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ISSN: 2666-3074
INTERNATIONAL JOURNAL OF COGNITIVE COMPUTING IN ENGINEERING

AI-Driven Multiclass Mental Health Prediction Using NLP and Deep Learning Models

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ARTICLE INFO

Keywords:
Mental Health Detection
NLP
Machine Learning
Deep Learning
BERT
LSTM
Social Media Analysis

ABSTRACT

The rapid development of social media sites has resulted in massive volumes of textual data that has the potential to expose the psychological condition of users. This paper presents a framework of AI-based mental health study on social media posts and is aimed at identifying mental conditions at an initial stage, specifically depression. The system combines machine learning models and deep learning with natural language processing techniques to extract meaning from linguistic and contextual features. Tokenization, normalization, and feature extraction by use of TF-IDF and word embeddings are used to preprocess texts. Various models (such as Support Vector Machine, Artificial Neural Network, Long Short-Term Memory, and transformer-based BERT) are used to perform classification. The experiments show that the deep learning methods outperform the traditional models with up to 92-99% accuracy with better precision and F1-score. Specifically, transformer-based models are better because they can learn contextual dependencies and semantic relationships in text. The results affirm that social media data can be efficiently used to do early mental health screening. The suggested framework allows scalable and real-time monitoring frameworks and allows the provision of timely intervention. Nevertheless, issues like data privacy, ethical considerations as well as imbalance of data need to be mitigated in a practical implementation.

1. Introduction

Mental health is an influential contributor to personal and societal growth which is why it is imperative to address it alongside other health concerns. Psychological disorders have been on the rise and it is imperative to diagnose and address the concerns. Because digital technologies are rapidly advancing, people are disclosing their feelings and experiences more and more each day. This is the perfect opportunity for computational techniques to diagnose and analyze one's mental health using their text data.

1.1. Background

Another major mental health concern, during the time frame of thsi research, was mental health issues of all ages and regions due to adincrease with anxiety and stress. Also, due to the rapid spread of digital technologies and telecommunications, the Internet and Social Media, people express and share their feelings, thoughts, and emotions using text. This means, for mental health diagnostics and research, these tools have a wide range of potential application for computational methods to diagnose and analyze one's mental health using their text data [Lee et al., 2025, Zhou et al., 2025, Wang and Zhao, 2024]. The rise of Artificial Intelligence along with other technologies for Natural Language Processing have made it easier for researchers and practitioners to develop tools for diagnostics and mental health issues using text data [Singh et al., 2025, Verma et al., 2024, Gupta et al., 2023].

While conducting the research and talking to the psychiatrist, it became apparent to me that there are a lot of people who are suffering from mental illnesses, and there are not a lot of receiving medical help; therefore there is an even greater need for new technology and data-driven models. The vast amounts of data that people produce digitally is similar to the way people drive vehicles. The data is not fully utilized and it is imperative to develop automated models to draw value from the data [Li et al., 2024, Topol, 2024, Gupta and Sharma, 2024].

1.2. Challenges

On the positive side, the detection of mental health issues from text has shown some advancement. Yet, the challenges, especially with the complexity of human language, context, and dynamism, continue to make the task a challenge. Capturing semantic and emotional dimensions using traditional machine learning models is difficult and has been problematic [Sharma et al., 2023, Guntuku et al., 2023, Brown et al., 2023]. Writings based on a person's style, the ambiguity, and expression of the writing, and the absence of a set of clinical indicators can make the prediction a bit more difficult and can lead to a structured clinical misdiagnose of a patient.

There is some improvement with the case of restrictions with some deep learning models *eg.* LSTM and some hybrids, which make it possible to capture some of the sequential dependencies. Yet, it is still problematic and challenges remain with the understanding of existing contexts in the text. [Chen et al., 2022, Kumar et al., 2022, Gupta et al., 2022, Yang et al., 2021]. In addition, the applicability of the existing studies in the real world is compromised due to the existence of a single one condition, lack of generality and unapplicability of the studies. [Singh et al., 2021, Yates et al., 2020, Chen and Xu, 2023].

