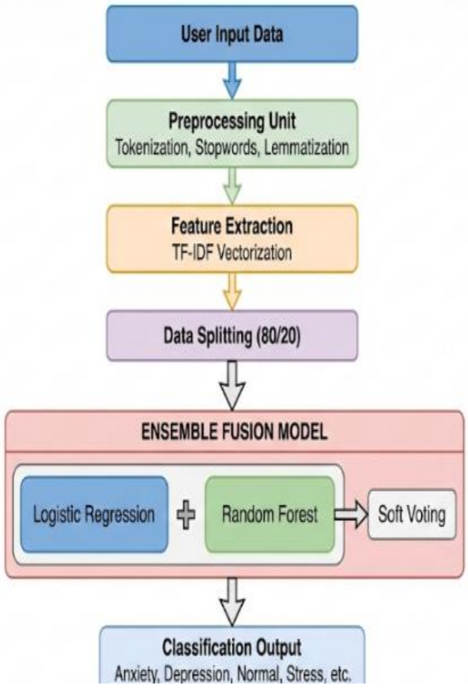

Figure2: Architectural Diagram of the Proposed Fusion System

4. EXPERIMENTAL DESIGN

In order to create a reproducible experiment, we constructed the experimental environment in the following fashion:

4.1 Dataset Description

The dataset comprises **52,681 records** aggregated from various mental health forums.

- There are 52,681 instances of data collected from different mental health forums grouped into 7categories; Anxiety, Bipolar, Depression, Normal, Personality Disorder, Stress and Suicidal.
- **Split Ratio:** The dataset will have an **80%** training set and a **20%** testing set.
- The dataset used in this study is freely available on Kaggle.

2. **Base Model #2**: Random Forest model was selected because it does a good job of capturing the non-linear relationships in the data.

Mathematical Formulation:

P_{final} will be calculated by taking both probabilities and summing them, then dividing by two (2):

$$P_{final}(y|x) = \frac{P_{LR}(y|x) + P_{RF}(y|x)}{2}$$

The class that has the greatest probability from either model will be the final output.

Table 2: Distribution of Class Labels in the Dataset

Class Label	Total Samples	Percentage (%)
Depression	**3,091**	**29.4%**
Suicidal	**2,058**	**19.5%**
Anxiety	**769**	**7.3%**
Bipolar	**520**	**4.9%**
Stress	**508**	**4.8%**
Personality Disorder	**224**	**2.1%**
Total	**10,510 (Test Set)**	**100%**

