**UNCOVERING MENTAL HEALTH DISORDERS USING MACHINE LEARNING TECHNIQUES**

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**Abstract**

Mental health disorders remain a significant global concern, posing challenges in their identification. Recent years have witnessed substantial progress in the field, driven by advancements in diagnostic techniques and computational methodologies. This abstract provides a succinct overview of the current state of mental health disorder classification and emerging trends. The utilization of machine learning algorithms, leveraging extensive datasets to discern intricate patterns and enhance predictive accuracy, holds the potential to transform the diagnostic process. This project proposes an innovative method for mental health disorder classification through the application of machine learning algorithms. The study utilizes a diverse dataset encompassing various mental health conditions, demographic details, and behavioral patterns. The primary aim is to develop a robust model capable of precisely categorizing individuals into distinct mental health groups based on their unique features. The project specifically addresses a classification problem, distinguishing among Major Depressive Disorder (MDD), Obsessive-Compulsive Disorder (OCC), Anxiety, Post-Traumatic Stress Disorder (PTSD), sleeping disorders, and Loneliness. Various machine learning algorithms, including Random Forest, Logistic Regression and Support Vector Classifier, are employed for mental health disorder classification. Furthermore, 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 rank among the leading causes of global disability, affecting an estimated 970 million individuals. Annually, approximately 14.3% of worldwide deaths, equivalent to 8 million people, are linked to mental disorders. Despite the widespread prevalence, access to adequate mental health care is hindered by factors such as insufficient facilities, with nearly 45% of the global population residing in nations where there is less than one clinical psychiatrist per 100,000 mentally ill patients. This limitation, combined with pervasive stigma and prejudice, results in only 15% of affected individuals receiving clinical care.

In response to these challenges, millions of people, often referred to as support seekers, turn to various text-based peer-to-peer support platforms like talklife.co and psychcentral.org to share their emotions and experiences, which are frequently stigmatized. Although well-intentioned, peer supporters on these platforms lack formal training and are often unaware of best practices in therapy. This knowledge gap leads to missed opportunities to provide sound and mutually engaging responses to those seeking support. The conventional approaches to training, such as in-person counselor training, face limitations in scalability when catering to the vast user base of online support platforms. The insufficient support for counseling and online therapies has spurred the exploration of human-computer interfaces, specifically virtual agents (VAs). These virtual agents are designed to detect and respond to users' emotional states effectively. Recent advancements 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 aim is to develop automated systems in this domain [6]–[8]. However, the scarcity of high-quality conversational data in the public domain, driven by privacy concerns, poses a significant obstacle to the study and automation of these systems.

**III BACKGROUND STUDY**

Braja Gopal Patra et al. [1] Mental health presents a significant challenge in the medical field due to privacy concerns and the absence of easily measurable indicators. Instead, much of the available data relies on subjective descriptions of patients' experiences, often in text form. Online sources, including social media and forums like ReachOut, provide valuable datasets for studying mental health. Leveraging datasets from the CLPsych shared tasks in 2016 and 2017, which classify forum posts based on severity, we developed an automated labeling system. Our system utilizes various machine and deep learning algorithms, incorporating supervised and semi-supervised embedding methods. By analyzing labeled and unlabeled data from ReachOut and unlabeled data from WebMD, we extract features such as metadata, syntax, semantics, and embeddings to categorize posts into four severity levels: green, amber, red, and crisis [1].

Ahmed Husseini Orabi et al. [3] Detecting mental illness through social media poses a significant challenge due to the complexity of mental disorders. However, with the widespread use of social media platforms, researchers have gained access to valuable insights into users' lives. Despite this wealth of information, employing supervised machine learning, particularly deep neural networks, has been hindered by the scarcity of annotated training data. In response, we aim to identify the most effective deep neural network architecture for detecting signs of mental illness, specifically depression, using limited unstructured text data from Twitter. We select architectures previously successful in natural language processing tasks and evaluate their efficacy in this context [3].

