Accessing Depression through AI: Machine-Learning Based Diagnostic Tool

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***Abstract*—In recent years, mental health discourse has gained significant momentum, highlighting its importance in our overall well-being. People often ignore their health due to the fast-paced life of today and the rat race in the world. While they might look healthy and fit on the outside, what goes on in their mind is a disarray of thoughts that they cannot put a rest to. We were taught to ignore our 'mindless thoughts' and focus on positivity. But is it that easy? Mental health illness is, as of now, still an ignored illness. People are afraid to seek professional help as they feel it may make them 'weak'. This research paper aims to analyze the various characteristics that contribute to depression and to study the severity of conditions based on these characteristics. This model classifies the degree of depression into 4 broad categories: no depression, mild, moderate, and severe. The predictive model employs the Random Forest Algorithm to generate accurate and reliable prediction data. The algorithm enhances performance through robust averaging, mitigating overfitting, and improving generalization to unseen data.**

***Index Terms*—Depression Diagnosis, Machine Learning, Artificial Neural Networks, Mental Health Screening, Feature Engineering**

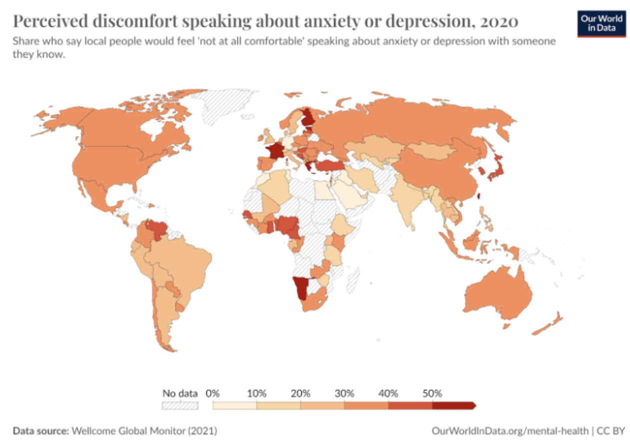

Fig. 1. A map highlighting the areas in accordance with their perceived discomfort in speaking about anxiety or depression, highlighting regional differences in mental health stigma.[ImageLink]

I. Introduction

A. Problem introduction and history and current relevant stats of who is affected by the problem:

As inferred from Fig. 1, the taboo surrounding mental health is still very prevalent in our society today. The fear surrounding this topic often causes people not to seek professional help. Areas like Central and North Africa, the Middle East, and some parts of Central Asia are highly stigmatized areas when it comes to discussing mental well-being. Looking at the map as a whole, the majority of the area lies in the 30–40 discomfort zone, which conveys that across the world, there is still a lot of taboo when it comes to talking about one's problems and mental health. As a result of this, many people around us have undiagnosed mental health conditions. This leads to the need for a machine learning model to help diagnose these conditions while simultaneously motivating people to proceed with their diagnosis.

This research paper will discuss diagnosing depression using an ML model [1].

But why use a Machine Learning (ML) model?

A machine learning model isn't a human. Hence, a patient sharing his problems won't feel 'weak' or 'judged' and will be able to answer the questions more freely. A machine learning model would also promise privacy to them as their data or anything the patient has saved would remain confidential.

But first, let's understand how a mental health practitioner diagnoses depression. Fig 2 explains the process that will be undertaken if someone approaches a psychologist. DSM-5 is The Diagnostic and Statistical Manual of Mental Disorders, Edition 5. It is a book containing the classification of mental disorders, and it is used by mental health professionals while diagnosing their patients. Edition 5 is the latest DSM and is open to more changes as more disorders come to light [2].

B. People Affected by depression

According to a 2021 survey by the National Institute of Mental Health (NIH), major depressive episodes were more prevalent among adult females (10.3%) compared to males (6.2%). Additionally, the highest prevalence of major depressive episodes was observed in adults aged 18-25, with 18.6% affected [3].

