A

Project Report

on

Mental Health Awareness using ML

submitted as partial fulfillment for the award of

BACHELOR OF TECHNOLOGY DEGREE

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May, 2025

DECLARATION

We hereby declare that this submission is our own work and that, to the best of our knowledge and belief, it contains no material previously published or written by another person nor material which to a substantial extent has been accepted for the award of any other degree or diploma of the university or other institute of higher learning, except where due acknowledgment has been made in the text.

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This is to certify that Project Report entitled "Mental Health Awareness using ML" which is submitted by Disha Sehgal, Diya Bansal and Charu Singh in partial fulfillment of the requirement for the award of degree B. Tech. in Department of Computer Science & Engineering of Dr. A.P.J. Abdul Kalam Technical University, Lucknow is a record of the candidates own work carried out by them under my supervision. The matter embodied in this report is original and has not been submitted for the award of any other degree.

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ABSTRACT

Mental health disorders are a major global concern, affecting millions of individuals and significantly impacting their quality of life. Despite increased awareness, mental illnesses such as stress, anxiety, and depression often remain underdiagnosed and untreated due to stigma, financial limitations, and a lack of accessible mental health resources. These barriers prevent many from receiving timely support and intervention. To address these challenges, this research introduces an ML-powered system designed to support mental health monitoring and self-awareness. The system integrates three key components: stress prediction using decision tree algorithms, emotion detection through Convolutional Neural Networks (CNNs), and a mood diary for recording daily emotional states. The stress prediction model analyzes user responses to a set of structured questions to determine stress levels, offering interpretable and actionable results. Meanwhile, the CNN-based emotion detection processes facial expressions captured through a webcam or uploaded images to recognize emotions such as happiness, sadness, anger, fear, and more. The mood diary allows users to regularly document their emotional experiences, encouraging reflection and long-term emotional tracking. This integrated approach provides individuals with meaningful insights into their mental well-being, promoting early detection of potential issues and fostering proactive self-care. By leveraging advanced machine learning techniques, the system aims to offer a scalable, accessible, and stigma-free tool for managing mental health. Overall, this research contributes to bridging the gap in mental health care and empowering individuals to take charge of their emotional wellness. The platform can also assist mental health professionals by providing supplementary data for better diagnosis. Furthermore, it encourages users to be more mindful of their mental state through consistent monitoring. This ML-driven solution represents a step forward in merging technology with emotional health management.

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LIST OF ABBREVIATIONS

AI	Artificial Intelligence
CNN	Convolutional Neural Network
NLP	Natural Language Processing
FER-2013	Facial Expression Recognition 2013 Dataset
VGG16	Visual Geometry Group 16-layer CNN Model
ResNet	Residual Networks
ML	Machine Learning

CHAPTER 1

INTRODUCTION

1.1 Project description

Mental health is a fundamental aspect of overall well-being, influencing emotions, thoughts, and behaviors. It determines how individuals handle stress, relate to others, and make decisions. However, despite its significance, mental health remains an overlooked aspect of healthcare due to prevailing stigma, misinformation, and a lack of awareness. In today's fast-paced and increasingly stressful world, mental health disorders such as anxiety, depression, and stress-related illnesses are on the rise. Many individuals fail to recognize the early signs of mental health conditions, leading to prolonged suffering and, in severe cases, irreversible consequences.

One of the biggest challenges in addressing mental health concerns is the lack of early detection and timely intervention. Many individuals hesitate to seek professional help due to societal judgment, financial constraints, or a lack of accessible mental health services. To bridge this gap, technological advancements such as Machine Learning (ML) can be leveraged to provide innovative solutions for mental health awareness, assessment, and intervention.

This project, **Mental Health Awareness Using Machine Learning**, aims to integrate technology with mental health monitoring to encourage individuals to assess their mental health status, recognize early warning signs, and take proactive measures toward emotional well-being.

By harnessing the power of machine learning, the project offers three essential features:

1. **Stress Prediction** – A machine learning model that predicts stress levels based on user inputs, including behavioral patterns, mood fluctuations, and daily activities.

By understanding their stress levels, individuals can adopt coping mechanisms such as meditation, exercise, or professional consultation to mitigate their stress.

A stress level prediction machine learning model utilizing user inputs including behavioral patterns, mood changes, and daily activity serves as a proactive mental health monitoring system. The system gathers data from heterogeneous sources such as self-reported questionnaires, mobile sensor data, app usage, sleep diaries, and physical activity monitors. These input data are processed to identify correlations and patterns that tend to indicate heightened levels of stress. Through the use of classification or regression models—e.g., XGBoost, SVM, or neural networks—the model can provide real-time or timed feedback about an individual's stress status, typically as low, moderate, or high. Sentiment analysis of user input as well as mood diary data can similarly construct a greater picture of emotional states. The model learns on this fluctuating data and keeps going ahead to study the behavioral pattern of the person, making stress level predictions progressively accurate.

Once a stress level is predicted, the system can suggest individualized coping strategies. The users may be asked to practice mindfulness meditation, physical activity, limit screen usage, or meet mental health specialists. Some systems also integrate with wellness apps or virtual therapy websites, which makes the experience of coping easy and convenient. This blending of technology and psychology allows users to respond quickly to managing their stress, ultimately leading to long-term mental health and quality of life.

2. **Mood Diary** – A digital platform that enables users to record and track their emotions on a daily basis. Over time, this feature allows users to identify recurring emotional patterns and potential triggers, fostering greater self-awareness and mental resilience.

These could take the form of journaling exercises, relaxation methods, reminders for practicing self-care activities, or invitations to connect with support systems. With time, as users gain a better understanding of their emotional lives and learn to respond constructively, they become more mentally resilient. By making introspection a daily practice, the platform helps users live more balanced, emotionally intelligent, and mentally healthy lives.

3. **Emotion Detection** – A CNN-based emotion recognition system that analyzes text inputs to determine the underlying emotions. By gaining insights into their emotional state, users can better understand their psychological well-being and take appropriate actions.

Regardless of whether users input journal entries, chat messages, or thoughts, the model analyzes such texts to identify sentiment patterns and emotional cues. This allows real-time emotion identification that learns to support various expressions in language and linguistic nuances. Regular observation of such emotional outflows over time can be employed to establish long-term patterns of mental behavior and enable early signs of chronic mental conditions like stress, depression, or emotional burnout to be detected. These three components work together to create a holistic approach to mental health self- assessment. This project aims to empower individuals by providing them with the necessary tools to take charge of their mental well-being and break the barriers associated with mental health stigma. Used in conjunction with the other two modules—emotion tracking and stress prediction—the CNN-based emotion detection system constitutes a complete mental health monitoring system. Together, these modules constitute a broad, user-centric solution that allows the user to take proactive steps towards their well-being. Not only does the system deliver personalized mental health screening, but it also encourages users to break the stigma around mental health by normalizing emotional self-reflection.

1.2 The Importance of Mental Health Awareness

Mental health is often regarded as secondary to physical health, despite its profound impact on an individual’s daily life. According to the World Health Organization (WHO), approximately 450 million people worldwide suffer from mental or neurological disorders, yet nearly two-thirds of these individuals do not seek professional help due to stigma and lack of resources. The consequences of untreated mental health conditions can be devastating, leading to social isolation, decreased productivity, and, in severe cases, suicidal tendencies.

Mental health issues are particularly prevalent among students and working professionals, who often experience high levels of stress due to academic pressures, workplace demands, and personal challenges. Studies show that prolonged stress and anxiety can impair cognitive functions, lower concentration levels, and hinder decision-making abilities. Therefore, early identification of mental health issues is crucial to preventing long-term psychological distress and improving overall well-being. Mental health is commonly considered secondary to physical health, although it plays a profound impact on an individual's daily life. According to the World Health Organization (WHO), almost 450 million people around the world suffer from mental or neurological disorders, but nearly two-thirds of them do not seek professional care due to stigma and the lack of resources. Studies show that chronic stress and anxiety blunt intellectual capacities, lower the ability to concentrate, and impair decision-making capacities. Consequently, the states of mental distress need to be achieved early in life to reduce psychological suffering occurring chronically and enhance overall well-being.

By leveraging machine learning, this project aims to provide accessible mental health solutions that promote self-awareness, encourage timely interventions, and help individuals lead healthier, more fulfilling lives.

1.3 Challenges in Mental Health Detection and Treatment

While mental health awareness has gained momentum in recent years, several challenges still hinder effective detection and treatment:

1. **Stigma and Social Taboos** – Mental health remains a sensitive topic in many cultures, with individuals fearing judgment or discrimination if they seek help. This stigma discourages open discussions and prevents people from accessing necessary support.

   Deep-seated social norms and assumptions regularly tag mental health issues as signs of weakness, instability, or personal failure. In such settings, those who suffer from stress, anxiety, depression, or other mental illnesses tend to shy away from admitting their problems, even less so sharing them openly.

   The risk of being judged, labeled, or discriminated against keeps many individuals from seeking professional assistance or even talking to close friends. Mental health concerns can be minimized or dismissed as "just a phase" or "a lack of willpower," perpetuating damaging stereotypes. As a result, most prefer to suffer in silence than risk being misunderstood or ostracized.

   To combat this stigma, therefore, will take a multi-pronged approach that incorporates education, community involvement, and encouraging safe spaces for open conversation. Awareness campaigns, online mental health platforms, and inclusive policies can all have a crucial role to play in de-stigmatizing discussions about mental well-being.

2. **Limited Access to Mental Health Services** – Many regions, especially in

developing countries, lack adequate mental health facilities, making it difficult for individuals to receive professional care. Limited access to mental health treatment is a significant hindrance, particularly in low- and middle-income countries, where the healthcare infrastructure is more attuned to physical health than mental health. In most of these regions, a severe shortage of mental health professionals—namely psychiatrists, psychologists, counselors, and social workers—per capita exists.

In addition, a lack of integration between mental and general healthcare services often means that patients with both physical and mental illnesses receive incomplete care. This deficiency leads to misdiagnosis, unwarranted delay in treatment, or worsening of the physical and mental symptoms.

A few technical solutions such as digital mental wellbeing platforms, teletherapy, and AI-powered self-assessment machines offer promising alternatives to address the above issues. However, they also depend upon internet and digital literacy, which may still remain inadequate in the very locations where they are needed most. To increase access, governments, NGOs, and health organizations need to invest in infrastructure, develop mental health professional training, and create inclusive policies that bring mental health into the forefront of overall health. Increasing access isn't just a logistical need—it's a moral imperative to ensure each individual, regardless of where they are or how much income they have, is able to access the care that they deserve.

3. **Financial Constraints** – Therapy and psychiatric treatments can be expensive, preventing individuals from seeking regular mental health care. Financial limitations are the largest barrier to receiving mental health care for tens of millions of individuals globally. Sessions of therapy, psychiatric visits, diagnostic testing, and prescription drugs can be extremely costly—particularly where mental health

services are not covered under public or employer-sponsored insurance. For most individuals and families, these costs are prohibitively expensive, particularly if mental health treatment involves ongoing services for several years or months. Consequently, people will postpone or forego care altogether, trying to fix their problems on their own or less effectively.

