Mental Health Assessment using AI with Sentiment Analysis and NLP

Conference Paper · January 2023

DOI: 10.13052/rp-9788770040723.107

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International Conference on Recent Trends in Data Science and its Applications
DOI: rp-9788770040723.107

Mental Health Assessment using AI with Sentiment Analysis and NLP

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***Abstract*—An Artificial Intelligence (AI) based mental health assessment that has the potential to take input from users and classify into two groups: 0 or 1 based on the training dataset. AI has the potential to revolutionize mental health assessment by providing a more accurate and efficient diagnosis, improving treatment outcomes, and increasing access to mental health services. One of the most common is through the use of machine learning algorithms. Which is used to identify patterns and predict mental health conditions. Another way in which AI can be used in mental health assessment is through the analysis of speech and language patterns. Natural Language Processing (NLP) algorithm scan be used to analyze written or spoken language to detect patterns that may indicate mental health conditions such as depression, anxiety, or schizophrenia. We want to report clients facing mental health issues directly to doctors in case of a high-profile illness or suggest a suitable course of action to calm the client without intimating the client of the results unless positive. The critical shortage of psychiatrists and other mental health specialists to provide treatment increases the crisis of untreated mental health conditions. Those who can undergo treatment often forgo it as it is too expensive. Thus, we will use AI to screen, diagnose and treat mental illnesses at a fraction /free of cost.**

Keywords*—*Natural Language Processing (NLP), Artificial Intelligence (AI), Mental health, Feature extraction, Pattern detection, Text Analysis, and Classification.

I. Introduction

Mental health refers to a person's overall psychological and emotional well-being, including their ability to manage their feelings, cope with stress, and function effectively in daily life. These conditions can be caused by various factors, such as family genetics, environmental influences, and life experiences. Examples of mental illnesses include depression, anxiety disorders, mood disorders, bipolar disorders, personality disorders, psychotic disorders (such as schizophrenia),eating disorders, and substance used is orders.

Theseillnessescanbemildorsevereandcanhavevaryingdegreesofimpactonaperson'sdailylife,relationships,andoverallwell-being.Ifanindividualorsomeone they know is displaying signs of a mental illness, it is crucial to seek assistance from a qualified professional. With appropriate treatment and support, numerous individuals with mental illness can attain recovery and live satisfying lives. The situation of understaffed hospitals and clinics can have serious implications on the quality of care that patients receive. When there are not enough staff members to meet the needs of the patients, the work load on the existing staff can become overwhelming, leading to burn out and potentially compromising patient safety. Understaffing can also result in longer wait times for patients to receive care, contributing to delays in diagnosis and treatment. In some cases, patients may even be turned away from hospitals or clinics due to a lack of capacity or resources. Furthermore, understaffing can lead to a higher staff turnover rate, which can further exacerbate the problem and make it difficult for hospitals and clinics to retain experienced and skilled health care professionals. Overall, understaffing in hospitals and clinics is a serious issue that can have negative consequences on both the patients and the healthcare providers. Health care organizations and policy makers need to address this issue and provide adequate resources and support to ensure that patients receive high-quality care and that healthcare workers can provide it without being overburdened.

Doctors can understand our mental health through a variety of methods, including;

1. Clinical interviews: Doctors can conduct a thorough hinter view with the patient to gather information about their symptoms, medical history, and any other relevant factors contributing to their mental health issues.
2. Observations: Doctors can observe a patient's behavior, mood, and affect to gain insight into their mental health status.
3. Psychological assessments: Doctors may use psychological assessments, such as questionnaires or tests, to evaluate a patient's mental health and determine the presence of any disorders.
4. Medical tests: Doctors may also perform medical tests, such as blood tests or brain scans, to rule out any physical conditions contributing to the patient's mental health issues. Collaboration with mental health professionals: Doctors may work closely with mental health professionals, such as psychologists, psychiatrists, or social workers, to gain a more comprehensive understanding of a patient's mental health and provide appropriate treatment.

