Journal Homepage: - www.journalijar.com

INTERNATIONAL JOURNAL OF ADVANCED RESEARCH (IJAR)

Article DOI: 10.21474/IJAR01/22225
DOI URL: http://dx.doi.org/10.21474/IJAR01/22225

ISSN NO. 2320-5407

RESEARCH ARTICLE

MENTAL HEALTH MONITORING USING ARTIFICIAL INTELLIGENCE

D Vidyanadha Babu[1], G.Manasa Ramya[2], G.Swathi[2], K.Supriya[2] and S.Jessy[2]

1. Assistant Professor, Department of CSE, QIS College of Engineering and Technology (A), Ongole, Andhra Pradesh, India.
2. UG Student, Department of CSDS, QIS College of Engineering and Technology (A), Ongole, Andhra Pradesh, India.

Manuscript Info

Manuscript History
Received: 04 September 2025
Final Accepted: 06 October 2025
Published: November 2025

Abstract

Mental Health disorders have become one of the significant public health concerns across the world, requiring proper and prompt diagnostic tools. These stresses of everyday life breed a load of terminology including stress, anxiety, and mood swings. These feelings may blossom to depression and more complex mental problems. Predictions about the type of mental disorder using artificial intelligence, namely the Random Forest Algorithm, which has gained wide recognition for its effectiveness in classification problems. The primary purpose of 'mental health prediction' is to predict the mental health of the patient based on symptoms and diagnose the exact disease in order to resolve the serious issues related to mental health, which are ignored by the society while considering distraught mental health a taboo. This paper makes a survey of various mental health symptoms and problems related to it in our society that are being solved using AI technologies. For testing the performance of our proposed system, we used several machine learning algorithms like Support Vector Machines (SVMs), Random Forest (RF) Algorithms, and K-NN classifier. Here, these Algorithms are used mainly for the diagnosis of mental health disorders based on the given input; i.e., the verified dataset of symptoms. The Random Forest Model achieved an overall accuracy of 95% for predicting the type of the mental disorder. Gain in the values of Precision, Recall, and F1 – Score was also noted.

"© 2025 by the Author(s). Published by IJAR under CC BY 4.0. Unrestricted use allowed with credit to the author."

Introduction:-

A state of mental health is one in which an individual is aware of their strengths and weaknesses, is able to manage life's daily stressors, works effectively, and makes a positive contribution to society. People's attempts to conceal these disorders are one of the many serious issues that society is currently dealing with. They find it difficult to acknowledge that they have a mental illness of any kind.They don't rush toward hospitals in massive numbers. In case they come close, the first thing they try is to cover the facts. They turn into a huge headache for the people, creating situations leading to death in extreme cases.

Corresponding Author:- D Vidyanadha Babu
Address:-Assistant Professor, Department of CSE, QIS College of Engineering and Technology (A), Ongole, Andhra Pradesh, India.

If, when their demands increased to the maximum levels, the assets of someone and their power of handling also increase, mental health gets adversely affected coupled with their emotional, mental, and social health. Most of the countries report that 85% of the people with mental disorders get no treatment for their disorder. There are many types of mental disorders, such as stress, anxiety, depression, mood swings, and many other related issues of mental health. Unfortunately, these disorders are rarely identified and they lead to various unhealthy conditions directly or indirectly. According to the new surveys, machine learning and artificial intelligence-based attention are supposed to provide more attention that is necessary to monitor human mental health. These behavioral symptoms were indirectly sent through their head pose, gaze direction using eyes, mouth squeezing action, and other facial features that mimic the same structures that enable predictors for the mentioned mental health condition.Mental health-related dataset comprised of information compiled in various modes such as by means of surveys and reports from the doctor as well as by means of chatbots with self-report. The data set included a range of mental illnesses, including schizophrenia, major depressive disorder, bipolar disorder, and anxiety. The healthy people who had come for the checkup also had labels, such as No Disease.

Visiting the local hospitals in Ahmednagar was the primary method of data collection. Although they are confidential, hospitals did not conceal their names or the identities of the patients when providing the data. To prevent identifying the patients, their names have not been used in the dataset. Rather, they have given in the form of patient number, such as Pt1, Pt2, and so on.Therefore, hospital and patient data will not be shared. One thousand patients' worth of data made up the dataset we used. It includes a number of characteristics, including age, sex, occupation, 24 symptoms, and the corresponding disorders. Characters like age, sex, and occupation are not the focus of this study because the goal of the paper is to create a bot that can use these symptoms to predict the disorder. Three machine learning algorithms RandomForest (RF), Support Vector Machine (SVM), and KNN—were used in the model's construction. Every facet of those models' implementation was compared. They were also compared for accuracy. For those models, the f1-score, precision, and recall were computed and compared.