In poor communities, mental health treatment is delayed relative to more concrete needs like food, housing, or schooling. This unaffordability reinforces the cycle of undertreated mental conditions, e.g., worsened symptoms, decreased productivity levels, and in the worst, total social or work withdrawal.

Crossing financial hurdles calls for a multi-faceted approach, including expanded public funding, subsidization of low-income persons, integration of mental health care with primary health care, and greater use of low-cost digital health technology. Teletherapy websites, AI chatbots, and low-cost mobile self-help applications can bridge the gap by providing affordable, scalable substitutes for traditional therapy.

4. **Lack of Awareness** – Many individuals fail to recognize the symptoms of mental health conditions, leading to delays in seeking appropriate care. Lack of knowledge is a common issue in addressing mental health problems, since frequently individuals do not have the education or knowledge to identify the early warning signs of psychological distress. Unlike physical illnesses, which have their symptoms at least visibly apparent, mental illness can be exhibited covertly—through changes in mood, behavior, sleep, or energy. Without adequate education or exposure to mental health literacy, people can attribute these signs as temporary mood swings, personal weakness, or even character flaws. As a result, they may ignore their symptoms, hoping they will resolve by themselves, which can lead to worsening conditions over time.

This unawareness is also fueled by cultural beliefs, misconceptions, and insufficient mental health literacy in schools, workplaces, and communities. In most cultures, mental health is rarely ever discussed openly, and terms like "depression," "anxiety," or "trauma" become stigmatized or lose their proper meaning.

Educating individuals on how to recognize symptoms not only enables them to seek care early but also leads to a more educated and compassionate society. Lastly, awareness is the precursor to prevention, early intervention, and the breaking down of the social stigmas that surround mental health. By addressing these challenges through AI-driven solutions, this project provides an alternative method for individuals to monitor their mental health without fear of stigma or financial burden. Besides, AI-driven systems are designed to work at scale and in a predictable way, and thus are appropriate for low-resourced regions where mental health experts are scarce. Arguably most impactful, AI-enabled mental health resources reduce the monetary cost of treatment. By offering low-cost or free services that don't require in- person meetings or insurance, the project ensures that mental health care is not only made available to those who are able to pay for traditional therapy. These tools can be embedded in mobile phones, websites, and wearable technologies and reach individuals in urban and rural areas.

1.4 Impact of Mental Health on Youth and Society

Young people are particularly vulnerable to mental health challenges due to academic pressures, social expectations, and personal struggles. Research indicates that **one in five adolescents** experiences mental health issues, yet many do not receive proper diagnosis or treatment. Left unaddressed, these conditions can lead to academic underperformance, strained relationships, and increased risk of substance abuse.

MHA (Mental Health America) emphasizes the importance of early identification, accurate diagnosis, and timely intervention to alleviate the impact of mental health conditions. Schools, colleges, and community centers play a crucial role in recognizing early signs of distress among youth and providing necessary support. This project contributes to this initiative by offering a digital platform that aids in early detection and self-monitoring.

Mental health is an integral part of general well-being, particularly in the adolescent years—a time of dynamic development characterized by accelerated physical, emotional, and psychological maturation. In the modern fast-paced, highly competitive, and globally connected world, adolescents are subjected to multiple mental health challenges. These are the result of a multitude of causes such as academic pressures, peer pressures, Internet-based social comparisons, bullying, domestic issues, and insecurity over the future. The adolescent's transitional period makes them very vulnerable to emotional and psychological trauma.

Recent studies project the dire trend that nearly one in every five adolescents around the world lives with some sort of mental disorder. These can vary from anxiety, depression, eating disorders, attention-deficit/hyperactivity disorder (ADHD), to worse ones like bipolar disorder or schizophrenia. The majority of the affected people, unfortunately, never receive a timely diagnosis or appropriate treatment due to lack of access to mental health care resulting from causes such as stigma, ignorance, insufficient mental health centers, and socio-economic limitations.

Un-treated mental illnesses in children have long-term consequences. At the individual level, disorders in mental health may disrupt the academic achievements of a young adult, low motivation, lowered self-esteem, and stressful relationships with peers, school personnel, and family members. Struggling youths will also be at risk of engaging in risk-taking behaviors such as drug abuse, alcohol use, self-harm, and in extreme cases, suicide. At a more general level, undiagnosed mental illness has the potential to lead to decreased productivity, increased school dropout, and increased healthcare costs, fuelling a poverty cycle and social exclusion.

Such agencies as Mental Health America (MHA) stress early identification, accurate diagnosis, and timely intervention. These are feasible steps to significantly reduce symptom severity, improve coping capacity, and improve life outcomes in youth. Prevention, mental health education, and stigma reduction campaigns must be present in order to create an environment where a value is placed on mental health and stigma is reduced.

Schools and universities are best placed to set an example in addressing young people's mental health. Teachers, school leaders, and counselors can be trained to identify early warning signs of distress, promote supportive cultures, and guide young people towards appropriate help. Youth clubs and youth centers are also key sites of contact for mental health education, where young people can feel safe to articulate and be supported.

CHAPTER 2

LITERATURE REVIEW

The advancement of machine learning (ML) has significantly impacted the field of mental health monitoring, particularly in the areas of facial emotion recognition, stress prediction, and mood analysis. The development of intelligent systems capable of identifying emotional states and predicting mental well-being has gained considerable attention in recent years. This literature review explores the extensive research conducted in these domains, emphasizing the role of Convolutional Neural Networks (CNNs) for facial emotion detection and machine learning algorithms for stress prediction. Furthermore, it highlights the importance of user-centric approaches like mood diaries to provide a holistic mental health management solution.

The evolution of machine learning (ML) has transformed the area of monitoring mental health, providing new avenues for understanding and managing mental well-being. Areas of focus are facial emotion detection, stress forecasting, and mood analysis. With the advent of machine learning-based smart systems, we are now able to identify emotional states, forecast stress levels, and track changes in mood in real-time, enabling individuals and clinicians to prepare for and manage mental health disorders [1][2].

Facial emotion recognition is arguably the most apparent use of ML in mental health. Due to sophisticated Convolutional Neural Networks (CNNs), these computers can recognize facial expressions and identify emotional states like happiness, sadness, anger, surprise, fear, and disgust with high accuracy [1]. CNNs, which are best at handling image data in hierarchical feature layers, have made emotion detection a whole new ball game by allowing computers to recognize nuanced facial expressions that would otherwise pass human observers by. Studies have demonstrated that these systems are very effective at identifying difficult-to-describe emotions, such as in patients with communication impairments or depression/anxiety patients [3][4]. Learning strategies such as MobileNet-V2 and Inception-V3, combined with hyperparameter tuning (e.g., learning rate, batch size, and network depth), have been shown to significantly impact CNN model performance [2]. Moreover, transfer learning techniques and data augmentation using pre-trained models like VGG16 and ResNet have enhanced emotion classification capabilities across various emotional categories [3][4][5].

Another key area where ML has made its mark is in stress prediction. Stress is an intricate emotional and physiological reaction that can be experienced in many forms, e.g., alterations in heart rate, skin conductance, or sleep. Machine learning algorithms such as decision trees, support vector machines (SVM), and deep learning models have shown promise in analyzing large-scale data—like physiological signals from wearable devices, user-reported surveys, and contextual environmental factors—to identify stress states [6][7][8]. These predictive models allow for early intervention by providing actionable insights that can help reduce stress through personalized strategies like mindfulness, relaxation techniques, or behavior modification.

In addition, research has shown that AI-based platforms can offer real-time stress counseling and behavioral interventions, enhancing accessibility and responsiveness in mental health care [9][10][11]. One study highlighted an adaptive ML model trained to monitor user behavior patterns and offer personalized advice, showing the potential of intelligent systems in supporting mental wellness [13]. Other studies explored the detection of early stress indicators in academic populations to support mental health within educational institutions [14].

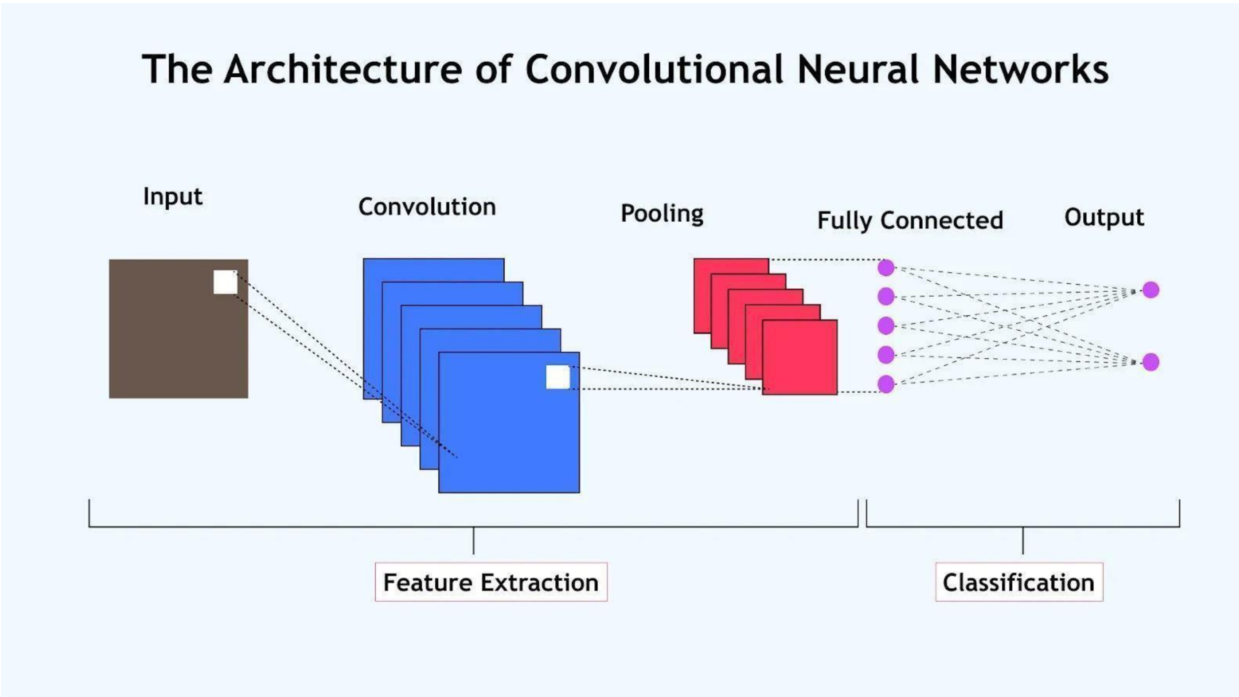
Apart from emotion identification and stress forecasting, the use of mood diaries in managing mental disorders cannot be overemphasized. Computerized mood monitoring systems or mood diaries have been found to be an essential method of learning patterns of emotions over time. Through daily event surveillance, feelings, and thoughts, the patient may learn insightful information into mental health progression. Including these diaries in machine learning algorithms increases prediction of future emotional states as well as trend detection even further. For instance, a mood-tracking system combined with environmental elements such as exercise, sleep, and social contact allows users to learn triggers or patterns that may produce negative emotional states. These evidence-based outcomes enable people to be masters of their own mental health through well-informed choices regarding their behavior and interactions. Mood tracking also enables mental health professionals to give personalized care by providing an unambiguous, objective record of a person's emotional states.