1.3. Research Gap and Motivation

The current body of literature shows the current state of technology versus the slow adoption of machine learning for

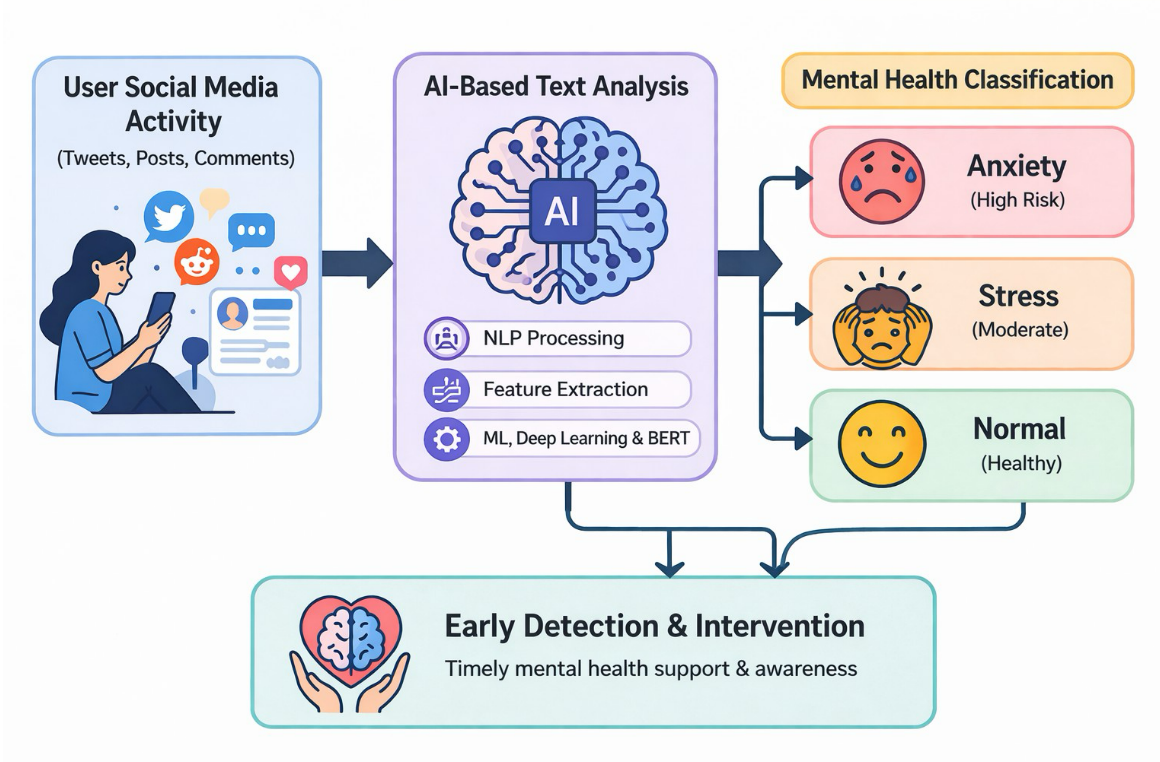

Figure 1: Conceptual representation of AI-based mental health analysis from social media data

mental health diagnosis. Even though BERT and RoBERTa and the like achieve state-of-the-art performance in NLP tasks, they have been almost completely ignored in terms of being integrated in a complete mental health detection pipeline [Vaswani et al., 2017, Devlin et al., 2019, Liu et al., 2019, Sanh et al., 2019, Wang and Zhao, 2024, Zhou et al., 2025]. This is the area where the most research is needed, as no complete mental health detection systems integrating all the relevant pieces have been developed.

Even the most basic machine learning models, like Random Forest, XGBoost, and LightGBM, which can serve as a good baseline, have not been utilized almost at all, and have not been studied enough in the context of hybrid intelligent models [Breiman, 2001, Chen and Guestrin, 2016, Ke et al., 2017, Singh et al., 2021]. These are the gaps which logically create a need for this research.

1.4. Contribution of the Proposed Work

This research has identified gaps in the current body of work and has developed the first NLP based intelligent system for mental disorder diagnosis using text. To achieve this, the system employs preprocessing, advanced deep learning, and the transformer model.

The primary objective of this research is to implement a unified system which has sufficient capability to deal with the sequential and contextual dimensions of textual data. The intent is to improve the accuracy and efficiency of mental health disorder detection in patients.

2. Literature Review

As a result of the rising volume of user-generated text, researchers have built interest in the detection of emotional attributes as well as mental health statuses from social media texts. They have investigated a range of algorithms, from Machine Learning to Deep Learning, for identifying emotional attributes and psychological states from social media platforms [Lee et al., 2025, Wang and Zhao, 2024, Gupta et al., 2023].