However, depressive symptoms can start to show at any age, changing from person to person. These symptoms can occur in many situations because of a cumulation of repressed emotions over a long period. How and when the body shows symptoms differs from one individual to another. Sometimes, it might even come up when you are old, but depression diagnosis

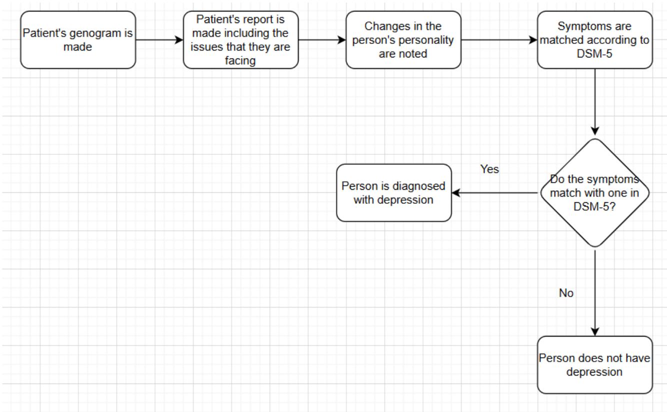

Fig. 2. A flow chart on how Mental Health Practitioners diagnose depression

is not good enough for senior citizens. Usually, their mental well-being is neglected [4].

Depression can also co-relate with hormonal changes, hence the reason why it is so frequently observed in women and young people. For example, common kinds of depression among women tend to be postpartum depression and post-menopausal depression [5]. In this paper, we mostly focus on the common symptoms associated with depression and how likely it is for someone to be diagnosed with depression if they face such symptoms.

C. Challenges to solve this problem

Diagnosing depression using AI and machine learning models presents several challenges that must be carefully considered. One significant issue is compromised accuracy [6]; the model may not always accurately gauge the severity of depression, as it is continuously evolving and heavily reliant on the quality and quantity of data it is trained on [7]. This brings us to the second challenge: the lack of data. A vast amount of diverse data from many individuals is necessary to create a robust model. Depression manifests uniquely in different people, so a comprehensive dataset that captures this complexity and variety is essential for training an effective model. The model's accuracy and generalizability can be severely limited without such data. Lastly, the loss of human connection is a prominent obstacle. Patients may find it difficult to trust a machine-learning model for diagnosis, and human professionals can interpret emotional and verbal cues more effectively, leading to a more accurate and empathetic diagnosis [8]. This human element is crucial for understanding the nuanced experiences of individuals dealing with depression, something that a machine cannot fully replicate.

II. Literature Review

The diagnosis of multiple mental health issues like depression using AI is a widely studied and researched field. According to the WHO, around 322 million people are suffering from depression in the world. According to a study, Plutchik's emotion model was used to identify various depressive profiles on Twitter [9].

There's another study that focuses on the ways that AI can diagnose psychological depression. It covers recommendations for appropriate treatment and techniques for emotional support and positive motivation [10].

There are various wearable devices, like watches, that are used to detect depression and anxiety. A study done on wearable devices discusses the types of devices, where they are worn, how the data is transferred, etc [11].

Another study done in China talks about how ML can be used to diagnose bipolar disorder. Major Depressive Disorder (MDD) diagnosis can be made using machine learning methods such as support vector machines (SVM) and random forests. The approaches are applied to neuroimaging and biomedical data, which help improve the quality of diagnostics by detecting specific patterns that make MDD different from normal individuals [12].

In another paper, "Machine Learning for Diagnosing Depression," some ML-based methods for identifying depression were estimated, including SVM, decision trees, and neural networks. Benchmarking in terms of those models' accuracy, precision, and recall values was pursued to show the applicability of various algorithms in predicting depression from sources as diversified as clinical interviews and self-reported surveys [13].

A study disputes the application of ML techniques in diagnosing psychiatric disorders. The researchers review different ML models and their potential to improve diagnostic accuracy, identify novel biomarkers, and predict treatment outcomes by integrating ML with neuroimaging information, genetic data, and electronic health records in diagnostic processes and personalized treatment plans [14].

The paper "Automated Depression Analysis Using Convolutional Neural Networks from Speech" envisions the implementation of a diagnostic system for depression using handcrafted and deep-learned features extracted from speech. The proposed system uses deep convolutional neural networks for feature learning from spectrograms and raw speech waveforms combined with handcrafted Median Robust Extended Local Binary Patterns features. Such a hybrid approach can improve the accuracy of depression severity prediction by utilizing these two kinds of features since they can complement each other. The method was proved robust and effective through experimental studies on AVEC2013 and AVEC2014 depression databases [15].

