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ORIGINAL ARTICLE

Hybrid Classifier for Optimizing Mental Health Prediction: Feature Engineering and Fusion Technique

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Abstract

A major worldwide health concern is mental health issues, which highlights the importance of early identification and intervention. In this paper, the effectiveness of two new hybrid classifiers is examined and compared to traditional machine learning techniques. Our study presents a novel hybrid classifier framework that combines Decision Trees with k-Nearest Neighbors (Hybrid_1) and Random Forest with Neural Networks (Hybrid_2). We do a detailed study with an emphasis on customized feature engineering techniques for mental health evaluation utilizing this novel fusion technique. The results of the experiments conducted on the Mental_health.csv dataset show how well the hybrid classifiers work; accuracy rates of 86.69% and 93.54%, respectively, for (DT + kNN) and (RF + NN) is attained. The aforementioned results highlight the potential of hybrid classifiers to improve mental health prediction and highlight the importance of feature engineering in optimizing predictive models. By combining Decision Trees with k-Nearest Neighbors and Random Forests with Neural Networks, respectively, our hybrid classifiers, Hybrid_1 and Hybrid_2, surpass current techniques and mark a breakthrough in the prediction of mental health. Our hybrids take advantage of the complimentary capabilities of various algorithms, in contrast to traditional techniques that could have trouble with complex feature connections or be less flexible when working with different datasets. In addition to showcasing the potential of hybrid classifiers in mental health assessment, our results offer insightful information on feature selection and model explainability, furthering our understanding of this important area.

Keywords Mental health · AI · Mental stress · Machine Learning (ML) · Deep learning · Neural network

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Introduction

Mental health disorders represent a significant global health challenge, affecting millions of individuals worldwide. According to the World Health Organization (WHO), approximately 450 million people suffer from mental or neurological conditions, making mental health disorders one of the leading causes of disability globally (World Health Organization, 2020). Despite the growing awareness surrounding mental health issues, timely detection and intervention remain critical for effective management and treatment. The complexity and heterogeneity of mental health disorders pose considerable challenges to accurate diagnosis and prediction. Traditional diagnostic approaches often rely on subjective assessments or limited sets of clinical criteria, which may result in delayed or inaccurate diagnoses (Kessler et al., 2005). To underscore the gravity of the mental health crisis, it's crucial to examine the treatment gap for various mental health disorders. Recent insights gleaned from the World Mental Health Surveys, meticulously compiled by Alonso et al. (2017) and meticulously processed by Our World in Data, cast light on the prevalence of anxiety disorders, depressive disorders, bipolar disorder, schizophrenia, and eating disorders (https://ourworldindata.org/mental-health). Astonishingly, the dataset unveils staggering figures: approximately, 577.7 million grapple with depressive disorders, 360.10 million individuals suffer from anxiety disorders, 105.4 million contend with bipolar disorder, 184.1 million wrestle with schizophrenia, and 37.2 million are affected by eating disorders as shown in the following Fig. 1. These figures not only highlight the sheer magnitude of mental health afflictions but also reveal a stark reality: a substantial portion of individuals suffering from these disorders are deprived of potentially adequate treatment. This glaring treatment gap underscores the pressing need for innovative approaches to mental health prediction and intervention, urging urgent action to bridge this chasm and alleviate the suffering of millions worldwide.

In light of the staggering prevalence of anxiety and depression, understanding how individuals cope with these mental health challenges is paramount. Recent global insights from the year 2020 shed light on the diverse coping mechanisms adopted by individuals grappling with anxiety or depression (Wellcome Global Monitor, 2021). Figure 2 reveals a spectrum of coping strategies embraced by individuals worldwide. Globally, individuals employ a variety of coping mechanisms: 78% seek solace in confiding with friends and family, 72.7% prioritize healthier lifestyle habits, 71.1% find peace in nature, 62.5% foster

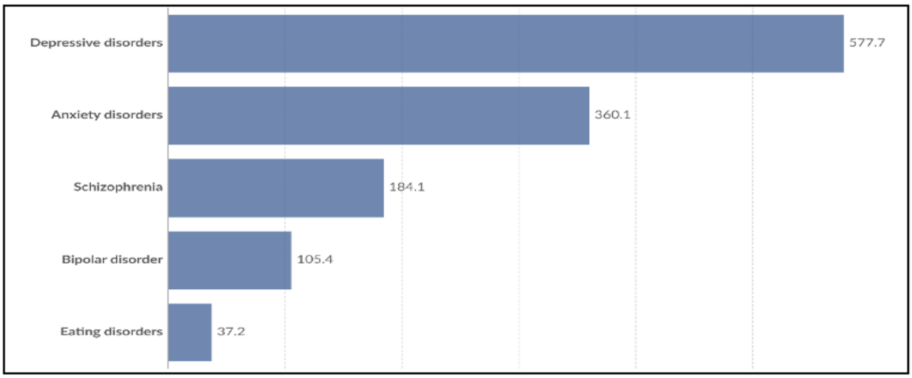


Fig. 1 Survey of different mental health disorder classifications over population

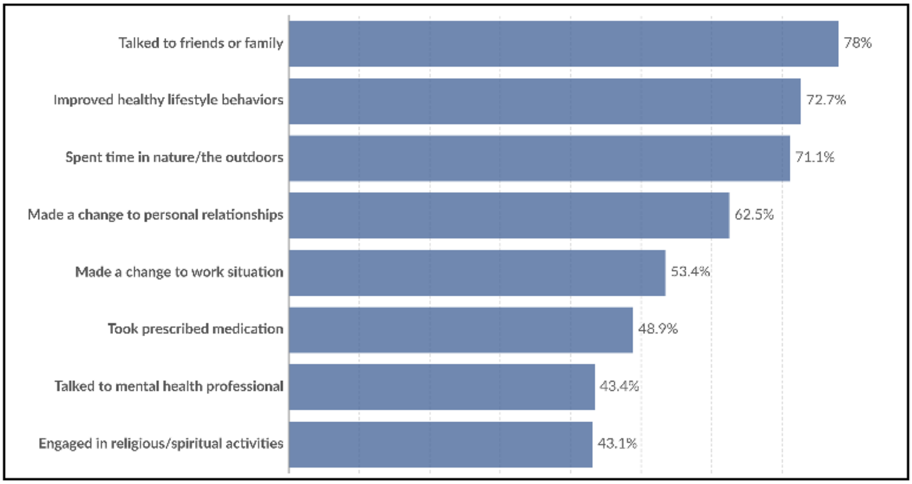


Fig. 2 How people deal with mental health issues across the world

healthier personal relationships, 53.4% address work-related stressors, 48.9% rely on medication, 43.4% seek professional guidance, and 43.1% find comfort in religious activities. This figure illuminates the multifaceted approaches people adopt to manage anxiety and depression, underscoring the need for holistic solutions in mental health intervention.

Additionally, the prevalence of mental health disorders varies across demographic and socio-economic factors, further complicating diagnostic efforts (McGrath et al., 2008). In recent years, advancements in machine learning (ML) and artificial intelligence (AI) have shown promise in improving mental health prediction and diagnosis. ML techniques offer the potential to analyze large volumes of data and identify complex patterns that may not be apparent to human clinicians (Dwyer et al., 2018). However, despite the growing interest in ML-based approaches, several challenges persist, including the need for robust feature selection methods and the integration of heterogeneous data sources (Marquand et al., 2016).

To address these challenges, this study introduces a novel hybrid classifier framework for optimizing mental health prediction. Our approach leverages the strengths of both traditional ML algorithms and deep learning techniques to improve prediction accuracy and model robustness. Specifically, we propose two hybrid classifiers: Hybrid_1, which combines Decision Trees with k-Nearest Neighbors (kNN), and Hybrid_2, which integrates Random Forests with Neural Networks (NN). By blending complementary algorithms, our hybrid classifiers aim to capture the intricacies of mental health data and enhance prediction performance. The primary objective of this research is to evaluate the effectiveness of hybrid classifiers in mental health prediction compared to traditional ML approaches. We conduct comprehensive experiments using a publicly available dataset, Mental_health.csv, to assess the performance of Hybrid_1 and Hybrid_2 in predicting mental health outcomes. Furthermore, we explore various feature engineering strategies tailored to mental health assessment, aiming to optimize predictive models and improve interpretability.

The findings of this study have significant implications for mental health research and clinical practice. By demonstrating the potential of hybrid classifiers in optimizing mental health prediction, we contribute to the growing body of literature on ML-based approaches for mental health assessment. Additionally, our research highlights the importance of feature engineering and model fusion techniques in enhancing predictive performance and model explainability. In the following sections, we provide a detailed overview of our methodology, experimental setup, and results, followed by a discussion of the implications of our findings and avenues for future research.

The motivation of the Research

Our research is driven by the urgent need for advancements in mental health prediction, transcending the limitations of existing methodologies. The motivation behind our work stems from the imperative need for more accurate and robust predictive models in the realm of mental health. Existing approaches often face challenges in effectively capturing the intricate relationships within mental health indicators and providing consistently reliable predictions.

- Limitations of Existing Approaches: Recognizing the shortcomings of conventional methodologies in accurately predicting mental health conditions, especially in capturing complex interdependencies among indicators.
- Need for Robust Predictive Models: Acknowledging the pressing demand for more resilient and adaptable predictive models that can navigate the challenges posed by diverse datasets and varying degrees of data noise.
- Enhancing Accuracy through Diversity: Motivated by the belief that a combination of diverse algorithms, such as Decision Trees, k-Nearest Neighbors, Random Forests, and Neural Networks, could collectively provide a more accurate and comprehensive predictive framework.
- Addressing the Complexity of Mental Health Data: Driven by the understanding that mental health data is multifaceted and requires a nuanced approach, necessitating the integration of various algorithms to capture subtle patterns and relationships.
- Strategic Fusion Technique: The motivation to employ a fusion technique arises from the aspiration to optimize the strengths of individual models, mitigating their weaknesses and enhancing overall predictive performance.

We were driven to develop our hybrid classifiers, Hybrid_1 and Hybrid_2, by recognizing the limitations of traditional methodologies. The integration of Decision Trees with k-Nearest Neighbors in Hybrid_1 and Random Forests with Neural Networks in Hybrid_2 was prompted by the understanding that a diverse set of algorithms could collectively address the complexity inherent in mental health prediction. Our motivation was further fueled by the realization that mental health prediction requires a nuanced approach that goes beyond the capabilities of single-model solutions. Conventional methods may struggle with interpretability, adaptability, or scalability, limiting their effectiveness across diverse datasets. By combining the strengths of decision trees, k-Nearest Neighbors, Random Forests, and Neural Networks, our hybrids offer a comprehensive and adaptable framework for mental health prediction. The fusion technique employed aims to synergize the strengths of individual models, resulting in a more resilient and accurate predictive tool.

The Contribution of Study The study makes a substantial contribution to the field of mental health prediction by introducing advanced hybrid models, optimizing feature engineering, addressing dataset adaptability, improving diagnostic precision, adopting a holistic approach, supporting early intervention, and establishing a framework for future research accomplishments. The following Table 1 shows the substantial contributions.