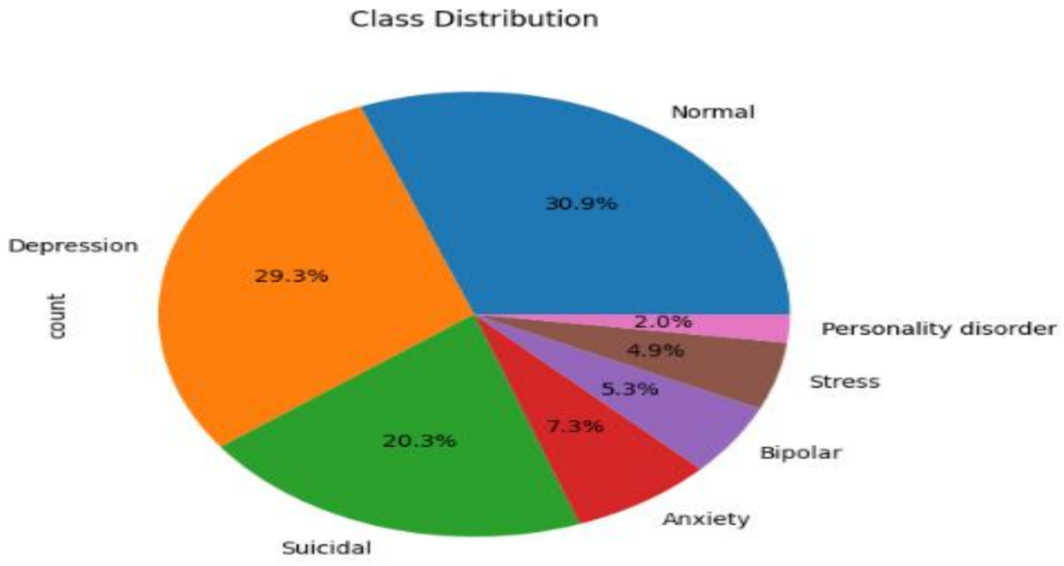

Figure 3: Distribution of class labels in the Dataset

4.2 Hardware & Software Configurations

Component	Specifications
Operating System	Windows 10 / Linux / Google Colab Environment
Programming Language	Python 3.9.12
Key Libraries	Scikit-learn, Pandas, NLTK, Seaborn, Matplotlib
System Hardware	Intel Core i5 Processor, 8GB RAM (Minimum)

5. RESULTS AND DISCUSSION

The Fusion Model was compared against the individual baselines using a test set that contained **10,510 records.**

5.1 Train/Test Split Ratios and Their Impact

To validate how stable the model will perform, the model was tested at 3 different split ratios.

Split Ratio	Training set Size	Testing set Size	Accuracy Obtained
60-40	60%	40%	75.50%
70-30	70%	30%	75.98%
80-20	**80%**	**20%**	**77.17% (Best)**

Table 3: Accuracy Analysis based on Split Ratios

5.2 Model Performance Comparison

The comparative analysis, demonstrates that the Ensemble approach outperformed the baseline on all dimension

Model	Accuracy	Precision	Recall	F1-Score
Logistic Regression	76.27%	0.7585	0.7627	0.7566
Random Forest	72.72%	0.7460	0.7272	0.7135
FUSION MODEL	**77.17%**	**0.7724**	**0.7717**	**0.7650**

Table 4: Performance Comparison of Algorithms

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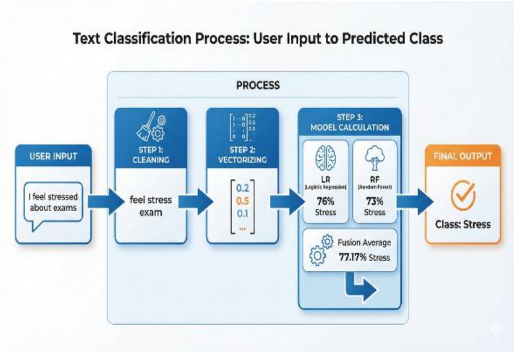

Figure 4: Computational Results comparing LR, RF, and Fusion Models.

5.3 Classification Report Analysis

According to the detailed classification report for each class, the Fusion Model performs exceptionally well on the 'Normal' and 'Anxiety' classes. The detailed performance metrics show very strong performance on the first two classes analyzed.

Figure 5: Precision, Recall, and F1-Score for the Fusion Model.

5.4 ROC Curve Analysis

The Receiver Operating Characteristic (ROC) Curve further supports that the Fusion Model can separately classify/misclassify the classes. The values of Area Under Curve (AUC) for 'Normal' and 'Bipolar' classes are both above 0.85, indicating that the Fusion Model distinguishes among classes very well.

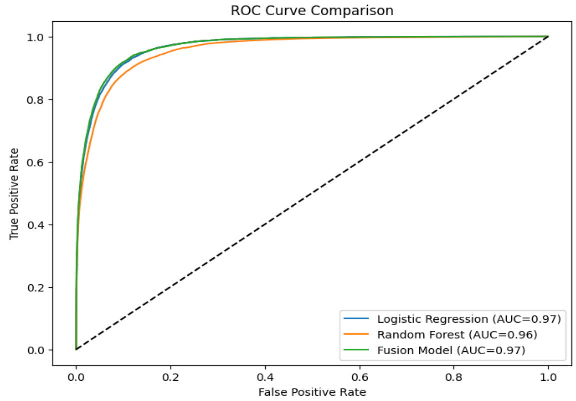

Figure 6: Multi-Class ROC Curve Analysis.