The paper presents a hybrid deep learning model for detecting depression from Reddit posts, using Bidirectional Long Short Term Memory, empowered with word-embedding techniques: Trainable Embeddings, GloVe, Word2Vec, and FastText, coupled with metadata features. This approach would increase the accuracy of early detection by analyzing textual data and user metadata to offer a robust solution for identifying depression through social media activity [16].

Table 1 discusses the various applications and research gaps of the above-referenced papers.

TABLE I
COMPARATIVE ANALYSIS OF STATE-OF-ART TECHNIQUES IN THE VARIOUS APPLICATION AREAS, USING THE ML TECHNIQUES AND THEIR CORRESPONDING RESEARCH GAPS FOR OUR RESEARCH MOTIVATION

S No.	Application	Highlights	Reference	Research Gaps
1	Identify depressive profiles, Twitter messages	Depression, Emotions, AI	Martins, Ricardo, et al.(2021) [9]	Tweet-based analysis only.
2	Genetic and medical data analysis	Psychological Depression, AI, Precision Medicine	Eid, Marwa M., et al.(2023) [10]	Dataset unspecified
3	Wearable AI for anxiety and depression	Wearable AI, Anxiety, Depression	Abd-Alrazaq, Alaa, et al. (2023) [11]	Lacks wearable AI insights
4	Clinical ADE adaptation: BDCC	Bipolar Diagnosis, China	Ma, Yantao, et al. (2019) [12]	Single-location data, i.e., China
5	ML method for depression diagnosis	Depression, Ensemble classifier, Quality of Life scales	Tao, Xiaohui, et al. (2021) [13]	Limited to binary classification only i.e. depressed or not.
6	Deep Learning and AI's impact on psychological assessment	AI, Psychological Interventions, Diagnosis	Zhou, Sijia, et al. (2022) [14]	English articles (2010-2020) only
7	Hybrid feature approach for depression severity	Automated depression analysis, convolutional neural networks, speech	He, Lang, and Cui Cao et al. (2018) [15]	No Multimodal data integration
8	Reddit post analysis for early depression detection	Early Depression Detection, Social Networks, Deep Learning Techniques	F.M. Shah et al. (2020) [16]	Time-consuming

III. METHODOLOGY

The algorithms used are Random forests and Decision Trees and ANN (Artificial Neural Networks) is incorporated to improve the model's accuracy.

A. Feature Reduction

Sometimes referred to as dimensionality reduction, feature reduction is an important step in the machine learning pipeline to reduce the number of input variables. Reducing the variables in the dataset helps eliminate unimportant information for training the machine-learning model. It helps increase the model's performance and reduce the overall computational time. Feature reduction can be done through different techniques depending on the dataset. Two such techniques are feature selection and feature extraction. Feature selection includes selecting the most important features of a dataset so that the unimportant features can be eliminated. It uses filter methods, wrapper methods, etc., to select the important features. On the other hand, feature extraction is a process that transforms raw data into manageable data. It compresses the data into lower dimensions and then reconstructs it. Feature extraction utilizes a technique called Principal Component Analysis (PCA). This technique transforms the original data into a coordinate system where the greatest variance lies on the first coordinates.

B. Conversion of data types of features

Sometimes, the different features of a dataset have different data types. It is important to have a uniform datatype across all features for the model to become efficient. Datatype conversion ensures the correct interpretation of the data by the machine learning model and an efficient processing of the data by the various machine learning algorithms. This can include various scenarios such as converting string to numeric, converting categorial to numeric, converting numeric to categorial, etc. In the dataset used for this study, we have converted text in the "depression state" column to numeric data to ensure the correct interpretation of the data. Datatype conversion can be done through the various functions in the pandas library.

C. Model Training

Model training includes training a model to make predictions and decisions based on previous data. We can train a model efficiently to make correct and precise predictions using correct algorithms.

1. Decision Trees

Decision trees are structures that are used in various fields, such as machine learning and data mining [17]. These structures are created by making a relationship between variables, providing a way to make correct and effective decisions. These variables are stored in nodes, and the nodes are connected through branches. Branches represent the outcome of a decision that leads to another node. There are three types of nodes including root nodes, which are nodes that represent the initial decision, intermediate nodes, which are nodes that lead to one or more branches and leaf nodes, which represent the final decision.

In Fig 3, we have to decide whether a person is fit or not. The intermediate nodes have questions: Eats a lot of pizzas?