The Ethical Implications of Research

The ethical considerations of our research into hybrid classifiers for optimizing mental health prediction are paramount and have been meticulously addressed throughout the study. Safeguarding the confidentiality and privacy of individuals' mental health data remains our top priority. The utilization of sensitive information necessitates robust data protection measures to mitigate concerns regarding potential stigmatization and discrimination. Ethical guidelines, encompassing informed consent and transparency, have been rigorously followed to ensure that participants are fully informed about the research objectives and the utilization of their data. Furthermore, our models are designed to positively impact mental health outcomes by facilitating early interventions and support, without perpetuating bias or exacerbating existing disparities. We have continuously strived to anticipate and mitigate any unintended consequences, fostering a responsible and ethical approach to advancing mental health prediction through innovative machine-learning techniques. This research is firmly rooted in ethical principles, leveraging technology to enhance mental health outcomes while upholding the well-being and privacy of all individuals involved.

Novelty and Advantages of Hybrid_01 and Hybrid_02

The public unveiling of the Hybrid1 and Hybrid2 classifiers represents a revolutionary advance in the field of mental health prediction, bringing cutting-edge approaches that go beyond conventional machine learning techniques. Combining the interpretability of Decision Trees with the adaptability of k-Nearest Neighbors, Hybrid1 provides a comprehensive

Table 1 Contribution of hybrid approach in mental health detection

Advancements	Description
Hybrid Model	The study introduces novel hybrid classifiers, Hybrid_1 and Hybrid_2, which synergistically combine Decision Trees with k-Nearest Neighbors and Random Forests with Neural Networks, respectively. These hybrids surpass traditional models in predictive accuracy
Optimized Feature Engineering	Tailored feature engineering techniques ensure that selected features effectively capture intricate nuances of mental health indicators, enhancing overall predictive capability
Adaptability to Diverse Datasets	Incorporating a diverse set of algorithms addresses dataset heterogeneity, allowing models to adapt to various mental health data complexities and noise levels
Improved Diagnostic Precision	Fusion techniques employed in Hybrid_1 and Hybrid_2 leverage individual classifier strengths, leading to improved diagnostic precision and reliability in predicting mental health conditions
Holistic Approach to Mental Health	Integration of machine learning techniques addresses interpretability, adaptability, and scalability issues, culminating in a comprehensive strategy that enhances the overall effectiveness of mental health prediction models

method of mental health evaluation. This combination not only makes Decision Trees more transparent, but it also makes use of k-Nearest Neighbors' flexibility to pick up on minute details in the data. Hybrid2, on the other hand, combines the advantages of Random Forests and Neural Networks, using the former's robustness in high-dimensional data settings and the latter's skill in pattern identification. Hybrid2, which incorporates several state-of-the-art methods, offers a dynamic framework for precise and thorough mental health assessment. These hybrids' transformational qualities mark a paradigm change in mental health prediction by providing a multimodal approach to the challenges of mental health data analysis.

This study is divided into the following seven sections. Following the introduction, the Background part provides insights on the topic along with the description of the dataset used in this study of predicting mental health followed by the discussion of machine learning techniques. The method and the experiment performed will be covered in the Methodology section in which machine learning methods are employed for forecasting mental health issues. The Results and Discussion sections then discuss the details of the outcome of the study and lastly, the paper will be concluded in the Conclusion section followed by the future extension of this study and references.

Literature Survey

In this literature review, we delve into several critical aspects essential for understanding mental health assessment and prediction. Beginning with an overview of the evolution of machine learning in mental health informatics, we then shift focus to its application in predicting mental health outcomes, starting with traditional assessment methods. We explore the opportunities and obstacles in precise mental health prediction, highlighting the research implications for health informatics. By integrating traditional and advanced approaches, our goal is to provide a comprehensive understanding of the field of mental health assessment and prediction strategies. To lessen psychological and physical stress, Kraft et al. (Kraft et al., 2021) for example, presented a notion in their study where they utilized a basic camera to record vital signs while at work, evaluated them using machine learning, and suggested interventions. This workshop aims to build a camera-based tool for detecting physical and mental exhaustion at work by discussing recent research on stress assessment and related difficulties. Similarly, participant data from 2 and 3D scans may be processed using deep learning and machine learning approaches to identify tiny facial micro-expressions of persons participating in stressful tasks, as shown by Lombardi and Marcolin (Lombardi & Marcolin, 2021) in their study. Using information from the accelerometer and gyroscope sensors on smartphone touchscreen panels, Saab et al. (Sağbaş et al., 2020) investigated the effects of stress. They gathered information from 46 people's smartphones in both relaxed and tense situations, identified distinctive characteristics, and classified writing practices using Bayesian networks, k-Nearest Neighbor, and C4.5 Decision Trees. They received classification scores of 74.26%, 67.86%, and 87.56%, in that order.

Moreover, the above to improve upon stress detection methods that did not include live detection and individual counseling were suggested by Nilanjana, M. et al. (Nilanjana et al., 2021). The physical and emotional stress levels of police officers and staff are monitored in real-time, and their levels are periodically analyzed as part of this process. Stress reduction and fostering a productive workplace are the system's two main objectives. It is essential to analyze the corpus of research currently available on machine learning for mental health detection. Various people's faces were analyzed in this study, and the results were reported as follows: Normal, Person is under stress, etc. According to the parameters used. The knowledge it provides allows researchers to create creative, practical, and morally good solutions while also ensuring that their work is positioned To detect overworked IT staff, Kanaparthi et al. (Kanaparthi et al., 2022) used machine learning and visual processing. This allowed them to build stress recognition techniques without the need for a specific therapy or real-time monitoring. To increase awareness of one's bodily state, Chiwande et al. (Chiwande et al., 2022) measured stress using three different facial expressions: fear, wrath, and sorrow.

Additionally, Migovich et al. (Migovich et al., 2021) proposed combining a virtual reality interview simulator with a stress detection system to enhance interviewing methods based on emotional responses. With an emphasis on stress reduction and a productive workplace, Chakraborty et al. (Chakraborty et al., 2023) developed a method for the early prediction of mental health disorders by combining facial expression detection and stress level evaluation. Using the E4 wristband, Lopez (Suni Lopez et al., 2019) investigated arousal-based statistical techniques for real-time stress detection. Smirnov et al.'s (Smirnov et al., 2015) method of emotion recognition from facial expressions involved the use of k-nearest neighbor and linear discriminant analysis, which produced results of over 90% accuracy. Using a KINECT sensor, Shan et al. (Shan et al., 2020) were able to accurately distinguish psychological tension, physical stress, and a calm state while remotely diagnosing and classifying human stress based on breathing patterns. In comparison to thermal-specific approaches, Kopaczka et al. (Kopaczka et al., 2017) showed how algorithms can be trained to function in thermal infrared pictures for face identification, resulting in greater detection accuracy.

Apart from the above automated AU detection was used by Giannakakis et al. (Giannakakis et al., 2022) to distinguish between neutral and stressful situations in movies with a high degree of accuracy. Using deep learning neural networks, Rodrigues and Marchetti (Rodrigues & Marchetti, 2022) created a model for stress detection that achieved an F1 score of 79.9% on a binary stress/non-stress dataset. Kraft et al. (Kraft et al., 2022) suggested recording behavior, posture, and physical motions at work with a basic camera and providing tailored therapy recommendations for stress relief. Sahu et al. (Sahu et al., 2021) provided comments based on daily reports and used sentiment analysis and web cameras to collect facial expressions to identify emotions. With great precision, Bindu et al. (Bindu et al., 2022) created an intelligent system that uses machine learning to determine an individual's stress level. A study by Herath et al. (Herath et al., 2022) used valence, arousal, and facial skin states to examine the link between mind and skin, with an accuracy of 80.83%. High-accuracy face expression detection was achieved by Nagaraju et al. (Nagaraju et al., 2022) using a video-based framework. An IoT-based machine learning stress monitoring system was described by Gupta et al. (Gupta et al., 2022), and they were able to produce reasonably accurate forecasts. To anticipate decision-making in a gaming environment, Guglielmo et al. (Guglielmo et al., 2021) examined facial expressions and were 81% accurate in their predictions. Destress, an Android app that offers a variety of stress-reduction strategies, was suggested by Udeshi et al. (Udeshi et al., 2021) for stress assessment. The descriptive study by Harbola and Jaswal (Harbola & Jaswal, 2020) included an overview of the different forms and analyses of stress while focusing on facial images and stress techniques for stress analysis and detection.

In the preliminary phase of this research, an extensive literature survey was conducted to comprehensively review and analyze previous works related to mental health prediction using hybrid classifiers. This literature review not only provides a foundational understanding of the existing landscape but also serves as a valuable resource for learners and researchers interested in this domain. To enhance accessibility and clarity, a dedicated literature survey Table 2 has been meticulously compiled and included in the paper. This table succinctly summarizes key aspects of each referenced study, such as methodologies employed, datasets utilized, and notable findings. This organized compilation aims to facilitate a quick grasp of the diverse approaches taken by researchers in the field, offering both novices and seasoned researchers a valuable reference point for exploring the rich landscape of mental health prediction through hybrid classifiers.

Methodology

The research employed advanced machine learning (ML) techniques to identify and forecast high-stress levels in individuals, with the overarching goal of mitigating potential adverse impacts on their well-being. Participants underwent comprehensive evaluations across diverse scenarios to gauge their stress levels accurately. The implementation of the project rigorously validated the efficacy of the stress detection model. Illustrated in Fig. 3, the proposed methodology encompasses a systematic approach comprising data collection, preprocessing, feature extraction, the application of ML algorithms (including the innovative hybrids Hybrid_1 and Hybrid_2), and a thorough comparative analysis of these methods based on comprehensive performance metrics.

Classification Algorithms

The classification algorithm is a unique data mining technique that splits down the data into its component cases. It puts the example in a certain class with a very low likelihood of error. Models that describe significant information classes are eliminated from the provided informational index. To determine people's stress levels, we used specific classification algorithms in this piece. We used a portion of our data to train our model, and then we tested it on the remaining data. Trains to Tests dataset ratio was 1:3.

Random Forest

This method considers many decision trees, resulting in a forest. It is also known as a collection of decision tree algorithms. This can also be used for classification in addition to regression. This method seeks to randomly choose the best attribute out of all of them. In our investigation, a random forest classifier was used to predict if mental health therapy would be necessary. The versatile ensemble learning technique Random Forest can be used to complete tasks involving both classification and regression. Throughout training, many decision trees are constructed, their predictions are combined, and accuracy is increased while overfitting is decreased. To guarantee the diversity of the model, every tree is built with a certain subset of the training data and characteristics.