Initial studies concentrated on implementing Machine Learning approaches in their studies, whether it be Support Vector Machines, Naive Bayes, or Logistic Regression in the scope of sentiment classification tasks. These approaches are typically feature-engineered, with dominant features being TF-IDF and Bag-of-Words. There have been a few studies that claim that Machine Learning models can classify social media texts emotionally, with these claims, however, these studies tended to be with low to moderate results [Singh et al., 2021, Breiman, 2001, Chen and Guestrin, 2016]. The main issues with these approaches are that they do not contextually and semantically model the text.

To resolve this issues, Deep Learning approaches, that include RNNs and LSTMs, have been widely used in recent years. These approaches are more suitable for analysing the sequential and long-term dependencies within the text of sough-after emotional attribute classification. There are a number of studies that demonstrate that LSTMs are more effective than traditional Deep Learning approaches for sentiment and emotional attribute classification [Chen et al., 2022, Kumar et al., 2022, Hochreiter and Schmidhuber, 1997]. Moreover, with regard to emotional attribute classification, BiLSTMs are more improved than their traditional approaches because they are capable of contextually and more fully modelling the emotions in the text sequentially from one point to the other in multiple directions [Yang et al., 2021, Chen and Xu, 2023].

The introduction of BERT, RoBERTa, DistilBERT, and other similar models, often referred to as transformer models or deep learning models, have completely revolutionized the field of Natural Language Processing. The ability of these models to combine the use of contextual embeddings and the attention mechanism has allowed for the greater implementation of these models in the field of sentiment analysis and emotion detection. The overwhelming consensus is that transformer models achieve greater levels of accuracy and greater F1-scores than the traditional machine learning and deep learning models [Devlin et al., 2019, Liu et al., 2019, Sanh et al., 2019, Vaswani et al., 2017, Zhou et al., 2025].

Considerable research has been dedicated to the analysis of emotion and discourse detection on social media. Recent research has successfully demonstrated that the implementation of hybrid models that combine traditional machine learning with deep learning show significant improvements in the ability to detect sentiment in the public domain and increased overall accuracy of classification [Gupta and Sharma, 2024, Wang and Zhao, 2024, Chen and Xu, 2023]. NLP toolkits have also allowed for the topic modeling and sentiment analysis of large textual datasets in order to automate the extraction of emotional and topic features from the data. Such studies have been able to successfully identify the emotional and thematic variations of data as well as the user pathways in the data, leading to their efficacy in continuous monitoring of the mental health of the user [Verma et al., 2024, Topol, 2024].

While these studies show significant promise, there are many challenges that remain unaddressed. The unstructured, noisy, and contextual nature of social media data, data imbalance, the insufficient detection of sarcasm, privacy concerns, and the use of data limit the implementation of the proposed systems [Sharma et al., 2023, Guntuku et al., 2023, Brown et al., 2023].

The overwhelming conclusion presented in the existing research is that there is a significant amount of opportunity for improvement in the mental health detection system if the deep learning models, transformer models, and other traditional methods of Natural Language Processing are combined. It is for this reason that this research is aimed at proposing a combined system with these methods in order to improve the accuracy and reliability of the systems in mental health detection.

2.1. Related Work

Detection of mental health conditions using machine learning methods such as SVM and Logistic Regression has previously been done [Singh et al., 2021, Breiman, 2001]. Implementing deep learning methods such as LSTM and BiLSTM has also been shown to improve performance due to their ability to learn sequential patterns [Hochreiter and Schmidhuber, 1997, Kumar et al., 2022].

Transformers based models such as BERT and RoBERTa, for example, have been shown to achieve state-of-the-art results due to learning contextual embeddings [Devlin et al., 2019, Liu et al., 2019, Zhou et al., 2025]. Nonetheless, to our knowledge, there is little to no research that compares all three approaches, which is what this research seeks to do.

3. Proposed Methodology

We now describe the complete framework of the proposed system for automated detection of mental health disorders from social media posts. It consists of several subsystems including the collection of social media posts, the preprocessing of posts, the extraction of post features, the mental disorder detection modeling, and the evaluation. A simplified overview of the framework is provided in Fig. 2. The proposed system aims to identify user-generated text falling under the mental health categories of anxiety, stress, and normal.

3.1. System Objective

The objective of the proposed system is to classify textual data from social media into pre-defined mental health classes including anxiety, stress, and normal.