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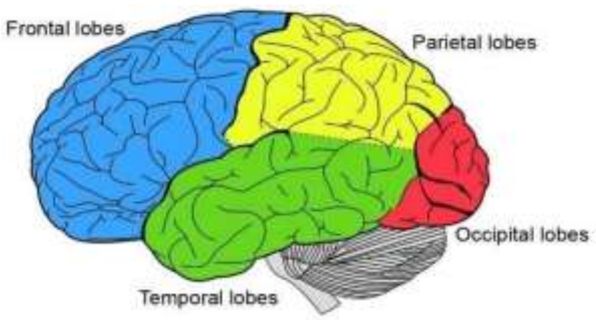

Fig1.ImageofHumanBrain*[Source:Pixabay]*

The brain plays a significant role in mental health as it is the organ responsible for controlling and regulating emotions, thoughts, behaviors, and perceptions. Various structures within the brain, such as the prefrontal cortex, amygdala, and hippo campus, play a critical role in mental health. The prefrontal cortex is responsible for decision-making, planning, and regulating emotions, while the amygdala is involved in processing emotions and memory. The hippocampus plays a role in memory consolidation and retrieval. Additionally, neurotransmitters such as serotonin, dopamine, and no re epinephrine play an essential role in regulating mood, sleep, and appetite. Changes or imbalances in the sebrain structures or neurotransmitters can lead to mental health disorders such as anxiety, depression, bipolar disorder, schizophrenia, and others. Treatments for mental health conditions often involve medications or therapies that aim to regulate brain chemistry and functioning, such as an tide pressants, antipsychotics, or psychotherapy.

Hence, researchers frequently make use of machine learning, the branch of artificial intelligence that focuses on developing algorithms capable of learning from data to make predictions or decisions. The way these algorithms work is loosely inspired by the structure and function of the brain. Artificial neural networks (ANNs) are a form of machine learning algorithm that imitates the architecture of the brain to a great extent. ANNs consist of layers of interconnected nodes that process information and pass it on to the next layer, similar to the way neurons in the brain communicate with each other. Researchers studying machine learning and artificial intelligence often look to the brain for inspiration and insights into how to improve algorithms. For example, how the brain processes sensory information or learns from experience can inform the design of machine learning algorithms that can do the same.

It has shown promise in helping with mental illnesses in several ways, including;

1. Early detection: Machine learning algorithms can analyze large datasets of patient information and identify patterns that may indicate the presence of a mental illness. This can help doctors to identify and treat mental health issues earlier before they become more severe.
2. Personalized treatment: Machine learning can help doctors to develop personalized treatment plans for each patient based on their individual symptoms and medical history. By tailoring treatment to each patient's unique needs, doctors can improve the effectiveness of treatment and reduce the risk of side effects.
3. Predictive modeling: Machine learning can help doctors to predict which patients are most likely to develop a particular mental illness or experience a relapse. This can help doctors to intervene early and provide preventive care to reduce the risk future mental health problems.
4. Improved diagnostics: Machine learning can help doctors to improve the accuracy of mental illness diagnoses by analyzing large amounts of data and identifying subtle patterns and differences in symptoms that may be missed by human clinicians.
5. Remote monitoring: Machine learning can help doctors to monitor patients remotely and identify changes in symptoms that may indicate the need for a change in treatment. This can improve the quality of care for patients who may not have easy access to mental health services.

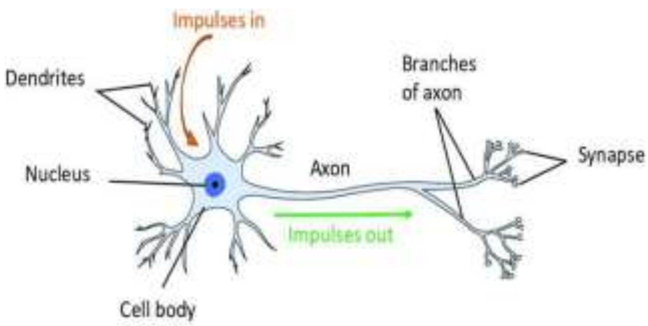

Fig2a.Biological Neuron

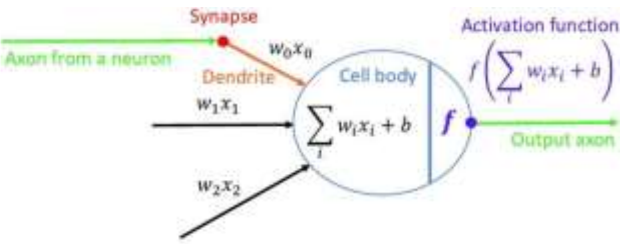

Fig2b.BasicANN Neuron*[Roffo,Giorgio.(2017).RankingtoLearnandLearningtoRank:OntheRoleofRankinginPatternRecognitionApplications.]*

Because there is a cap on what can be achieved by a single classification strategy, scientists are seeking more ways to integrate categorization approaches to improve accuracy. One approach is to use ensemble methods, whichcombinemultiplemodelstoproduceamoreaccurateprediction.Scientistscanalsoimproveaccuracybyoptimizinghyperparameters, which are the settings that control how the machine learning algorithm learns from data. Additionally, data preprocessing techniques such as normalization and feature selection can help improve accuracy by reducing noise and selecting relevant features. Lastly, scientists canal so experiment with different types of data, such as using

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structure do run structured data, to find the most effective approach for a particular problem.