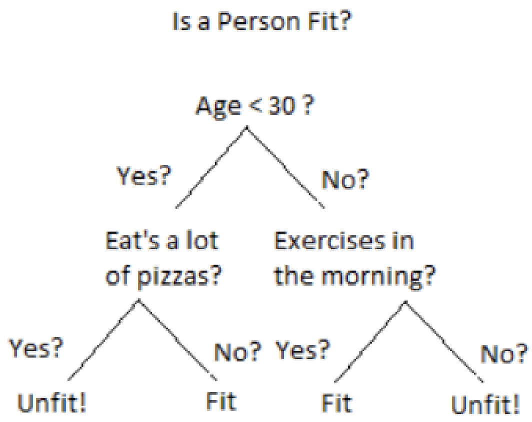

Fig. 3. Decision Trees:intuitive machine learning models that split data based on feature values to make predictions.[ImageLink]

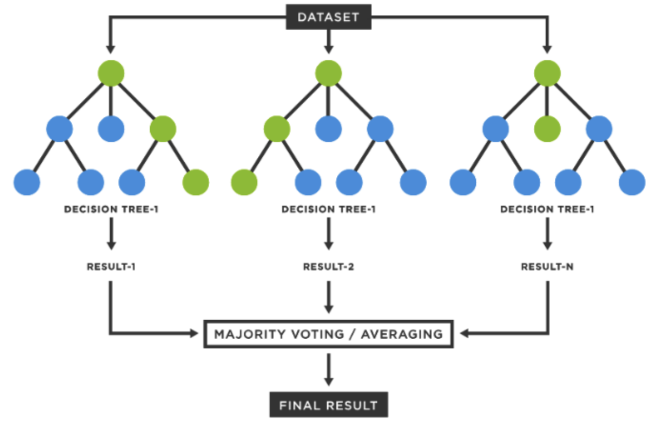

Fig. 4. Random Forest: A versatile machine learning algorithm that builds multiple decision trees and merges them for accurate predictions.[ImageLink]

And exercises in the morning? The branches contain the Yes or No answers, which, once answered, take us to our next node until we reach the leaf node that tells us the decision. In this case, it tells us whether the person is fit.

2. Random Forest Algorithm

Random Forest Algorithm [18] is an ensemble learning machine learning technique used for classification and regression purposes. It uses the training data to create multiple decision trees; each tree comprises a random subset of the data. In an ensemble model such as a random forest, multiple models team up to improve performance. Each model contributes so that the overall limitations are reduced, and the trained model can have the collective advantages of all the contributing models. The randomness of the trees reduces the chances of over-fitting and helps make more diverse and efficient predictions.

Random Forest Algorithm utilizes multiple steps, including making decision trees, as shown in Fig 4, for ensemble learning, random feature selection, bagging or bootstrap aggregating, decision making, and voting. This algorithm offers several key advantages for efficient model training. It is versatile and achieves high prediction accuracy by aggregating multiple decision trees. The ensemble approach mitigates overfitting by averaging outcomes, making it robust for handling large datasets with high dimensionality. Random Forest also evaluates feature importance. Additionally, it is robust to noise, requires minimal pre-processing, and supports parallel training, enhancing computational efficiency.

IV. Data Collection

A. Description of the Dataset

We used the ”Mental Health Detection Dataset” dataset (Hamja S. Shaikh, 2024) available on Kaggle under the Apache 2.0 license. The dataset [19] includes data from 540 people, who were asked a set of 14 questions, which were the symptoms of depression, and it has to be answered on a scale of 1 to 6, depending on the frequency of the symptoms(where 1: Never, 2: Always, 3: Often, 4: Rarely, 5: Sometimes, 6: Not at all). Based on the frequency of the symptoms, the severity of the depression was received. Plus, it has to be noted that all the symptoms do not equally affect the severity of the depression.

The 14 questions/symptoms that the dataset uses are listed below:

TABLE II
Survey Questions

S.No	Label	What We Infer From Our Questions
1	Sleep	Too much sleep or too little sleep
2	Appetite	Drastic change in appetite
3	Interest	Less interest in work/hobbies
4	Fatigue	Getting tired too easily
5	Worthlessness	Thoughts on self
6	Concentration	Lack of concentration
7	Agitation	Getting irritated too easily
8	Suicidal Ideation	Suicidal or not
9	Sleep Disturbance	Quality of sleep
10	Aggression	Anger issues
11	Panic Attacks	Severity
12	Hopelessness	Thoughts on future
13	Restlessness	Finicky
14	Low Energy	Level of cheerfulness/energy

B. Experimental Setup

The code was run using Jupyter Notebooks. It is an open-source web application that allows you to code, visualize data and data cleaning. It supports algorithms like random forest that help build a training model to predict depression among individuals. The dataset was used to figure out the symptoms that are the most important and play a vital role in determining the severity of depression. The first feature, “number,” was removed as it was irrelevant and increased the dataset’s size. Duplicate and null values were also removed to make the dataset more accessible.