Mathematically, the algorithm aggregates the predictions of individual decision trees:

$$\text{PredictionRF}(x) = 1/N \sum_{i=0}^{N} \text{PredictionTree } i(x) \tag{1}$$

where,

Table 2 Summarized Literature Review

Sr	Authors	Purpose of the Study	Dataset	ML Technique/Methodology	Results/Accuracy	Research Gaps	Implications of Research
1	Kraft, D et al.(Kraft et al., 2021)	CareCam: Concept of a new tool for Corporate Health Management	Image dataset	Conceptual framework development, prototype design, data collection and analysis, usability testing	Successful demonstration of CareCam as a promising tool for corporate health management	The effectiveness of CareCam in real-world corporate environments needs further validation	Implementation of CareCam can lead to enhanced monitoring and management of employee health in corporate settings
2	Livia Lombardi and Federica Marcolin (Lombardi & Marcolin, 2021)	Identification of Psychological Stress via 2D and 3D Face Image Processing	Facial expression dataset	Neural network	NA	Lack of comparison with traditional stress detection methods	Provides a novel approach to stress identification through facial image processing, potentially improving accuracy and efficiency
3	Sagbas et al. (Sağbaş et al., 2020)	Stress Identification via Keyboard Typing Patterns Using Machine Learning and Smartphone Sensors	CNN DS-C, C4.5 DS-C	BN, KNN, C4.5	BN- 67.86%	Need for evaluation on a larger and more diverse dataset	Offers a non-intrusive method for stress identification, potentially applicable in various environments such as workplaces
4	Nilanjana et al. (Nilanjana et al., 2021)	Automated Image Processing with Machine Learning for Stress Identification	Face images dataset	ANN	Keywords like: Normal, Person under stressed shown by image processing	Need for validation on a larger dataset	Provides an automated approach to stress identification using image processing, potentially aiding in quick assessment and intervention

Table 2 (continued)

Sr	Authors	Purpose of the Study	Dataset	ML Technique/Methodology	Results/Accuracy	Research Gaps	Implications of Research
5	Kanaparthi et al. (Kanaparthi et al., 2022)	Stress Detection in IT Workers using Machine Learning Approach	Data of employees	Visual Processing and KNN Classifier	NA	Lack of comparison with other stress detection methods	Offers a method for stress detection in a specific occupational group, potentially aiding in targeted interventions for IT workers
6	Chiwande et al. (Chiwande et al., 2022)	Deep Learning-Based Stress Detection and Raspberry Pi-Based Health Parameter Monitoring	heart rate, oxygen level, and BMI using Raspberry pi	Deep Learning Classifier	Results framed based on facial expressions sad, angry, and fear	Need for evaluation in real-world scenarios	Provides a non-invasive method for stress detection and health monitoring, potentially useful in remote or resource-limited settings
7	Migovich et al. (Migovich et al., 2021)	Developing and Verifying a Stress Detection Model for Utilising a Virtual Reality Interview Simulator for Young Adults with Autism	Neurotypical participants, wrist-worn physiological sensor	ML Classifier	NA	Lack of evaluation on individuals with autism spectrum disorder	Offers a tool for stress detection in a specific population, potentially improving their experience with virtual reality interventions
8	Chakraborty et al. (Chakraborty et al., 2023)	A Structure for Sensible Mental Health Tracking in Smart Cities and Communities	Facial emotions	RF, SVM	The results framed as acute depression, moderate depression, and not depressed	Need for integration with existing mental health tracking systems	Provides a framework for mental health tracking, potentially useful in urban planning and community health programs

Table 2 (continued)

Sr	Authors	Purpose of the Study	Dataset	ML Technique/Methodology	Results/Accuracy	Research Gaps	Implications of Research
9	Lopez (Suni Lopez et al., 2019)	Moving Towards Automatic Stress Detection in Real-Time for Office Settings	E4-wristband	Not disclosed	The results disclosed in the form of emotional triggers	Lack of evaluation in office settings with varying stress levels	Offers a real-time method for stress detection, potentially useful for workplace health and productivity monitoring
10	Smirnov et al. (Smirnov et al., 2015)	A Comparative Analysis of Fusion Techniques and Facial Features for Emotion Recognition	Discrete Cosine Transform (DCT), Discrete Sine Transform (DST), the Walsh-Hadamard Transform (FWHT)	Linear discriminant analysis and k-nearest neighbor	90%	Need for comparison with other fusion techniques and feature sets	Provides insights into fusion techniques for emotion recognition, potentially improving accuracy in emotion recognition systems
11	Shan et al. (Shan et al., 2020)	Human stress and respiratory signal: non-contact stress detection using an inexpensive depth-sensing camera	On the 84 volunteers with the KINECT sensor	features extracting from the respiration signal, psychological stress, physical stress, and relaxing state are	93.90%, 93.40%, and 89.05%	Lack of evaluation in real-world scenarios	Offers a non-contact method for stress detection, potentially useful in healthcare and wellness monitoring
12	Kopaczka et al. (Kopaczka et al., 2017)	An Algorithm- and Machine-Learning-Based Approach to Face Detection in Thermal Infrared Images Comparison	Face images	Projection Profile Analysis (PPA), Eye Corner Detection (ECD), DPM, HOG	NA	Lack of evaluation in thermal imaging scenarios	Provides a method for face detection in thermal images, potentially useful in security and surveillance applications

Table 2 (continued)

Sr	Authors	Purpose of the Study	Dataset	ML Technique/Methodology	Results/Accuracy	Research Gaps	Implications of Research
13	Giannakakis et al. (Giannakakis et al., 2022)	Automatic evaluation of stress using deep facial action unit detection in face videos	UNBC and BOSPHORUS	Deep Pipelined AU Classifier	Classification accuracy between neutral and stress states using this study's pipeline reached 81.1%	Need for evaluation in real-world scenarios	Offers a method for stress evaluation in face videos, potentially useful in psychological research and mental health assessment
14	Fatima Rodrigues and Jacqueline Marchetti (Rodrigues & Marchetti, 2022)	A Deep Learning Method for Tracking Office Stress in Workers	Binary dataset	CNN	F1 = 79.9%	Lack of comparison with other stress-tracking methods	Provides a method for tracking office stress, potentially aiding in employee well-being and productivity management
15	Kraft et al. (Kraft et al., 2022)	CareCam: A Camera-Based, Intelligent Health Companion for the Workplace	Record vital signs, posture, and behavior	Unobtrusive and software-based monitoring	Recommendation for stress reduction based on the captured data	Need for validation in workplace environments	Offers a tool for workplace health monitoring, potentially improving employee health and well-being
16	Sahu et al. (Sahu et al., 2021)	Sentiment Analysis for Office Workers' Stress Identification	facial expressions (angry, disgusted, happy, sad, fear, surprise, neutral)	NLP and Day-wise report on "How was your day?"	Feedback based on the reports generated at the end of the month	Lack of evaluation in other occupational settings	Provides a method for stress identification in office workers, potentially aiding in personalized stress management strategies

Table 2 (continued)

Sr	Authors	Purpose of the Study	Dataset	ML Technique/Methodology	Results/Accuracy	Research Gaps	Implications of Research
17	K N et al. (Bindu et al., 2022)	IT Professional Stress Identification and Analysis Using 5 ML Techniques	IT professionals	Decision Tree, Logistic Regression, KNN, SVM, and Random Forest	Decision tree algorithm 97.40%, other four algorithms 98.70%	Lack of generalization to other professional domains	Offers a method for stress identification in IT professionals, potentially improving their well-being and job performance
18	Herath et al. (Herath et al., 2022)	Using Affective Computing to Track Stress's Effect on Facial Skin	mind (stress) and skin (facial skin)	V-A	80.83%	Need for validation in real-world settings	Provides insights into the effect of stress on facial skin, potentially useful in dermatological and psychological research
19	Nagaraju et al. (Nagaraju et al., 2022)	Video processing employs double OptconNet architecture for face expression recognition	Affectiva-MIT Facial Expression Dataset, BAUM-1 s, and Real-world affective faces	Double optimization-based convolution network model	NA	Lack of comparison with other video processing techniques	Offers a method for face expression recognition, potentially useful in emotion analysis and affective computing
20	Gupta et al. (Gupta et al., 2022)	An Internet of Things-based Hybrid Approach Stress Monitoring System for Office Environments	WSEAD	Hybrid Model (IoT and Machine learning-based stress monitoring system including RF, LSTM & WBAN)	NA	Need for validation in office environments	Provides a method for stress monitoring in office environments, potentially improving workplace health and productivity

Table 2 (continued)

Sr	Authors	Purpose of the Study	Dataset	ML Technique/Methodology	Results/Accuracy	Research Gaps	Implications of Research
21	Guglielmo et al. (Guglielmo et al., 2021)	Deep Learning for the Identification of Complex Decision-Making Facial Markers	facial expressions	CNN	81%	Lack of evaluation in decision-making scenarios	Offers a method for identifying facial markers in decision-making, potentially useful in psychology and human behavior research
22	Harbola, A., & Jaswal, R. A. (Harbola & Jaswal, 2020)	Review of Literature—Analysis and Detection of Stress Using Facial Images	Facial Images	Literature review on the analysis and detection of stress using facial images	Comprehensive overview of existing methods and techniques for stress analysis and detection using facial images	Future research should focus on addressing the identified gaps and challenges to improve the effectiveness of stress detection methods	Identification of gaps and challenges in the current state-of-the-art in stress detection using facial images
23	Khosrowabadi et al. (Khosrowabadi et al., 2011)	An Interface between the Brain and Computer to Categorise EEG Correlates of Prolonged Mental Stress	8 EEG channels	KNN, SVM, Proposed BCI	BCI-90%	Lack of validation in real-world conditions	Offers an interface for categorizing EEG correlates of mental stress, potentially aiding in mental health research and interventions
24	Jia-Pao Cheng, Su-Cheng Haw (Cheng & Haw, 2023)	Predicting Mental Health Issues using Machine Learning Methods	patients' data	Logistic Regression, K-Nearest Neighbors, and Random Forest	RF 83.23%	Lack of evaluation on a larger and more diverse dataset	Provides a method for predicting mental health issues, potentially aiding in early intervention and treatment planning

Table 2 (continued)

Sr	Authors	Purpose of the Study	Dataset	ML Technique/Methodology	Results/Accuracy	Research Gaps	Implications of Research
25	Karim, Mohammad Safkat, et al. (Karim et al., 2021)	Vip stress detection from various situations utilising machine learning methods and EEG signals	EEG Signal	Random Forest (RF) classifier Support Vector Machine (SVM), K-Nearest Neighbors (KNN) and Linear Discriminant Analysis (LDA)	RF: accuracy 99%. For other classifiers > 89% accuracy	Need for validation in various real-life scenarios	Offers a method for stress detection from EEG signals, potentially useful in healthcare and mental health monitoring
26	Reddy, Y. H. et al. (Reddy et al., 2020)	Machine Learning for the Identification of Mental Disorders in Social Networks	3126 informal community customers dataset	SNMD-based Tensor Model (STM)	NA	Need for evaluation in other social network platforms	Provides a method for identifying mental disorders in social networks, potentially aiding in early intervention and support
27	Borah, T., & Ganesh Kumar, S. (Borah & Ganesh Kumar, 2022)	Leveraging NLP and Machine Learning to Enhance Mental Health	Reddit, Twitter posts	Logistic Regression, Random Forest, SVM, deep learning Long Short-Term Memory (LSTM) and BERT transfer learning algorithms	The highest accuracy and f1 score achieved is more than 85%	Need for evaluation in other social media platforms	Offers a method for enhancing mental health through NLP and machine learning, potentially improving mental health interventions and support systems