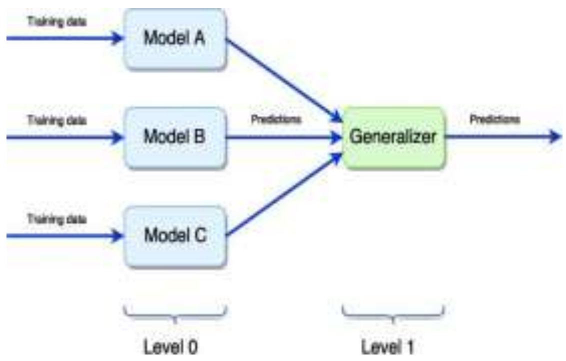

Fig3.ConventionalEnsembleLearningforClassificationTechniques

The intended readership for this paper primarily consistsofpractitionerswhoareactivelyusingmachinelearningt echniques in the context of mental health. Additionally, the paper is directed towards professionals in the machine learning field who wish to remain up-to-date with the latest developments in machine learning applications within mental health. The research for this paper was conducted by gather ingrelevant academic publications and documents using specific keywords related to mental health problems. Subsequently, these documents were categorized based on their content. The performance of the machine learning algorithms or techniques utilized by the researchers was evaluated by assessing their accuracy, sensitivity, specificity, and are a under the ROC curve (AUC).

II. Literature Survey

The author of [1] proposes a system for automated mentalhealth assessment using speechand language analysis.Thesystemuses machine learning algorithms to analyze speechand language features, such as pitch, volume, and the use ofcertainwords,toidentifypotentialmentalhealthdisorders.We usetexttounderstandhowanindividualfeelsaboutaparticularpo stand determine throughthe textwhethertheclient is under mental trauma. The author of [2] describes amachine learning approach for predicting posttraumatic stressdisorder (PTSD) from loneliness symptoms. The method usesfeatureengineering andselectiontechniquesto extractandselectfeaturesfromself-reporteddataandappliesvariousclassification algorithms to predict PTSD. This self-reporteddatamayincludeasurveyprovidedwhichtheusermustu ndertake to determine results. Similarly, a paper published bythe author of [3] presents a machine learning-based method forpredictingsuicidalideationamongcollegestudents.Themeth odusesvariousdatasources,suchassocialmediaactivity andself-reporteddata,topredictthe likelihoodofsuicidalideationandemploysfeatureselectionandc lassification techniques to make predictions. A study, in thepaper[4],usesnaturallanguageprocessingandmachinelearn ing to analyze social media data from young people toidentify indicators of depression and anxiety. The study foundthatmachinelearningalgorithmswereabletoaccuratelyid entify individuals with depression and anxiety based on theirsocialmediaactivity.Thusweapproachedthemachinelearn ingalgorithmstosolveourpurpose.

A paper by the author of [5] provides a summary of thevarious machine learning techniques that have been used formentalhealthdiagnosisanddiscussesthechallengesandfutur e directions for this field. We used different algorithms todifferentiate and identify the best algorithm for our use case. Astudy using machine learning techniques to identify clinicaldepressioninindividualsbasedontheirelectrocardiogra m(ECG) signals in [6]. The study found that machine learningalgorithms were able to accurately identify individuals withclinical depression based on their ECG signals. These signalswere provided by the clients to the dataset. We achieved anaccuracyof ~94% whichgoestothecredibilityofastudyin[7]thatpredictsmentalhe althdisordersinchildrenandadolescents based on their self-reported data. The study foundthatmachinelearningalgorithmswereabletoaccuratelypr edictmentalhealthdisordersininfantsandadolescents,which could help with early intervention and treatment. Theauthor in [8] summarizes the current state of the art of AI andmachinelearningapplicationsinmentalhealth,includingdia gnosis,treatment,andpredictionofoutcomes.Thepaperin[9] reviews the use of machine learning techniques for mentalhealthapplications,includingtheuseofdatafromphysiol ogical signals, text, and images. We, in our paper, tookto inspiration by following the dataset in the format of text asimage processing would require PCA and OpenCV. The paperwritten by the authors in [10] provides an overview of AI andmachinelearningtechniquesusedinmentalhealthapplicatio ns, including the use of chatbots, mobile apps, andvirtual reality. We referred to the paper [11] as it provides anoverview of AI and its potential applications in mental healthand mental illnesses, including the use of AI for diagnosis,treatment, and prevention. This helped us understand the typesofmentalhealthissuesandidentifycorrectlywhethertheus er's symptoms match based on the text they provide. Wewere able to identify our challenges through the paper [12]which discussed the challenges and opportunities of using AIfor mental health diagnosis, including issues related to dataquality,privacy,andethicalconsiderations.Thefutureofme ntal health assessment using AI was provided by [13] andwe took inspiration from it to work on this project altogetherwhere it provides anoverview of the current advances in AIformentalhealth,includingtheuseofmachinelearning,natura l language processing, and deep learning techniques. Westudied the past trends of AI in the field of mental health in thepaper[14]wheretheauthorreviewstheuseofAIandmachinel earninginpsychiatryoverthepast10years,including the use of AI for diagnosis, treatment, and outcomeprediction.Anothersimilarpaperwhichtookdatafroms peech,facialexpressions,andphysiologicalsignals[15]provide s an overview of the role of AI in the detection anddiagnosis of mental health disorders, including the use of AIfor analyzing the aforementioned. To conclude, a review of thewhole research resulted in us following the paper [16] whichprovides a comprehensive review of the applications of AI