A machine learning algorithm called the Random Forest Algorithm was used to train the model. A correlation matrix was created to show the correlation of other features to the "depression state" feature. Furthermore, a heatmap was created from the correlation matrix to provide an overview of the correlation of features. To determine the highly correlated features to the depression state, the correlation threshold was kept at 0.1. Random forest was used to cumulate the feature importance scores. A plot showed the importance of each feature with features on the y-axis and feature importance on the x-axis. Afterward, to increase the importance, new features were added that were the combination of previous features. For example, the "fatigue energy ratio" was created by dividing the "fatigue" feature by the "energy" feature. Similarly, a new feature called "stress" was created by the addition of the "agitation", "panic attacks" and "restlessness" features. These new features were plotted along with the other features and were shown to be more important.

C. Performance Measure

In this study, we utilize the accuracy_score function to get the model's accuracy. We have to import the accuracy_score from sklearn to use this function.metrics library [20] as well as import the classification_report from sklearn to get a full classification report.metrics library. The classification_report function collectively computes the model's precision, recall, and F1 score. Accuracy is The ratio of correctly predicted instances to the total instances. It is one of the simplest classification metrics to implement. The formula is shown in equation(1). Precision (equation(2)) is the ratio of correctly predicted positive observations to the total predicted positives. It is used to overcome the limitation of accuracy. Recall is The ratio of correctly predicted positive observations to all the observations in the actual class. Recall determines the performance with respect to a false negative, i.e., it includes positives that were falsely identified as negative. The formula is shown in equation(3). The F1 score is the harmonic mean of both precision and recall. It utilizes both precision and recall to provide a single score. The formula is shown in equation(4).

$$\text{Accuracy} = \frac{\text{Number of correct predictions}}{\text{Total Number of predictions}} \tag{1}$$

$$\text{Precision} = \frac{TP}{TP + FP} \tag{2}$$

$$\text{Recall} = \frac{TP}{TP + FN} \tag{3}$$

$$\text{F1 Score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{4}$$

D. Optimization Strategy

Using techniques like correlation matrix and Random Forest algorithm, an accuracy of around 44% could be obtained. We had to change some of the techniques and evaluate the result to increase the accuracy.

We have used a neural network to increase the accuracy. Neural Networks is a concept in machine learning that is slightly derived from the neurons in a human body. A single neural network may contain many layers, including input, output, and hidden layers. Each neuron in the hidden layer calculates a weighted sum of the input features, fed into the activation function, which decides which neuron/input feature should be activated.

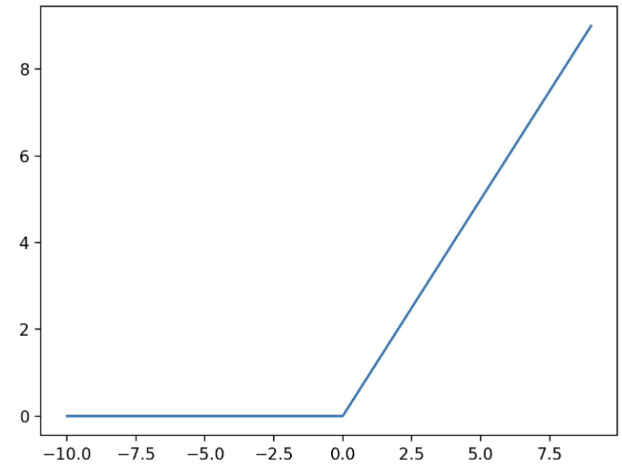

Fig. 5. ReLU: A simple yet powerful activation function that introduces non-linearity and combats the vanishing gradient.The graph of the ReLU activation function is linear for positive inputs and remains flat at zero for all negative inputs.[ImageLink]

Neural networks are stochastic [21], meaning we can have different results for the same data on which the network has been trained. Neural networks intentionally incorporate randomness as part of their design to enhance their ability to learn and approximate the target function for a given problem. This randomness is crucial because it helps these algorithms achieve better performance. But, sometimes, we must have the same results to ensure reproducibility and consistency.