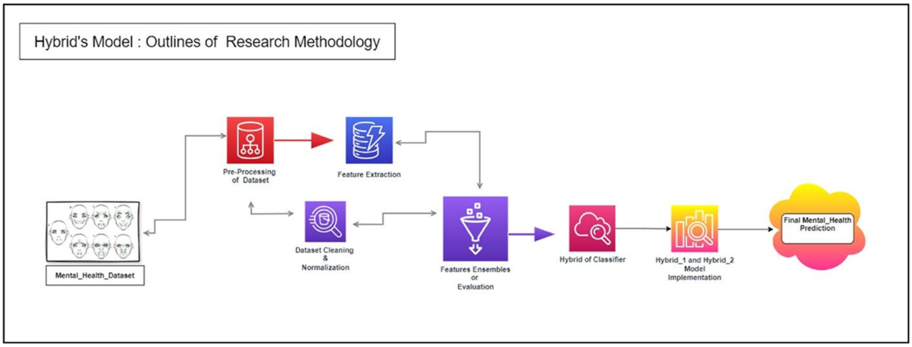


Fig. 3 Flow-chart of Research methodology of hybrid approach

- PredictionRF(x) represents the Random Forest's forecast for the input x.
- The decision trees in the forest total N.
- The i^{th} decision tree's prediction is represented by Prediction Tree i(x).

Support Vector Machine

The hyperplane is a commonly used classifier. The ideal hyper plane is used in this method, which is better suitable for organizing fresh graphics. It is a line that divides a two-dimensional plane into two parts, one side being occupied by each class. For applications involving regression and classification, a Support Vector Machine (SVM) is a useful machine learning tool. SVM seeks to maximize the margin between multiple classes in a dataset in order to identify a hyperplane that best divides them. The margin represents the distance for each class between the closest data points and the hyperplane. Because SVM uses kernel functions, it can handle both linear and nonlinear classification problems, and it performs exceptionally well with complicated datasets with high-dimensional features. Through data transformation into a higher-dimensional space, Support Vector Machines (SVM) can determine the optimal decision boundaries for precisely classifying new, unknown data bits. Small-to-large dataset management and excellent generalization make Support Vector Machines (SVM) a flexible and widely used technique in many fields, including image processing. The SVM attempts to resolve the following optimization issue for a binary classification problem mathematically:

$$Min\ w,\ b_{2}^{1}||\ \mathrm{w}\ ||^{2} \tag{2}$$

$$subject\ to\ \left(y_i\left(w * x_i + b\right) > 1\right)\ \ for\ \ i = 1, \cdots .n \tag{3}$$

where,

- b: bias-term.
- x_i: data-point.
- y_i: class label (-1 or 1) of xi.
- n: number of data points.
- w: weight vector perpendicular to the hyperplane.

K- Nearest Neighbor

The K-Nearest Neighbors (KNN) algorithm is a straightforward yet powerful classification and regression technique. It works by first storing all available cases and then classifying new cases based on a similarity measure (e.g., distance functions). For regression, it calculates the average of the k-nearest neighbors' outputs. One of the key features of KNN is that it's a non-parametric algorithm, meaning it doesn't make any assumptions about the underlying data distribution. This flexibility makes KNN a popular choice for various machine-learning tasks, especially when the data is not linearly separable. However, a drawback of KNN is that it can be computationally expensive, particularly with large datasets, as it needs to calculate the distance between each data point.

Mathematically, for classification, the algorithm operates as follows:

$$distance(Xnew, Xtrain) = \sum_{i=1}^{n} \sqrt{\left(x_{new}, i - x_{train}, i\right)^2} \tag{4}$$

- Calculate the distance between the input data point (Xnew) and all the training data points (Xtrain) using a distance metric (commonly Euclidean distance).
- Select the k nearest training data points based on the calculated distances.
- Determine the majority class among these k neighbors, and classify the input data point as that class

Artificial Neural Network

A neural network, as described by, is a layered arrangement of interconnected neurons designed to replicate the functioning of the human brain. The input layer constitutes the network's initial layer, while the expected output layer forms the final layer. Sandwiched between the input and output layers, the hidden layers utilize the output of neurons as input and perform computations before producing an output. Each layer is sequentially added, with the previous layer's output serving as the subsequent layer's input. An Artificial Neural Network (ANN) is a computational model inspired by the structure and function of the human brain. It consists of interconnected nodes, often referred to as neurons or artificial neurons, including an input layer, one or more hidden layers, and an output layer. The strength of each neuron's connection is determined by its weight. Neurons within a layer use an activation function, typically a nonlinear function like a sigmoid or rectified linear unit (ReLU), to process information from the layer below and transmit it to the layer above.

Mathematically, the output y of a neuron in an ANN is calculated as follows

$$y = f\sum_{i=0}^{n} (w_i * x_i + b) \tag{5}$$

where

- Y represents the neuron's output.
- F stands for activation function.
- w_i represents the connections' weights.
- The inputs from the layer before are x_i.
- The bias expression is b.

Decision Tree

The Decision Tree algorithm is a versatile and easy-to-understand machine learning model used for both classification and regression tasks. It works by recursively splitting the dataset into subsets based on the most significant attribute at each node. This process creates a tree-like structure where the leaves represent the class labels or numerical values. Decision Trees are advantageous because they can handle both numerical and categorical data, require little data preprocessing, and implicitly perform feature selection by selecting the most informative attributes for splitting. However, they are prone to overfitting, especially with complex trees, which can be mitigated using techniques like pruning.

Dropout

Dropout serves as a popular regularization method in neural networks to mitigate overfitting. It operates by randomly deactivating a fraction of neurons during each training iteration, effectively excluding them from the network. This process enhances the model's robustness and reduces its dependence on individual neurons. By discouraging neuronal co-adaptation, dropout promotes better generalization of the model to unseen data.

Mathematically, during training, neurons undergo dropout with a probability of p. For each neuron, the dropout mask *M* is a binary vector containing values of 0 or 1, representing whether a neuron is active (1) or dropped out (0) for a specific training iteration.

$$yi = M_i * f \sum_{i=0}^{n} (w_{ij} * x_i + b_i) \tag{6}$$

where,

- y_i is the output of the neuron.
- M_i: dropout mask for the neuron.
- f: activation function.
- w_{ij}: weights of the connections.
- x_j: inputs from the previous layer.
- b_i is the bias term.

Activation Function

The activation function is a crucial component of artificial neural networks, introducing nonlinearity into the model. It calculates the output of a neuron, which is then passed as input to subsequent neurons. By incorporating non-linear transformations, activation functions enable neural networks to model complex relationships within data. The mathematical formula for the activation function is typically represented as:

$$\mathrm{f(x)} = \frac{1}{1 + \mathrm{e}^{-\mathrm{x}}} \tag{7}$$

$$\mathrm{f(x)} = \max(0, \mathrm{x})$$

- *ReLu:* The Rectified Linear Unit (ReLU), whose mathematical definition is as follows, is a frequently employed activation function.

In this formula, f(x) represents the output of the neuron, and x is the input. When x is positive, the output is equal to x; otherwise, it is 0. Despite its simplicity, this non-linear function has gained popularity for its computational efficiency and effectiveness in addressing the vanishing gradient problem. Activation functions such as ReLU allow neural networks to approximate complex functions and capture intricate patterns in data, making them valuable tools in a variety of machine-learning applications.

Loss function

In machine learning, a loss function, also referred to as a cost or objective function, plays a critical role in training models like neural networks. It quantifies how closely the model's predictions match the actual target values, providing a measure of its performance. The choice of loss function depends on the nature of the task, such as regression or classification, and the specific problem being addressed. For example, in linear regression, the Mean Squared Error (MSE) is a widely used loss function, defined as follows:

$$MSE = \frac{1}{n}\sum\nolimits_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{8}$$

where,

- n: number of data points,
- y_i represents the true target values, & $\hat{y}_i$ denotes the model's predictions. Lower values in the MSE indicate a better match by quantifying the average squared difference between the anticipated and actual values.

In classification tasks, Cross-Entropy Loss (also known as Log Loss) is frequently used, defined as:

$$Cross\ Entropy\ Loss = \frac{1}{n}\sum\nolimits_{i=1}^{n}\left[\left(y_i.\log(\hat{y}_i)\right) + \left(1 - y_i\right).\log(1 - \hat{y}_i)\right] \tag{9}$$

In this context, "i" represents the predicted probability of the positive class, while "ŷi" represents the actual class label (0 or 1). The goal of this loss function is to encourage the model to assign higher probabilities to the true class.

Experimental Setup

The experimental setup section delineates the framework and conditions under which the research was conducted, providing essential context for subsequent results and analysis. It details the hardware and software configurations, performance parameters, dataset specifications, and any pre-processing steps taken to ensure experiment reliability and reproducibility. Additionally, it specifies the parameters and hyperparameters selected for each algorithm and classifier, along with any cross-validation or validation techniques used to validate the approach. This comprehensive setup establishes the groundwork for robust experimentation and enhances understanding of the methodology and results.

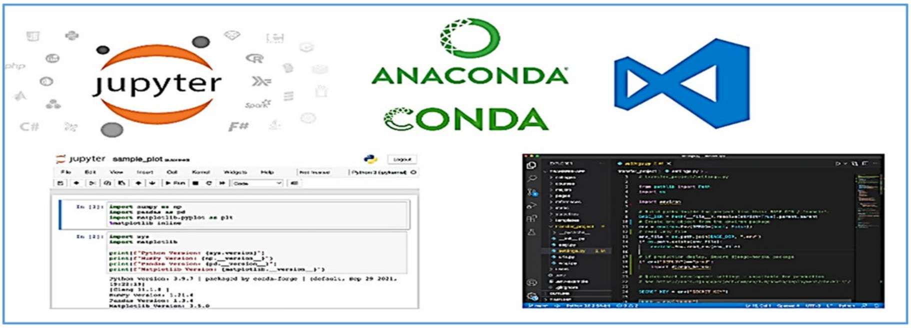
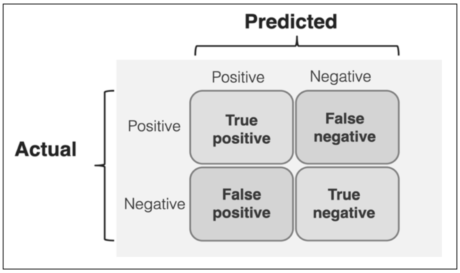


Fig. 4 Software and Platform used for implementation

Fig. 5 Confusion matrix



Hardware & Software

The experimentation utilized a robust hardware setup, including a high-performance workstation with multi-core processors and ample RAM to support computationally intensive tasks. Anaconda served as the primary Python distribution platform, providing a comprehensive suite of pre-installed libraries and tools essential for data analysis and machine learning tasks. Jupyter Notebook was used as the interactive computing environment, enabling seamless code execution, visualization, and documentation. By leveraging Python's extensive ecosystem of libraries and frameworks for machine learning and data analysis, the experiments were conducted efficiently and reliably. All the tools and platforms used for the experiment are shown in following Fig. 4.

