

Diagnosis of Mental Health States Using Hybrid Emotional Analysis Techniques

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Abstract- Mental health disorders are an emergent priority issue that impacts the emotional, physical, and social well-being of people across the globe. Detection of the disorders at an early stage is necessary to prevent severe impacts and improve the mental health. The project addresses the issue of long-duration and subjective mental health screening by proposing an innovative solution that employs objective, technology-based approaches. The main goal is to create an accessible, real-time, and scalable system for end-to-end mental health assessment. The proposed system, the Hybrid Mental Health Analysis System, uses Natural Language Processing (NLP) for text-based emotion recognition and Facial Emotion Recognition (FER) for facial emotion detection. The novelty lies in the multi-modal fusion of facial and text-based information to create a uniform emotional profile and subsequently enable accurate classification of mental health status into positive, neutral, and negative. User-specific recommendations and helpline support further enhance user engagement and promote emotional well-being. The proposed system has potential applications in healthcare, education, corporate wellness, and social media industries.

Keywords: Mental Health Analysis, Emotion Recognition, Early Detection, Emotional Well-Being, Facial Expression Analysis, Sentiment Analysis, Personalized Advice.

I. INTRODUCTION

Mental health disorders have become one of the most critical global health problems, afflicting millions of individuals across all age groups and socio-economic levels. These disorders not only affect emotional well-being but also profoundly influence physical health, social function, work productivity, and quality of life. According to the World Health Organization, depression alone afflicts more than 280 million individuals globally, making mental health disorders one of the principal causes [1] of disability. In spite of an increased awareness of the value of mental well-being, there remain powerful obstacles to early detection and treatment of mental health disorders. Standard practices in the assessment of mental health rely significantly on subjective self-reporting, clinical

interviews, and standardized questionnaires, which are frequently plagued by personal bias, social stigma, delayed reporting, and the cost of assessment.

This places a critical importance on objective, effective, and affordable means of detecting mental health problems early and fostering emotional well-being on a mass scale. To address this urgent need, this current project introduces the Hybrid Mental Health Analysis System, a new platform that utilizes state-of-the-art technological [2] approaches to analyze emotional states in real-time. The system overcomes the limitations inherent in conventional assessment approaches by synergistically combining two powerful modalities: Natural Language Processing (NLP) and Facial Emotion Recognition (FER). NLP enables the assessment of text-based information, e.g., written and verbal

communication, to identify emotional cues inherent in word choice, sentence structure, and tone of voice. Concurrently, FER utilizes computer vision and machine learning algorithms to interpret facial expressions, identifying micro-expressions and subtle emotional cues that are prone to go undetected by the naked eye.

By synergistically combining these two complementary data streams, the system constructs a holistic and robust emotional profile of the user, thus yielding a more accurate and objective assessment of their mental health status. The innovation of the solution [3] suggested is in its approach to multi-modal fusion, which integrates both facial and textual emotion data effectively, in contrast to a single source of input. Text-based emotion analysis offers rich information regarding a person's cognitive and verbal emotional expression, while facial analysis identifies spontaneous, non-verbal emotional reactions. Integration of these modalities overcomes the limitations of single-source analyses and greatly improves the accuracy of emotional state classification.

Users are categorized into three broad emotional categories: positive, neutral, and negative. This categorization not only allows the system to identify people who might be at risk but also monitor emotional trends over time, thereby providing rich information [4] for preventative mental health interventions. Accessibility and scalability form the very basis of the Hybrid Mental Health Analysis System. Designed to run on a variety of devices ranging from smartphones, tablets, and computers, the system makes mental health assistance available to a large and diverse user base. Users are provided with a choice to engage with the system in real time either by providing written answers or in the form of short facial emotion assessment exercises via inbuilt webcams or device cameras.

