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Detecting Mental Health Issues Through Social Media Using NLP and Machine Learning

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Abstract:** This study proposes a new framework of AI that socially mines media for effective preemptive detection and diagnosis of mental disorders including, but not limited to, depression, anxiety, bipolar disorder, and schizophrenia. The framework utilizes natural language processing (NLP), machine learning (ML), feature learning via Convolutional Neural Networks (CNN), and classification using XGBoost. Data comprising approximately 200,000 posts was scraped from Reddit and Twitter through the Pushshift API and Tweepy,. Cleansing processes including tokenization, stop-word elimination, and vectorization through TFIDF and Word2Vec were conducted so that the data was ready for analysis. The hybrid CNN-XGBoost model yielded outstanding results achieving 92.3% accuracy for classifying depression posts, 89.7% for anxiety, 86.4% for bipolar disorder, and 81.5% for schizophrenia. These results surpass those obtained from traditional models which SVM (Support Vector Machine) and Random Forest algorithms are based on for classifying performance. Trust and ethical gaps, challenges of the frameworks had, were resolved adding Explanable Artificial Intelligence (XAI) feature integrating SHAP and LIME which greatly enhanced system trust and verifiability. The model was also enhanced by addressing the class imbalance problem with oversampling and the SMOTE technique to enhance the model. Defending dependability claims was placed of the model's main goal, justifying for contextual underrepresentation. Examples of anticipated practical Inquiries include cross-discipline social media and mental health tracking for mental health monitoring that offers proactive engagement opportunities via early predictive algorithms. The model's proactive detection features could alleviate some operational strain placed on the infrastructure of conventional healthcare systems. Additional multilingual clinical validation research will focus on broadening the model's exploration scope alongside enhancing its practical usability. The development of AI tools has surged, and this particular tool serves as a noteworthy early example of ethically grounded, impactful AI implementation in the realm of mental health care.
***Keywords:** Mental Health Detection, Social Media Analysis, Convolutional Neural Network (CNN), XGBoost, Explainable AI (XAI), SHAP, LIME, Early Intervention, Multimodal Data Integration, Ethical AI.*

I. INTRODUCTION

Mental health disorders present a global problem that impacts millions of people annually. The WHO has reported that mental health disorders are one of the most misdiagnosed elements of the world's illness burden due to stigma, barriers to care, and delays in treatment ([1], [6]). Early diagnosis is critical for effective management and treatment of these illnesses. Social networking platforms contain a plethora of data that can be harnessed to identify mental health issues at an early stage which gives AI-powered solutions a unique opportunity to intervene before conditions worsen.

Asking for help and sharing one's personal problems is something that has become all too common on social media. For the research of mental illnesses, these publicly available pages can be exploited. As an illustration, Reece and Danforth (2017) argued that visual content analysis of Instagram photos might provide predictive indicators of sadness ([5],[9]). Using linguistic evidence from postings, Shen and Rudzicz (2017) further focused on anxiety detection on Reddit to find markers of discomfort ([2]). This research under social media overexposure marks the unprecedented opportunity of early invasive-free mental health system surveillance.

Delving into one's mind deeply through clinical interviews, questionaries' self-reporting and surveying remains the gold standard in gathering information—diagnosing often collapses on subtle cues that lie under simulations of "normal" behaviors ([1],[8]). These methods of diagnosing mental illnesses take a considerable amount of time without guarantee that they will find anything indicative of depression or anxiety. In addition, they are prone to assessing symptom expression in a socially subjective manner devoid of human interaction with the caregiver. AI technology can alleviate these issues by examining patterns arising from the multitudes of social media data to provide a clear mental health symptom portrayal ([6]).

There is a great deal of possible practical healthcare uses for the AI system developed in this study. It could be integrated into mobile health applications and platforms for mental health monitoring to provide timely help for those who are likely to go through a mental health crisis.