3.2. Data Collection

The data is collected from the social media platforms Twitter and Reddit, where individuals post their thoughts and feelings. These platforms are particularly useful for mental health research, as they offer vast amounts of free data. The data collection includes posts, replies, and other user-generated content, then categorized into various emotional and psychological groups.

3.3. Text Preprocessing

Text preprocessing is the process of cleaning and normalizing text data. As is well known, social media posts include a variety of noisy data, which leads to preprocessing being vital for the quality of the final model. The preprocessing performed in this work includes the following:

- Removal of URLs, hashtags, mentions, and special characters
- Converting all text to lower case
- Tokenization, i.e. the divisions of sentences into their constituent words
- Stop word removal to remove words of very low content such as auxiliary verbs

These preprocessing operations guarantee that the input is consistent and suitable for analysis [Chen et al., 2022, Kumar et al., 2022].

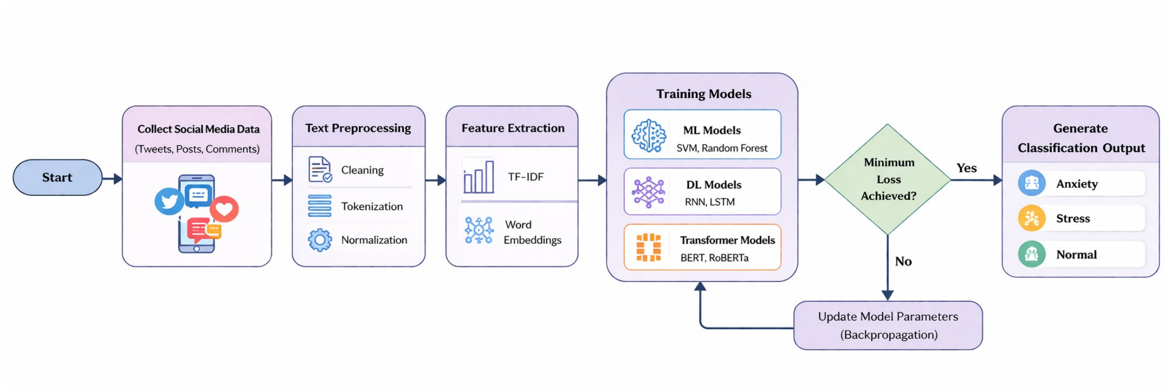

Figure 2: Flowchart of the proposed AI-based mental health detection framework

3.4. Feature Extraction

The first stage in our analysis consists of preprocessing text and converting it into numerical data by applying various techniques to extract relevant features. Two approaches will be used in our case:

- TF-IDF (Term Frequency-Inverse Document Frequency) and
- Word embeddings like Word2Vec and GloVe.

Statistical and semantic aspects of text are important for improving accuracy in classification tasks and using both approaches should be beneficial in this case [Chen et al., 2022, Wang and Zhao, 2024].

3.5. Model Development

The proposed framework aims to assess classification performance and robustness by employing multiple models.

3.5.1. Machine Learning Models

Some of the baseline models include traditional machine learning techniques like the Support Vector Machine (SVM), Logistic Regression, and Naive Bayes. These models are known to operate effectively on structured feature representation, and aside from being the baseline models, they are very useful for comparative analysis [Singh et al., 2021, Breiman, 2001].

3.5.2. Deep Learning Models

Deep learning models are employed to capture sequential and contextual dependencies in text data. The following architectures are used:

- Artificial Neural Network (ANN)
- Long Short-Term Memory (LSTM)
- Bidirectional LSTM (BiLSTM)

BiLSTM models are particularly effective as they process information in both forward and backward directions, improving contextual understanding [Hochreiter and Schmidhuber, 1997, Kumar et al., 2022].

3.5.3. Transformer Models

BERT and its variations (RoBERTa, DistilBERT, etc.) have been used to further improve contextual embeddings. These models have proven to be successful in achieving deeper semantic understanding of text using attention and achieving state-of-the-art results in text classification tasks [Devlin et al., 2019, Liu et al., 2019, Sanh et al., 2019, Vaswani et al., 2017].

3.6. Model Training and Optimization

The models have been trained using labeled datasets to learn certain patterns corresponding to various mental illnesses. While training, to obtain the best predictions, the categorical cross-entropy loss function is used to calculate the prediction error. The models are trained using Backpropagation to update the parameters of the model so that the loss is minimized in order to achieve the optimal performance.