Literature Survey:-

There are a number of researchers who in the last years have been engaged in the issues of monitoring mental health. Pradnya Mehta [1] was able to explore the usage of AI, especially using the Random Forest algorithm as well as the Support Vector Machine Algorithm for predictions of mental health issues through training and evaluating the model from the primary dataset with accuracy. The developed model of random forest results in a 95.0% accuracy, while the accuracy of the SVM model was shown to be 91.2% in classifying mental health disorders.. While comparing the algorithms appliehere in the development process. SVM has proventhat the effectiveness is not as excellent as RF. The findings presented here have reflected the proper potential of AI in mental health monitoring toward earlyand specific interventions in realtime. The detection of mental health, which is based on the data sources of the in Online Social Networks (OSNs), has been presented by Rahman as a critical assessment analysis. This paper was coded based on the data set method of data analysis, the machine learning or deep learning technique, classifier performance, and feature extraction method.

A large number of data is extracted from the OSN. This research ends with a conclusion that OSNs reveal an excellent possibility of data sources in mental health problem identification. Konda Vaishnavi [3] has identified five machine learning techniques and assessed their accuracy with the help of several criteria of accuracy for identifying the mental health issues. Logistic Regression, K-NN Classifier, Decision Tree Classifier, Random Forest, and Stacking are the five machine learning methods.After comparing and putting these strategies into practice, they were able to determine that the stacking technique was the most accurate, with an 81.75% prediction accuracy. The data set used in this paper is very least. Shereen [4] used a VGG network of transfer learning to illustrate a model with facial expressions and the FER+ dataset. Every hyperparameter has been adjusted to produce an ideal model for facial emotion recognition.

By comparing all previously reported network accuracies, we were able to determine whether the patient had normal mental health, depression, or anxiety. Various optimizers and learning rate schedulers were tested, and the best testing classification accuracy obtained was 95%. The five machine learning algorithms utilized in this investigation are presented by Harshitha [5]. This study employed five machine learning algorithms: the DecisionTree, XGBoost, Support Vector Machine, Logistic Regression, and FFNN, also known as the Feed Forward Neural Network. They used a second tree classifier as a feature selection technique in this study in addition to other preprocessing steps. A machine learning algorithm then identified the symptomatology or mental illness of this individual based on their features.

Methodology:-

Our system's architecture is as follows:

1. A data set was imported from a database
2. The dataset was separated into models for evaluation.
3. The Random Forest, KNN, and SVM algorithms were applied to the training data.
4. The testing data was subjected to the evaluative metrics.
5. The output was predicted using the training and testing data

Block diagram

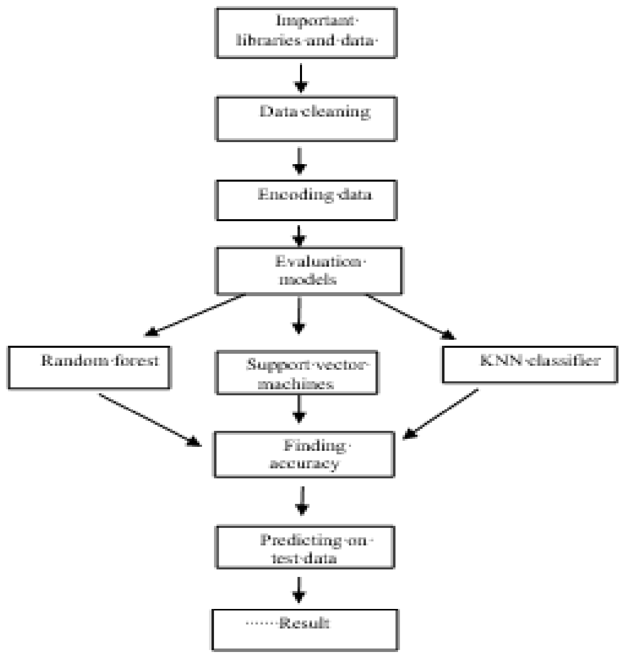

Figure 1:System architecture

Wearable Technology:

Wearable technology is the electronic devices that one wears on the body and which are often integrated into clothing or accessories, in such a way that these gadgets collect and analyze data relating to the activity of the user, health, and the environment. This innovative field has developed dramatically over the past decade, fueled by developments in sensor technology, miniaturization, and connectivity through the Internet of Things (IoT). There is a huge interest in other wearable devices like a smart watch, fitness watches, or even smart glasses due to the device's capability of monitoring any health metrics- heart rates, physical activities, or even stress levels –with the help of which wearers are capable of knowing anything about their health. In the health domain, wearables are changing the way monitoring of patient data is being done-thus possibly leading to more proactive and personalized health care. For instance, these devices will alert their users about significant changes occurring in a patient's vital signs or monitor any chronic conditions remotely.