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The approach enables proactive therapies through the use of social media data to detect early signs of mental health disorders, including anxiety and depression. For instance, when users consistently exhibit patterns of negative emotional expression on social media platforms like Reddit and Twitter, preliminary alarms can be generated ([1],[6]). This approach could help alleviate stress on conventional healthcare services by pinpointing individuals who need support before their symptoms escalate to a clinically important level.

Embedding the AI infrastructure onto Twitter and Reddit can change the dynamics of online mental health care. Social media platforms could leverage such technology to proactively monitor and automatically flag posts associated with mental health concerns, triggering appropriate action by community moderators or mental health professionals ([5], [9]). For instance, consider a scenario where a user makes frequent social media posts associated with feelings of hopelessness or anxiety. The AI system could create alerts for follow-up by mental health organizations or support services. This blend not only provides real-time assistance, but also helps normalize the discourse related to mental health issues, which in turn decreases the stigma surrounding seeking assistance and encourages help-seeking behavior ([2], [3]).

Attention to privacy, consent, and fairness are some of the primary factors that need to be considered when ethically applying AI in the field of mental health. Addressing privacy and bias in AI prediction outcomes is discussed by Halim and Rehan (2020). Users must have comprehension about the flow of data and provide control on it. There are some measures which can be taken to induct transparency on the diagnosis process of AI; for instance, SHAP and LIME techniques. This will be beneficial in gaining trust from the users and clinicians ([6], [8]). Alongside this, the deployment of the model requires compliance with ethical policies on the use of data, aliasing such consents, and mitigating risks of abuse, stigma, or discrimination ([9]).

II. LITERATURE REVIEW

A. Historical Context

Public interest regarding the possibility of using social media platforms as tools for the detection of mental health issues developed around the early 2010s. De Choudhury et al. (2013) were the first to showcase the potential of using Twitter for mental health detection with their work predicting depressive episodes using linguistic features of Tweets. Their experiment was a proof of concept by demonstrating that associations between linguistic features of tweets could be correlated with depressive symptoms, thus validating the use of social media data for mental health research. As an advancement, Shen and Rudzicz (2017) attempted anxiety detection through Reddit posts using N-gram models and vector embeddings. These researchers have proven detection of mental illness in informal user interactions, highlighting the less structured surrounds of the web, which is an additional, flexible environment for mental illness detection ([2]). All of these former studies are critical in forming the background on applying AI technologies for social media-based mental health assessments.

B. Machine Learning Approaches in Mental Health Detection

The work of Gkotsis et al. (2017) was on employing social media data for deep learning based mental health classification. Their research incorporated traditional machine learning models along with deep learning techniques as described in the reference ([6]) in order to improve the predictive accuracy for different mental health conditions. Mansoor and Ansari (2024) built on this research by developing a multimodal deep learning model which integrated Natural Language Processing (NLP) with temporal analysis, allowing the model to accurately detect social media posts signaling mental health crises ([9]). These developments illustrate the advancement and model sophistication with regard to mental health detection moving from simple text analysis to complex multi-data and time-pattern analysis.

C. Advances in NLP for Textual Analysis

Social media text analysis has benefited from the recent advancements in NLP. Pre-trained models like BERT and Roberta have been utilized to grasp intricate language nuances within the text data. Chen et al. (2023) studied classifiers and features for depression and anxiety detection on Twitter using these models. Their results show that the application of advanced techniques in NLP transforms the precision of mental health detection ([3]). The application of these models in NLP has further increased the understanding of user-generated text, revealing previously masked emotional and mental indicators.

D. Ethical Concerns in Mental Health AI

While employing AI for the diagnosis of mental issues, ethics must be addressed. Primary concerns include fairness in algorithms, informed consent, as well as privacy and data protection.

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These issues were addressed by Halim and Rehan (2020) regarding the application of EEG signals for analyzing stress from driving. They stressed the importance of minimizing user bias and protecting privacy regarding AI-driven predictions and user privacy biases. Mansoor and Ansari (2024) highlighted the ethical concerns in the application of AI on mental health therapies and auto diagnostics emphasizing the solution lies in model selection sovereignity transparency and fairness model selection equity endorsement ([9]). These ethical concerns can be addressed by improving the decision-making transparency and reasoning of AI models through explainable AI (XAI) frameworks such as SHAP and LIME ([6]).