One solution to this is using a fixed seed for the random number generator. A "seed" is the initial value that is used by the random number generator to produce a set of numbers. By setting the value of the seed to a fixed number, we ensure that the random numbers generated are the same every time. This will help us produce consistent results. Without a fixed seed, our model performs differently every time, making it challenging to analyze its performance.

We have used the ReLU (Rectified Linear Unit) activation function. It is a widely used activation function that can make your neural network learn faster. The formula of the ReLU function is:

y=f(x)={0,x}

Where y is the output and x is the input.

In other words, no negative values are given as an output by the ReLU. The graph goes like this in Fig 5:

As shown in Fig 5, the output remains zero for all the values less than zero, and there is no deviation in the output. Once the input exceeds zero, the input value is given as the output.

V. Results and Discussion

Our model's accuracy is 47%, which has increased from its initial accuracy of 44%. Initially, we used the Random Forest algorithm to train our model, and a correlation heat

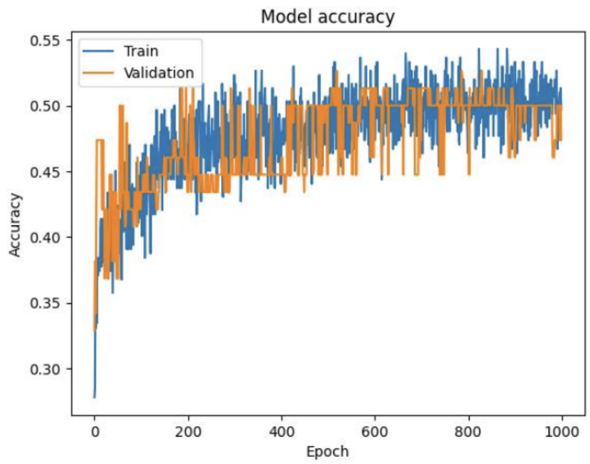

Fig. 6. The graph shows training and validation accuracy over 1000 epochs. Both rise initially, reflecting learning progress, but fluctuations suggest potential instability. Their alignment indicates reasonable generalization

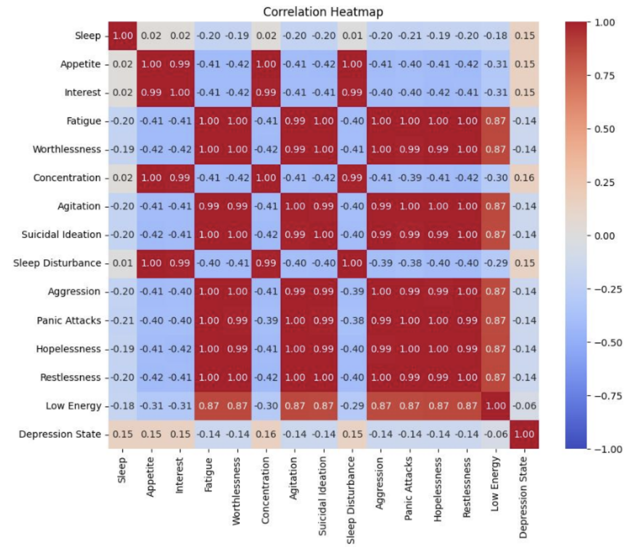

Fig. 7. Correlation Heatmap: Key features like 'Fatigue,' 'Low Energy,' and 'Hopelessness' strongly correlate with 'Depression State,' highlighting their predictive significance, while 'Sleep' shows weaker correlations.