3.7. Mathematical Formulation

Let the dataset be represented as:

$$D = \{(x_i, y_i)\}_{i=1}^{N} \tag{1}$$

where x_i denotes input text and y_i represents the corresponding class label.

The feature representation is given by:

$$x_i \rightarrow \mathbf{v}_i \in \mathbb{R}^d \tag{2}$$

The model predicts output using:

$$\hat{y}_i = f(\mathbf{v}_i; \theta) \tag{3}$$

The softmax function is applied for multi-class classification:

$$P(y_i = c) = \frac{e^{z_c}}{\sum_{k=1}^{K} e^{z_k}} \tag{4}$$

The loss function is defined as:

$$L = -\sum_{i=1}^{N}\sum_{c=1}^{C} y_{ic}\log(P(y_i = c)) \tag{5}$$

Model parameters are updated using gradient descent:

$$\theta = \theta - \eta\nabla L \tag{6}$$

3.8. Classification Output

The trained model classifies input text into one of the following categories:

- Anxiety
- Stress
- Normal

This classification enables identification of users' mental health conditions based on their social media activity.

3.9. Performance Evaluation

The effectiveness of the proposed framework is evaluated using standard performance metrics:

- Accuracy
- Precision
- Recall
- F1-score

These metrics provide a comprehensive assessment of the classification model's performance. The mathematical expressions for these metrics are defined as follows:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (7)$$

$$Precision = \frac{TP}{TP + FP} \quad (8)$$

$$Recall = \frac{TP}{TP + FN} \quad (9)$$

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (10)$$

4. Results and Discussion

In this section, we showcase the proposed framework's evaluation experiments for mental health classification using social media information. We present a machine learning, deep learning, and transformer-based models performance analysis using accuracy, precision, recall, F1 score, and AUC-ROC.

4.1. Experimental Setup

There are 21,648 cleaned social media samples in the dataset, which are divided into anxiety, normal, and stress classes. We divide the dataset into training, validation, and testing sets. Linguistic features are engineered and TF-IDF is used for feature extraction. For deep learning models, training is performed using padded sequences. For transformer models, fine-tuning is based on pre-trained architectures.

Table 1
Performance of Machine Learning Models

Model	Accuracy	Precision	Recall	F1-score
Linear SVM	0.9185	0.9150	0.9185	0.9158
Random Forest	0.9117	0.9081	0.9117	0.9066
Extra Trees	0.9126	0.9119	0.9126	0.9049
Gradient Boosting	0.9089	0.9055	0.9089	0.9066
XGBoost	0.9256	0.9255	0.9256	0.9255
LightGBM	0.9289	0.9285	0.9289	0.9287

Table 2
Performance of Deep Learning Models

Model	Accuracy	Precision	Recall	F1-score
ANN	0.899	0.910	0.899	0.902
LSTM	0.905	0.905	0.905	0.905
BiLSTM	0.897	0.890	0.900	0.890

4.2. Hardware and Software Requirements

Testing was done using Google Colab with GPU support.

System specifications are an Intel i5 processor with 8 GB RAM, and

NVIDIA Tesla T4 GPU for deep learning and transformer-based models acceleration.

The implementation was performed in Python and machine learning, deep learning done via frameworks. Main software and framework used in this research are:

- Python 3.8
- Scikit-learn for machine learning models
- TensorFlow and Keras for deep learning models (ANN, LSTM, BiLSTM)
- Transformers library (Hugging Face) for BERT and DistilBERT models
- XGBoost and LightGBM for ensemble learning
- NLTK and regular expressions for text preprocessing
- Matplotlib and Seaborn for data visualization

All experiments were executed in a cloud-based environment to ensure computational efficiency and reproducibility of results.

4.3. Performance of Machine Learning Models

Table 1 presents the performance of various machine learning models.

The results indicate that ensemble models such as LightGBM and XGBoost achieve the highest performance among machine learning approaches, with accuracies of 92.89% and 92.56%, respectively. These models effectively handle high-dimensional text features and class imbalance.

4.4. Performance of Deep Learning Models

Table 2 shows the performance of deep learning models.