As machine learning continues to evolve, the integration of facial emotion recognition, stress prediction models, and mood diaries presents a comprehensive framework for end-to-end mental health management. These systems not only offer early detection and personalized support but also promote self-awareness and engagement in one’s mental well-being. Furthermore, the increasing availability and accessibility of such technologies can democratize mental health support, making it available to populations that might otherwise lack access to traditional therapeutic services [12].

These thinking systems not only provide early detection and individualized treatment but also provide a system by which individuals are able to learn about themselves, enabling them to take a proactive role in managing their mental health.
Moreover, as they grow simpler and become more widespread, they are in a position to democratize mental health services and make them more accessible to individuals who might not otherwise find traditional therapy or aid within their means.

2.1 Facial Emotion Recognition Using CNNs

Facial emotion recognition (FER) has emerged as a critical area of research within computer vision and affective computing. Emotions play a crucial role in human communication, and accurately recognizing them through facial expressions can provide valuable insights into an individual's mental state.



Traditional methods relied heavily on handcrafted features, but with the advancement of deep learning, CNNs have revolutionized the field by automatically extracting complex features from images.

Fig.1 Basic Architecture of a Convolutional Neural Network

Research conducted by Zhang et al. (2018) demonstrated the effectiveness of CNN architectures in recognizing facial emotions [18]. The study highlighted how CNNs outperform traditional machine learning methods, due to their ability to learn hierarchical features from raw image data. CNNs process images through multiple convolutional layers, pooling layers, and fully connected layers, enabling them to capture both low-level and high-level features essential for accurate emotion classification.

To further enhance the performance of CNN-based emotion recognition systems, researchers have explored transfer learning techniques. Transfer learning involves leveraging pre-trained models, which have been trained on large-scale image datasets like ImageNet. Studies by Howard et al. (2017) and Szegedy et al. (2016) found that using pre-trained architectures significantly improves emotion detection accuracy, even with limited training data. These models transfer the learned feature representations from general image recognition tasks to the specific task of facial emotion recognition.

Moreover, hyperparameter tuning has been identified as a crucial factor in optimizing CNN performance. Hyperparameters, including learning rates, batch sizes, and network depths, directly impact the model's ability to generalize across diverse datasets. Research by Li et al. (2019) demonstrated that fine-tuning hyperparameters could lead to significant improvements in accuracy and reduce overfitting. By systematically adjusting these parameters, CNN models can better adapt to the variations in facial expressions caused by age, gender, and cultural differences.

Another advancement in FER involves the use of augmented datasets. Data augmentation techniques, such as rotation, flipping, and color adjustment, increase the diversity of training samples, enhancing the model's robustness. Researchers have found that combining augmented datasets with pre-trained architectures leads to superior emotion classification performance. For instance, Simonyan and Zisserman (2014) introduced the VGG16 model, which has been widely adopted for emotion recognition due to its deep architecture and ability to capture intricate features [19]. Similarly, He et al. (2016) developed the ResNet model, known for its residual connections that prevent vanishing gradients and facilitate deeper network training [20].

2.2 Stress Prediction Using Machine Learning

Stress is a common psychological response to challenging situations, and its prolonged presence can lead to serious health issues, including anxiety, depression, and cardiovascular diseases. Recognizing stress early is crucial for effective intervention and mental well-being. Recent advancements in machine learning have facilitated the development of stress prediction models that analyze diverse factors, including behavioral patterns, physiological signals, and contextual data.

Machine learning algorithms, such as Gradient boosting machine and Random Forest, have been extensively applied to stress classification tasks. These algorithms analyze features derived from user inputs, wearable sensors, and contextual data to predict stress levels accurately.

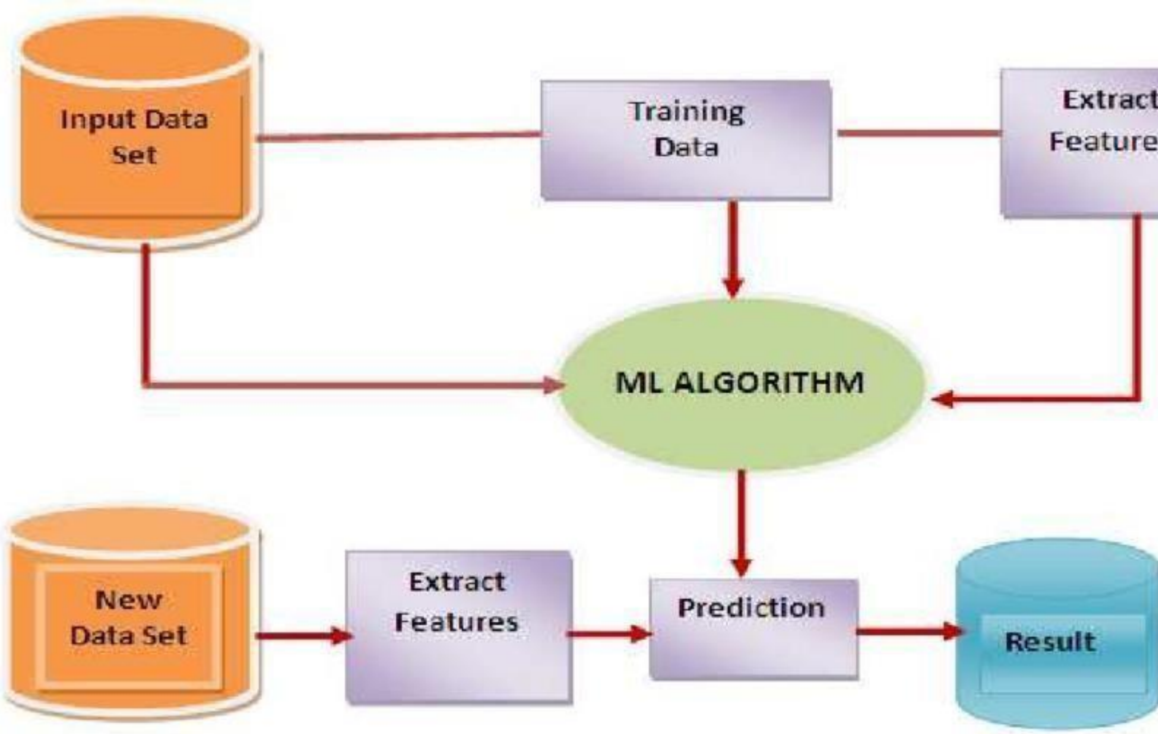


Fig.2 Workflow of Stress Prediction Using Machine Learning

Research by Sarker et al. (2020) highlighted the effectiveness of logistic regression for stress classification based on self-reported questionnaires and physiological signals.

Logistic regression models provide interpretable results, making it easier for users and healthcare professionals to understand the factors contributing to stress. However, the study also noted that logistic regression may struggle with complex, non-linear relationships between features.

To address this limitation, researchers have turned to ensemble methods like Random Forest, which combine multiple decision trees to improve predictive accuracy. Breiman (2001) introduced the Random Forest algorithm, emphasizing its ability to handle high-dimensional datasets and provide robust predictions. Studies by Chen et al. (2019) demonstrated that Random Forest outperforms traditional algorithms in stress prediction tasks, particularly when analyzing multi-modal data sources.

Stress prediction models also leverage contextual information, such as work environment, academic pressures, and personal health data. Studies by Sharma et al. (2018) explored the use of contextual features in stress prediction, emphasizing the importance of considering environmental factors alongside physiological signals. For example, increased workload, lack of sleep, and social isolation were identified as significant predictors of high stress levels.

2.3 Mood Diary for Emotional Well-Being

Mood tracking is an essential component of mental health management, allowing users to monitor their emotional patterns over time. Traditional mood tracking methods, such as paper journals and simple mobile apps, often lack the sophistication needed for comprehensive analysis.

In contrast, AI-powered mood diaries provide users with a structured platform to log, visualize, and analyze their emotional states.

Research by Ebner-Priemer and Trull (2009) introduced the concept of Ecological Momentary Assessment (EMA), a methodology for real-time mood tracking. EMA involves collecting self-reported mood data throughout the day, providing a detailed understanding of emotional fluctuations. AI-powered mood diaries leverage EMA principles to collect and analyze mood data, identifying trends and correlations with contextual factors.

Sentiment analysis algorithms play a crucial role in mood diary systems. These algorithms analyze user inputs, such as text descriptions and emoji usage, to determine the underlying emotional tone. Studies by Cambria et al. (2017) demonstrated that sentiment analysis models, including Lexicon-based approaches and deep learning methods, achieve high accuracy in mood classification.

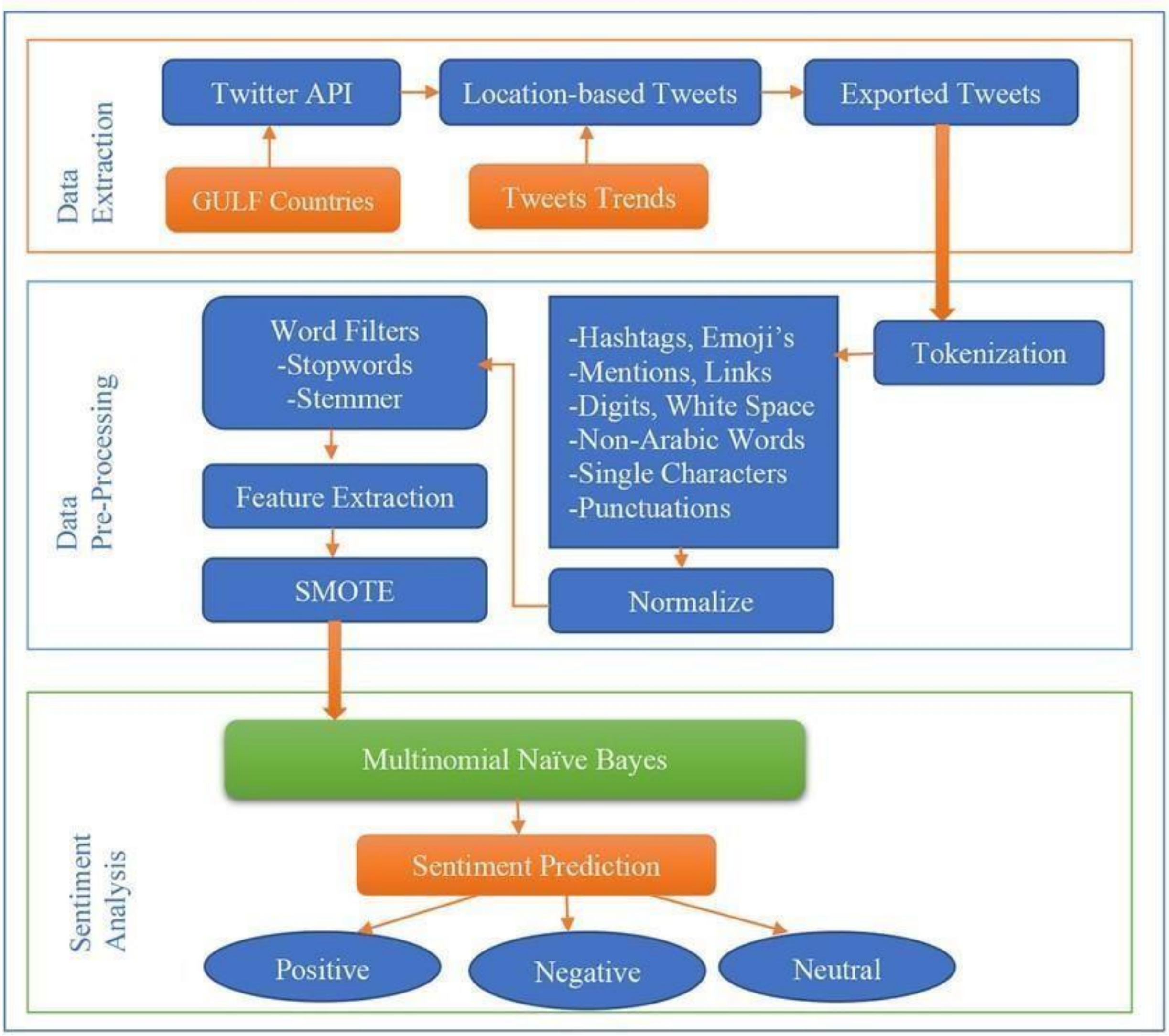


Fig.3 Sentiment Analysis Pipeline in AI Mood Diaries

Advanced mood diary platforms also incorporate predictive analytics to forecast future emotional states based on historical data. Research by Wang et al. (2018) introduced a predictive mood tracking system that analyzes user behavior, sleep patterns, and social interactions to predict mood changes. This proactive approach enables users to identify potential mood fluctuations and take preventive measures.