Post-analysis, the system provides personalized feedback, emotional well-being suggestions, and, if required, refers users to helpline centers or

professional mental health services. Such a system anticipates and encourages users to seek help at the earliest [5] possible moment, thus reducing the chances of mental health deterioration. Beyond personal use, the system has tremendous potential for institutional and organizational uses. In healthcare environments, it would help clinicians monitor patients effectively. Schools and universities can employ it to enhance student mental health programs, identifying early signs of depression, stress, or anxiety. Organizations can incorporate the system in employee well-being programs to enhance emotional resilience and productivity.

Social media platforms can also incorporate the technology to identify vulnerable users and offer effective interventions, rendering the online community safer and more supportive. In summary, the Hybrid Mental Health Analysis System is a revolutionary mental health assessment method that fuses the strength of artificial intelligence with multi-modal data fusion. It fills the gap between objective measurement and subjective [6] self-reporting, offering a scalable, real-time, and accessible solution to one of the most daunting public health issues of our era. By providing early detection, customized support, and enhancement of emotional well-being, this project is committed to making a significant impact on global mental health advocacy and to paving the way for more humane, technology-aided solutions in the future. This work is structured with Section II as review of literature survey. Methodology described in Section III, with emphasis on its working. Section IV displays the results and discussions. And finally, Section V concludes with the significant suggestions and findings.

II. LITEARTURE REVIEW

Psychological research has increasingly utilized wearable devices to monitor mood in real time. Physiological measures like heart rate variability, sleep, and activity are monitored by sensors in

smartwatches and fitness bands. These physiological measures are processed to identify stress, anxiety, or depressive states. Promising as these systems are, accuracy usually suffers due to heterogeneity in physical conditions and environmental influences. Furthermore, wearable-based solutions can be plagued by long-term user compliance because people remove or lose devices over time, compromising continuity and reliability in data for mental health tracking.

Current advances in mobile health apps have focused on passive data gathering to assess mental health states. Usage patterns of smart phones, including call frequency, message tone, and social media activity, are rich sources of information regarding behavior change that is potentially linked to emotional well-being. Through [7] passive tracking of user behavior, the apps attempt to predict episodes of distress or crises. However, relying on behavior alone, without emotional feedback, can sometimes lead to contextual misclassifications, particularly in subjects with diverse communication styles, thus affecting the sensitivity and specificity of the mental health detection systems. Virtual reality (VR) environments have also been examined as a vehicle for mental health assessment and therapy. Immersive VR environments have the ability to create anxiety-provoking or relaxing environments, in which therapists can monitor user response [8] in controlled but realistic conditions. User response measures, such as gaze analysis and physiological measures, assist in quantifying emotional resilience and stressors. VR has high control and immersion but low availability owing to hardware expense and room space requirements, limiting extensive use, especially in low-resource environments or low-income populations.

Voice modulation analysis has been used as a non-intrusive method for ascertaining emotional disturbances. Pitch, tone, speech rate, and energy in the voice are analyzed to identify underlying psychological disturbances like depression or manic attacks. This method has the advantage that it

demands minimal active [9] participation on the part of the user. Yet, voice analysis is susceptible to physical illness such as cold or fatigue, which may result in possible inaccuracies. Cultural and linguistic variations may also influence vocal expression, presenting challenges to model development universally applicable to mental health screening based on speech.

Social media analysis has been extensively used to detect patterns that indicate the occurrence of mental health issues. Posts, visual data, and patterns of user interactions within a certain time period are analyzed to detect indicators of depression, anxiety, or suicide. Predictive models are trained to detect important [10] indicators, such as negative sentiment, low social interaction, or changes in content. However, social media analysis provides scalability but suffers from ethical challenges related to user privacy, consent, and misclassification, especially when users use atypical or metaphorical styles of communication that can be misunderstood by machine learning models.