Wouter Eekhout et al. [10] Cultural and gender norms play a crucial role in shaping perceptions of mental illness and therapy, yet there's a lack of substantial empirical evidence concerning these dimensions. This study employs social media as a tool to explore these aspects, treating it as a "lens" through which to analyze cultural and gender dimensions. Using a substantial dataset of Twitter users who openly disclose underlying mental health concerns, we utilize semi-supervised learning to identify genuine disclosures. By examining differences in their posts, measured through linguistic attributes and topic models, we uncover significant distinctions between content shared by female and male users, as well as those from Western and Majority World countries. Specifically, males tend to express higher negativity and lower desire for social support, while users from Majority World countries exhibit greater inhibition in their expression. These findings shed light on the relationship between gender, culture, and mental health, offering insights for gender and culture-sensitive health interventions.

**IV PROBLEM DEFINITION**

Creating models and systems for classifying individuals based on their mental health status and predicting the likelihood of specific mental disorders is crucial for organizing and forecasting mental health conditions. This plays a pivotal role in the field of mental healthcare by enabling early intervention, tailoring treatment strategies, and optimizing resource allocation. Establishing a robust system to group individuals into specific mental health categories, considering symptoms, behavior, and other relevant criteria, can significantly improve personalized mental healthcare, facilitate timely intervention, and ultimately enhance mental health outcomes. The successful implementation of such a system aims to diminish the stigma associated with mental health disorders while simultaneously boosting the efficiency of mental health care and treatment.

**V PROPOSED MODEL**

This study focused on utilizing machine learning algorithms to predict mental disorders by leveraging data to build models capable of forecasting mental health outcomes. Random Forest, Logistic Regression and Support Vector Classifier, three pivotal ML algorithms, were employed in the prediction process. The Kaggle dataset, which includes measurements of pollutants in different environments, was used as the basis for training and evaluating the effectiveness of the models.

Data Collection

Data Preprocessing

Train Model

Test the Algorithm

Prediction

Figure 1: Proposed architecture

**RESULTS AND DISCUSSION**

The focal point of this research is the Results and Discussion section, where the study's discoveries are unveiled and thoroughly examined. This section reveals crucial facts, patterns, and insights that emerged from an in-depth investigation. The subsequent discussion interprets these findings within the context of existing literature, theoretical frameworks, and the overall goals of the study.

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 imperative to thoroughly clean and preprocess the data until it was suitably fitted. Python libraries such as NumPy, pandas, and matplotlib were instrumental in this process. To optimize our results, we subjected each of our datasets to multiple machine learning algorithms, including Logistic regression (LR), Support Vector Classifier (SVC), and LR. The outcomes of these algorithms yielded accuracies of SVC (77%), LR (97%) and RF (99%)., respectively. We selected the algorithm that provided the true and highest accuracy for our system. Additionally, we explored hyperparameter fine-tuning to assess if further improvements in accuracy could be achieved.

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

**Table.1**

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Figure 2: Algorithm comparison

**CONCLUSION**

In our research, we harnessed the capabilities of Random Forest (RF), a robust machine learning technique, to tackle the vital task of categorizing and predicting mental disorders. The Kaggle dataset, containing comprehensive information on mental health conditions, served as the foundational source for training and evaluating our models. RF exhibited several merits in this context, including robustness, interpretability, and the ability to handle intricate, non-linear associations within the data. Throughout our experiments, RF consistently demonstrated high accuracy in effectively classifying individuals into distinct mental health categories.

In contrast to proposed methods, our suggested Random Forest (RF) approach surpassed them in terms of accuracy (99%), precision (99%), and F-measure (99%). The interpretability of the RF proved pivotal in identifying key factors contributing to the classification of mental disorders. This newfound knowledge serves as a valuable asset for mental health providers, enabling targeted intervention and personalized treatment planning. It is essential to acknowledge that the success of the RF model relies on the quality and representativeness of the training data. Ensuring the model's ability to generalize necessitates addressing biases within the dataset and promoting diversity.

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