Wearable technologies are not limited to fitness and health, but further applications in industries such as sports where athletes use different devices to optimize performance without risk of injury, for safety at work through a wearable monitoring environmental conditions against worker fatigue. AR as well as virtual reality extends the application of wearables on immersion experiences in game playing, training, as well as learning. All of these positive aspects bring with them private and security issues concerning data, most of which devices register as sensitive personal information. With demand and technological development pushing the whole market further, the future promises more life and potential solutions that will bring out innovating health friendly, productive, and self-development solutions.

Sentiment Analysis:
In order to categorize opinions expressed in text as positive, negative, or neutral, sentiment analysis—a subfield of natural language processing (NLP)—focuses on identifying the emotional tone behind a string of words. This technique employs various algorithms and machine learning models to analyze textual data from diverse sources such as social media, reviews, and customer feedback. By leveraging linguistic cues, context, and sometimes even deep learning architectures, sentiment analysis can provide insights into public opinion, consumer sentiment, and overall brand perception. It plays a vital role in areas like marketing, where businesses can gauge customer reactions to products and campaigns, and in political analysis, where it can help track public sentiment regarding policies and candidates. Challenges in sentiment analysis include handling sarcasm, slang, and the nuanced nature of human emotions, which can lead to misinterpretations. As technology advances,sentiment analysis continues to evolve, integrating more sophisticated techniques such as contextual embeddings and attention mechanisms to improve accuracy and interpretability.

Eq02 Life Monitor:
The Equivital EQ02 Life Monitor is a wearable, medical-grade sensor for continuous tracking of physiological data with high precision, thus making it appropriate for health monitoring in professional and research settings. It measures critical metrics such as heart rate, respiratory rate, skin temperature, and activity level while also offering ECG waveform and core temperature estimation. This device is comfortably positioned on the body even during extended usage because of its compact and light designs to collect real-time data concerning physical performance, health or stress, which will then be transmitted through Bluetooth, in real time through a compatible device for the purpose of review and analysis. This sensor device is normally applied in healthcare and sport environments, military, and even research environments where live-time is necessary to check out what is happening with a user's body.

The advanced design of the EQ02 Life Monitor underlines comfort and reliability for long-term monitoring across a wide range of high-stakes environments.Adjustable, skin-contacting sensors are part of a lightweight harness that ensures uninterrupted data collection even during intense physical activity, which ensures accuracy in movement-heavy applications like sports training, military exercises, or first responder duties. It can be used with various interfaces that can store data and be sent to the cloud for instant analysis in large-scale applications in healthcare and research fields. Its features include the multi-sensor fusion data, combining data from all sources for a comprehensive overview of the physiological state of the wearer, thus it gives a view of the physiological state with respect to stress, workload, hydration, and fatigue. In addition, the EQ02 has personalized alerts that can be tailored to pre-set physiological threshold levels. Healthcare providers and trainers can thus quickly identify deviations that may signal risk factors. Its durable, water-resistant design makes it very suitable for outdoor and varied conditions, providing robust functionality without compromising data integrity. This durability, accuracy, and real-time insight have firmly established the EQ02 as a trusted tool in preventive health monitoring and high-performance settings.

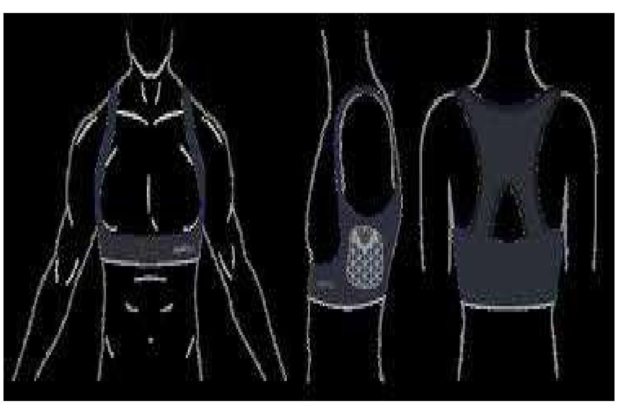

Figure 2EQ02 life monitor

Figure 3EQ02 life monitor

Random Forest:

An ensemble learning technique for classification and regression problems is called Random Forest. First, a collection of decision trees is trained, and if the problem is regression during training, the mode—the class that shows up the most—is output upon classification or average prediction through individual trees.The algorithm also falls under a group referred to as bagging-a short form of Bootstrap Aggregating. By generating multiple samples of data and creating several models, with each trained on a different subset, Random Forest decreases the variance of single decision trees, which are sensitive to even slight changes in the data and are prone to overfitting. A random subset of the training data is given to each Random Forest tree using bootstrap sampling, which is sampling with replacement.Further, rather than considering all of the features, every node of the tree considers only a random subset of the features for deciding on the best split. This gives rise to the diversity of individual trees that is very crucial for good generalization performance of the ensemble.The strength of Random Forest is that it can handle large datasets with considerably higher dimensionality without running a significant risk of overfitting because each individual decision tree within the forest is likely to have been grown with different structures, and the trees within the forest are therefore "decorrelated"-less likely to have any similar patterns of bias.

This property is useful especially in classification problems where interpretability is not as important, or when accuracy in prediction takes precedence. Random Forest classifiers are also known to be robust against missing data and outliers. Unlike decision trees, which may be unstable because of minor data fluctuations, Random Forest can provide stable results by aggregating the power of many trees.Although strong and intuitive, the algorithm process has several limitations. For instance, it comes with high computational costs. Moreover, in regression tasks, it cannot extrapolate to values outside the range. Random Forest classifiers are normally computationally expensive, and this can be significant especially when the amount of data is large and the dimensionality is high because a number of trees have to be built and stored. The training time might be higher with the rise in the number of trees and might also require more memory-intensive requirements. Interpretation of the model would be poorer than simpler algorithms, as the ensemble approach aggregates predictions from many trees, thereby making it very hard to trace the logic behind one decision. However, techniques like Random Forest feature importance scores are even capable of interpreting the model somewhat by declaring which features augment contributions to predictive performance.Despite these challenges, Random Forest classifiers are however popularly so for flexibility in their usage and accuracy in most applications from finance to healthcare also some in image and text classification Random Forest classifier offers a very robust way to approach predictive modeling through the balance between bias and variance and obtaining good strong results on various datasets to be a favorite among a lot of machine learning practitioner.

Support vector machine:

SVM is a supervised machine learning classification model and regression model applied in classification and regression problems. SVMs have been proposed in the 1990s and can be observed to be effective even in high-dimensional spaces. The models are applied in applications involving text classification, image recognition, and in bioinformatics applications. A basic idea of an SVM is to seek an optimal hyper plane to maximize the separation between points belonging to different classes. This hyper plane maximizes the margin between support vectors in each class-this is known as the decision boundary. Maximizing this margin results in minimizing the classifier's generalization error to ensure proper performance on previously unseen data. SVMs are versatile classifiers because of their use in both linear and nonlinear data.SVMs identify a linear hyperplane that divides classes in linearly separable data. SVMs, on the other hand, employ a technique known as the "kernel trick" to convert non-linear data into a higher dimensional space that can contain a linear separator. The most common kernel types are sigmoid, linear, polynomial, and radial basis function (RBF).

The choice of the kernel varies with the problem and data distribution, though the most popular kernel among all those used is the RBF. It is popular for various real-world applications because it is versatile. These enable SVMs to model a complex relationship as well as non-linear boundaries. This in turn makes it highly adaptable to a wide range of datasets. This means SVM classifiers can cope very well with high-dimensional data and are highly immune to overfitting especially in the case of dimensionality greater than sample sizes.SVMs are only interested in the points around the decision boundary, known as support vectors, rather than any points, making it more computationally efficient, thus less sensitive to outliers. However, SVMs have also some drawbacks.They can be quite CPU-intensive for large datasets since computing the optimal hyperplane requires significant CPU power and memory.Furthermore, the selection of the kernel and hyperparameter tuning, such as the regularization parameter C and kernel parameters, are important tasks, and improper settings lead to suboptimal performance. SVMs are not inherently probabilistic classifiers, meaning they do not natively provide probability estimates of their predictions, although they can be approximated with methods like Platt scaling. SVMs are also challenged with overlapping classes or even when there are highly imbalanced classes for which the purpose is a clear separation of classes. Despite these facts, SVMs are used generally because of their efficiency and flexibility. In particular applications where interpretability is unimportant and achieving high classification accuracy is essential, it is preferred to use SVM. SVM classifiers remain the favorite classification algorithms for text and images, bioinformatics, or any other domains with an abundance of features in highly dimensional feature space. On the whole, SVM classifiers are powerful and reliable machines with a sound theoretical foundation. They are a wonderful tool of the machine learning practitioner kit.