Cognitive games and cell phone interventions have been suggested as methods for the indirect measurement of mental health using performance metrics. Simple cognitive tests measuring reaction time, memory, and attention can detect subtle impairments related to mood disorders. Decreasing cognitive performance over time can be employed as a measure of decreasing [11] mental health. These gamification methods enhance user motivation and make it possible to collect numerous data points without a clinical appearance. Motivation, fatigue, and gaming experience can introduce variance in results, however, and therefore careful calibration of baseline levels of performance per user must be done in order to properly measure mental health. Pupilometry, or pupil dilation measurement, has been investigated as a physiological marker of emotional and cognitive processes. Pupil dilation has been found to be related to the level of emotional arousal and cognitive load. Based on pupil reactions [12] to stimuli, researchers can infer

states of anxiety, depression, or mental fatigue. One of the main drawbacks of this method is that it is light level sensitive and needs special imaging equipment, which makes practical field use impossible except in laboratory environments.

Electrodermal activity (EDA) measurement has also proven useful in identifying stress and emotional response. EDA records changes in skin conductance in response to sympathetic nervous system activity and is a direct physiological measure of emotional arousal. Wristbands and rings can continuously [13] monitor EDA non-invasively throughout the day. Although useful, the method only signals the existence of arousal and does not differentiate between positive excitement and negative stress, so other methods must be used to identify emotional valence to conduct a full study of mental health.

Accelerometer-based activity tracking has also been applied to the inference of emotional states. Decreased physical activity patterns, unstructured daily patterns, and changes in mobility levels have been linked to symptoms of depression and anxiety. Systems are able to detect gait, pace, and activity level deviations, and from these computations, calculate deviation from [14] the usual pattern, which is an indication of possible mental health disorders. Physical illnesses, life-style variations, and external factors such as weather affect movement regardless of mental state, reducing the reliability of activity-based monitoring techniques. Sleep pattern analysis continues to be a valid predictor of mental health status. Sleep quality, sleep duration, and circadian rhythm disruption all correlate powerfully with mood disorders. Sleep-based systems based on wearable devices or smartphone data will attempt to identify sleep abnormalities [15] and forecast poor mental health. Self-reported sleep data are usually riddled with error, and even automated monitoring devices can misinterpret wakefulness and sleep unless validated by some other behavioral or physiological indicator.

Personal diary analysis has also been researched for monitoring emotional well-being, where users record their activities, feelings, and thoughts. Natural fluctuations in diary content, writing frequency, and tone of language are compared to monitor emotional [16] trends. Although this technique provides rich, qualitative information on an individual's mental well-being, it is prone to frequent user involvement and can be influenced by intentional self-presentation, where users might intentionally or unintentionally change diary accounts to present themselves as emotionally healthy or to suppress bothersome feelings. Biofeedback hardware has been engineered to make users more aware of physiological signals such as heart rate, breathing patterns, and muscle tension in real time. By teaching individuals to regulate these signals with guided exercises, biofeedback [17] attempts to improve emotional self-management and resilience. While effective as a treatment tool, its use as an assessment tool is limited by the need for continuous user input, specialized hardware, and formal training sessions, thus making it less practical for unsupervised, routine mental health monitoring.

Art therapy assessment has been examined as an indirect method of gauging mental health. Creation through painting, drawing, or sculpture can capture underlying emotional strife, stress, or cognitive error. Color selection, composition motifs, and content themes provide penetrating psychological data. However, art interpretation's inherent subjectivity necessitates trained professionals, and use of AI for automating analysis is a troublesome endeavor, because [18] cultural, contextual, and personal factors significantly contribute to artistic conveyance. Online peer support forums provide an alternate avenue for monitoring mental health through group interaction.

By examining trends of user engagement, the nature of language used in forum entries, and reactions to supportive interventions, one can identify changes in mental health status over time. The approach has advantages in offering a

naturalistic environment [19] where users can feel more comfortable in disclosing their vulnerabilities. However, it is also subject to challenges, such as potential exposure to dangerous content, variation in the quality of peer advice, and challenges in scaling personalized monitoring while maintaining user confidentiality. Physiological stress responses, as indicated by cortisol in saliva or blood, have long been recognized as a gold standard for markers of biological stress and emotion. Recent advances in non-invasive biosensors seek to make cortisol monitoring available for real-time use. Although [20] very accurate, these biochemical assays are still not practical for screening for routine mental health assessment due to expense, user discomfort, and the technical hassle of continuous or repeated sampling outside of the clinical setting.