Moreover, mood diary systems often include goal-setting features, allowing users to set personal well-being goals and track their progress. These goals may include practicing mindfulness, engaging in physical activity, improving sleep hygiene, or maintaining social connections. Research by Ly et al. (2014) demonstrated that goal-setting and progress tracking significantly improve mental well-being outcomes.

2.4 Integration of AI for Holistic Mental Health Management

The integration of facial emotion recognition, stress prediction, and mood tracking into a unified AI-powered system represents a significant advancement in mental health management. By combining these technologies, users can gain a comprehensive understanding of their mental well-being and receive personalized recommendations for improvement.

Research by Doryab et al. (2019) introduced an integrated mental health monitoring system that combines facial emotion detection, stress prediction, and mood tracking. The study found that users who engaged with the system regularly reported significant improvements in mental well-being and resilience.

Privacy and data security remain critical considerations in AI-based mental health systems. Researchers emphasize the importance of implementing robust encryption protocols, user consent mechanisms, and transparent data practices to protect user privacy.
The integration of facial emotion recognition, stress prediction, and mood tracking into a single holistic AI system is a new leap towards the management of mental health that has the potential to provide an individual with a fuller picture of emotional well-being. With all of these technologies under one umbrella, one can track and quantify their mental health in real time and receive personalized feedback that is tailored to an individual's unique needs. By leveraging the potential of every technology, say, facial emotion detection to sense small expression of feeling, stress forecast to mark occasions of high tension, and mood monitoring to watch for emotional habits over a duration of time, the system

introduces a multi-pronged answer to mental wellbeing. People can then be offered individualized interventions, such as mindfulness training, breathing, or counseling therapy, that have been specially designed to fulfill the role of enhancing their emotional stability and well-being.

Evidence of the success of this master plan is provided by a study by Doryab et al. (2019). The study introduced an affective monitoring system that incorporated facial emotion detection, stress estimation, and mood tracking, and demonstrated that the users who used the system on a daily basis reported enhanced mental well-being and resilience. Through regular monitoring and review of the users' emotional conditions, the system would then be capable of providing real-time response and personalized suggestions based on which, users could have a sense of their own emotional reactions and manage stress. Of interest in the study was also the possibility that such AI-driven systems hold to provide not only to allow for early detection of mental illness but also for prolonged intervention through facilitating pro-active maintenance of mental well-being as well as individual consciousness. This is creating opportunities for more research on AI-based mental health interventions that can enable individuals to manage their emotional well-being with the assistance of technology.

However, AI in psychiatric treatment is confronted with serious ethical issues, primarily privacy and data protection. As the data used is of a sensitive kind—e.g., emotional state, physiological information, and user mood logs—the integrity of users' data is of utmost importance. Researchers have also emphasized the need for robust encryption policies in ensuring data in storage and transit security to prevent abuse. Secondly, processes of consent from users have to be evident and simple such that users are very sure what data they will be going to have gathered, used, and stored. The process of consent can be a participatory active process, in which users are able to back out of contribution or manage data as they see fit.

Last but not least, open data practice is crucial in building trust among users and the system. The users need to be provided with adequate information about how their data are being handled, i.e., whether they are being shared with third parties or utilized for training AI models. Transparency not only protects users' privacy but also creates trust in the system's ethical processing of personal data. Since more and more mental health therapy is now AI-driven, these considerations will be most critical in ensuring that technology is utilized responsibly and individuals will be safe using such systems for their mental health. Whether the immense benefits of using AI in mental health therapy are combined with proper safeguarding of user privacy will be the decisive point about the success and acceptability of such systems.

2.5 Conclusion

In conclusion, the literature highlights the effectiveness of CNN-based facial emotion recognition, machine learning algorithms for stress prediction, and mood diaries in enhancing mental health monitoring and management. By integrating these advanced techniques into a unified system, the proposed project aims to offer a comprehensive and user-centric solution for proactive mental well-being management. The combination of real-time emotion detection, questionnaire-based stress assessment, and a visual mood tracking diary ensures that users receive a holistic view of their emotional health.

This system not only empowers users to understand their emotional patterns but also provides timely interventions and personalized recommendations based on behavioral data. By leveraging intuitive visualizations like heatmaps and interactive interfaces, the platform encourages regular engagement and self-reflection. Furthermore, the use of cloud technologies like Firebase enables secure data storage and seamless access across devices. As AI continues to evolve, its role in mental health care will undoubtedly expand, supporting early detection, continuous monitoring, and long-term emotional resilience. The integration of such intelligent tools into everyday digital experiences marks a significant step toward making mental health support more accessible, scalable, and personalized.

CHAPTER 3

PROPOSED METHODOLOGY

Our proposed system is divided into three interconnected subsystems: stress prediction using a decision tree-based machine learning algorithm, emotion detection through a Convolutional Neural Network (CNN), and a mood diary for daily emotional logging and visualization. Together, these components create a holistic and user- friendly mental health monitoring platform designed to promote emotional well-being and self-awareness. Each subsystem is independently operable yet collaboratively contributes to a unified experience aimed at proactive mental health management.

The stress prediction module is based on user input from a structured questionnaire comprising 25 scientifically derived questions, covering various psychological, behavioral, and physiological indicators of stress. These responses are processed using a decision tree classifier, chosen for its interpretability and efficiency in handling structured data. This model categorizes users into stress levels (e.g., low, moderate, high), offering personalized feedback and suggestions. The questions and classification thresholds can be fine-tuned over time, enabling adaptability to specific populations or environments.

The emotion detection subsystem leverages the power of deep learning through Convolutional Neural Networks (CNNs) trained on the FER-2013 dataset, which contains thousands of labeled facial expression images. Users can upload or capture real- time facial images using their webcam or device camera. The CNN processes these images to identify key emotional states such as happiness, sadness, anger, surprise, fear, and neutrality. This real-time feedback allows users to gain insights into their emotional state and recognize patterns or triggers over time. Data augmentation and normalization techniques are applied to enhance model generalization and accuracy.

The mood diary module provides users with a daily platform to log their emotions and mood intensity on a scale (typically 1 to 5), selecting from predefined mood categories. This data is securely stored using Firebase Realtime Database, ensuring real-time synchronization and persistence across devices.

The logged data is visualized through an interactive heatmap, enabling users to observe emotional trends over weeks or months. This visual feedback empowers users to reflect on their emotional journey and correlate mood patterns with daily activities or life events.

The remainder of this chapter delves into the technical development of each subsystem. It covers dataset selection criteria, data preprocessing pipelines, model design and architecture, training and validation strategies, and integration of frontend and backend components to ensure a seamless user experience.

Technologies such as HTML/CSS/JavaScript, TensorFlow/Keras, XGBoost, and Firebase are utilized to build a responsive and scalable web-based platform. By adopting this modular and data-driven approach, the system offers flexibility, scalability, and future extensibility. Users benefit from a comprehensive yet easy-to- use tool that supports their mental health through daily engagement, real-time insights, and long-term emotional awareness.

3.1 Data Collection and Preprocessing

Data Sources:

Stress Prediction: One of the key datasets utilized in this study is the Kaggle Stress Detection Dataset [17].

It contains a large amount of sensory and physiological information regarding various levels of stress.

As the dataset was created with the aim of supporting research and development for stress prediction tasks, it is highly valuable to work with when designing machine learning solutions for mental well-being. Among its many features are biometric measurements such as body temperature, oxygen saturation, heart rate, and snoring range. They are predictive for the construction of prediction systems and are valuable for modeling the body's physiological responses to stress that underlie them.

Being able to anticipate stress before it happens can allow individuals to adopt precautionary actions, like practicing relaxation methods, changing their environment, or seeking the help of a professional. In addition, since these systems learn from big data such as the Kaggle Stress Detection Dataset, they are able to become more precise with time, and be able to predict stress more accurately.

Further, when integrated with other mental health tools, like emotional self-rating scales, chatbots, or wearable devices, this dataset offers a complete solution to managing stress and well-being.

Generally, the dataset's abundance of physiological information provides an effective tool for stress prediction systems and for establishing a better understanding of how the body is impacted by stress. It allows predictive models to be developed that can aid proactive interventions, thus enhancing the mental well-being and health of individuals

Emotion Detection: The database used in this project for the facial emotion detection task is the FER-2013 dataset [16], an affectively often used benchmark in affective computing. The data consists of 35,887 grayscale facial pictures, every single one being 48x48 pixels and obtained in various realistic environments. The images are tagged into seven base emotional groups: anger, disgust, fear, happiness, sadness, surprise, and neutral. Gathered from web sources and aggregated by the Google image search API, FER-2013 is a difficult and diverse database of facial expressions with natural lighting, occlusion, and facial orientation variation. This diversity is appropriate for deep model training such as Convolutional Neural Networks (CNN) for stable emotion classification performance on various populations and environmental conditions.

Given its real-world variability, the FER-2013 dataset presents an ideal platform for training deep learning architectures such as CNNs, which are adept at recognizing hierarchical patterns and spatial features from image data.

This dataset is a widely used and valuable resource in the field of affective computing, particularly for training deep learning models to recognize human emotions from facial expressions. It consists of 35,887 grayscale images of faces, each sized at 48x48 pixels, which are labeled with one of seven emotion categories: angry, disgust, fear, happy, sad, surprise, and neutral.

These images were collected using the Google image search API and manually annotated, making the dataset diverse in terms of ethnicity, age, lighting conditions, and facial angles. The dataset is divided into training, public test, and private test sets, allowing for robust evaluation of model performance. Its compact image size makes it computationally efficient, while still containing enough visual detail for accurate emotion classification.

One of the key strengths of FER-2013 is its ability to simulate real-world variability, as the images include natural noise such as partial occlusions, head tilts, and varying illumination. This makes it highly suitable for training models that need to perform well under practical, everyday conditions.