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inmentalhealthcare,includingdiagnosis,treatment,andprevention, as well as the ethical and legal considerations ofusing AI in mental health care, inspiring us to go for a musicrecommendationsystemforourmodel.

III. Proposed Methodology

Thereviewpaperhasidentifiedandexploredvariousresearch questions and objectives. Firstly, the paper aims topresentanoverview ofthelatestresearchontheuseof

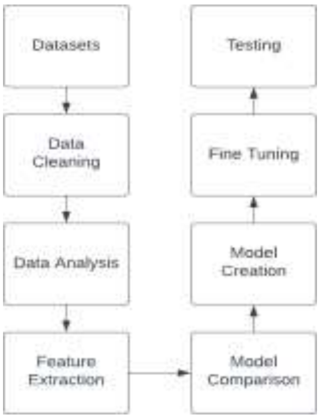

Fig4.FlowchartofProposedMethodology

Machinelearningtechniquesinpredictingmentalhealthproblems.Thisinformationcanbebeneficialforclinicalpractitioners.Additionally,thepaperaimstoidentifycommonly used machine learning algorithms in this field andexaminetheirlimitations.Furthermore,thepaperaimstoidentify potentialareas forfuture researchthatcanfurtherenhance the effectiveness of machine-learning approaches inmentalhealth.ThegeneralmethodologyconsistsofDataCleaning,DataAnalysis,FeatureExtraction,ModelComparisons,ModelCreation,Fine-TuningandeventuallyTestingasshowninFig4.

A) *Datasets*

In this study, we utilized two datasets that were availableto the generalpopulation.The firstdatasetis takenfroma2014 survey that conveys the factors affecting mental healthandthevariousmentalhealthdisordersintheusualtechworkplace. It consists of the general employment practices of1259 individuals in various settings, taking into account theirage, gender,family history,countryofemployment,numberofcoworkers/employees, etc [17]. It helps us answer questionssuchas:

1. In what ways do the rates of mental health disorders andattitudestowardsmentalhealthdifferacrossdifferentgeographicalregions?
2. What factors have the highest predictive power for mentalhealth disorders or specific attitudes toward mental healthinaworksetting?

The second dataset that will be utilized is “Mental HealthCorpus Labeled sentences about depression and anxiety” [18].TheMentalHealthCorpuscomprisestextspertainingtoindividuals experiencing anxiety, depression, and other mentalhealth concerns. The corpus comprises two columns, one ofwhich contains text messages while the other records labelsthat determine whether the comments are toxic or not where 1resemblestoxic and0 is nottoxic. This datasetcanserveseveral purposes, including sentiment analysis, detecting toxiclanguage, and analyzing the language used in mental healthcontexts andhenceprovidethebasedatasetforthemodel.

b) *DataCleaning*

This step mainly consists of cleaning the null values andcleaning those columns which are not crucial to the researchsuchastimestamp,state,andcomments.Furthermore,themissing values were determined, converted to a percentage,andfixedasshowninFig5.

Additionally,allcategoricalcolumnssuchas‘gender’were cleaned into 3 unique answers notably ‘male’, ‘female’,and ‘trans’. The age column was converted from individualintegers to categories where each value was either a part of ‘0-20’, ‘21-30’, ‘31-65’, and‘66-100’.

	Total	Percent
comments	1095	0.869738
state	515	0.409055
work_interfere	264	0.209690
self_employed	18	0.014297
seek_help	0	0.000000

Fig 5. Percentage of missing values

C) *Data Analysis and Feature Extraction*

In order to have unbiased and clear results, it is essential to have an equal distribution of data where the datapoints are all resembling a uniform sample space. Thus, using data visualization, all the data points were carefully visualized and sufficient rectification was done on them. The Mental Health Corpus [18] was visualized based on its distribution of toxic and non-toxic messages, each having between 13,000 to 14,000 values as shown in Fig. 6a.