Performance Parameters

Performance metrics are pivotal in machine learning for assessing how well predictive models perform. They offer valuable insights into a model's effectiveness across various tasks, such as classification or regression. Here are some key performance parameters and their mathematical representations.

Fig. 6 Hybrid Framework 01

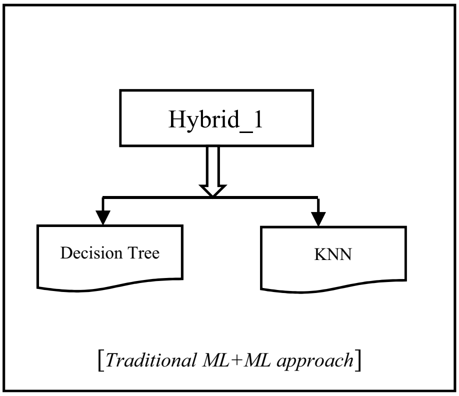
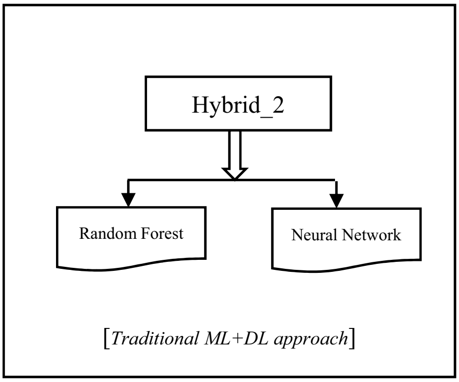


Fig. 7 Hybrid Framework 02



a) ***Sensitivity**:* This parameter's sensitivity, also known as the true positive rate (TPR), measures the ratio of true positives to the sum of true positives and false negatives (TP and FN). It indicates the model's ability to accurately identify the diseases listed in the equation.

$$Sensitivity = \frac{TP}{TP + FN} \tag{10}$$

b) ***Specificity**:* This parameter, known as the specificity or true negative rate (TNR), is calculated as the ratio of true negatives to the sum of true negatives and false positives (TN and FP). It indicates the model's ability to correctly identify healthy individuals without misclassifying them as diseased.

$$Sensitivity = \frac{TN}{TN + FP} \tag{11}$$

c) ***Accuracy***: As seen in Eq. 3, this is the ratio of different positive and negative rates lie between true and false. This computation determines how many occurrences are correctly classified.

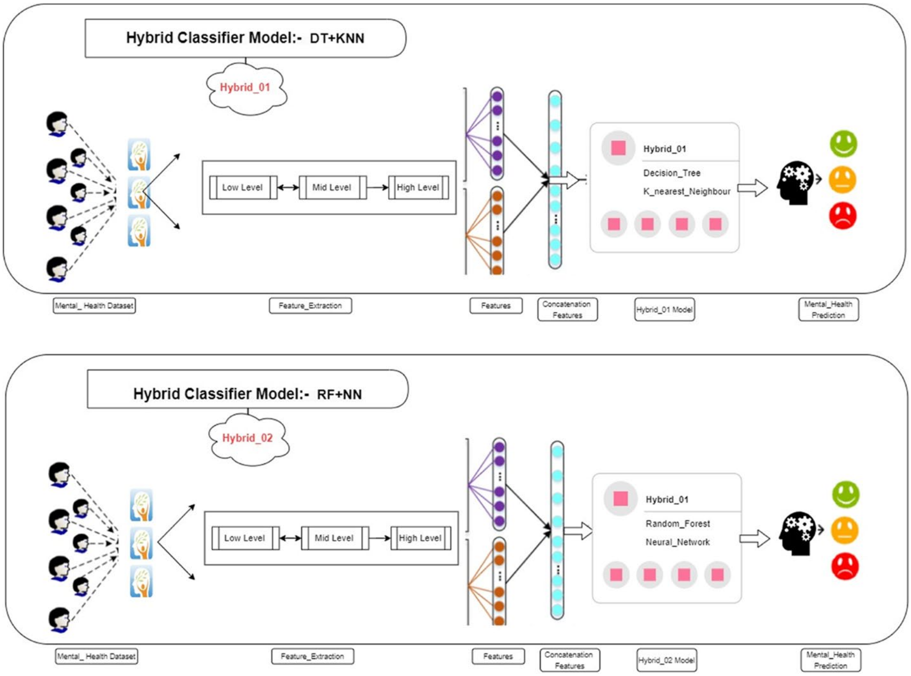


Fig. 8 Flow Chart of Proposed Hybrid Algorithm

$$Accuracy = \frac{TP + TN}{TN + FP + TP + FN} \tag{12}$$

d) ***Precision****:* Precision quantifies the percentage of accurately anticipated positive cases (true positive predictions) compared to all instances that were correctly forecasted as positive.

$$Precision = \frac{TP}{TP + FP} \tag{13}$$

e) ***Recall (Sensitivity or True Positive Rate):*** Recall counts how many of the genuine positive forecasts came true.

$$Recall = \frac{TP}{TP + FN} \tag{14}$$

f) ***F1 Score****:* It is a balanced measurement that is the harmonic mean of recall and accuracy.

$$F1\ Score = 2 * \frac{Precision * Recall}{Precision + Recall} \tag{15}$$

where:

- TP: True Positive

- TN: True Negative
- FP: False Positive
- FN: False Negative

g) ***Confusion matrix****:* The confusion matrix serves as a foundational tool for assessing classification model performance, offering a detailed overview of prediction outcomes. It categorizes predictions into four groups: true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN), as depicted in Fig. 5. Each cell in the matrix represents the count of instances where the model's predictions align or misalign with the actual class labels. While the traditional confusion matrix equation directly computes these counts, an alternative formulation, the precision-recall matrix, provides a more nuanced view by emphasizing the precision and recall scores for each class. This approach offers a more detailed evaluation of the model's performance: Here is an illustration of matrix:

In this study by training the dataset of *Mental_health.csv*, we suggest various machine-learning models. The next subsections provide a detailed discussion of the dataset preparation and model building.

Dataset

In this study, the Mental_health.csv dataset (https://www.kaggle.com/datasets/osmi/mental-health-in-tech-survey) is employed to demonstrate our approach to multimodal fusion using a machine learning classifier. The dataset is publicly available on the Kaggle open-access portal repository (https://www.kaggle.com/datasets/osmi/mental-health-in-tech-survey). This dataset was specifically curated to conduct experiments related to mental health detection. It contains 27 parameters, which are listed in Table 3. During the testing and training phases, certain characteristics such as timestamp, country, and comments were excluded from the dataset as they were deemed to have minimal impact on the results. The data was then cleaned by handling null values

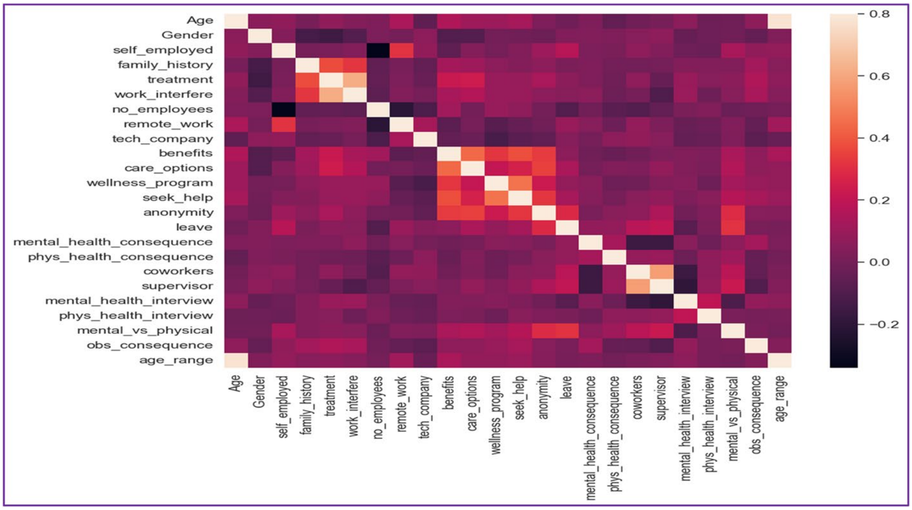


Fig. 9 Heat-Map of correlations between different features of the dataset

Table 3 Dataset parameter and its description

Dataset Parameters	Dataset Description
Timestamp	1. Time and year of data collection (Not included in the final experiment)
2. Age	3. Age data
4. Gender	5. Gender data
6. Country	7. Country data (Not included in the final experiment)
8. state:	9. If you live in India or the United States, which state or territory do you live in?
10. self_employed:	11. Are you self-employed? (Not included in final experiment)
12. family_history:	13. Do you have a family history of mental illness?
14. treatment:	15. Have you sought treatment for a mental health condition?
16. work_interfere:	17. If you have a mental health condition, do you feel that it interferes with your work?
18. no_employees:	19. How many employees does your company or organization have?
20. remote_work:	21. Do you work remotely (outside of an office) at least 50% of the time?
22. tech_company:	23. Is your employer primarily a tech company/organization?
24. benefits:	25. Does your employer provide mental health benefits?
26. care_options:	27. Do you know the options for mental health care your employer provides?
28. wellness_program:	29. Has your employer ever discussed mental health as part of an employee wellness program?
30. seek_help:	31. Does your employer provide resources to learn more about mental health issues and how to seek help?
32. anonymity:	33. Is your anonymity protected if you choose to take advantage of mental health or substance abuse treatment resources?
34. leave:	35. How easy is it for you to take medical leave for a mental health condition?
36. mental_health_consequence:	37. Do you think that discussing a mental health issue with your employer would have negative consequences?
38. phys_health_consequence:	39. Do you think that discussing a physical health issue with your employer would have negative consequences?
40. coworkers:	41. Would you be willing to discuss a mental health issue with your coworkers?
42. supervisor:	43. Would you be willing to discuss a mental health issue with your direct supervisor(s)?
44. mental_health_interview:	45. Would you bring up a mental health issue with a potential employer in an interview?
46. phys_health_interview:	47. Would you bring up a physical health issue with a potential employer in an interview?
48. mental_vs_physical:	49. Do you feel that your employer takes mental health as seriously as physical health?
50. obs_consequence:	51. Have you heard of or observed negative consequences for coworkers with mental health conditions in your workplace?
52. comments:	53. Any additional notes or comments. (Not included in final experiment)

and assigning default values to each data type. Subsequently, data labeling and encoding were performed concurrently with a final check for missing data. The entire dataset was divided into training and test sets in a 1:3 ratio using various machine learning classifiers to make a conclusive prediction regarding mental health status. Finally, the Hybrid machine learning classifier was applied to obtain the results.