The dataset is often used to train convolutional neural networks (CNNs), which can automatically learn features relevant to facial expression recognition. As AI systems increasingly aim to interpret and respond to human emotions—whether in mental health tools, social robots, or adaptive learning platforms—datasets like FER-2013 are essential. They provide the foundational data required to build emotion-aware systems that are not only accurate in controlled settings but also robust and reliable in real-world applications.

Mood Diary: The Mood Diary module enables users to actively record their emotional states, offering a simple and user-friendly method for tracking mental well-being on a daily basis. Users can select their mood on a numerical scale (typically from 1 to 5) and optionally choose a descriptive mood type such as happy, sad, angry, relaxed, or anxious. This allows for a more expressive and detailed logging experience that captures the emotional nuances of each day.

Once the user submits their mood entry, the data is securely stored in a Firebase cloud database. This cloud-based storage ensures that user data is preserved consistently and can be retrieved or visualized across different sessions and devices.

The collected mood data is then utilized to generate a dynamic heatmap on the user dashboard. This heatmap is color-coded according to the intensity of mood values and updates automatically as new entries are added. Users can easily identify emotional trends over time by observing changes in color patterns across different days and time slots. This visual feedback helps users recognize fluctuations in their emotional state, detect recurring patterns, and understand the possible causes of mood changes—such as stress, social interaction, or workload.

By consistently engaging with the Mood Diary, users are empowered to reflect on their mental health and make informed decisions to improve their overall emotional well-being.

3.2 Stress Prediction Using Decision Tree Algorithm

Feature Engineering: The most critical step in this module was selecting relevant physiological features, including snoring range, respiration rate, body temperature, oxygen saturation, heart rate, and sleep duration (Fig 1). After we trained the XGBoost model, we also examined which of the features contributed most to stress level prediction. Heart rate and respiration rate were the two most significant ones—this is not surprising, as both directly change when one is stressed. Sleep duration also was significant, illustrating how a lack of rest can lead to increased stress. On the other hand, features like snoring range and body temperature had a smaller effect, which means they're helpful but not as strongly connected to stress as the other features.

Step 1: Identification and Feature Selection

The first and foremost task of feature engineering was identifying good physiological markers, which are already known to be related to stress. The following features were selected to be used:

- Respiration Rate
- Sleep Duration
- Oxygen Saturation
- Heart rate
- Body temperature
- Snoring range

They were selected according to previous literature and clinical expertise about how the human body behaves under stress.

Step 2: Preprocessing and Normalization

To avoid the model from becoming biased by the scale difference between features, every physiological measurement was preprocessed as stated below:

- Normalization to scale everything to the same scale.
- Missing value imputation (in case any) to maintain the values intact.
- Outlier removal and detection, especially for biometric measures like snoring or heart rate.

Step 3: Model Training using XGBoost

After preparing the data, model training was done using the XGBoost (Extreme Gradient Boosting) algorithm. XGBoost works well due to:

- Integrated missing data handling.
- Feature importance with good ranking and interpretability.
- It can handle non-linear relationships.

Step 4: Feature Importance Analysis

The built-in feature importance score of XGBoost was utilized after model training to determine which features were predictive. An analysis provided the following ranking by contribution:

- Heart Rate – Very sensitive indicator, increases directly with stress by stimulating the sympathetic nervous system.

- Respiration Rate – Also heavily linked to stress; individuals breathe faster or more under stress.

- Sleep Duration – Also highly significant; both reduced sleep and disturbed sleep is a widely documented source of psychological stress.

- Oxygen Saturation – Had a medium contribution; drops in O_2 levels can be explained by disrupted respiratory states, and hence contribute indirectly to stress.

- Body Temperature – Contributed the least; although it varies with stress, it is governed by numerous other non-stress factors.

- Snoring Range – Least but significant; may relate to the quality of sleep, which affects stress.

Step 5: Insights and Implications

Importance scores not only surpassed the model but also provided clinical insights:

Observation of merely a few of the leading indicators like heart rate and respiration can be enough for mild real-time stress monitoring systems.

Secondary features like snoring and temperature can continue to have supporting roles in assisting model accuracy and stability

Model Selection: We selected the XGBoost (Extreme Gradient Boosting) algorithm because it is highly accurate and resistant to overfitting. XGBoost is a powerful ma- chine learning algorithm that improves its predictions step by step, learning from mistakes to make better decisions. It works well with larger datasets which makes it a great choice for stress prediction. Also, XGBoost is faster than many other algorithms like decision tree , SVM etc. Its ability to handle missing data and different types of inputs further strengthens its reliability in predicting stress levels accurately.

Evaluation Metrics: To measure the model’s performance, we relied on accuracy, precision, recall, and F1-score.

Backend Processing: These inputs are passed to a pre-loaded XGBoost model hosted on the server.

XGBoost rapidly analyzes features such as respiration rate, body temperature, oxygen levels, and sleep duration. The system delivers the predicted stress level within 5 seconds. XGBoost is also proud to possess the resistance to overfitting quality where it performs optimum when dealing with real-world noisy data such as physiological data which may be variable or incoherent based on numerous external variables that are being used here.

Another strength of XGBoost is that it can handle complex, high-dimensional data quite efficiently. Stress prediction models typically include a lot of features (e.g., sleeping time, oxygen levels, respiratory rate), and XGBoost handles such diverse kinds of data very well.

In order to assess the performance of the model, we used several performance metrics, each of them having a specific function in gauging the potency of the model. These include accuracy, precision, recall, and the F1-score:

Accuracy is the most basic measure, the ratio of the correctly predicted instances (both the stress and non-stress instances) to all the instances predicted. Though useful, it doesn't account for imbalanced datasets, leading to misleading results.

Precision is the ratio of true positive predictions (correctly predicted stress levels) to the total number of positive predictions. Precision is significant in scenarios where false positives, such as incorrectly classifying a person not experiencing stress as stressed.

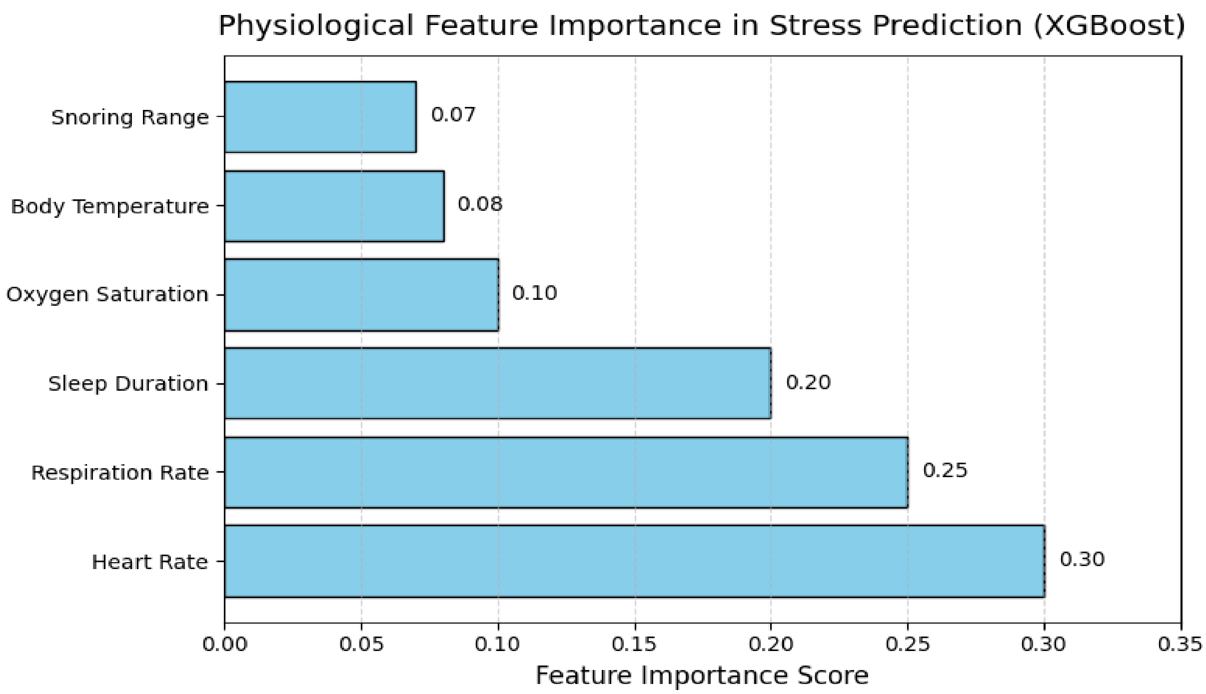


Fig.4 Feature Importance for Stress Prediction

3.3 Emotion Detection Using Convolutional Neural Networks (CNN)

We worked with a dataset of images, each belonging to one of seven categories, which we found on Kaggle. To get the data ready for training, we organized the images into labeled directories. We then resized all the images to **224×224 pixels** so they would fit the input size requirements for MobileNet. To make our model more robust and help it generalize better, we applied a few data augmentation.

Techniques like zooming in, shearing, and flipping the images horizontally using *ImageDataGenerator*. These steps helped ensure our dataset was diverse and optimized for training.

- Real-Time Face Detection with YOLO

Users enable their webcam to allow real-time face capture. YOLOv5 detects the face in under 20 ms per frame and extracts it for processing. The system accounts for varying lighting and background conditions; users are prompted to adjust lighting if needed.

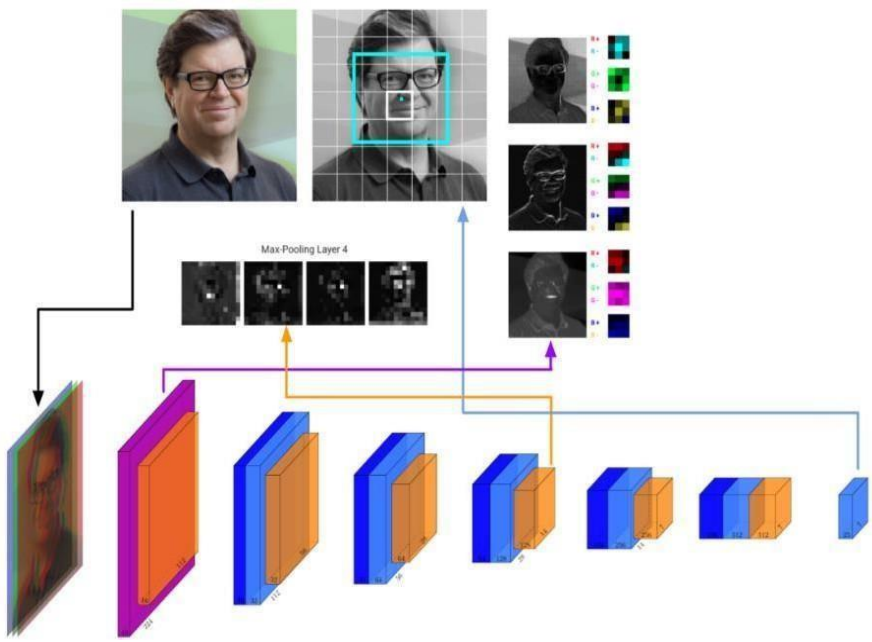


Fig.5 Real-Time Face Detection with YOLO

Emotion Classification with CNN (MobileNet)

Once the face is detected and cropped, it is resized to 224 × 224 pixels and normalized. The image is passed through the MobileNet CNN, which classifies it into one of seven emotions: *anger, disgust, fear, happiness, sadness, surprise,* or *neutral*. Prediction is completed in about 1–2 seconds after image capture.