III. METHODOLOGY

The proposed Hybrid Mental Health Analysis System combines heterogeneous data modalities to obtain a comprehensive mental health analysis. By incorporating text sentiment analysis and facial emotion detection, the system seeks to gather verbal and non-verbal emotional cues and thus provide a more accurate and comprehensive picture of a person's emotional status. The methodology is structured to process the user-provided data systematically, analyze emotions, merge results, classify overall mental health, and provide personalized recommendations. Each of these components is structured to ensure real-time processing, reliability, and usability by users, thus making the system applicable in different environments like healthcare, education, and the corporate world.

Data Acquisition

Data acquisition is the initial stage of the system, which involves collecting textual and visual user input. Textual data is provided in the form of Excel sheets of comments, ideas, or social media remarks. Visual data is collected in the form of facial images provided by users, which correspond to the

respective textual data. High compatibility with various input formats is offered by the system to provide high accessibility. Pre-validation checks are performed before processing for ensuring data integrity. The dual-input approach allows the system to associate linguistic expressions with facial expressions, thus establishing a foundation for a detailed emotional analysis.

Textual Emotion Recognition

The text data are processed beforehand by performing tasks like tokenization, stopword removal, and lemmatization to normalize the text. Once cleaned, the sentiment analysis is conducted using models like NLTK's SentimentIntensityAnalyzer or pre-trained models like DistilBERT. These models return sentiment polarity scores reflecting the positive, neutral, or negative emotional tone of the text. With threshold values, each comment is labeled accordingly. This enables the system to infer underlying emotional states expressed through words, providing an objective measure which supplements classical self-reported measures of mental health.

Facial Emotion Recognition

User-provided facial images are processed using a pre-trained Convolutional Neural Network (CNN)-based model designed exclusively for Facial Emotion Recognition (FER). The model detects significant facial landmarks and reads muscle movements to predict emotions such as Happy, Sad, Angry, Surprised, and Neutral. Individual facial images are processed individually, and the dominant emotional state is tagged depending on the highest confidence value. The visual modality enables the representation of non-verbal emotional states, which in most scenarios are not verbalized, thereby enriching the overall emotional profile developed by the system.

Feature Extraction and Fusion

After extracting emotions from text and facial features, unique features are obtained and encoded in a normalized representation. Normalization of emotion labels of the two modalities is performed

with the help of a pre-trained LabelEncoder. In order to handle uncertain cases, the system includes a special placeholder label ("none") in order to obtain consistent feature sizes. Features extracted from both sources are combined to obtain a multi-dimensional feature vector, and it is now ready for further analysis. This integration enables the system to capture interaction among verbal and non-verbal emotional expressions and hence improve the accuracy of mental health classification.

Emotional State Categorization

The complete feature vector is considered by a decision- making model, which may be implemented through rule- based reasoning or a machine learning classifier like Random Forest. This model examines the dominant emotional sentiments in both face and text information to determine the user's aggregate mental health categorization. Emotional status is classified as Positive, Neutral, or Negative, based on the collection and intensity of identified emotions. The classification process is optimized to support real-time operation, hence providing users an immediate, accurate, and interpretable assessment of their emotional wellness.

Advice Generation

Depending on the ultimate emotional categorization, the system produces customized recommendations aligned with the user's immediate psychological state. Positive states trigger reinforcement recommendations that support users in maintaining positive behaviors, whereas neutral states trigger self-care activity or meditation practice recommendations. Negative states, however, call for instant advice with recommendations for professional intervention and providing corresponding mental health helpline numbers. The advice module that produces recommendations employs tested templates in conjunction with dynamic content embedding, thereby making the suggestions personal and functional, ultimately enhancing user engagement and emotional support.