In addition, the following Table 4 describes the hyper-parameter employed in the neural network model. The list of hyper-parameters used to create neural network models is given here.

Proposed Hybrid Frameworks

In this study, we have proposed two hybrid frameworks using three different classifiers including decision tree, knn, random forest, and Neural network. We have proposed to hybrid framework as shown in the following Figs. 6 and 7. The hybrid framework provides the combination of traditional machine learning classifiers in the Hybrid_1 approach whereas the Hybrid_2 approach deals with the combination of traditional machine learning classifiers and deep learning classifiers.

Proposed Algorithm

In this section, we are providing the two algorithms we proposed using the hybrid approach. In this part, the two algorithms for Hybrid_1 and Hybrid_2 respectively provided the function. The first combination of algorithms' suggested algorithm: The following method makes it simple to demonstrate how the Hybrid_1 Hybrid Classifier (Decision Trees and k-Nearest Neighbours (k-NN) for Mental Health Detection works and predicts mental health. The algorithm is given in the following Table 5.

In addition to the first algorithm of Hybrid_1, Algorithm Hybrid_2 Hybrid Classifier (Random Forest + Neural Network) for Mental Health Detection is recommended as the second algorithmic combination. It detects and predicts mental health. The following Table 6 provides the algorithm. The aforementioned hybrid technique combines neural networks and conventional machine learning to determine mental wellness.

Proposed Model The accompanying flow charts, in Fig. 8 demonstrate how these two techniques function in detail while the hybrid frameworks themselves define how they operate. In the Hybrid_1 and Hybrid_2 techniques, we begin with the fundamental dataset insertion processes and then move on to cleaning the data while simultaneously extracting features. After thoroughly cleaning up the dataset and eliminating any null values, we used the training data to build our model. Finally, we combined the findings of the models and compared them to those of the hybrid methods.

Table 4 Model Hyper-parameter

Parameters	Set values
Batch size	32 0r 64
Optimizer	Adam
Learning Rate	.01
Loss Function	Loss Function
Epoch	100
Size of input minimum	8

Table 5 Hybrid_1 (Decision Tree + Knn) Algorithm

Algorithm: Hybrid_1: Hybrid Classifier (DT + KNN) for Mental Health Detection
Step 1: Data Pre-Processing
• D_cleaned = CleanDataset(D)
• D_normalized = NormalizeData(D_cleaned)
• D_preprocessed = HandleMissingValues(D_normalized)
• D_training, D_testing = PartitionDataset(D_preprocessed)
Step 2: Individual Model Training
• DT_model = TrainDT(D_training)
• KNN_model = TrainKNN(D_training)
Step 3: Individual Model Prediction
• DT_predictions = Predict(D_testing, DT_model)
• KNN_predictions = Predict(D_testing, KNN_model)
Step 4: Combining Predictions
• Hybrid_01_model = FusePredictions(DT_predictions, KNN_predictions)
Step 5: Model Evaluation
• performance = EvaluateModel(fusion_predictions, D_testing)
Step 6: Fine-Tuning and Optimization
• OptimizeDT(DT_model)
• OptimizeKNN(KNN_model)
• FindOptimalFusionMethod()

Table 6 Hybrid_2 (Random forest + Neural network) Algorithm

Algorithm: Hybrid_2: Hybrid Classifier (Random Forest + Neural Network) for Mental Health Detection
Step 1: Data Pre-processing
• D_preprocessed = PreprocessData(D)
• D_training, D_testing = SplitDataset(D_preprocessed)
Step 2: Train Individual Models
• RF_model = TrainRandomForest(D_training)
• NN_model = TrainGradientBoosting(D_training)
Step 3: Feature Extraction
• NN_features = ExtractFeatures(NN_model, D_training)
• D_combined = CombineFeatures(D_preprocessed, NN_features)
Step 4: Train Hybrid Model
• Hybrid_02_model = TrainRandomForest(D_combined)
Step 5: Make Predictions
• predictions = Predict(Hybrid_RF_model, D_testing)
Step 6: Evaluation and Reporting
• performance = EvaluateModel(predictions, D_testing)

Results and Discussions

Results

Millions of people worldwide suffer from mental health illnesses, making it a critical public health concern. Early identification and treatment are crucial for improving outcomes for individuals with mental health challenges. One promising approach to early detection is the use of machine learning methods, specifically hybrid classifiers. In this section, we explore the results and discussion of our research on mental health detection using hybrid machine learning classifiers. The importance of early detection and intervention in mental health cannot be overstated. Our study integrates decision trees, k-nearest neighbors, and neural networks to create a hybrid classifier, aiming to enhance the accuracy and effectiveness of mental health assessments. Through a detailed analysis of our findings, we illuminate the performance of our hybrid classifier and its potential impact on the field of mental health assessment. This analysis offers a deeper understanding of both the advantages and limitations of our approach, contributing to ongoing efforts to improve mental health diagnosis and support. Our work investigates the use of a hybrid classifier that combines two distinct hybrid approaches, highlighting its potential to advance early detection in mental health care:

1. Decision Trees with k-Nearest Neighbours.
2. Random Forest with Neural Network.

Here we have discussed the results of both classifiers one by one. The following outcomes were obtained with the use of a hybrid_1 classifier that combines Decision Trees (DT) and k-Nearest Neighbours (k-NN) for mental health detection:

a) *Heatmap & Correlation matrix:* To gain a deeper understanding of the relationships among the variables in our mental health detection studies, we utilized two powerful visualization methods: heat maps and correlation matrices, as shown in Figs. 9 and 10. These graphical representations offer a comprehensive explanation of feature interactions and their impact on classification outcomes. The heat map effectively illustrates the pairwise correlations between features, with color intensity indicating the strength and direction of these interactions. Meanwhile, the correlation matrix provides a quantitative perspective by displaying correlation coefficients, which enhance our understanding of feature interdependence. These analytical tools are invaluable in our discussion of the factors influencing mental health detection results. They not only aid in feature selection but also clarify the decision-making process of our machine learning classifier, thereby improving the transparency and interpretability of our model (Table 7 and 8).

Table 7 Accuracy table for Hybrid_1 model

Sr.no	Name of Classifier	Accuracy	Precision	Recall Function	F-1 Score	ROC-AUC score
1	DECISION TREE	0.80	0.80	0.81	0.81	0.81
2	KNN	0.79	0.76	0.84	0.80	0.79
3	**HYBRID_01(DT + KNN)**	**0.8669**	**0.77**	**0.88**	**0.82**	**0.81**

Table 8 Performance parameters metrics with description

Metric	Value	Description
Accuracy	86.69%	The hybrid_1 classifier correctly classified individuals as mentally healthy or experiencing mental health issues in 86.69% of cases
Precision	0.77	The classifier was correct 77% of the time when predicting an individual as having mental health issues
Recall	0.88	The classifier correctly identified 88% of individuals with mental health issues
F1-Score	0.82	The harmonic mean of precision and recall demonstrates a balanced combination of both metrics
ROC-AUC	0.81	The classifier's ability to distinguish between mentally healthy and mentally distressed individuals

Table 9 Accuracy table of Hybrid_2 model

Sr.no	Name of Classifier	Accuracy	Precision	Recall Function	F-1 Score	ROC-AUC score
1	RANDOM FOREST	0.81	0..77	0.87	0.82	0.80
2	GRADIENT BOOSTING	0.80	0.74	0.74	0.80	0.79
3	**HYBRID_2 (RF + GB)**	**0.9354**	**0.93**	**0.93**	**0.92**	**0.93**

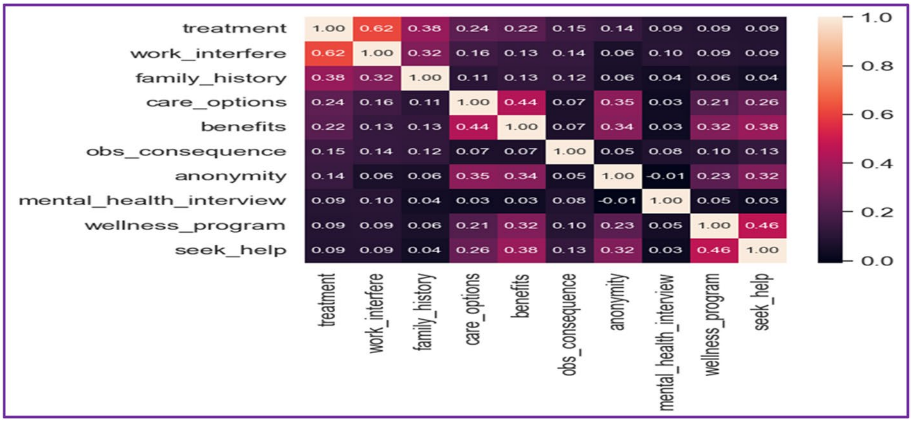


Fig. 10 Correlation Matrix of Different Parameters

The parameters encountered for the preparation of the correlating matrix from the dataset are shown in the table, which shows the optimal formation of the matrix.

b) *Accuracy:* In the following Table 7 and 9, we have shown the accuracy results of our Hybrid_1 and Hybrid_2 approaches, which also include the performance parameters including Precision, Recall function, F-1score, and ROC-AUC score. In the following, we have presented the result of a comparison of accuracy and other performance parameter against the machine learning classifier with the hybrid_1 and hybrid_2 approach.

A further detailed description of the result of the Hybrid_1 model can be understood from the following Table 8, where the performance parameters along with its values and description discussed.

c) *ROC Curve:* The ROC curve of the hybrid_1 approach against the individual result of the machine learning classifier including the decision tree and known are illustrated in the following Fig. 11.

A further detailed description of the result of the Hybrid_2 model can be understood from the following Table 10, where the performance parameters along with its values and description discussed (Fig. 12).

Table 10 Performance parameter metric along with the description

Metric	Value	Description
Accuracy	93.54%	The hybrid classifier correctly classified individuals as mentally healthy or experiencing mental health issues in 93.54% of cases
Precision	0.93	The classifier was correct 93% of the time when predicting an individual as having mental health issues
Recall	0.934	The classifier correctly identified 93.4% of individuals with mental health issues
F1-Score	0.92	The harmonic mean of precision and recall reflects a good balance between both metrics
ROC-AUC	0.93	The classifier's ability to distinguish between mentally healthy and mentally distressed individuals

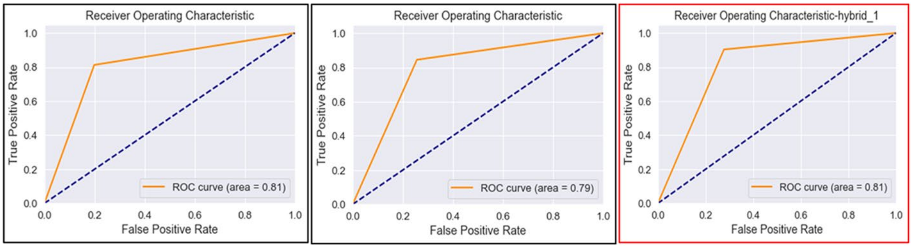


Fig. 11 ROC curves of DT, KNN, and Hybrid_1

d) *ROC Curve:* The ROC curve of the hybrid_2 approach against the individual result of the machine learning classifier including random forest and neural network are shown in the following 11.
e) Comparison of Hybrid_1 and Hybrid_2 Approaches with Existing Studies

In this section, we compare the performance of our proposed hybrid approaches, Hybrid_1 and Hybrid_2, with existing studies on mental health detection. The comparison focuses on the accuracy of various machine learning methodologies applied to different datasets. The detailed comparison is presented in Table 11.