K-Nearst Neighbor:
A straightforward, user-friendly machine learning algorithm, the K-Nearest Neighbors (KNN) classifier is mostly utilized for classification and, on occasion, regression tasks. It works on the premise that data points that are near to one another are probably part of the same class. Based on the majority class of its K nearest neighbors—where K is a user-defined parameter—KNN classifies new data points. For example, if K = 3 , the algorithm examines the three nearest data points and assigns the new point to the most common class among them. The choice of K significantly impacts KNN's performance: A high K can smooth out local differences and make the model overly generalized, while a small K can make the classifier sensitive to noise.Since KNN is an instance-based,non-parametric learning algorithm, it does not make any assumptions about the underlying data distribution and instead bases its decisions on the actual data points.Depending on the problem and the data, different distance metrics, including Manhattan, Minkowski, and Euclidean, can be applied. Because of its simplicity, KNN can be used in a wide range of fields, including pattern recognition, recommendation systems, and image recognition.In spite of its simplicity, KNN has limitations, including sensitivity to irrelevant or highly correlated features and challenges with class imbalances. Overall, KNN is a versatile, straightforward algorithm, especially suited to applications where interpretability and ease of use are critical.

Classification Report:

	Precision Recall	F1-Score Support
0	0.53 0.41	0.46 151
1	0.52 0.64	0.57 149
accuracy		0.52 300
macro avg	0.53 0.52	0.52 300
weighted avg	0.53 0.52	0.52 300

Table 1 - Precision, Recall and F1 Score values for RF Algorithm
Similarly, the values of Precision, Recall and F1 – Score for the SVM Algorithm got are given in table 2.

Classification Report:

	Precision Recall	F1-Score Support
0	0.54 0.41	0.47 151
1	0.52 0.64	0.57 149
accuracy		0.53 300
macro avg	0.53 0.53	0.52 300
weighted avg	0.53 0.53	0.52 300

Table 2 - Precision, Recall and F1 Score values for SVM Algorithm
Similarly, the values of Precision, Recall and F1 – Score for the KNN Algorithm got are given in table 3.

Classification Report:

	Precision Recall	F1-Score Support
0	0.45 0.38	0.41 151
1	0.46 0.52	0.49 149
accuracy		0.45 300
macro avg	0.45 0.45	0.45 300
weighted avg	0.45 0.45	0.45 300