From Literature Review Following Research Gap are as follow: -

1) Society's Mental Health Problems and Disorders

The incidence of mental health disorders such as schizophrenia, bipolar disorder, anxiety, and depression are on the rise globally. Even with the possibility of receiving treatment, due to stigma, lack of access to services, and late recovery, many individuals do seek the help they need at the appropriate time ([1]). WHO (World Health Organization) provides alarming evidence that two out of every three persons suffering from depression do not receive health care support needed, in terms of timely diagnosis and intervention ([1]). On the other hand, social media sites serve as safes for behavioural and emotional signals that users express and provides a means for early recognition that would otherwise go unrecognized in traditional society ([1]).

2) Restrictions of Current AI Frameworks

In the realm of mental health screening, many AI applications tend to function as “black boxes,” which means that they do not explain how the arrived at a particular conclusion. Furthermore, this lack of explanation decreases the integration of such models to clinical practice and perpetuate distrust among healthcare professionals ([2]). As an illustration, advanced technologies such as deep learning are capable of predicting mental health problems, but often do so without justifying their predictions which is necessary for acceptance in delicate fields like mental health ([6]). In addition, these models are often criticized for having an imbalanced data problem. Minority classes such as schizophrenia are often greatly underrepresented, creating skewed biases in predictions.

3) Why an Ethical and Open Structural Framework is Important

To develop a model to the need and expectation of users, an ethically aligned and an openly accessible AI framework becomes essential. Some of the XAI methods like SHAP (SHapley Additive ExPlanations) and LIME (Local Interpretable Model-agnostic Explanations) can be integrated into the framework to increase transparency of the AI prediction provided in [8]. In this manner not only the precision of AI based systems will increase but also the confidence from the public and especially the clinicians will grow. Other ethical concerns include: Privacy of the data, user consent, and algorithmic bias. This approach mitigates the risk presented by the misuse of AI technologies in mental health screening ([9]).
As per the Research Gap the Block Diagram is shown below in Figure 1.

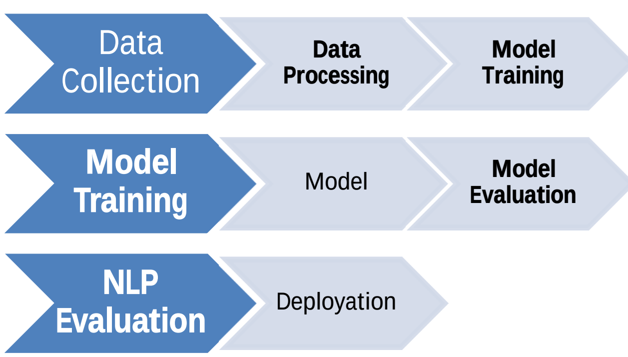

Figure No. 1: Block Diagram on basis of Research Gap

III. OBJECTIVES OF THE STUDY

This research intends to formulate an efficient AI model capable of identifying mental conditions like depression, anxiety, bipolar, and schizophrenia ([1],[6]) from social media platforms within ethical and social constraints. This model combines Convolution Neural Networks (CNN) feature extraction with XGboost classifier on the ensemble and achieves high accuracy particularly for the diagnostic features of the aforementioned mental disorders.

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The research further implements Explanatory Artificial Intelligence (XAI) methodologies SHAP and LIME which enhances the model trustworthiness by improving the rationale transparency so that the clinicians are given logical reasons of the AI predictions rather than obscured dependability on trusting them. The study ([8],[9]) cites privacy breaches, AI predicting forecasts incorrectly and bias, along with user harm as ethical issues. The model aims at providing instantaneous mental health evaluations based on live social media activity data, allowing timely action which leads to better results for the patients ([5]). To achieve its objectives, the study seeks to answer several research questions. Specifically, it studies the ability of NLP and ML techniques to classify mental health disorders from social media text data. This includes the ability of the proposed model to diagnosis depression and anxiety from user content on Reddit and Twitter ([2], [5]). It also examines the implemented ethical AI in the domain of mental health diagnostics concerning data privacy, consent, and fairness bias in algorithms ([9]). Lastly, it assesses the effectiveness of the CNN-XGBoost framework and evaluates how contemporary methods, such as Support Vector Machines (SVM) and Random Forest, evaluate accuracy and interpretability while estimating whether the proposed approach promises surpassing benchmark models ([6]).