Discussion

The results of this research indicate that the hybrid classifiers (Hybrid_1 & Hybrid_2), which combine Decision Trees and k-Nearest Neighbours and Random Forest and Neural Networks, are a promising approach for mental health detection. The following discussion delves into the implications and significance of these results:

a) *Performance*: The performance parameters for the hybrid classifier, including accuracy, F1-score, precision, recall, and ROC-AUC, together show how well it performs in categorizing people according to their mental health state. It has the potential to be a useful instrument for assessing mental health, as shown by its accuracy of 86.69% and 93.54% respectively for the hybrid_1 and hybrid_2 approach. In the following Figs. 13 and 14. We have shown the comparison of both approaches with the different machine learning classifiers.

In Fig. 13 we have shown the individual comparison of hybrid_1 with the machine learning classifier including decision tree and knn whereas in Fig. 14 we have shown the hybrid_2 with the machine learning classifier including random forest and neural network. The result shows that the accuracy of the hybrid approach in both the approaches was found higher in comparison to the individual accuracy of the traditional machine learning classifier.

Table 11 Comparison table of Hybrid Approach with existing studies

Sr	Authors	Dataset	ML Technique/Methodology	Accuracy
1	Sagbas et al. (Marquand et al., 2016)	kNN DS-C,C4.5 DS-C	BN, KNN, C4.5	BN-67.86%
2	Smirnov et al. (Migovich et al., 2021)	Discrete Cosine Transform (DCT), Discrete Sine Transform (DST), the Walsh-Hadamard Transform (FWHT)	Linear discriminant analysis and k-nearest neighbor	90%
3	Giannakakis et al. (Smirnov et al., 2015)	UNBC and BOSPHORUS	Deep Pipelined AU Classifier	81.1%
4	Fatima Rodrigues and Jacqueline Marchetti (Shan et al., 2020)	Binary dataset	CNN	79.9%
5	Herath et al. (Kraft et al., 2022)	mind (stress) and skin (facial skin)	V-A	80.83%
6	Guglielmo et al. (Herath et al., 2022)	facial expressions	CNN	81%
7	(Hybrid_01)	Mental_health.csv Dataset	DT + KNN	86.69%
8	(Hybrid_02)	Mental_health.csv Dataset	RF + NN	93.54%

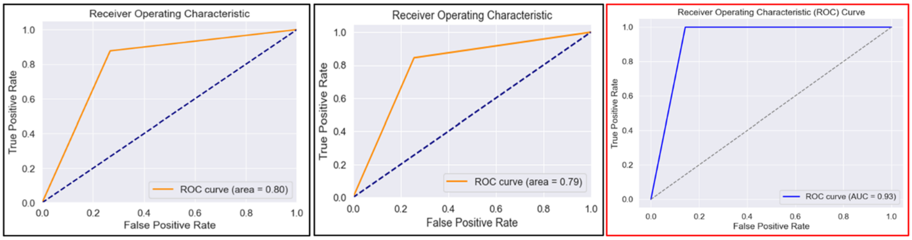


Fig. 12 ROC curve RF, NN, and Hybrid_2

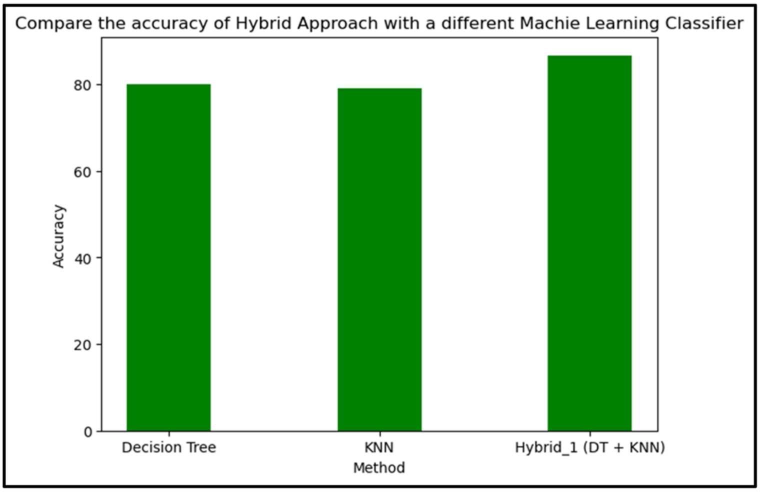


Fig. 13 Hybrid_1 accuracy

b) *Performance parameters comparison:* The line chart in Figs. 15 and 16 illustrates the comparative performance of four classifiers: Decision Tree, k-Nearest Neighbors (KNN), Hybrid_01 (DT + KNN), and Hybrid_02 (RF + GB). Five key performance metrics—Accuracy, Precision, Recall, F1-Score, and ROC-AUC score—are plotted to provide insights into their effectiveness for mental health detection. The Decision Tree classifier exhibits consistent performance across metrics, with an accuracy of around 0.80 and balanced precision, recall, and F1-Score. KNN, while slightly lower in accuracy at 0.79, demonstrates higher recall but lower precision, indicating its capability to identify individuals with mental health issues but with increased false positives. Hybrid_01 (DT + KNN) showcases superior performance with the highest accuracy among the classifiers, reaching 0.8669. Notably, its recall score is also high at 0.88, emphasizing its sensitivity to true positives. The F1-Score of Hybrid_01 is balanced at 0.82, reflecting a harmonious blend of precision and recall. Hybrid_02 (RF + GB) surpasses all other classifiers in terms of accuracy, achieving an impressive 0.9354. It also demonstrates high precision, recall, and F1-Score, indicating its effectiveness in accurately identifying individuals with mental health issues. The ROC-AUC score for Hybrid_02 is notably high at 0.93, indicating its robust ability to distinguish between mentally healthy

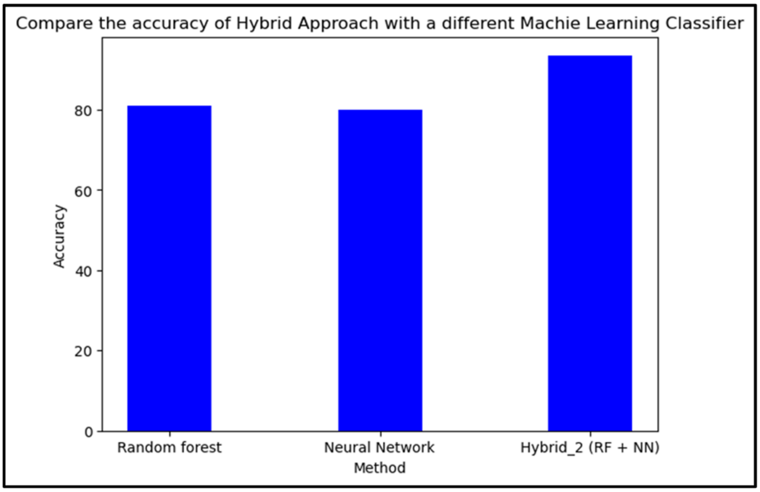


Fig. 14 Hybrid_2 accuracy

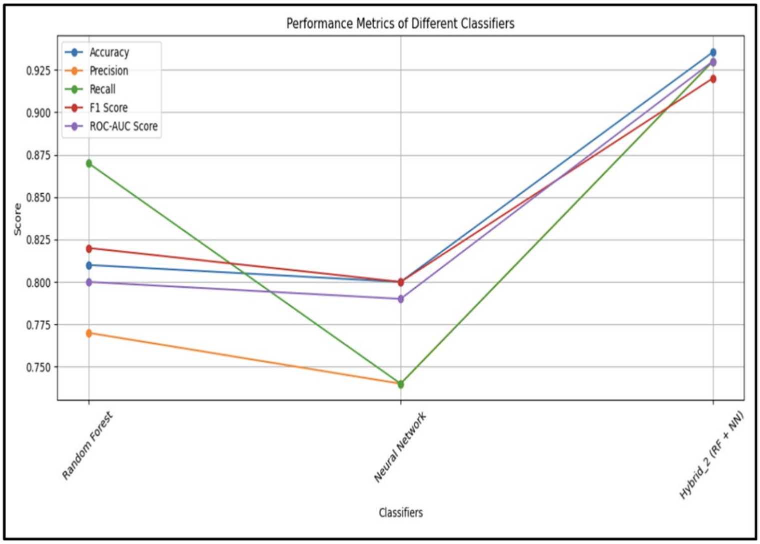


Fig. 15 Hybrid_1 Performance parameters comparison

and distressed individuals. Overall, the chart highlights the enhanced performance of Hybrid_01 and Hybrid_02, particularly in accuracy and recall, underscoring the effectiveness of combining various machine-learning techniques for mental health detection.