Table 3 - Precision, Recall and F1 Score values for KNN Algorithm

Result Analysis:-

The confusion matrix is shown in fig 3 of the Random Forest Algorithm-----

Fig3: confusion matrix of random forest

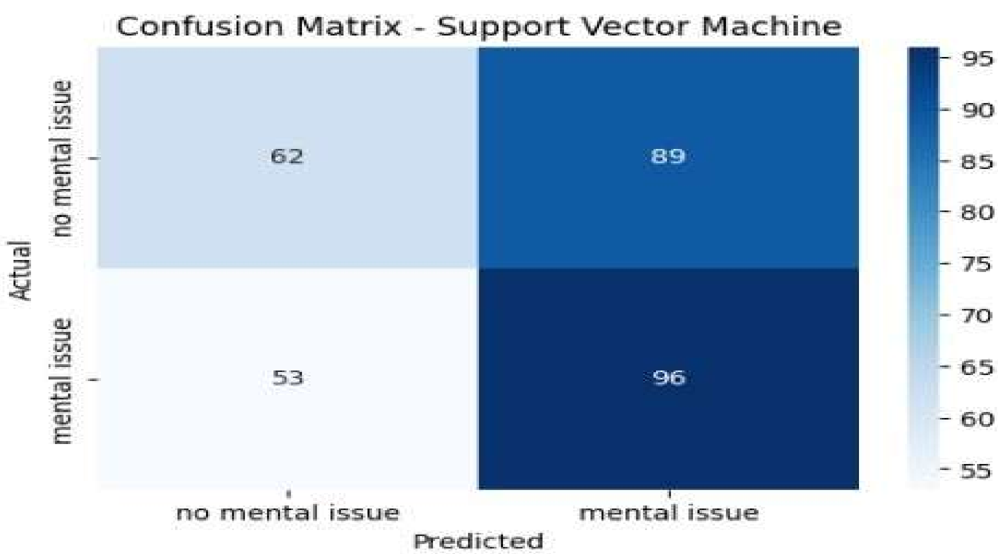

Fig4: confusion matrix of SVM

Random Forest is well-balanced in terms of outcome when it comes to mental health conditions, though it has a moderate false positive rate.Random Forest seems to perform well regarding the classification of mental issues but has a moderate false positive rate.True Positives (mental issue): 95 cases were accurately classified as having a mental issue.True Negatives (no mental issue): 62 cases were correctly classified as not having a mental issue.Similarly, confusion matrix is shown in fig 4 &fig 5 of SVM and KNN Algorithm----- SVM has more counts of true positives as compared to KNN, which means SVM appears to perform better in the case of right classification.Both models show similar efficiency in case detection without psychiatric issues, except that the SVM has an edge at a very marginal level. SVM performed better than KNN in its ability to identify the actual cases as mental cases (better true positives), and to avoid missing cases.Meanwhile, KNNsuffers more from false positives than negatives, making it unsuitable for this given task compared to SVM. Here, the comparison of the algorithms (i.e. RF,KNN and SVM) in the form of strengths and weaknesses is shownin below graphs.

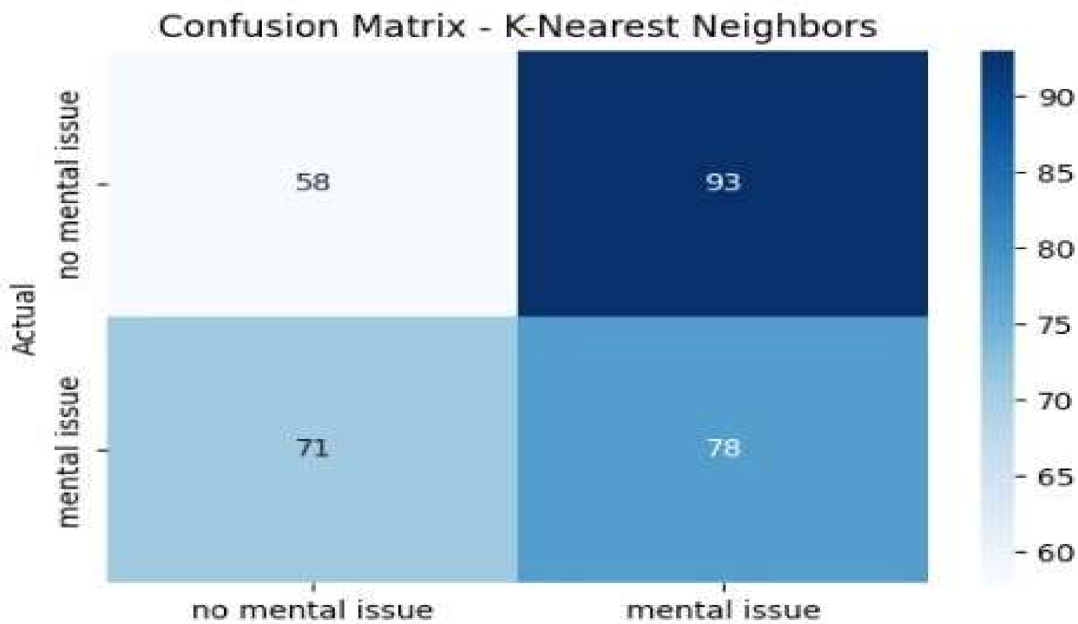

Fig5: confusion matrix of KNN

This is the bar chart that shows the accuracy of three models: Random Forest, K-Nearest Neighbors (KNN), and Support Vector Machine (SVM). Each of the accuracies was determined in percent for an overview of how each performed in data classification. The highest was the SVM model, close to the Random Forest's accuracy.