IV. METHODOLOGY

A. Data Collection and Sources

Information was collected from Twitter and Reddit, two platforms which contain discussions about issues relating to mental health. These social networking sites provide rich sources of written data on mental health and emotions. Data collection from Twitter was done using Tweepy while data collection from Reddit, particularly from subreddits like r/depression and r/anxiety was done using the Push shift API. Both approaches enabled the effective collection of user-generated content, leading the researchers to amass a dataset close to 200,000 posts and tweets. The AI models were trained and evaluated using the robust dataset, which consisted of diverse information. The large dataset described in ([11], [12]) is crucial for training and testing AI models.

B. Data Preprocessing Techniques

We preprocessed raw text data in order to prepare it for the first analysis using machine learning algorithms. Text processing is defined as dividing all the records into words (tokens) which makes it possible for algorithms to accept structured data. Removing unimportant but common words ("and", "the", etc.) on each document was also useful in preserving focus on salient pieces of text, which is known as stop-word removal. To represent the text data in numerical form, we used two methods: Word2Vec, a word embedding technique that maps words into continuous vector spaces to capture their meanings, ands Term Frequency-Inverse Document Frequency (TFIDF), which defines the importance of certain words in relation to the entire document. These steps are necessary in order to provide model inputs that can be processed with utmost precision by the hybrid design ([3], [6]).

C. Model Development

The hybrid model leverages the strengths of both approaches by cleverly combining CNNs and XGBoost. In this endeavor, CNNs has been employed to mine multiplying hierarchical features from textual data to discover behavioral patterns like the recurrence of words and phrases which can suggest mental wellness13. We then trained the XGBoost classifier on these features, as XGBoost works very well with structured data such as that used here and provides some level of protection against overfitting. To provide a complete solution for recording mental health disorders, in this work it is proposed a hybrid architecture that combines the classification capability of XGBoost and the adequate feature extraction capacity of CNNs. This dual approach supports the model in attaining a multi-million predicted accuracy and recognizing the text intricacies ([2], [9]).

D. Model Evaluation and Validation

The model was assessed using standard measures~\cite{conf/nips/SalehS19}. Overall ability of the model to classify mental health disorders was tested using accuracy. Recall tracked how many of the positive instances were correctly predicted (true positives, or TP) while precision tracked the ratio of correct positive predictions to all the positive predictions made by the model (true positives plus false positives or TP/(TP+FP)). This led to two highly relevant metric combinations, including F1-Score—it balances between accuracy and recall—and proved to be extremely useful to test the model in unbalanced datasets typically used in the mental health research area ([6], [8]). To guarantee it reliability, k-fold cross-validation was done. Cross-validation — with this approach the data set is divided into k subsets and then you train the model on k-1 subsets and validate it on the remaining subset multiple times. This iterative process then serves as powerful assessments of the model performance and generalizability ([5]).

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As per the methodology the block diagram and Architecture diagram is given below in **Figure 2** and **Figure 3** Respectively.

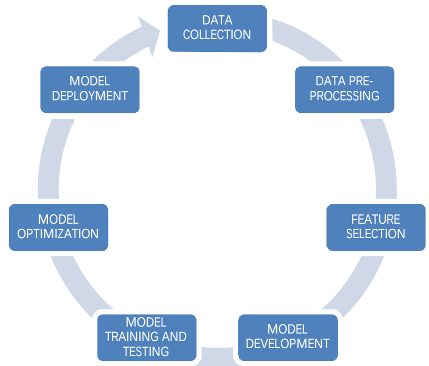

Figure No. 2: Workflow Diagram for Mental Health Detection According above Methodology