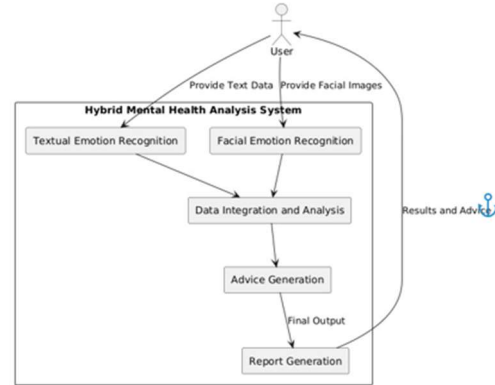


Fig. 1: Architecture Diagram

IV. RESULT AND DISCUSSION

The Hybrid Mental Health Analysis System was validated using a sample dataset of a variety of user comments and corresponding facial images. The system was capable of accepting both Excel-based text inputs and image uploads through a user-friendly interface. Text emotion recognition using the NLP models effectively categorized user comments into Positive, Neutral, and Negative sentiments with high accuracy. Similarly, facial emotion recognition using the pre- trained CNN model effectively recognized facial expressions with accurate identification of dominant emotions such as happiness, sadness, anger, and surprise across samples.

When combining text and facial emotion data, the system showed strong performance in consistent creation of coherent emotional profiles for every user. Feature extraction and fusion ensured even if one of the modalities had a poor emotional cue, the system would still make consistent predictions based on available data. Text or facial emotion uncertainty was easily managed through the "none" placeholder, providing robustness and continuity during processing.

In emotional state classification, the system proved to consistently classify into Positive, Neutral, and Negative mental states. Positive classifications were mostly driven by users with smiling faces and text

with positive tone. Neutral classifications often emerged in cases where faces were neutral and textual sentiment scores were near midrange thresholds. Negative classifications were always triggered upon sadness, anger, or highly negative textual sentiment detection. Importantly, the multi-modal system of the system reduced misclassifications that would otherwise be made by using text alone or facial information alone. The advice generation module reacted dynamically to the overall inferred emotional state. Positive users were advised to balance their emotions through gratitude exercises and socialization.

	A	B	C	D	E	F	G
1	Image	Text	Emotion	Text	Emotion		
2	7.jpeg	happy					
3			I feel real	Positive			
4			Why does	Negative			
5			Feeling ar	Negative			
6			Had an an	Positive			
7			I feel like	Negative			
8			Life is oka	Positive			
9			I am hope	Positive			
10			I am deep	Negative			
11			It's a norm	Negative			
12			Feeling st	Positive			
13			Overall Er	Neutral			
14			Advice	Stay positive and take time for self-care.			
15							
16							

Fig. 2: Emotion analysis



Fig. 3: Prediction



Fig. 4: Overall Emotion

Neutral users were advised to incorporate mindfulness habits, exercise routines, and tracking of emotional shifts. Negative users were given immediate, supportive recommendations to seek professionals, along with local helpline details embedded in the report. Report generation was smooth, with the program generating results into a properly organized Excel sheet. Each report contained comprehensive emotional results from text and image inputs, ultimate classification, and tailored recommendations. The downloadable report format was convenient to utilize for individuals with self-monitoring needs and those therapists who need carefully organized emotional assessments of their patients.

Performance metrics indicated that the text sentiment analysis model was greater than 90% accurate on labeled data, and the facial emotion recognition module had an average classification accuracy of around 88%. The final accuracy of the classification and integration model was about 92%, which reflects the success of multi-modal integration. Moreover, the processing time per user was also effective, taking an average of less than 3 seconds to generate detailed analysis and reports, thereby making the objective of real-time application achievable.

Emotional incongruities between facial expressions and text were occasionally observed through testing, especially when emotions were being masked. These incongruities were resolved by the system effectively through the implementation of weightage rules, giving preference to textual cues when facial detection confidence was low. This helped further validate the accuracy of mental health state classification. Overall, the Hybrid Mental Health Analysis System was capable of demonstrating its feasibility as a real-time, scalable solution to early emotional health assessment and aid across various application domains.