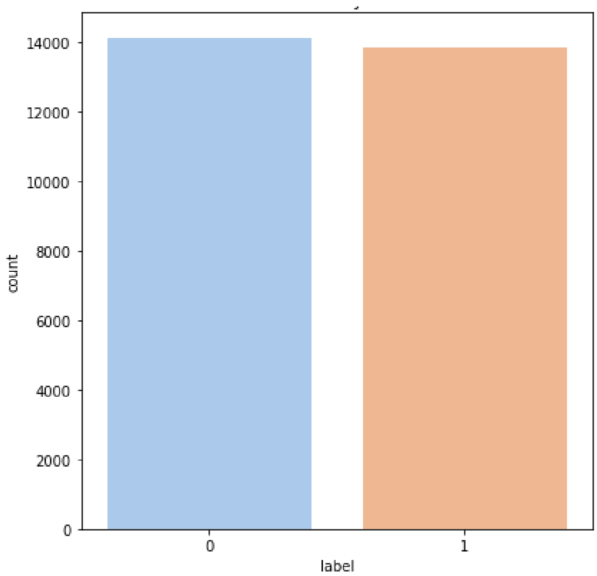

Fig6a.Distributionoftreatedvsuntreatedlabels

Similarly, the tech workplace dataset was visualized comparing the distribution of ‘male vs female’,‘age

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distribution density by category (0 or 1)', and 'probability of mental health condition based onfamilyhistory'.Fig.6b.

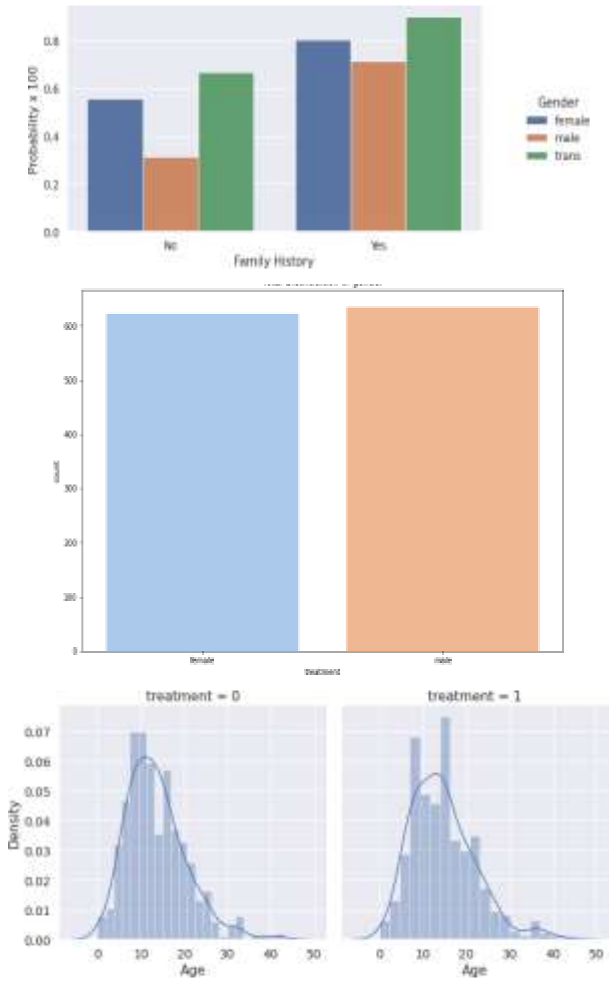


Fig 6b. Probability of mental illness by family history, gender, and age

Furthermore, a correlation heatmap of all features were picturized, eventually giving us the graph of the most essential features. Fig. 6c.