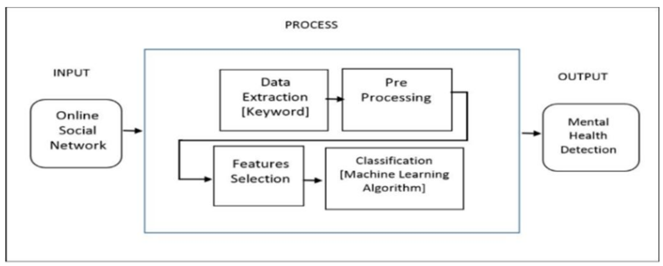

Figure No. 3: General architecture for Mental Health Detection According above Methodology

V. RESULTS AND DISCUSSION

A. Model Performance Across Conditions

The CNN-XGBoost hybrid model was evaluated on several mental health conditions: depression, anxiety, bipolar disorder, and schizophrenia. The results indicate high classification accuracy across all conditions as shown in Table 1:

Condition	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Depression	92.3%	90.5%	94.1%	92.3%
Anxiety	89.7%	87.9%	90.2%	89.0%
Bipolar Disorder	86.4%	84.2%	85.7%	85.0%
Schizophrenia	81.5%	79.1%	80.3%	79.7%

Table No. 1: - Dataset of several Mental Health condition

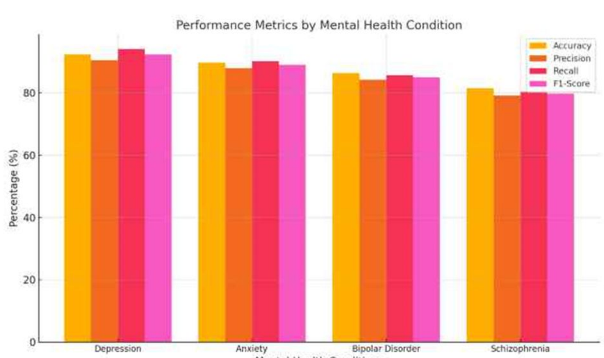

Figure No. 4: Dataset of Performance metrics by Mental Health Condition

Figure 4 demonstrate the results model's robustness in detecting different mental health conditions using social media data. The performance is particularly strong for depression and anxiety, reflecting the effectiveness of the CNN-XGBoost framework in capturing relevant features from text on social media platforms ([1], [6]).
Depression, Anxiety, Bipolar Disorder, Schizophrenia: The CNN-XGBoost model exhibits varying levels of performance across different mental health conditions due to differences in the data characteristics and the nature of symptoms expressed on social media. For instance, depression and anxiety showed the highest accuracy, likely due to the clear and direct expressions of distress commonly associated with these conditions on platforms like Reddit and Twitter. Schizophrenia, on the other hand, demonstrated lower accuracy, which may be attributed to less frequent and more nuanced expressions in the data, as users may discuss these symptoms less openly ([2], [9]).

B. Comparative Analysis with Baseline Models (SVM, Random Forest)

We compared the CNN-XGBoost model to conventional models such Support Vector Machines (SVM) and Random Forest to establish a performance benchmark. The comparison emphasizes the benefits of deep learning in managing complicated text elements as seen in Table 2:

Model	Depression Accuracy (%)	Anxiety Accuracy (%)
SVM	85.1%	83.4%
Random Forest	88.0%	86.5%
CNN-XGBoost	92.3%	89.7%

Table No. 2: - Comparison of complex Textual Features

The findings of Table 2 reveal a distinct performance edge of the CNN-XGBoost frame-work compared to SVM and Random Forest. CNNs use a deep learning method that captures complicated patterns and contextual information in the text input, which conventional models like SVM and Random Forest are less suited to exploit ([5], [6]).