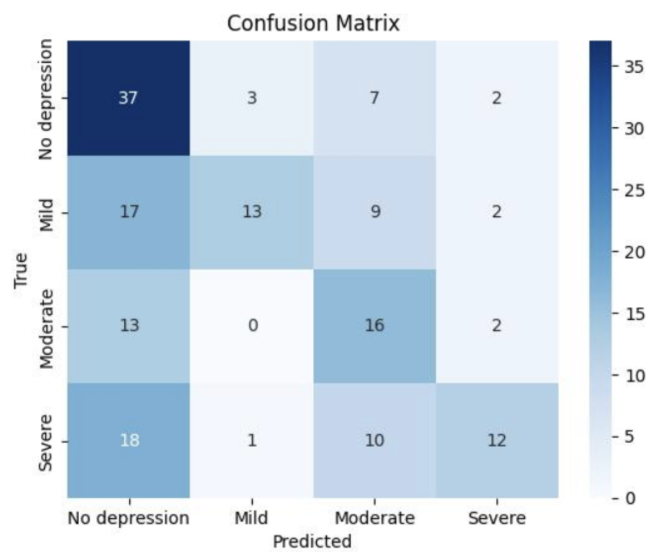

Fig. 8. This confusion matrix shows classification performance across four depression levels. While "No Depression" is mostly accurate, "Moderate" and "Severe" are often misclassified, highlighting challenges in distinguishing these categories.

map was used to find the most appropriate input features. Still, since we needed to improve its accuracy, we switched to ANN (Artificial neural network) to train it.

A. Model Accuracy Determination

First, the data was divided into test, train, and cross-validation sets. We plotted the accuracy and loss of our model on the train and cross-validation sets before doing it on the test set. The training accuracy curve should show an upward trend as the number of epochs increases; it means that the model is learning and improving with each epoch.

As for the cross-validation set, an initial increase in the curve is expected as the model learns and improves and should keep on increasing with more data. Now, there might be two things that might happen, first, the curve keeps on rising, which means that the model is improving and working well on unseen data, but if the curve stops increasing after a certain level, that means that there will not be any increase in the model performance with more of the training data. We either need to fetch more training data or if the model has reached its required accuracy, then we may test the model on the test data. Fig 6 shows the results of testing our model.

B. Checking for the most suitable features using a correlation heatmap

Fig 7 is a correlation heatmap of our data. It uses the varying intensity of colors to symbolize how related the features are. The co-relation values may be negative or positive, in the map below, deep red indicates a high correlation, while dark blue indicates a low correlation. A threshold is set in our code, it is 0.95, which means that we desire the variables that have a high correlation for our model to work well.

C. Model Performance Evaluation

Fig 8 is a Confusion Matrix. It is used to evaluate the performance of a model by comparing the actual and predicted classifications. The rows represent true values while the columns represent predicted values.

To explain it, the '3' in row 1 and column 2 means that 3 instances of 'No depression' were wrongly predicted as 'Mild'. The diagonal values show the instances where the predictions were correct.

From Fig 8, we observed that our model does well when it comes to predicting 'No depression' but isn't as efficient when it comes to predicting the other results. Hence, a confusion matrix not only helps us evaluate the overall performance of a model but also tells us which feature our model might be lacking. In this case, our model is not efficient enough.

D. Limitations

We even had a few limitations, such as the dataset that we selected was pretty small, and it had a fair amount of missing values, which we dropped. So, a better dataset was needed to make our model even more accurate. Another limitation that we faced was that the data was overfitting. Even after repeated attempts, the over-fitting prevailed.

VI. Conclusion

Diagnosing depression using AI / ML has a long way to go. We cannot trust that the diagnosis of ML-based depression is independent. Healthcare, whether physical or mental, is a time-varying field. New diseases and complications are coming under the light. ML cannot treat such diseases as there isn't enough data for them. Understanding that AI is there to help us, not replace us, is beneficial. AI still hasn't achieved the understanding or comfort a human practitioner may provide their patients. Recognizing a specific type of disease may prove better or faster if the input symptoms match the already existing data. Hence, they are helpful in an early diagnosis of the disease [22]. However, as for giving patients the correct prescription and steps to overcome their mental illness, AI is still not entirely efficient.

VII. Acknowledgement

This study uses the "Mental Health Detection Dataset" dataset by Hamja S. Shaikh, licensed under Apache 2.0, available at https://www.kaggle.com/datasets/hamjashaikh/mental-health-detection-dataset. The dataset was used in compliance with the Apache 2.0 license, and modifications were made to preprocess the data for analysis.

References

[1] Cho, Gyeongcheol et al. "Review of Machine Learning Algorithms for Diagnosing Mental Illness." *Psychiatry investigation* vol. 16,4 (2019): 262-269. doi:10.30773/pi.2018.12.21.2

[2] Regier, Darrel A., et al. "The DSM-5: Classification and Criteria Changes." *World Psychiatry*, vol. 12, no. 2, 2013, pp. 92-98, https://doi.org/10.1002/wps.20050. Accessed 9 Sept. 2024.