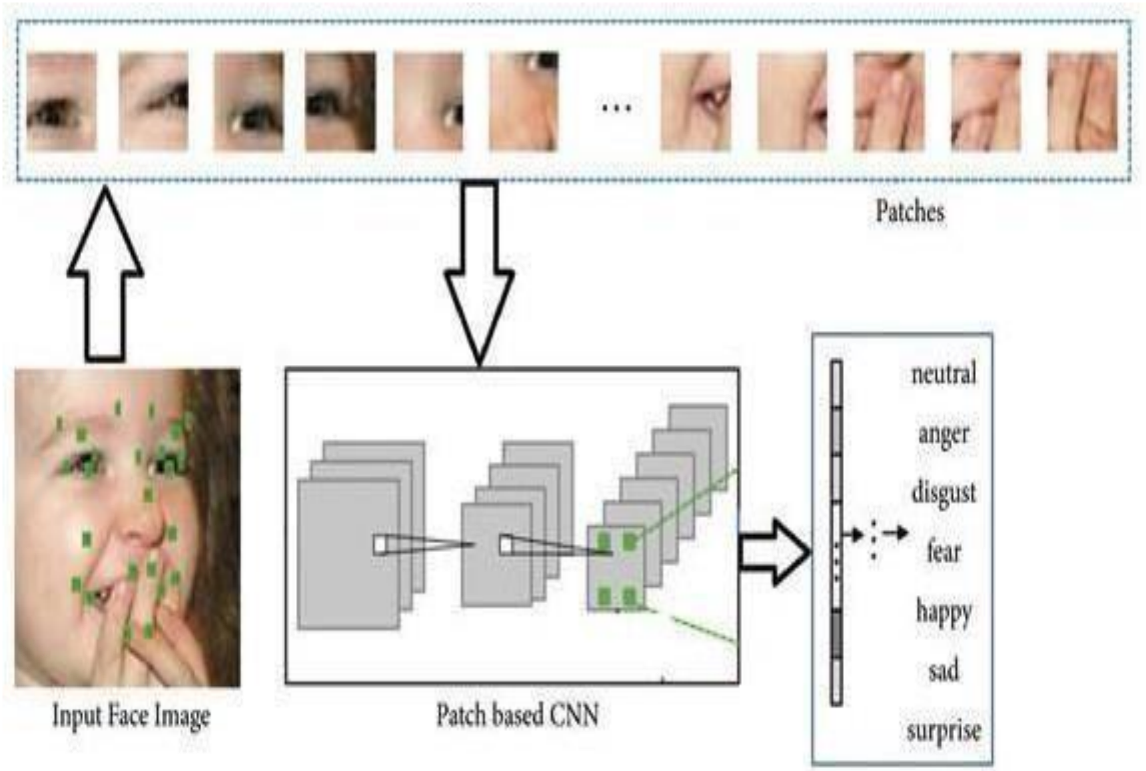


Fig.6 Emotion Classification

-Data Augmentation for Real-World Accuracy

During model training, we used ImageDataGenerator for augmentation to simulate real-world scenarios:

- Horizontal flipping
- Zooming
- Shearing
- Slight rotations
- Brightness adjustments

This ensures the model performs well under real-time conditions involving lighting changes, facial angles, and occlusions.

STEPS INVOLVED:

Step 1: Data Preparing and Formatting

A face emotion dataset labeled with seven emotions was downloaded from Kaggle. The images were reformatted to labeled directories by emotion: anger, disgust, fear, happiness, sadness, surprise, and neutral.

The images were resized to 224×224 pixels all in preparation to satisfy MobileNet's input shape needed as it is a light CNN model best used in mobile and real-time applications.

Step 2: Data Augmentation using ImageDataGenerator

To avoid overfitting and enhance generalization to real-world conditions, Keras' ImageDataGenerator was utilized to carry out:

Horizontal Flipping – replicates reflection-like feelings.

Zooming – simulates vision at different distances from the camera.

Shearing – adds skew for angle face posture adjustment.

Tiny Rotations – takes head tilt into account.

Brightness adjustments – simulates different illumination conditions.

All the above augmentations allow the model to become invariant to real-world variation such as lighting, face pose, and camera pose.

Step 3: Real-Time Face Detection using YOLOv5

As soon as a webcam is turned on by the user, YOLOv5 (You Only Look Once, version 5) is executed in real-time to detect and locate faces in each frame.

- Frames are processed by the system in less than 20 milliseconds per frame, silky enough for operations.
- When face detection takes place:
- It is cropped and separated from the video frame.
- Light and background are validated; in case poor, users are invited to set ambient conditions to higher precision.

Step 4: Preprocessing of Face Image to CNN Input

Extracted face image is:

- Scaled to 224×224 pixels that can accommodate MobileNet's input requirement.
- Normalized (pixel values reduced to 0–1 range) for optimum CNN performance.
- Grayscale conversion as an option if required but MobileNet accepts RGB inputs in the majority of scenarios.
-

Step 5: Classification of Emotions with MobileNet

The preprocessed image is forwarded to the MobileNet CNN, which:

- Captures spatial and hierarchical face information.
- Classifies the expression into one of the seven pre-defined emotional classes.

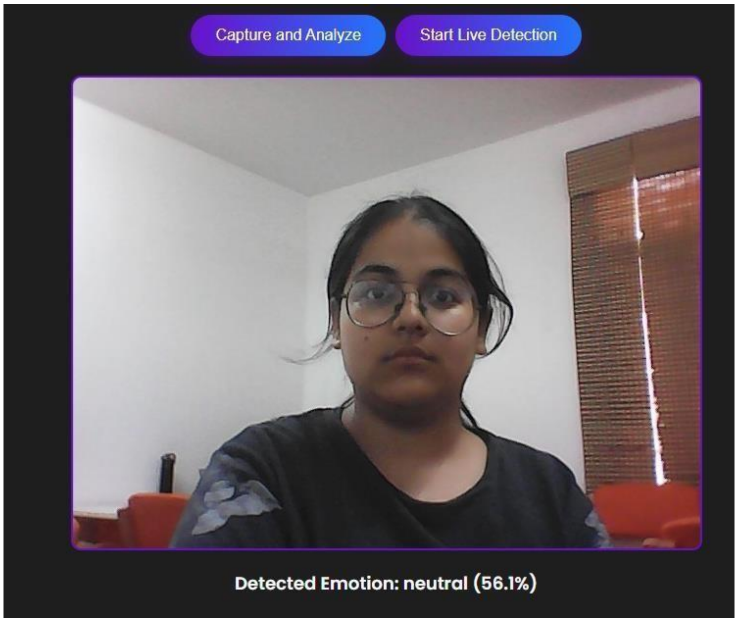


Fig 7. Real time emotion detection on our model

3.4 Mood Diary Development

Mood Tracking Interface: We developed a user- friendly interface on the website that allows users to log their daily moods on a scale from 1 to 5. To provide more context, we also included fields to track additional factors, such as the user's activity and sleep quality.

- User Interaction and Logging

  Users can log daily moods on a scale of 1 to 5 through an intuitive web interface. Optional fields allow users to describe events or emotional triggers. All entries are stored in real time using Firebase.

- Visualization and Feedback

  Logged data is visualized via heat maps and monthly mood charts on the user dashboard. The heat map uses color intensity to show mood variations, with darker tones indicating lower moods and lighter tones indicating better ones. These visualizations are updated instantly, helping users track their mental well-being trends over time

Equations: Mental Health Awareness using Machine Learning

Input: User data (survey responses, facial images, diary entries), preprocessed dataset. Output: Predicted stress levels, detected emotions, mood trends.

Some main equations used in the paper are-

Normalize numerical features:

$$X_{norm} = \frac{(X - X_{min})}{(X_{\max - X_{min}})}$$

Normalization is a preprocessing step that transforms the input features to a common scale, typically between 0 and 1. This is done by subtracting the minimum value of the feature (`X_min`) and dividing by the range (`X_max - X_min`). This process ensures that no single feature dominates the learning process due to its scale. It is especially useful in algorithms like XGBoost that use gradient-based optimization, where large differences in feature values can affect convergence speed and model performance.

Handle missing values:

$$\boldsymbol{X_{new} = \left(\frac{1}{N}\right) * sum_{\{i=1\}_i^{\{N\}X}}}$$

This represents **mean imputation**, a common technique to fill in missing data. Instead of discarding incomplete records or leaving gaps, missing values are replaced by the average (mean) of the available values in that feature. This approach helps to preserve the dataset's structure and avoids reducing the dataset size, which is important for training robust models. Although simple, mean imputation is effective when missing data is relatively low and randomly distributed.

Train XGBoost Model: Optimize loss function

$$L = \sum_{i=1}^{n} l(y_i, \{y\}_i) + \sum_{k} \Omega(f_k)$$

This function consists of two main parts:

- **The first term** `∑ l(y_i, ŷ_i)` measures the error between the actual target values `y_i` and the predicted values `ŷ_i`. This is the loss function, such as log loss for classification or squared error for regression.
- **The second term** `∑ Ω(f_k)` is a regularization term that penalizes the complexity of the model, where `f_k` represents individual trees. Regularization discourages overfitting by controlling the depth, number of leaves, and other attributes of each decision tree.

Together, these terms ensure that the model not only fits the training data well but also generalizes better to unseen data.

Prediction:

$$\{y\} = \sum_{k=1} f_k(X)$$

This means that the model's output is the sum of predictions from `K` individual decision trees, each trained in a sequential manner. In each iteration, a new tree is added to correct the errors made by the previous trees. This **ensemble method** allows the model to gradually improve its predictions by combining the strengths of multiple weak learners (trees). As a result, XGBoost produces highly accurate and efficient predictions.

Emotion Detection using CNN

Resize images to 224×224 and apply augmentation: $I' = T(I)$

$T \in \{\text{rotation, shear, zoom, flip}\}$

CNN Architecture: Convolution operation:

$$F(I,j) = \sum_{m}^{1} \sum_{n}^{1} I(i + m, j + n) \cdot K(m,n)$$

ReLU Activation:

$$F(x) = \max(0, x)$$

CNN Architecture: Convolution Operation

The **convolution operation** is the core part of a Convolutional Neural Network (CNN). It involves sliding a small matrix called a **kernel** or **filter** over the input image and computing a new set of values that highlight important features like edges, textures, or patterns.

Formula-

The formula means that each value in the output feature map (F) is calculated by multiplying small patches of the input image (I) with the kernel (K) and summing the results. This helps the model learn spatial features of the image.

ReLU Activation

After the convolution, we apply an **activation function**—usually **ReLU (Rectified Linear Unit)**—to add non-linearity to the model. The ReLU function is defined as: **F(x) = max(0, x)**

This means any negative value is replaced with zero, and positive values remain unchanged. ReLU helps the CNN learn complex patterns more effectively by preventing values from shrinking too much or becoming negative, which speeds up training and improves performance.