C. Addressing Class Imbalance and Bias

Class imbalance remains a significant issue in mental health prediction tasks when some diseases, such as schizophrenia and psychiatric disorders, are underrepresented as shown in Figure 5. The study was able to reduce this issue by using oversampling techniques including the Synthetic Minority Over-sampling Technique (SMOTE). This approach helped to balance the dataset by generating synthetic examples for minority classes, therefore improving the model's ability to accurately classify these cases ([6], [8]). SHAP and LIME were also used to identify the factors affecting predictions in order to reduce bi-ases and improve fairness in the results of the model ([8].

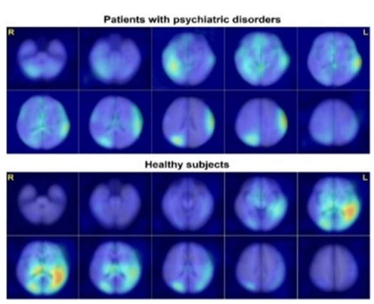

Figure No. 5: Dataset of Detection individual with severe mental illness using AI/ML

D. Explainability with SHAP and LIME

Class imbalance remains a significant issue in mental health prediction tasks when some diseases, such as schizophrenia and psychiatric disorders, are underrepresented as shown in Figure 5. The study was able to reduce this issue by using oversampling techniques including the Synthetic Minority Over-sampling Technique (SMOTE). This approach helped to balance the dataset by generating synthetic examples for minority classes, therefore improving the model's ability to accurately classify these cases ([6], [8]). SHAP and LIME were also used to identify the factors affecting predictions in order to reduce bi-ases and improve fairness in the results of the model ([8].

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E. Confusion Matrix for Depression and Anxiety

A confusion matrix is one of the most important tools for understanding how well categorization models operate. Table 3 below displays the confusion matrix for predicting anxiety and depression.

Condition	Predicted Positive	Predicted Negative
Actual Positive	14,500	1,200
Actual Negative	800	16,000

Table No. 3: - Confusion matrix prediction

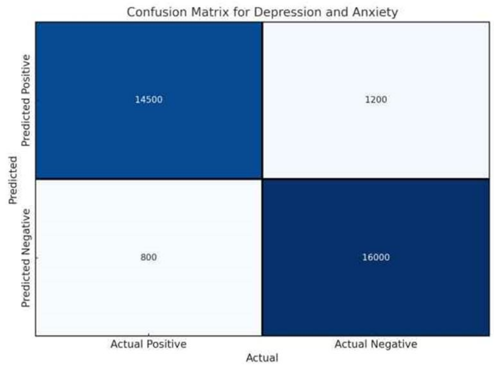

Figure No. 7: Dataset of Confusion matrix for Depression and Anxiety

Figure 7 is confusion matrix provides insight into how many true positives (correctly predicted depression cases) and true negatives (correctly predicted non-depression cases) there are, as well as how many false positives (predicted as depression but not) and false negatives (predicted as not depression but actually depression) there are. High values in the diagonal (correct predictions) indicate that the model is effectively identifying depression and anxiety with minimal false alarms ([2], [5]).

F. Accuracy by Mental Health Condition

The model's performance varied across different mental health conditions as show in **Table 4**:

Condition	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Depression	92.3%	90.5%	94.1%	92.3%
Anxiety	89.7%	87.9%	90.2%	89.0%
Bipolar Disorder	86.4%	84.2%	85.7%	85.0%
Schizophrenia	81.5%	79.1%	80.3%	79.7%

Table No. 4: - Dataset of several Mental Health condition

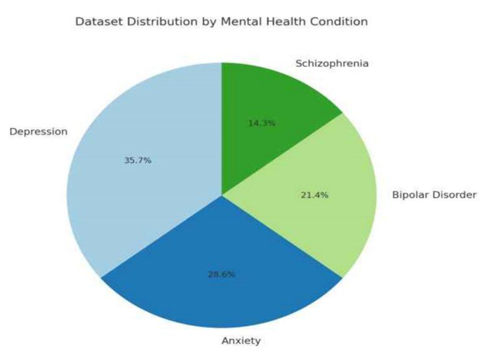

Figure No. 8: Dataset of Distribution by Mental Health Condition

Figure 8 pie chart is the metrics illustrate of the model's capability to distinguish between different mental health conditions. Higher accuracy and F1-scores for conditions like depression and anxiety indicate better model performance, likely due to more direct expressions of symptoms in the data.