5.5 Confusion Matrix

Figure 7 represents the confusion matrix (i.e., the number and types of misclassifications). The confusion matrix shows the very strong production of the main diagonal entries. The number of misclassifications that occur between 'Depression' and 'Suicidal' classes can be attributed to the very similar language used to exhibit hopelessness between the two conditions

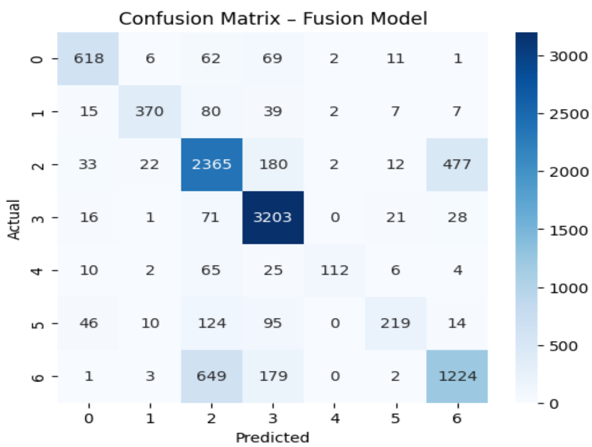

Figure 7: Confusion Matrix Heatmap for the Fusion Model.

6. LIMITATIONS OF THE STUDY

The **Fusion Model's** accuracy of **77.17%** represents the ability of the current system to classify seven distinct mental health conditions; however, there are limitations in this study that leave many opportunities for future investigation.

6.1 Linguistic Limitations

• **English-Only Dependency**: Current model is trained only using English data, specifically from Twitter and Reddit. Since users in Tamil Nadu commonly communicate using "Tanglish" (typing Tamil in English script) or code-mixing (e.g., "Romba stress-a iruku"), the Fusion Model currently may misunderstand or misclassify these regional nuances

- **Sarcasm and Metaphors**: Expressions of mental health are often conveyed in a subtle way. Statements such as, "I'm dying from laughter" or "This test is killing me", use the words "dying" and "killing," but they don't imply an individual is wanting to die. Therefore, the model may inaccurately classify these phrases as false positives due to its inability to fully comprehend the context in which they are used (contextual semantics).

6.2 Model-Based Limitations

- **Static Learning:** The Fusion model (logistic regression combined with random forests) is a static learning model. Because it does not learn from new data in real time, this model will need to be manually retrained to reflect the evolution of internet slang (new words for depression).

- **Lack of Temporal Analysis**: The system analyzes each post separately and does not account for a user's previous history. Someone could be experiencing a bad day (one time stressful event) versus someone who is chronically depressed, making it difficult to differentiate between these two conditions due to a lack of historical context.

6.3 Clinical and Ethical Limitations

- **Not a Diagnostic Tool:** Because this AI model is a Decision Support System(DSS) and not a substitute for an actual psychiatrist, it is critical to clarify that the model does provide a probability of an individual's mental state based on their text, but it is not equivalent to a clinical diagnosis

- **Data Bias:** Data bias has been identified in the research study as the dataset was sourced from social media and as a result may reflect potentially relate to a self-selection bias as only posts from persons willing to provide details about their problems were analysed. Because the research study did not incorporate data provided by 'silent sufferers' who do not post on social media, there was a possibility that these individuals were not part of the sample and therefore the amount of data could have been insignificant for the results of this research study.

7. CONCLUSION AND FUTURE SCOPE

7.1 Conclusion

In summary, the research study demonstrated that ensemble machine learning has been effective in helping to develop a system capable of providing a mental health analytics framework. By combining **logistic regression and random forest**, the **ensemble machine learning** approach achieved a total accuracy of **77.17%**, which was higher than the accuracies achieved by either of the individual models. This machine learning approach can accommodate the complexities associated with the natural language and represents a non-intrusive and scalable solution for early mental health screening in Tamil Nadu.

7.2 Future Enhancements

1. **Tanglish Integration:** We will collect a dataset of Tamil-English code-mixed text to create a regional model.

2. **Deep Learning:** We will investigate the use of transformer-based models (BERT/RoBERTa) for better sensitivity to context than our current models.

3. **Real-Time Dashboard:** Developing an application to connect to live Twitter feeds allowing for real-time monitoring of mental health.

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