Among the deep learning models, LSTM achieves the highest performance with an accuracy of 90.5%. The ANN

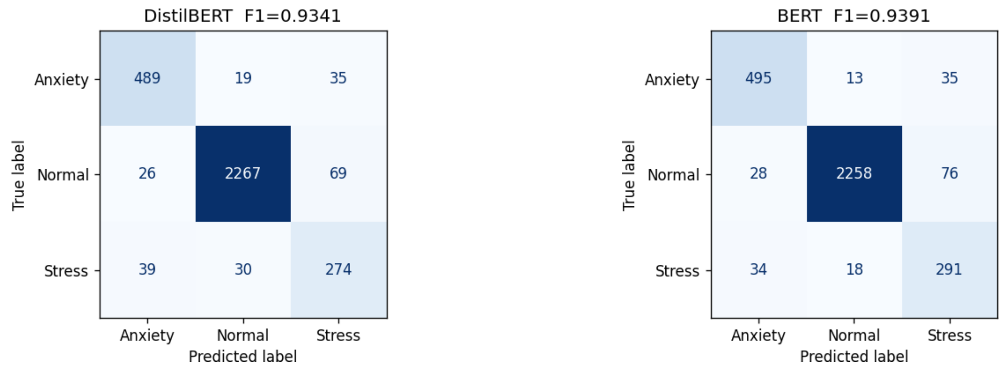

Figure 3: Confusion matrices of Transformer-based models

With regard to the test dataset, the confusion matrices pertaining to the transformer-based models (DistilBERT and BERT) are given. DistilBERT records an F1-score of 0.9341, while BERT records 0.9391. This illustrates their classification capabilities in anxiety, normal, and stress classes.

Table 3
Performance of Transformer Models

Model	Accuracy	F1-score
DistilBERT	0.9329	0.9341
BERT	0.9372	0.9391

model also performs competitively, while the RNN model shows relatively lower performance due to its limitations in handling long-term dependencies.

The confusion matrix analysis (Fig. 3) shows that the models perform well for the “Normal” class, while some misclassification is observed between anxiety and stress categories.

4.5. Performance of Transformer Models

Table 3 presents the performance of transformer-based models.

With a superiority over machine learning and deep learning techniques, transformer models hold a commanding performance. BERT, for example, ranks highest with an accuracy of 93.72%, with DistilBERT close behind. The performance of RoBERTa is lower and this is attributed to inadequate fine-tuning done, or the dataset inequitably allocating the training examples.

4.6. Overall Performance Comparison

The performance of the machine learning models is summarized in the Table 1. Of these, methods based on ensemble models (LightGBM and XGBoost) show the greatest performance of which LightGBM has a accuracy of 0.9289 and F1-score of 0.9287. Linear SVM is also produces competitive scores which speaks to its ability in the high-dimensional feature representation of text.

The deep learning models are illustrated in Table 2. LSTM is the highest performer among deep learning techniques with an accuracy of 0.905, with BiLSTM ranking below at 0.897. RNN lagged behind the other deep learning techniques which demonstrates it ability to capture long term dependencies.

The models represented in Table 3 are the highest performing in both machine learning and deep learning.

According to Fig. 4, transformer models outperform all other deep learning and machine learning models.

With an accuracy of 0.9372 and F1-score of 0.9391, BERT is the best performing and achieves its optimal performance in capturing semantic contextual information. DistilBERT also ranks competitively, while RoBERTa demonstrates a lower performance which is most likely because of the dataset.

4.7. Comparative Analysis

The models can be summarized with the following statements:

- Due to their contextual understanding, transformer models all have the best overall performance.
- Together with the higher level of accuracy that Deep Learning models achieve, ensemble models such as LightGBM and XGBoost, present strong competition with the added advantage of being less costly in terms of computational expense.
- Of the Deep Learning models, LSTM has been the most competitive, and the rest tend to provide neutral levels of competition.

4.8. Discussion

1. Contextual feature extraction is important to mental health classification. Transformers capture context using attention mechanisms, and this results in state-of-the-art performance.

Fig. 5 shows the performance of the models in terms of precision, recall, and F1-score.