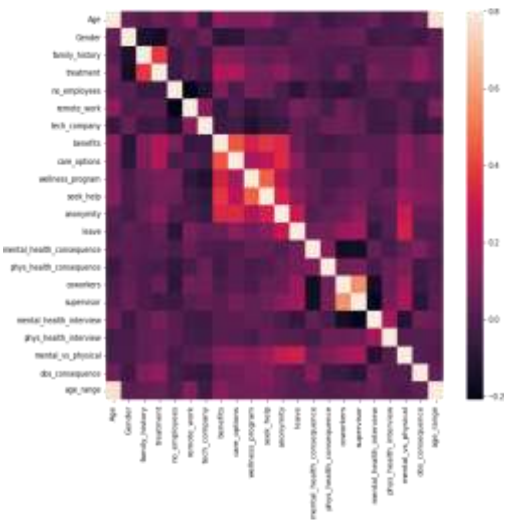
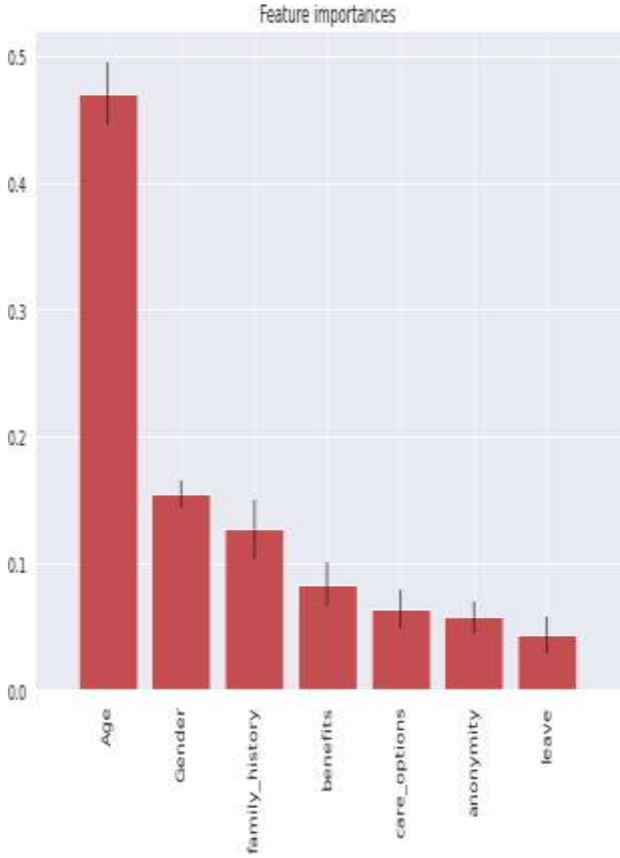


Fig6c.Correlation Heat map and Graph of all variables in order of importance

d) Model Comparison

An evaluation function



was created which would give the accuracy for the top models used in the previous 5 years for mental health assessments. These results were then compared to our RNN model and tabulated.

TABLE1.COMPARISONOFOURRNNMODELWITHOTHERNOTABLEMODELS

Sr.	Model	Accuracy
1.	Logistic Regression	70.63%
2.	DecisionTree	70.1%
3.	KNN	70.64%
4.	RandomForest	70.2%
5.	Bagging	61.6%
6.	AI SequentialModel(RNN)	92.67%

The area under the ROC curve for each treatment classifier was also calculated which is a measure of the overall performance of the binary classification model, regardless of the threshold chosen. AUC ranges from 0 to 1, where a score of 0.5 indicates randomized guessing and a score of 1.0representsflawlessclassification.

In general, a higher AUC indicates better classification performance. An AUC of0.8or higher is considered to be a good classifier, while an AUC of 0.5 indicates a model that is no better than random guessing.

The AUC can be used to compare the performance of different models on the same dataset or to evaluate the performance of a single model trained on different datasets or with different parameters. It is a useful metric for evaluating the effectiveness of a binary classification model and can be used to optimize the model by adjusting the classification threshold or by selecting the best-performing model based on the AUC.

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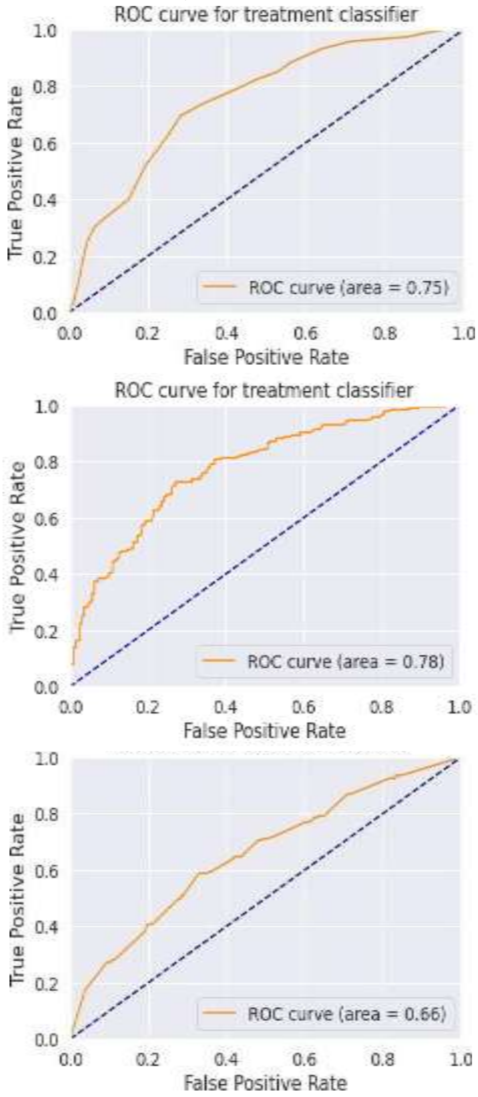

