UNCOVERING MENTAL HEALTH DISORDERS USING MACHINE LEARNING TECHNIQUES

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Abstract

Mental health disorders continue to be a significant global concern, presenting challenges in their identification. Recent advancements in diagnostic techniques and computational methodologies have driven substantial progress in this field. This abstract offers a concise overview of the current state of mental health disorder classification and highlights emerging trends. Machine learning algorithms, which leverage extensive datasets to identify intricate patterns and improve predictive accuracy, have the potential to revolutionize the diagnostic process. This project introduces an innovative approach to classifying mental health disorders using machine learning algorithms. It employs a diverse dataset that includes various mental health conditions, demographic details, and behavioral patterns. The primary goal is to develop a robust model capable of accurately categorizing individuals into distinct mental health groups based on their unique characteristics. Specifically, the project addresses the classification of Major Depressive Disorder (MDD), Obsessive-Compulsive Disorder (OCD), Anxiety, Post-Traumatic Stress Disorder (PTSD), sleeping disorders, and Loneliness. Multiple machine learning algorithms, such as Random Forest, Logistic Regression, and Support Vector Classifier, are utilized for this classification. Additionally, the project aims to introduce advanced features to enhance accuracy and broaden its scope.

Keywords: Mental health disorder, Classification, Random Forest, Logistic Regression, SVC Algorithm.

I INTRODUCTION

Mental health disorders are among the top causes of global disability, impacting an estimated 970 million people. Each year, around 14.3% of global deaths, roughly 8 million individuals, are associated with mental disorders. Despite their widespread prevalence, access to adequate mental health care is severely limited by factors such as insufficient facilities. Nearly 45% of the global population lives in countries with fewer than one clinical

psychiatrist per 100,000 mentally ill patients. This shortage, combined with widespread stigma and prejudice, means that only 15% of affected individuals receive clinical care.

In response to these challenges, millions of individuals, known as support seekers, turn to text-based peer-to-peer support platforms like talklife.co and psychcentral.org to express their emotions and experiences, which are often stigmatized. While these platforms are well-intentioned, peer supporters typically lack formal training and are often unaware of best practices in therapy. This knowledge gap leads to missed opportunities for providing effective and engaging responses to those seeking support. Traditional training methods, such as in-person counselor training, face scalability issues when addressing the large user base of online support platforms. The lack of adequate support for counseling and online therapies has driven the exploration of human-computer interfaces, particularly virtual agents (VAs). These VAs are designed to detect and respond to users' emotional states effectively. Advances in text mining, natural language processing, and messaging services within major social media companies have paved the way for innovative research in mental health. The goal is to develop automated systems in this field [6]–[8]. However, the scarcity of high-quality conversational data in the public domain, largely due to privacy concerns, presents a significant challenge to the study and automation of these systems.

III BACKGROUND STUDY

Malmasi et al. [6] describe their approach for predicting the severity of user posts in a mental health forum, developed to participate in the 2016 Computational Linguistics and Clinical Psychology (CLPsych) Shared Task. The system utilizes a meta-classifier composed of base classifiers that leverage lexical, syntactic, and metadata features. These classifiers are created for both the target posts and their contextual information, encompassing both preceding and subsequent posts. The output from these classifiers is then employed to train the meta-classifier, surpassing the performance of individual classifiers and an ensemble classifier. The success of this meta-classifier leads to its extension into a Random Forest of meta-classifiers, resulting in further enhancements in classification accuracy. In the competition, their approach achieves competitive results, securing the top rank among a total of 60 submitted entries [6].

Glen Coppersmith and colleagues (Coppersmith et al., 7) point out that conventional mental health studies heavily rely on information gathered through direct interaction with healthcare professionals. While recent research has successfully utilized social media data to explore depression, there is a scarcity of evaluations concerning other mental health conditions. The focus of their study is post-traumatic stress disorder (PTSD), a prevalent and severe condition affecting millions globally, particularly prevalent among military veterans. The authors introduce an innovative approach to develop a PTSD classifier for social media by employing straightforward searches of publicly available Twitter data. This method significantly reduces the cost of training data compared to previous methodologies. The authors showcase the effectiveness of their approach by analyzing linguistic differences between individuals with PTSD and randomly selected individuals, creating classifiers to distinguish between these two groups. Additionally, they apply their classifiers to identify heightened rates of PTSD in and around U.S. military bases [7].

According to Satvik Gurjar et al [11], mental health issues have emerged as a significant concern in 21st-century healthcare, primarily attributable to a lack of awareness among the general population. The objective of this paper is to raise awareness among individuals regarding potential mental health issues such as depression, anxiety, PTSD, and insomnia by employing machine learning techniques. To implement these algorithms, a diverse set of data was gathered from individuals spanning various ages, professions, genders, and lifestyles. This data was acquired through a survey form containing questions commonly utilized by psychologists to gain a comprehensive understanding of their patients' issues [11].

IV PROBLEM DEFINITION

Developing models and systems for classifying individuals based on their mental health status and predicting the likelihood of specific mental disorders is essential for organizing and forecasting mental health conditions. This is crucial in the mental healthcare field as it enables early intervention, personalized treatment strategies, and optimized resource allocation. Establishing a reliable system to categorize individuals into specific mental health groups, based on symptoms, behavior, and other relevant criteria, can greatly enhance personalized mental healthcare, facilitate timely interventions, and ultimately improve mental health outcomes. Successfully implementing such a system aims to reduce

the stigma associated with mental health disorders while simultaneously increasing the efficiency of mental health care and treatment.