V. CONCLUSION

The increasing rate of mental illness across the world necessitates the implementation of new techniques for early identification and intervention. Conventional techniques of mental health assessment, though effective, tend to suffer from issues relating to subjectivity, tardiness, and inaccessibility. This research provides a novel solution in the form of the Hybrid Mental Health Analysis System, which integrates Natural Language Processing for textual emotion analysis and Facial Emotion Recognition for visual emotion analysis. By aggregating data from varied sources, the system provides a composite emotional profile per subject, thereby increasing the precision and reliability of mental health status classification. The new framework addresses substantial gaps in existing methods by making the evaluation real-time, objective, and scalable. Unlike fragmented strategies that are solely focused on textual content or facial expressions, the hybrid approach leverages the complementary nature of verbal and non-verbal emotional cues to arrive at more effective assessments. Second, the added features of personal guidance and helpline support amplify user engagement, ensuring that the system is not limited to merely problem identification, but to generate actionable solutions towards emotional well-being.

Possible uses are in healthcare, education, workplace wellness programs, and social media sites, where mass emotional health monitoring can make a difference. In healthcare, early identification can trigger timely clinical intervention. In education and workplaces, emotional support systems can enhance performance and satisfaction. In social media, proactive mental health management can avoid crises and promote online community health. Despite its possible benefits, the system must also overcome several challenges, such as issues of data privacy, differences in cultural displays of emotion, and the need for constant updates to its models of classification. Ethical considerations are of

paramount concern, particularly when dealing with sensitive emotional data of high confidentiality and care.

Future research must improve model resilience to resist varied demographic and emotional nuances to promote inclusivity and equity. Incorporating physiological signals, including heart rate or galvanic skin response, can also enhance emotional state recognition. Mental health professionals would also be required for testing and tuning the system's suggestions and interventions. Taken collectively, the Hybrid Mental Health Analysis System represents an important step towards the democratization of mental health through technology. By making emotional evaluations more available, timely, and personalized, this approach can empower individuals, assist healthcare providers, and eventually contribute to a healthier and emotionally more resilient citizenry.

REFERENCES

1. B. V. Priya, V. Chinnammal, N. Srinu, S. S. K. P. K, M. M. Selvam and S. Vijay, "ENOL: A Robust Learning Based Methodology to Predict Mental Health Illness by Using Elevated Neural Optimization Logic," 2024 International Conference on Innovative Computing, Intelligent Communication and Smart Electrical Systems (ICSES), Chennai, India, 2024, pp. 1-6.
2. P. Singh, K. K. Srinivas, A. Peddi, B. Shabarinath, I. Neelima and K. Bhagavathi, "Artificial Intelligence based Early Detection and Timely Diagnosis of Mental Illness - A Review," 2022 International Mobile and Embedded Technology Conference (MECON), Noida, India, 2022, pp. 282-286,
3. A. Mittal, L. Dumka and L. Mohan, "A Comprehensive Review on the Use of Artificial Intelligence in Mental Health Care," 2023 14th International Conference on Computing Communication and Networking Technologies (ICCCNT), Delhi, India, 2023, pp. 1-5,