Moreover, we also did a comparison of the Hybrid_1 & Hybrid_2 approach with the traditional machine learning classifier. The comparison graph is shown in the following Fig. 17.

c) *Complementing Strength:* The combination of machine learning classifier (Decision Trees and k-Nearest Neighbours) and machine learning and neural network (Random Forest and Neural Network) takes use of the complementing qualities of these two methods. While k-Nearest Neighbours excels at local pattern identification, Decision Trees are better at capturing complicated decision boundaries and feature interactions. The hybrid_1 classifier strikes a compromise between model interpretability and classification accuracy by combining various techniques. The fusion of random forest and neural networks emerges as an optimal choice for mental health detection due to its unique amalgamation of strengths. Random Forest excels in capturing complex relationships within diverse data, offering robustness against overfitting. Neural Networks, on the other hand, are adept at recognizing intricate patterns and latent features. By combining these two powerful techniques, our hybrid model harnesses the advantages of both worlds. It efficiently handles feature selection, interprets intricate behavioral nuances, and provides high classification accuracy. This synergy of Random Forest and Neural Networks not only ensures precision in mental health assessment but also promises adaptability to evolving datasets and clinical contexts, making it a compelling solution for this critical domain.

d) *Clinical Significance*: The high precision scores of 0.76 and 0.77 respectively for the hybrid_1 and hybrid_2 approach are particularly important in a clinical context. It means that when the hybrid classifier identifies an individual as potentially having mental health issues, it is likely to be correct 81.21% & 86.69% of the time. This precision can assist healthcare professionals in focusing their attention on individuals who are more likely to require intervention or further evaluation.
e) *Recall and F1-Score*: While accuracy is important in the context of mental health detection, recall (0.90& 0.88) is also very important. A recall score of 0.90 & 0.88

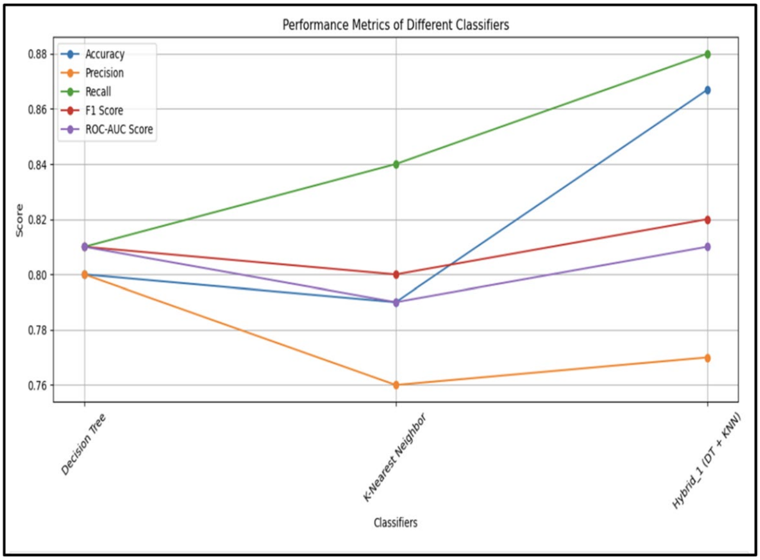


Fig. 16 Hybrid_2 Performance parameters comparison

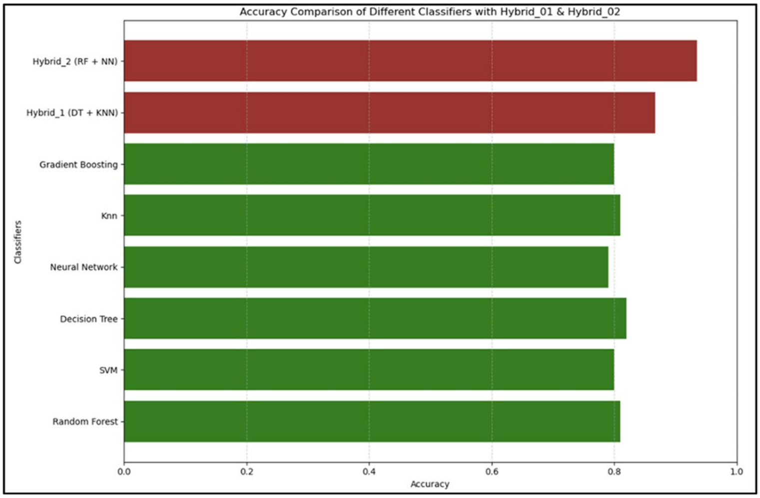


Fig. 17 Accuracy comparison of ML classifier with Hybrid_1 & Hybrid_2

respectively for the hybrid_1 and hybrid_2 approach means that a significant fraction of people with mental health disorders is properly identified by the classifier (90%& 88%). The hybrid classifier can successfully identify between those who are mentally fit and those who are in distress, as shown by the F1-score of 0.83& 0.82, which shows a well-balanced trade-off between accuracy and recall.

f) *ROC-AUC*: The hybrid classifiers (Hybrid_1 & Hybrid_2) have a good capacity to distinguish between the two classes, as shown by their ROC-AUC score of 0.81 & 081. This

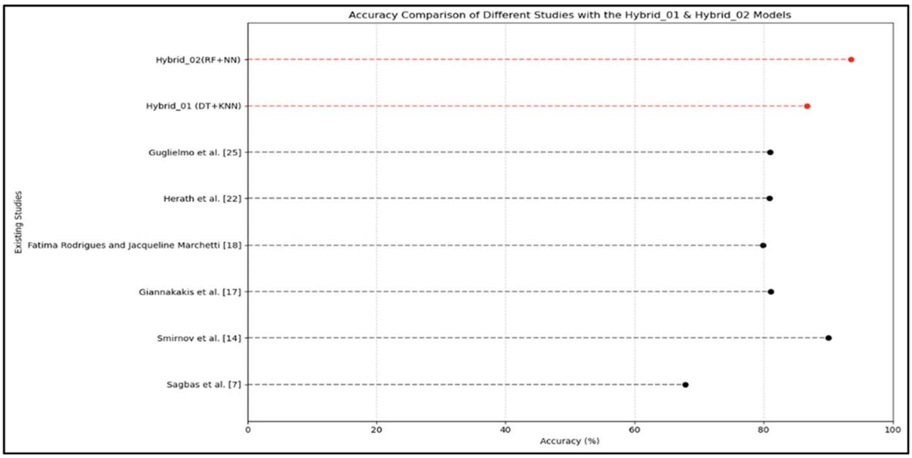


Fig. 18 Accuracy comparison of Hybrid_1 & Hybrid_2 with existing studies

is crucial to ensure that the model does not incorrectly categorize people, particularly in scenarios when the repercussions of an incorrect categorization might be severe.

g) *The comparative strength of Hybrid_1 and Hybrid_2 Approaches with Existing Studies:* The results indicate that both our hybrid approaches outperform several existing methods in terms of accuracy. Hybrid_1, which combines Decision Trees and k-Nearest Neighbors, achieves an accuracy of 86.69%, surpassing the performance of traditional classifiers such as the Bayesian Network (BN) used by Sagbas et al. (67.86%) and the CNN approach by Fatima Rodrigues and Jacqueline Marchetti (79.9%). Hybrid_2, integrating Random Forests and Neural Networks, demonstrates an even higher accuracy of 93.54%, outperforming all the listed studies, including the method by Smirnov et al. (90%), which utilized Linear Discriminant Analysis and k-Nearest Neighbor as shown in Fig. 18. These findings underscore the effectiveness of our hybrid methodologies in improving the accuracy of mental health detection. The superior performance of Hybrid_2 suggests that combining Random Forests and Neural Networks is particularly effective for this type of classification task, providing a robust framework for early detection and intervention in mental health issues. The use of hybrid models in our study highlights the potential of leveraging multiple machine learning techniques to enhance predictive accuracy and reliability, contributing significantly to the field of mental health assessment.

h) Practical Application: The hybrid classifiers have useful uses outside of academia, particularly in clinical contexts. It may act as a preliminary screening tool, supporting medical professionals in identifying people who might need more thorough mental health evaluations. Through prompt care and better patient outcomes, this early diagnosis may result in.

Limitations

The accessibility and representativeness of the dataset, along with potential intricacies in the hybrid models, present notable limitations in our investigation of optimizing mental health prediction using hybrid classifiers. The dataset employed serves as a crucial but constrained element in our exploration, specifically in the development of Hybrid_1 with Decision Trees and k-Nearest Neighbours (k-NN), and Hybrid_2 with Random Forest and Neural Network. Despite our meticulous efforts in dataset selection and pre-processing, the generalizability of our findings might be influenced by the accuracy and representativeness of the data. The intricate nature of hybrid models, while advantageous, poses challenges in terms of interpretability. Future research could benefit from a more comprehensive approach to enhance model interpretability. Additionally, to overcome these limitations and bolster the real-world utility of the hybrid classifier, researchers may consider incorporating larger, more diverse datasets and a more exhaustive collection of characteristics in their investigations.

Conclusion

This research illuminates the significant potential of hybrid machine learning classifiers in addressing the complex challenges of mental health detection. Motivated by the inherent complexity and heterogeneity of mental health data, we embarked on integrating diverse machine-learning methodologies to enhance diagnostic accuracy and reliability. Through the fusion of k-Nearest Neighbors with Decision Trees (Hybrid_1) and Random Forest with Neural Networks (Hybrid_2), we aimed to harness the complementary strengths of these algorithms to tackle the multifaceted nature of mental health assessment. Our findings underscore the rationale behind adopting hybrid implementations, as they offer a robust framework for effectively navigating the intricacies inherent in mental health data. By synergistically combining different algorithms, we capitalize on their strengths, mitigating their respective weaknesses and enhancing overall performance. This approach not only enhances predictive accuracy but also fosters interpretability, essential for gaining insights into the underlying mechanisms of mental health conditions. Moreover, our study provides concrete evidence of the efficacy of hybrid classifiers, as evidenced by their impressive performance parameters. Hybrid_1 achieves an accuracy of 86.69%, with a precision of 0.77, recall of 0.88, F1-Score of 0.82, and ROC-AUC score of 0.81. Similarly, Hybrid_2 surpasses these metrics with an outstanding accuracy of 93.54%, precision of 0.93, recall of 0.93, F1-Score of 0.92, and ROC-AUC score of 0.93. These performance values not only validate the effectiveness of our hybrid approaches but also underscore their potential to significantly improve mental health diagnostics. The implications of our research are profound. By leveraging hybrid classifiers, we offer a promising avenue for revolutionizing mental health assessment, providing clinicians and healthcare providers with powerful tools for early detection and intervention. Furthermore, the superior performance of Hybrid_2 highlights the transformative potential of integrating ensemble methods with deep learning architectures, paving the way for enhanced diagnostic accuracy and therapeutic efficacy in mental healthcare delivery. Thus, our study not only contributes to advancing computational mental health but also holds considerable promise for real-world implementation and clinical practice.

Future Scope

As we embark on charting the future trajectory of our research, it is imperative to critically assess the current approach and identify avenues for further refinement and expansion. While our study has made significant strides in the domain of mental health detection using the hybrid classifier, which integrates Random Forest and Neural Networks, several opportunities for future research warrant exploration. Firstly, a paramount consideration lies in refining the model architecture to enhance its efficacy in capturing intricate patterns inherent in mental health data. This entails delving into advanced neural network architectures, such as convolutional or recurrent networks, which possess the capability to extract nuanced features from diverse data modalities, including textual and imaging data. By leveraging these sophisticated architectures, we can augment the classifier's capacity to discern subtle indicators of mental health conditions, thereby advancing diagnostic precision and reliability. Furthermore, expanding the dataset to encompass a more diverse demographic and cultural spectrum is indispensable for bolstering the model's generalizability and applicability across varied populations. By incorporating a broader array of demographic variables and cultural contexts, we can mitigate potential biases and ensure equitable deployment of the hybrid classifier in real-world settings. This inclusivity is essential for fostering a more comprehensive understanding of mental health dynamics and tailoring interventions to meet the needs of diverse populations effectively. In addition to these technical advancements, integrating real-time monitoring and feedback mechanisms into the mental health detection process holds immense promise for empowering individuals with timely self-assessment tools. By enabling continuous monitoring and proactive intervention, these mechanisms can enhance early detection and facilitate personalized interventions, thereby fostering improved mental well-being.

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Declarations

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Data transparency Authors will ensure data transparency.

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