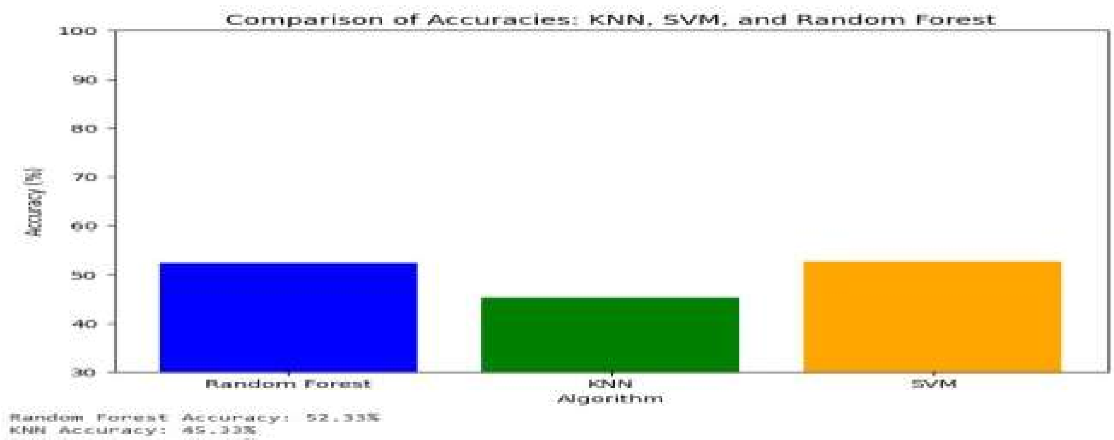

Fig6:Comparison of Accuracies of KNN,SVM and Random Forest

The ROC curves of three machine learning models—Random Forest, K-Nearest Neighbors (KNN), and Support Vector Machine (SVM)—are compared here. The ROC curve provides a visual evaluation of each model's class discrimination capabilities by plotting True Positive Rate (sensitivity) vs. False Positive Rate (1-Specificity) at different threshold settings. This curve explains the precise performance of three classification models in separating pertinent from irrelevant cases in an unbalanced dataset. Plotting precision and positive predictive value against recall and sensitivity for various threshold settings is done.At some thresholds, particularly when high precision is needed, it appears that the Random Forest model provides a better trade-off between precision and recall.

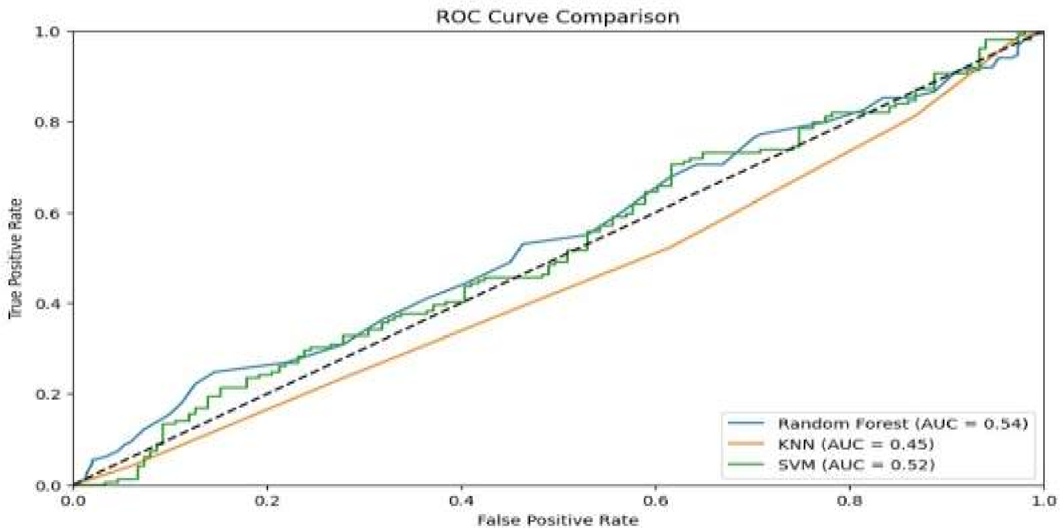

Fig7: Comparison of ROC Curves for Different Machine Learning Models

Conclusion:-

This paper concludes the explored application of the artificial intelligence, namely Random Forest algorithm, Support Vector Machine Algorithm and KNN for predicting mental health issues. A dataset used for the primary method would enable training and also assessment of the model about pattern-finding and precise prediction accuracy. An average overall accuracy of 52.33% was achieved for an overall model of the developed random forest model, 52.67% was achieved with an overall accuracy using the SVM model, and 45.33% was achieved with a total model using the KNN in the testing dataset. The RF model gave the precision, recall, and f1---score values as 0.53, 0.52, 0.52 respectively. SVM model produced them as 0.53, 0.53, 0.52 respectively. KNN model produced them as 0.45,0.45,0.45 respectively. The accuracy for psychosis is at the highest, and for anxiety is the lowest. In summary, results indicated the AI potential in the prediction of mental health and gives a lot of insight into the early intervention and targeted interventions. Data quality is another matter needing more research