[3] NIH "Major Depressive Episode Among Adults"

[4] Barry, Lisa C., et al. "Under-treatment of Depression in Older Persons." *Journal of Affective Disorders*, vol. 136, no. 3, 2012, pp. 789-796, https://doi.org/10.1016/j.jad.2011.09.038. Accessed 9 Sept. 2024.

[5] Mayo Clinic "Depression in Women: Understanding the Age Gap" capitalized," J. Name Stand. Abbrev., in press.

[6] Koutsouleris, Nikolaos, et al. "From promise to practice: towards the realisation of AI-informed mental health care." *The Lancet Digital Health* 4.11 (2022): e829-e840.

[7] Richter, Thalia, et al. "Machine learning-based behavioral diagnostic tools for depression: advances, challenges, and future directions." *Journal of personalized medicine* 11.10 (2021): 957.

[8] Formosa, Paul, et al. "Medical AI and Human Dignity: Contrasting Perceptions of Human and Artificially Intelligent (AI) Decision Making in Diagnostic and Medical Resource Allocation Contexts." *Computers in Human Behavior*, vol. 133, 2022, p. 107296, https://doi.org/10.1016/j.chb.2022.107296. Accessed 9 Sept. 2024.

[9] Martins, Ricardo, et al. "Identifying Depression Clues using Emotions and AI." ICAART (2). 2021.

[10] Eid, Marwa M., et al. "Treating Psychological Depression Utilising Artificial Intelligence: AI for Precision Medicine-Focus on Procedures." *Mesopotamian Journal of Artificial Intelligence in Healthcare* 2023 (2023): 76-81.

[11] Abd-Alrazaq, Alaa, et al. "Wearable artificial intelligence for anxiety and depression: scoping review." *Journal of Medical Internet Research* 25 (2023): e42672.

[12] Ma, Yantao, et al. "Implementing Machine Learning in Bipolar Diagnosis in China." *Translational Psychiatry*, vol. 9, no. 1, 2019, pp. 1-7, https://doi.org/10.1038/s41398-019-0638-8. Accessed 9 Sept. 2024.

[13] Tao, Xiaohui, et al. "Detecting depression using an ensemble classifier based on Quality of Life scales." *Brain Informatics* 8 (2021): 1-15.

[14] Zhou, Sijia, et al. "Application of Artificial Intelligence on Psychological Interventions and Diagnosis: An Overview." *Frontiers in Psychiatry*, vol. 13, 2022, p. 811665, https://doi.org/10.3389/fpsyt.2022.811665. Accessed 9 Sept. 2024.

[15] He, Lang, and Cui Cao. "Automated Depression Analysis Using Convolutional Neural Networks from Speech." *Journal of Biomedical Informatics*, vol. 83, 2018, pp. 103-111, https://doi.org/10.1016/j.jbi.2018.05.007. Accessed 9 Sept. 2024.

[16] F. M. Shah *et al.*, "Early Depression Detection from Social Network Using Deep Learning Techniques," *2020 IEEE Region 10 Symposium (TENSYMP)*, Dhaka, Bangladesh, 2020, pp. 823-826, doi: 10.1109/TENSYMP50017.2020.9231008

[17] Song, Yan-Yan, and L. U. Ying. "Decision tree methods: applications for classification and prediction." *Shanghai archives of psychiatry* 27.2 (2015): 130.

[18] Biau, Gérard, and Erwan Scornet. "A random forest guided tour." *Test* 25 (2016): 197-227.

[19] Hamja S. Shaikh , "Mental Health Detection Dataset," Kaggle, 2024. [Online]. Available: https://www.kaggle.com/datasets/hamjashaikh/mental-health-detection-dataset

[20] Balfer, Jenny, Jürgen Bajorath, and Martin Vogt. "Compound Classification Using the scikit-learn Library." *Tutorials in Chemoinformatics* (2017): 223-239.

[21] "How to Get Reproducible Results with Keras" By Jason Brownlee on August 19, 2019, in Deep Learning

[22] Hegde, Shruthi, et al. "Artificial Intelligence in Early Diagnosis and Prevention of Oral Cancer." *Asia-Pacific Journal of Oncology Nursing*, vol. 9, no. 12, 2022, p. 100133, https://doi.org/10.1016/j.apjon.2022.100133. Accessed 18 Oct. 2024.