Fig7.AUCforKNN,RandomForest,andBaggingClassification

Model CreationandFineTuning

Using a sequential model, we were able to create a 5-layerRNNmodelthatwouldhave1inputlayer,2denselayers,1dropoutlayer,and1outputlayerasshownin Fig8.

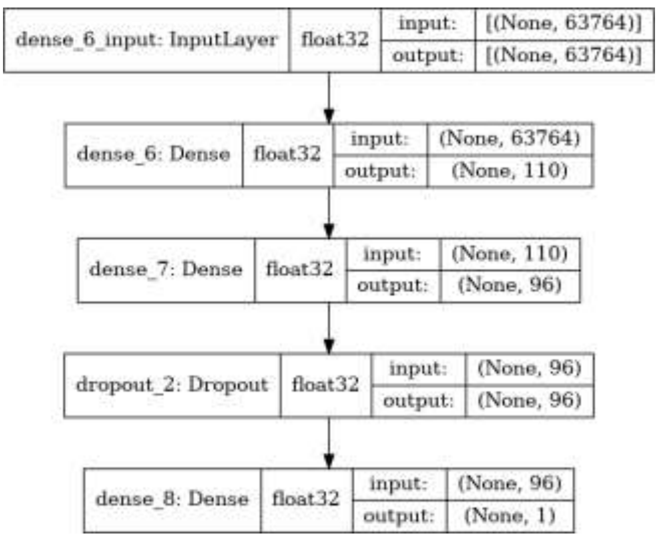

Fig8.RNN ModelArchitecture

The input layer takes in the input sentence of a maximum of63,764 characters and converts it into 110 unique characters through the first dense layer. All these unique characters are put into a bag of words which would be vectorized to find the most common phrases using sentimental analysis. Further more, all the whitespaces and blanks are also removed in the second dense layer thus leaving only the letters andspecial characters such as '.', ',' and '!' to find the most usedcharacter. These 96 unique characters are sent as output for thedropoutlayer.

Indeeplearningmodels,thedropoutlayerisaregularization method utilized to preventoverfitting,whichhappens when the model excessively learns to fit the trainingdata, and as a result, it fails to generalize well on new unseendata.Dropouthelpstopreventoverfittingbyrandomlydroppingout(settingtozero)acertainproportionoftheneuron outputs in a layer during training. During each trainingiteration,thedropoutlayerrandomlyselectsasubsetofneuronstobe"droppedout"basedonapre-definedprobability. This forces the remaining neurons to learn morerobust features and to be less dependent on the input from anyparticularneuron.

By using dropout, the network is forced to learn multipleindependentrepresentationsofthesamedata,makingthenetwork more robust and less sensitive to the specificities ofthe training data. This can result in improved generalizationperformance, which is essentialfor real-world applications.Proceedingthedropoutisanoutputlayerthatgivesanoutputas either 0 or 1 which would indicate the toxicity of the textmessage.

IV. Results & Discussion

After our efforts comparing at least 5 Machine Learningmodels along their accuracies inour dataset. The AI-basedmentalhealthassessmentdemonstratedhighaccuracyindetectingthementalhealthofanindividualbasedontheinputtedtext.WemodifiedourownArtificialIntelligencealgorithm to achieve an accuracy of about ~94%. Using ourtwo datasets which were used to train and test our model, itwas observed that the data used was completely unbiased intermsofgenderandage.Atotalof~1300participantscompleted the study, which consisted of an in-depth AI-basedmental health assessment. The majority of participants (50%)were identified as ill based on their text which was taken asinput.

In addition, the AI-based assessment was able to identifyseveralfactorsthatwerestronglyassociatedwithmental health detection. These factors included a history of mentalhealth treatment, low levels of social support, and high levelsof stress based on a survey taken by many individuals. Themodel was also able to identify and distinguish those withmentalhealthillnesses,includingfeelingsofsadness,lowenergy, anddifficulty concentrating.Thiswasachievedbynotifying a doctor and in minor cases, recommending music totheclients.