V PROPOSED MODEL

This study aimed to predict mental disorders using machine learning algorithms by leveraging data to build models capable of forecasting mental health outcomes. The prediction process utilized three key ML algorithms: Random Forest, Logistic Regression, and Support Vector Classifier. The Kaggle dataset, containing measurements of pollutants in various environments, served as the basis for training and evaluating the models' effectiveness.

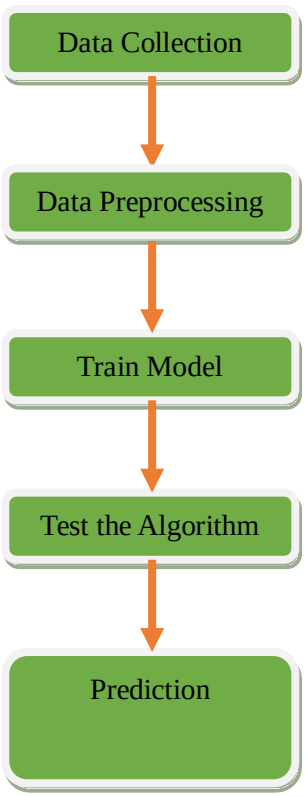

Figure 1: Proposed architecture

RESULTS AND DISCUSSION

The core of this research lies in the Results and Discussion section, where the study's findings are presented and thoroughly analyzed. This section uncovers important facts, patterns, and insights derived from an in-depth investigation. The following discussion interprets these findings in the context of existing literature, theoretical frameworks, and the study's overarching objectives.

Random Forest is a versatile and widely-used machine learning algorithm that belongs to the ensemble learning techniques. It is particularly well-suited for both classification and regression tasks and is known for its robustness, accuracy, and ease of use.

Belonging to the category of supervised learning algorithms, Logistic Regression (LR) is employed to address classification problems. This model is designed to handle binary variables, such as 0 and 1 or yes and no. Logistic regression utilizes a sigmoid function, also known as the logistic function, which involves a sophisticated cost function in its operations.

The Support Vector Classifier (SVC) is a notable algorithm employed for both regression and classification purposes. Its objective is to establish an optimal line or decision boundary capable of partitioning n-dimensional space into classes, facilitating the accurate categorization of new data points in the future. This optimal decision boundary is referred to as a hyperplane. SVC identifies the crucial points or vectors at the extremes that contribute to the creation of this hyperplane. These pivotal instances are termed support vectors, hence the algorithm is named Support Vector Classifier.

To ensure high accuracy in the model, it was crucial to thoroughly clean and preprocess the data until it was appropriately prepared. Python libraries like NumPy, pandas, and matplotlib played a key role in this process. To optimize our results, we applied various machine learning algorithms to each dataset, including Logistic Regression (LR), Support Vector Classifier (SVC), and Random Forest (RF). The outcomes of these algorithms resulted in accuracies of 77% for SVC, 97% for LR, and 99% for RF, respectively. We selected the algorithm that provided the highest true accuracy for our system. Additionally, we explored hyper parameter fine-tuning to determine if further enhancements in accuracy were attainable.

Algorithm	Accuracy	Precision	Recall	F-measure
LR	97%	97%	97%	97%
SVC	76%	73%	76%	72%
RF	99%	99%	99%	99%

Table.1

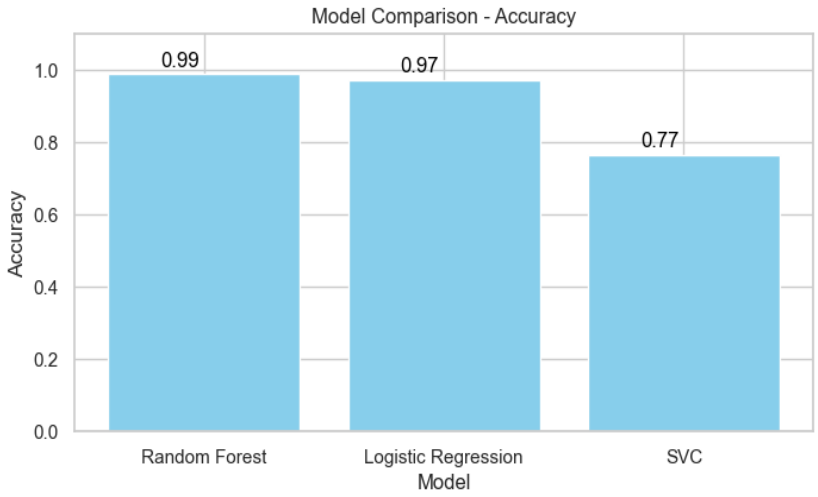

Figure 2: Algorithm comparison

CONCLUSION

In our study, we utilized Random Forest (RF), a powerful machine learning method, to address the critical challenge of categorizing and predicting mental disorders. The Kaggle dataset, which offers comprehensive information on mental health conditions, served as the primary data source for training and assessing our models. RF displayed numerous advantages in this scenario, such as resilience, interpretability, and the capacity to manage complex, non-linear relationships within the data. Across our experiments, RF consistently showed high accuracy in accurately classifying individuals into different mental health groups.

In contrast to other proposed methods, our suggested Random Forest (RF) approach outperformed them in terms of accuracy (99%), precision (99%), and F-measure (99%). The interpretability of RF was crucial in identifying key factors contributing to the classification

of mental disorders. This newfound knowledge serves as a valuable resource for mental health providers, facilitating targeted intervention and personalized treatment planning. It's important to recognize that the success of the RF model depends on the quality and representativeness of the training data. Ensuring the model's ability to generalize requires addressing biases within the dataset and promoting diversity.

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