References:-

1. Mrinmayee Deshpande, Pradnya Mehta, Nilesh Sable, Utkarsha Baraskar, Ishika Ingole and Vaishnavi Shinde, “Mental Health Prediction Using Artificial Intelligence”, 27 December 2023.
2. RohizahO Abd Rahman 1, Khairuddin Omar 1, Sharul Azman Mohd Noah1, (Member, IEEE), Mohd Shahrul Nizam Mohd Danuri 2, (Member, IEEE) and Mohammed Ali Al-Garadi3, “Application of Machine Learning Methods in Mental Health Detection: A Systematic Review”, 20 October 2020.
3. Konda Vaishnavi, U Nikhitha Kamath, B Ashwath Rao and N V Subba Reddy, “Predicting Mental Health Illness using Machine Learning Algorithms”,12 January 2021.
4. Shereen A. Hussein, Abd El Rahman, S. Bayoumi and Ayat M. Soliman. “Automated detection of human mental disorder”, 2023.
5. Harshita Singh, “Identification of Mental Disorder based on Changes in Personal Behavior using Machine Learning Algorithms”, National College of Ireland, 2023.
6. Management of Physical Health Conditions in Adults With Severe Mental Disorders: WHO Guidelines, World Health Org., Geneva, Switzerland, 2018.

7. The World Health Report 2001: Mental health: New Understanding, New Hope, World Health Org., Geneva, Switzerland, 2001.
8. M. Marcus, M. T. Yasamy, M. van Ommeren, D. Chisholm, and S. Saxena, ‘‘Depression: A global public health concern,’’ World Health Org., Geneva, Switzerland, Paper Depression, 2012, pp. 6–8.
9. Promoting Mental Health: Concepts, Emerging Evidence, Practice. World Health Org, Geneva, Switzerland, 2004.
10. Mental Health Action Plan 2013-2020, World Health Org., Geneva, Switzerland, 2013.
11. N. Abaei and H. A. Osman. A hybrid model for bipolar disorder classification from visual information. In ICASSP 2020 - 2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), pages 4107–4111, 2020. doi:1.1109/ICASSP40776.2020.9054648.
12. H. Elmunsyah, R. Mu’awanah, T. Widiyaningtyas, I. A. E. Zaeni, and F. A. Dwiyanto. Classification of employee mental health disorder treatment with k nearest neighbor algorithm. In2019 International Conference on Electrical, Electronics and Information Engineering (ICEEIE), volume 6, pages 211–215, 2019.
13. M. K. Othman and M. S. N. M. Danuri, ‘‘Proposed conceptual framework of dengue active surveillance system (DASS) in Malaysia,’’ in Proc. Int. Conf. Inf. Commun. Technol. (ICICTM), 2016, pp. 90–96.
14. Mental Health Action Plan 2013-2020, World Health Org., Geneva,Switzerland, 2013.
15. Ch.M.H. Saibaba; K V K Alekhya; K Yeshwanth; Praveen Tumuluru, “Prediction of Public Mental Health by using Machine Learning Algorithms”, 2022 Second International Conference on Artificial Intelligence and Smart Energy (ICAIS).
16. Adrian BR Shatte, Delyse M Hutchinson, and Samantha J Teague. Machine learning in mental health: a scoping review of methods and applications. Psychological medicine, 49(9):1426–1448, 2019.
17. M Srividya, S Mohanavalli, and N Bhalaji. Behavioral modeling for mental health using machine learning algorithms. Journal of medical systems, 42(5):1–12, 2018.
18. Gopika, Haritha H, Sabira Reshni IK, Hema PM (2021) Automatic prediction of depression and anxiety. Int J Curr Eng Sci
19. Jaiswal S, Song S, Valstar MF (2019) Automatic prediction of depression and anxiety from behaviour and personality attributes. In: 8th International conference on afective computing and intelligent interaction (ACII).
20. H. Lin, J. Jia, Q. Guo, Y. Xue, J. Huang, L. Cai, and L. Feng, ‘‘Psychological stress detection from cross-media microblog data using deep sparse neural network,’’ in Proc. IEEE Int. Conf. Multimedia Expo (ICME),Jul. 2014, pp. 1–6 .