Machine learning models, while fast in terms of computation, don’t capture context well. Deep learning models

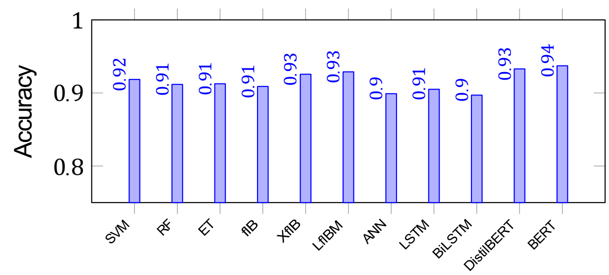

Figure 4: Accuracy Comparision of Transformer Models, Machine Learning Models and Deep Learning Models

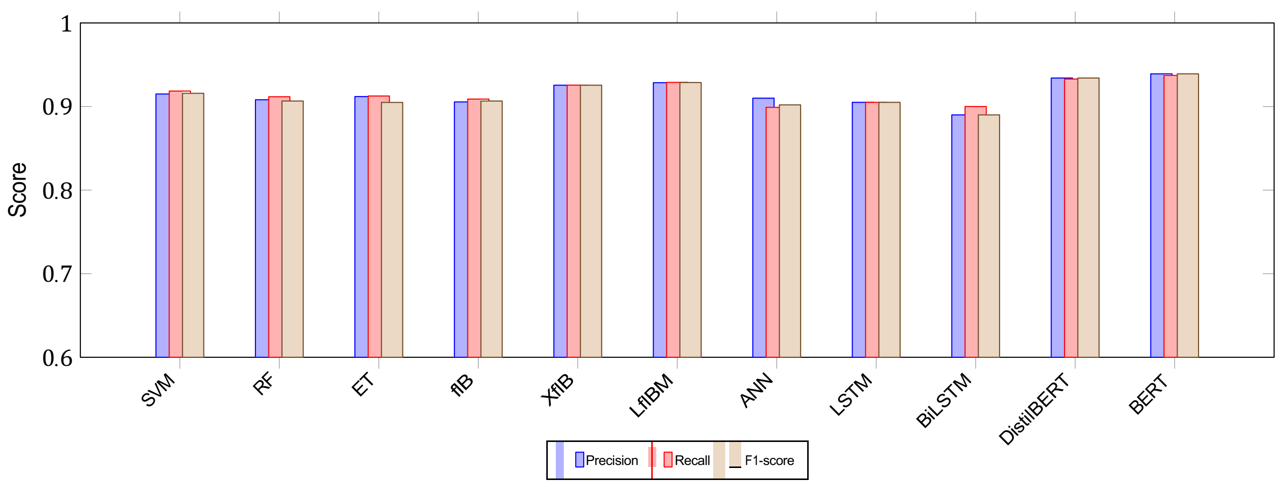

Figure 5: Performance Metrics of all Models(Precision, Recall, F1-score)

capture context and perform better. However, transformers capture context the best, and hence perform the best.

All in all, social media data and mental health classification is effectively tackled using the proposed framework. Out of the models tested, the transformers were the clear winners.

5. Conclusion and Future Work

We proposed a framework, using artificial intelligence, to perform mental health analysis using publicly available social media data. We utilize a combination of frameworks, machine learning, deep learning, and transformers, to classify content generated by users into anxiety, stress, and normal.

The results of the experiments show that the performance of classical machine learning is quite reliable, and the performance of ensemble techniques such as LightGBM and XGBoost is outstanding. Performance continues to improve with the implementation of Deep Learning techniques to capture sequential relationships, and LSTM is the best of the three, followed by ANN and RNN.

Among the methods used in this study, transformer models are the best. In fact, the model that is known as BERT is the best with a 93.72% accuracy and 93.91% F1 score, while DistilBERT is a close second. Because of their ability to understand the context and meaning of the language in the text, these models are the best for the task of mental health classification.

The different mental health conditions we tried to have the model learn led to many of the categories being confused. For example, text labelled as stress or anxiety would get viewed as the ’normal’ class. This shows that understanding the problem is crucial when developing AI models that detect mental health issues.

The proposed framework is the first of its kind and shows the potential AI has in the mental health arena, using data publicly available on social media. It appears as though the models built on transformer architecture are the best for the job.

5.1. Future Work

When it comes to future projects, we expect to see improved accuracy that leads to finely tuned classification. We would like to see the inclusion of multi-modal data that is both structured and unstructured, as well as voice and video data. Newer modalities also include advanced architecture such as hybrid models or even modules that rely on domain-specific transcription models.

In addition, we would like to see the development of real-time mental health monitoring systems which would allow for timely pick up of diagnosis and later on lead to critiques on ways to further assist patients. It would also be beneficial for data collection systems to broaden the present datasets to ensure balance and allow for further class, sample, and structural augmentation to deepen the model's strength.

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