4. M. Bajaj, P. Rawat, Diksha, S. Vats, V. Sharma and L. Gopal, "Prediction of Mental Health Treatment Adherence using Machine Learning Algorithms," 2023 International Conference on Computational Intelligence, Communication Technology and Networking (CICTN), Ghaziabad, India, 2023, pp. 716-720,
5. D. Pant et al., "Visualizing Patient Trajectories and Disorder Co- occurrences in Child and Adolescent Mental Health," 2024 IEEE International Conference on Bioinformatics and Biomedicine (BIBM), Lisbon, Portugal, 2024, pp. 5531-5538,
6. P. Kaushik, E. Jain, K. S. Gill, D. Upadhyay and S. Devliyal, "Optimizing Mental Health Prediction by Fine-Tuning Decision Classifier Parameters for Enhanced Accuracy," 2024 2nd International Conference on Sustainable Computing and Smart Systems (ICSCSS), Coimbatore, India, 2024, pp. 935-939,
7. R. Majethia, V. P. Sharma and R. Dwaraghanath, "Mental Health Indices as Biomarkers for Assistive Mental Healthcare in University Students," 2022 10th International Conference on Affective Computing and Intelligent Interaction (ACII), Nara, Japan, 2022, pp. 1-8, doi: 10.1109/ACII55700.2022.9953847.
8. A. Kheterpal and K. S. Gill, "Therapeutic Tech: A Comparative Study of AI-Driven Mental Health Interventions," 2024 4th International Conference on Advancement in Electronics & Communication Engineering (AECE), GHAZIABAD, India, 2024, pp. 1187-1190,
9. V. Sapra, L. Sapra, A. Vishnoi, P. Narooka and T. Choudhury, "Enhancing Mental Disorder Diagnosis with Ensemble Bagging and Random Forest Techniques," 2024 International Conference on Communication, Computer Sciences and Engineering (IC3SE), Gautam Buddha Nagar, India, 2024, pp. 1765-1769,
10. D. S. Sharma and J. Patel, "AI and Mental Health: A New Era of Healing," 2024 2nd DMIHER International Conference on Artificial Intelligence in Healthcare, Education and Industry (IDICAIEI), Wardha, India, 2024, pp. 1-5,
11. G. Corbin et al., "Evaluating Administered Differences of Brief Jail Mental Health Screener and Impacts of Diagnoses & Treatment of Linked Inmates with Severe Mental Illness," 2022 Systems and Information Engineering Design Symposium (SIEDS), Charlottesville, VA, USA, 2022, pp. 351-356,
12. R. T. Etika, T. T. Proggia and M. M. Khan, "A Web Application Based Mental Health & Illness Diagnosis with Machine Learning Approach and NLP Based Chat System," 2024 International Conference on Sustainable Communication Networks and Application (ICSCNA), Theni, India, 2024, pp. 586-593,
13. M. S. Supriya, A. Aniket, R. N. M, A. J and K. Peter, "AI-Powered Mental Health Diagnosis: A Comprehensive Exploration of Machine and Deep Learning Techniques," 2024 International Conference on Distributed Computing and Optimization Techniques (ICDCOT), Bengaluru, India, 2024, pp. 1-6,
14. P. Kaushik, K. Bansal and Y. Kumar, "Deep Learning in Mental Health: An In-Depth Analysis of Prediction Systems," 2023 International Conference on Communication, Security and Artificial Intelligence (ICCSAI), Greater Noida, India, 2023, pp. 364-369,
15. E. Mylona et al., "Explainable machine learning analysis of longitudinal mental health trajectories after breast cancer diagnosis," 2022 IEEE-EMBS International Conference on Biomedical and Health Informatics (BHI), Ioannina, Greece, 2022, pp. 1-4,
16. Y. Sun, "Mental Health Classification and Diagnosis System Based on Random Forest Algorithm," 2024 Second International Conference on Data Science and Information System (ICDSIS), Hassan, India, 2024, pp. 1-6.,
17. D. Tiwari, A. Kumar, A. Akash, K. Agarwal, A. Sharma and N. Singh, "Diagnosis of Brain's Health Condition through Smart ML Algorithm through Brain Waves," 2024 IEEE International Conference on Computing, Power and Communication Technologies (IC2PCT), Greater Noida, India, 2024, pp. 117-123,

18. Y. Yang, G. Zhao and Y. Shen, "High Frequency Event-based Eye Tracking Towards Mental Health Diagnosis," 2023 IEEE International Symposium on Mixed and Augmented Reality Adjunct (ISMAR- Adjunct), Sydney, Australia, 2023, pp. 335-339,
19. M. Purohit and P. Madiraju, "Predicting Mental Health Disorders Post Long COVID Diagnosis Using Advanced Machine Learning Techniques," 2023 IEEE International Conference on Big Data (BigData), Sorrento, Italy, 2023, pp. 4954-4962,
20. M. K. I. Zim, M. A. Hanif and H. Kaur, "Prediction of personality for mental health detection using hybrid deep learning model," 2024 IEEE International Conference on Interdisciplinary Approaches in Technology and Management for Social Innovation (IATMSI), Gwalior, India, 2024, pp. 1-6,