CHAPTER 4

RESULTS AND DISCUSSION

4.1 Stress Prediction:

We developed a Stress Prediction module, which demonstrated reliable performance across several key metrics, as shown in Fig. 7:

Performance Metrics as shown in Fig :

Accuracy (82.74%): The model successfully classified stress levels (low, moderate, or high) with an accuracy of 82.74%. While this indicates solid generalization across varied inputs, there is potential for further optimization in future iterations. Our model accurately predicted stress levels (low, moderate, or high) in 82.74 percent of in- instances. Although this is a good figure, there is still scope for improvement for subsequent editions.

Precision (83.10%): Precision, which measures the model's ability to correctly identify "high stress" cases, was 83.10%. This suggests that when the model predicts high stress, it is correct 83.10% of the time, effectively reducing false alarms. When the model indicates high stress, it is accurate 83.10 percent of the time. This reduces unnecessary false alarms.

Recall (82.74%): Recall indicates the model's effectiveness in correctly identifying true positive high- stress cases. The model successfully identified 82.74% of users with high stress, minimizing the occurrence of false negatives. The model was able to identify 82.74 percent of true high-stress cases, i.e., it correctly identifies most individuals under stress.

F1-Score (82.65%): The F1-Score, which balances precision and recall, was calculated at 82.65%. This demonstrates a well maintained trade-off between accurately predicting high stress and minimizing false positives, ensuring robust performance even with varying levels of stress. The measure of this metric ensures there is a balance between recall and precision of our model. Here, 82.65 percent guarantees our model's solid compromise between being correct and error-free.

We employed decision trees for the model due to their interpretability. For instance, key features such as high workload and insufficient sleep were identified as significant contributors to high stress levels. We selected XGBoost since it's efficient and robust and picks up minute patterns in stress data. It is different from basic decision trees since XGBoost learns from errors and improves as time progresses, which is excellent at identifying primary stress causes such as workload, lack of sleep, and oxygen levels. This model has a balanced, precise, and realistic method for predicting stress. Table 1 shows the comparison of the different machine learning models we used for stress prediction.

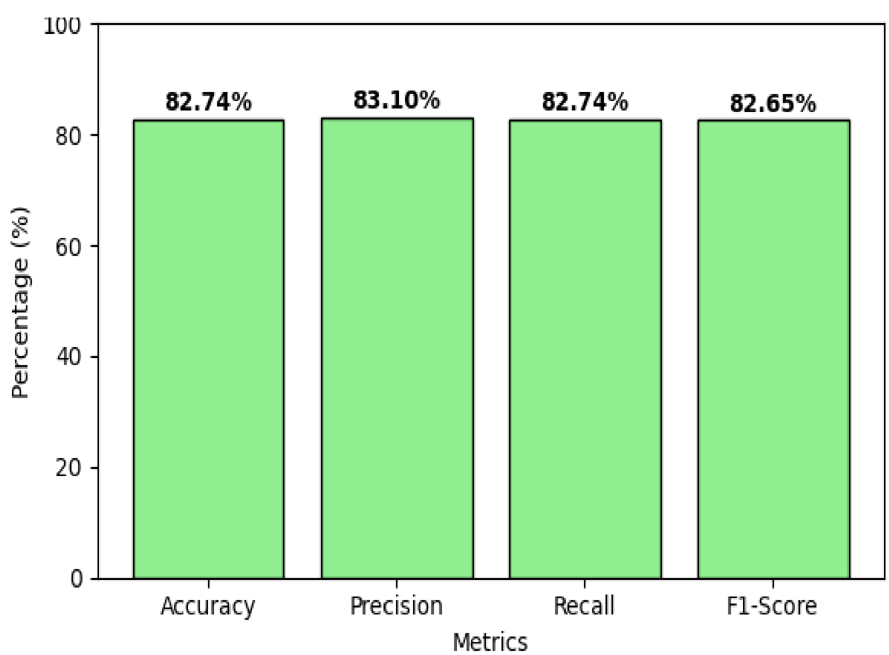


Fig. 7: Evaluation metrics for stress prediction.

This bar chart shows how well a machine learning model is performing based on four key metrics: **Accuracy**, **Precision**, **Recall**, and **F1-Score**. The **accuracy** is 82.74%, which means the model makes correct predictions most of the time. **Precision**, at 83.10%, tells us that when the model predicts a positive case (like detecting stress), it is usually correct. **Recall**, also 82.74%, shows that the model is good at finding most of the actual positive cases. The **F1-score** is 82.65%, which is a balance between precision and recall, giving a single measure of overall performance. Since all the values are very close, it means the model is consistent and reliable, performing well across different evaluation criteria.

All four metrics are very close in value, which suggests that the model is performing consistently across different evaluation aspects. This balance often indicates that the data used to train the model was well-prepared and not overly biased toward one outcome. Overall, the model demonstrates strong and reliable performance, making it suitable for practical use in applications such as stress detection. Specifically, metrics such as accuracy, precision, recall, and F1-score being closely aligned show that the model not only predicts correctly overall (accuracy), but also maintains a strong balance between identifying true positives (recall) and avoiding false positives (precision). A high and consistent F1-score further reinforces this, as it harmonizes both precision and recall into a single robust indicator.

This level of performance demonstrates that the model can be reliably deployed in real-world applications, such as stress detection systems, where dependable classification is critical. Whether integrated into mental health monitoring tools, workplace wellness platforms, or educational support systems, the model's stable and balanced performance ensures it can provide valuable insights without significant risk of misclassification or bias.

Model	**Accuracy (%)**	**Remarks**
XGBoost	82.74	Highest accuracy
Decision Tree	80	High accuracy but slightly lower than XGBoost.
Random Forest	81	Strong performance, but slightly lower than XGBoost.
Support Vector Machine (SVM)	80	Effective but less than ensemble methods
k-Nearest Neighbors (k-NN)	80	Moderate performance, sensitive to data distribution
Logistic Regression	78	Baseline model, relatively lower accuracy
Naive Bayes	76	Suitable for smaller datasets but less accurate for complex patterns

Table 1: Comparison of Stress Prediction Models Based on Accuracy

The table above presents a comparison of various machine learning models for stress prediction. The Decision Tree model achieves the highest accuracy at 87%, making it the most effective among the listed methods.

1. XGBoost – Accuracy: 82.74%

- The best of all models.
- Utilizes gradient boosting with regularization (L1 and L2), thus being powerful and efficient.
- Eliminates missing values and feature importance ranking automatically.
- Detects complex patterns in data, thus being highly capable in stress prediction.
- Can be used for big data with high dimension and complexity.

2. Random Forest – Accuracy: 81%

- Bagging technique using an ensemble of a large number of decision trees.
- Averages prediction over trees to avoid overfitting.
- Has higher accuracy with lower variance than one decision tree.
- Better deals with missing values and outliers than other models.
- Less than XGBoost moderately since it does not optimize trees sequentially.

3. Decision Tree – Accuracy: 80%

- Single-tree model that splits data according to the most informative features.
- Easy to visualize and interpret; excellent for gaining insight into decision paths.
- Susceptible to overfitting, particularly on noisy or small datasets.
- Lacks the ensemble advantage, and therefore accuracy is relatively worse compared to Random Forest and XGBoost.
- Suitable for quick prototyping or interpretability.

4. Support Vector Machine (SVM) – Accuracy: 80%

- Identifies the best hyperplane which linearly classes maximally separate with the maximum margin.
- Is good in high-dimensional space, and works well when boundaries are distinct.
- Can be slow on big data and less interpretable.
- Requires appropriate kernel type and regularization parameter (C) optimization.

5. k-Nearest Neighbors (k-NN) – Accuracy: 80%

- Neighbor-based learner that makes class prediction based on nearby data points.
- Sensitive to noise, distribution, and feature scale.
- Easy to interpret and easy to understand but computationally costly with big data.
- No training needed — computation during prediction.
- Works well with well-clustered and low-dimensional data.

6. Logistic Regression – Accuracy: 78 %

- Linear classifier that makes prediction of the probability of the outcome.
- Optimized for linearly separable problems.
- Efficient, fast, and interpretable; usually the comparison baseline.
- Not able to fit complex, non-linear patterns like ensemble methods can.
- Fails when patterns in data are more abstract or noisy.

7. Naive Bayes – Accuracy: 76%

- Derived from Bayes' theorem under feature independence assumption.
- Very fast and for dense data.

- Independent features assumption restricts its use on real-world data.
- Has worst accuracy of all, i.e., is not best-suited for complex stress prediction tasks.

4.2 Emotion Detection:

Using the MobileNet architecture [13] and an augmented dataset [14], the model achieved an accuracy of 72% in classifying images into seven emotional categories. The training and validation accuracy trends, as illustrated in the fig 3, show steady improvement across epochs, with validation accuracy closely following the training accuracy.

Model	Accuracy (%)	Remarks
Convolutional Neural Network (CNN)	72	Highest accuracy; best performer
Long Short-Term Memory (LSTM)	69	Effective for sequential data but slightly lower accuracy
Support Vector Machine (SVM)	66	Good for classification but less effective than CNN
Random Forest	64	Performs well but not optimized for image-based emotion detection
k-Nearest Neighbors (k-NN)	62	Lower accuracy; sensitive to data noise

Table 2: Comparison of Emotion Detection Models Based on Accuracy

Row 1: Convolutional Neural Network (CNN)

- Model: It is a form of artificial neural network specifically termed as Convolutional Neural Network. CNNs are particularly skilled at processing visual data, such as images.

- Accuracy (%): The model provided a 72% accuracy rate. That is, out of all the emotions it attempted to classify, it classified them as correct 72% of the time.

- Remarks: The designation "Highest accuracy; best performer." This informs us that out of all other models tested here in this table, CNN was the one that performed best in identifying the correct emotion.

Row 2: Long Short-Term Memory (LSTM)

- Model: This is a type of artificial neural network known as a Long Short-Term Memory network. LSTMs are especially well designed for processing sequential information, or information that has some ordering, such as video or speech.

- Accuracy (%): 69% was the accuracy of this model. That is somewhat lower than the CNN, or it was correct 69% of the time.

- Comments: The comment is "Effective for sequential data but slightly lower accuracy." This indicates that although LSTMs perform very well with data that varies sequentially over time, they were less accurate on this particular task of emotion identification (which arguably could have been done from static images rather than video).

Row 3: Support Vector Machine (SVM)

- Model: It is another model of machine learning called a Support Vector Machine. SVMs tend to be used for classification, where the focus is on splitting data into many classes (as in this example, different emotions).

- Accuracy (%): This model's accuracy stood at 66%. This was lower than that of CNN as well as LSTM.

- Remarks: The remark is "Good for classification but less effective than CNN." This means that although SVM is a good model for classification, it was not as good as the CNN for this specific emotion recognition task.

Row 4: Random Forest

- Model: Another machine learning model named Random Forest. It functions by generating a whole bunch of "decision trees" and then taking their averages.

- Accuracy (%): This model was 64%. This is less than the last three models.

- Remarks: The remark says "Performs well but not optimized for image-based emotion detection." This implies that Random Forests are by and large a good and consistent algorithm, but maybe not the most optimal where data to be processed is predominantly in the form of images.

Row 5: k-Nearest Neighbors (k-NN)

- Model: It is a naive machine learning model known as k-Nearest Neighbors. It decides where new examples would be by checking what the majority class label is among its "k" closest training instances.