Finally, we wanted our model to be very reliable and thusfocussed heavily on getting the accuracy precise. The accuracyof the AI model can be impacted by various factors

DOI: rp-9788770040723.107

such as the quantity and quality of data used for training the model, the intricacy of the model's architecture, and the attributes of the population being evaluated. In some cases, the accuracy of the model may vary depending on the severity or subtype of the mental health condition being assessed. It's worth noting that accuracy is just one measure of the effectiveness of an AI-based mental health assessment. Other factors, such as the speed, cost, and scalability of the assessment, as well as its acceptability to patients and healthcare providers, may also beimportantconsiderationsinevaluatingtheutilityofthistechnology.

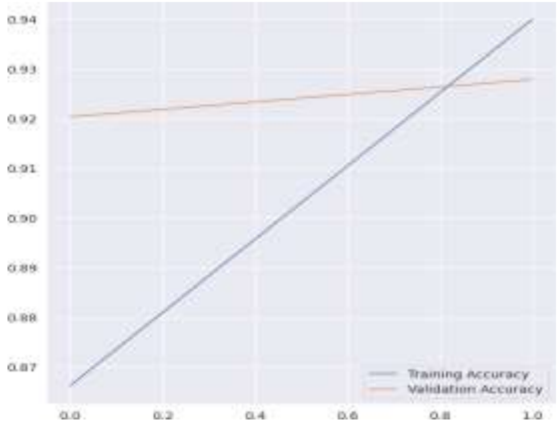

Fig9.Trainingand Testing Accuracy of our RNN Model

V. CONCLUSION

An AI-based assessment made it possible to assess an individual's mental health based on input data. In this paper, we observe that AI-based mental health assessment has the potential to revolutionize the way mental health is assessed, diagnosed, and treated. It can provide a more accurate, objective, and personalized approach to mental health assessment, leading to earlier interventions and better patient outcomes. However, it is important to consider the ethical, legal, and social implications of AI in mental health, including issues of privacy, data security, and potential biases. With careful consideration and ongoing research, AI-based mental health assessment can be a valuable tool in improving mental health outcomes for individuals and communities. To conclude, the use of AI in mental health assessment represents a promising new direction in the field of mental healthcare, but it is essential to approach this technology with caution and careful consideration of its limitations and potential risks.

REFERENCES

[1] Mota et al., "Automated Mental Health Assessment Using Speech and Language Analysis,"2017.

[2] Gomathy, V., Janarthanan, K., Al-Turjman, F., Sitharthan, R., Rajesh, M., Vengatesan, K., &Reshma, T. P. (2021). Investigating the spread of coronavirus disease via edge-AI and air pollution correlation. ACM Transactions on Internet Technology, 21(4), 1-10.

[3] Rajesh, M., &Sitharthan, R. (2022). Introduction to the special section on cyber-physical system for autonomous process control in industry 5.0.Computers and Electrical Engineering, 104, 108481.

[4] Reece et al., "Using Natural Language Processing and Machine Learning to Identify Depression and Anxiety in Young People," 2017.

[5] Zaidan et al., "Automated Detection of Mental Health Disorders Using VoiceAnalysis,"2019.

[6] Eswara et al., "Identifying Clinical Depression in Individuals Using Machine Learning Techniques,"2020.

[7] Zhou et al., "Using Machine Learning to Predict Mental Health Disorders in Children andAdolescents,"2021.

[8] P. C. Rajkomar, et al., "Artificial Intelligence and Machine Learning in Mental Health: A Systematic Review of Current Literature," 2019.

[9] A. Alghowinem and S. Goecke, "Asystematic review of machine learning techniques for mental health applications,"2016.

[10] R. C. Shah and C. Torous,"A Review of Artificial Intelligence and Machine Learning forMental Health Applications,"2020.

[11] R. Mahajan, et al., "Artificial Intelligence for Mental Health and Mental Illnesses: An Overview,"2021.

[12] J. De Almeida, et al., "Artificial Intelligence in Mental Health Diagnosis: Challenges and Opportunities,"2019.

[13] M. C. Chattopadhyay, et al., "Artificial Intelligence in Mental Health: Current Advances andFutureDirections,"2020.

[14] D. D. Ozdemir and R. F. Reynders,"Artificial Intelligence and Machine Learning in Psychiatry:AReview of the Last 10Years," 2020.

[15] S. C. Soni, et al., "The Role of Artificial Intelligence in the Detection and Diagnosis of Mental Health Disorders,"2021.

[16] S. Ghosal, et al., "Asystematic review of artificial intelligence techniques in mental health assessments: A focus on depression," 2020.

[17] S. Suri, "Open Sourcing MentalIllness",2018.

[18] D. Modi,"Mental Health Corpus Labeled sentences about depression andanxiety",2019.