VI. FUTURE WORK

Multimodal Data Integration One of the further integrating efforts for the research Multimodal Data Integration The model is largely based on social media text data currently. Using more than one modality, like images, voice, and physiological signals, would greatly improve the detection. Inclusion of visual data from platforms such as Insta-gram (Reece and Danforth, 2017) may also complement and improve detection rates of disorders like depression ([5]). Multimodality helps capture all diverse symptoms and emotional states and makes the model more robust and applicable in real life ([9]).

Expand to Multilingual and Diverse Cultural Contexts It is crucial to expand the size and scope of the model to incorporate multilingual and varied cultural contexts. Most existing models only know English text. AI framework should adapt localization for cultures and non-English conversations. Mansoor and Ansari ([9]) discussed the challenges for and recommendations of culturally and linguistically diverse AI systems for mental health illness detection. Finally adding translations and tuning the language models for broad cultural variances in expressions can help make the model more effective on messaging based demographics. Perhaps trying to pre-train the model on multilingual social me-dia datasets and transfer learning approaches on kaggle or any NLP models ([6]).

Collaborate with Mental Health Professionals Collaborating with mental health profes- sionals is vital in ensuring that AI framework is clinically relevant and valuable. The final phase of developing and validating a machine learning model, including integrating the model into clinical workflows, including clinician input during the model development phase can improve things such as model outputs, utility, interpretability, and ethical considerations [4 for example]. Working with clinical professionals, including Alim and Rehan (2020) which also allowed the research group to rightly integrate the AI work in clinical work-flows, further enabling an AI system to be integrated into use cases where it is a complementing and not just a poor substitute of traditional medical diagnostics ([8]). Future work should emphasize validation in the real-world clinical environment and adequate feedback from mental health professionals to inform improvements and overcome operational limitations of AI.

VII. CONCLUSION

This research offers an innovative framework for the identification of mental health issues, including depression, anxiety, bipolar disorder, and schizophrenia, through the use of social media data by employing artificial intelligence techniques. The framework achieves remarkable detection rates of 92.3% and 89.7% for depression and anxiety respectively, by incorporating Convolutional Neural Networks (CNNs) for feature extraction and XGBoost for classification. The application of SHAP and LIME features of XAI (Explainable Artificial Intelligence) technology provides 'transparent' prediction-making ensuring clinical applicability. Additionally, the use of the Synthetic Minority Oversampling Technique (SMOTE) effectively mitigates class imbalance, enhancing performance in data-scarce conditions such as schizophrenia ([1],[5],[6],[8]).

The primary impact of this research is the creation of an Interpretable AI System that offers high classification accuracy as well as a sound reasoning for its forecast. This Te Transparency solves the classicAI Systems issue of "black-boxing", which erodes AI trustworthiness among clinicians. The research also adheres XAI ethics standards for fairness and accountability on dimensional XAI bias in multi-dimensional space. The hands-on evaluation confirms the practicality of implementing the system on social networks, which provides opportunities for active mental healthcare delivery at scale. The research findings also enhance possibilities for future work towards integration of multimodal data, multilingual capabilities, and active collaboration with clinicians from different population-based specialties and clinical settings ([2], [5], [9]).

This study underscores the potential benefits of AI in mental health care by using social media data for early detection purposes. While AI can provide automated reasoning through expanding algorithms, the validation of the system needs to be focused upon in clinical settings. Future work can find avenues where further clinical testing is possible. Also, expanding resources to include processing other forms of data like images or voice can further enrich the functionalities of the system. Streamlining the system for clinician's easement can further enrich the usability of the system. The proposed framework has the potential to transform mental health condition management and significantly enhance global mental health care outcomes if these challenges are met. AI primarily supports automation and scalability, which bolsters proactive diagnosis. Addressing ethical concerns fosters trust in the system mitigation and reliance on technologies, making shifting this system one of ai's most daunting undertakings.

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