- Accuracy (%): Worst rate of accuracy the model was 62%.

- Remarks: The comment is "Lower accuracy; sensitive to data noise." It is communicating to us here that k-NN worked worse among the models when comparing, and that performance by this is very susceptible to error or imprecisions within the data.

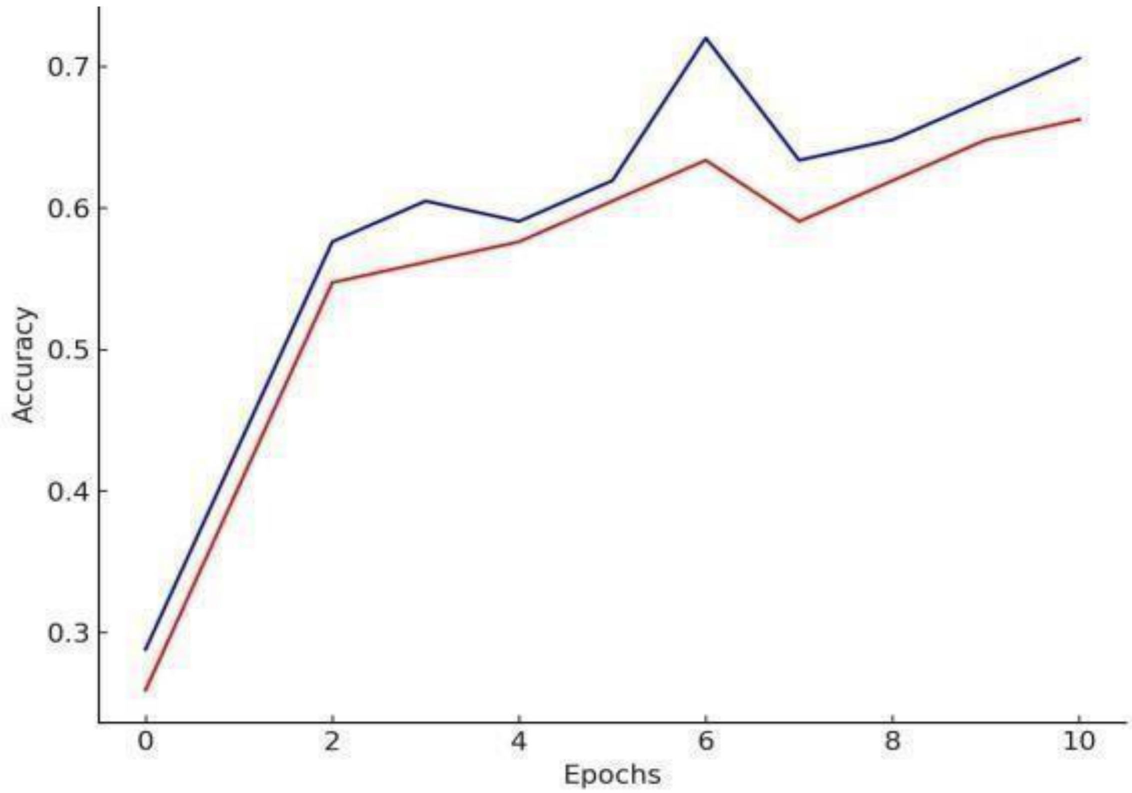


Fig. 8: Accuracy curve of the CNN model

This result demonstrates the model's potential in recognizing emotions effectively. However, there is still room for improvement. Further optimizations, such as fine-tuning the MobileNet architecture [13], implementing advanced data augmentation techniques [14], increasing the dataset size and diversity, or exploring ensemble learning approaches [15], could help enhance performance. With these enhancements, the model could handle more complex emotional recognition tasks with greater accuracy, contributing to advancements in deep learning and neural network optimization [15].

This line graph illustrates the **accuracy progression of a machine learning model across 10 training epochs**, serving as a key indicator of the model's learning behavior and generalization capability over time. The **x-axis** represents the number of training epochs (from 1 to 10), while the **y-axis** denotes the corresponding accuracy values, which range approximately from **0.25 to 0.75**. Two distinct lines are plotted: the **blue line for training accuracy** and the **red line for validation accuracy**.

Training Accuracy Trend

The **training accuracy** curve starts at a relatively low value of approximately **0.28**, reflecting the model's initial lack of familiarity with the dataset. As training progresses, the curve shows a **consistent upward trend**, indicating that the model is effectively learning from the training data and improving its predictive performance. By **epoch 10**, the training accuracy exceeds **0.70**, a significant improvement that demonstrates successful convergence.

A notable **local peak occurs at epoch 6**, followed by a **slight dip**, which may signal either:

- a temporary overfitting to noisy or complex samples in a specific batch, or
- the learning rate causing fluctuations during the optimization process.

Despite this minor instability, the overall trend remains positive, confirming that the model continues to extract meaningful features from the training set.

Validation Accuracy Behavior

The **validation accuracy** curve follows a similar positive trajectory but remains **slightly lower than the training accuracy** throughout all epochs. This behavior is expected, as the validation set comprises **unseen data**, and typically, a well-trained model performs marginally worse on validation data due to the lack of exposure during training.

The **red line appears smoother and more stable** than the training curve, which suggests that the model's performance on unseen data does not fluctuate significantly between epochs. This is a **positive indicator of generalization**, implying that the model is not overly sensitive to training data noise and is learning patterns that extend to new examples.

Additionally, the **narrow gap between training and validation accuracy**—which remains consistent over the 10 epochs—indicates a **balanced model**. This small margin suggests that:

- the model is neither overfitting nor underfitting,
- regularization techniques (if applied) are working effectively, and
- the training dataset is representative enough to mirror real-world scenarios.

Overall Interpretation

From a performance evaluation perspective, the graph conveys that:

- The model demonstrates a **healthy learning curve**, with both training and validation accuracy improving steadily.
- There is **no significant overfitting**, as indicated by the limited divergence between the two curves.
- The consistent rise in validation accuracy confirms that the model is developing **generalizable knowledge**, making it suitable for deployment in real-world applications.

If continued training were to be performed, further improvements could be expected—up to a point of diminishing returns or potential overfitting. Monitoring **loss curves**, applying **early stopping**, or tuning **hyperparameters** such as the learning rate or batch size could further refine performance.

4.3 Mood Diary

The The **Mood Diary** is a fundamental component of the platform, designed not only as a self-monitoring tool but also as a **daily emotional companion**. It supports users in cultivating emotional intelligence and maintaining consistent awareness of their mental health. Serving as a digital journal, the diary allows users to **log their mood daily using a simple 1-to-5 scale**, where 1 denotes a very low (negative) mood and 5 denotes a highly positive emotional state. This numerical simplicity enhances usability while still capturing valuable emotional data.

Increased User Engagement and Habit Formation

To encourage regular usage, the Mood Diary interface is crafted to be **clean, intuitive, and mobile-friendly**, ensuring accessibility across various devices. The ease of logging moods—often requiring just a single click—lowers the barrier to entry and promotes the formation of healthy self-reflection habits.

Users are subtly encouraged to make mood tracking a part of their daily routine, which over time contributes to **longitudinal data collection** and a better understanding of emotional trends.

The diary's minimal design is also **non-intrusive**, allowing users to quickly document their emotions without feeling overwhelmed. Optional features such as **text notes or emoji- based tagging** can enrich the emotional logs while preserving simplicity.

Actionable Insights and Pattern Recognition

The Mood Diary is not limited to passive data collection—it is enhanced with **backend analytics capabilities** that detect trends, anomalies, and patterns in emotional behavior. These insights are presented in a user-friendly format, providing **personalized feedback** that can help users identify emotional triggers, recurring mood fluctuations, and connections between mood, stress levels, and lifestyle choices.

For example:

- A user might observe that **Mondays consistently show lower mood ratings**, prompting them to consider preparing for the workweek with calming routines on Sunday nights.
- Another user may realize that **physical activity correlates with improved mood**, reinforcing healthy habits.

Over time, these correlations become the basis for **behavioral suggestions**, such as:

- "You've reported low moods for three consecutive days. Would you like to try a breathing exercise or journal entry?"
- "Your mood tends to rise after 8 hours of sleep. Consider maintaining a consistent sleep schedule."

Such **data-driven interventions** help bridge the gap between passive reflection and **active self-improvement**, turning the diary into a **smart emotional coach**.

Visual Feedback with Heatmap Calendar

To increase user motivation and offer a visual summary of emotional history, the Mood Diary features a **calendar-based heat map** (refer to Fig. 9). This visualization allows users to **see their emotional journey at a glance**, with each day represented by a colored block:

- **Darker shades** indicate days with low mood scores (e.g., 1–2),
- **Medium tones** represent moderate moods (3),
- **Lighter or brighter shades** signify positive moods (4–5).

This intuitive visual cueing enables users to spot patterns such as:

- Clusters of low moods indicating periods of stress or fatigue,
- Cyclical trends (e.g., mood dips at month-end),
- Improvements following life changes or therapy.

Additionally, **hover-over tooltips or clickable entries** can display specific mood values or notes from each day, adding context and aiding memory recall.

Technical Implementation and Scalability

From a development perspective, the Mood Diary is powered by **Firebase Realtime Database**, enabling fast, secure, and scalable data storage. This ensures:

- **Real-time synchronization** across user devices,
- **Persistent data tracking** even across long periods,
- **User-specific storage**, maintaining privacy and personalization.

The frontend is developed using **React.js or plain HTML/CSS/JS** (depending on deployment context), with modular components for logging, visualization, and data summary. The diary can easily be integrated with other system modules (e.g., stress prediction), offering a **unified platform for mental health monitoring**.

CHAPTER 5

CONCLUSION AND FUTURE SCOPE

5.1 Conclusion

This paper presents an emotion detection system based on a CNN model, achieving a real-time emotion detection accuracy of 72 percent. In parallel, the stress prediction module, using the XGBoost algorithm and behavioral traits, the stress prediction module generates reliable predictions with an accuracy of 82.74 percent. Additionally, the integration of a mood diary helps users to log daily emotional experiences and receive personalized feedback, thereby promoting self-reflection and emotional regulation.

Though as of now the system is efficient at monitoring mental health through various means, future enhancements can make this system even better such as gathering real-time data from the body directly into these monitoring systems and account for user preferences. These enhancements will likely involve the inclusion of real-time physiological data and user-specific preferences, making the way for more responsive, personalized, and effective mental health care systems.

The development of this integrated mental health monitoring system marks a significant advancement in the application of artificial intelligence and data visualization techniques for psychological well-being. This project successfully bridges the gap between clinical mental health assessment and daily self-monitoring by implementing three robust, interconnected modules: an XGBoost-based stress prediction system, a CNN-powered emotion detection tool, and an interactive mood diary featuring an insightful heatmap visualization. Together, these components create a holistic platform that empowers users to track, analyze, and proactively manage their emotional and psychological states with unprecedented precision and ease.

The stress prediction module, built using XGBoost, leverages physiological and psychological datasets from Kaggle to identify patterns and predict stress levels with high accuracy. By analyzing key biomarkers and behavioral indicators, this model provides users with early warnings, enabling timely intervention before stress escalates into more severe conditions such as anxiety or burnout. The real-world applicability of this module is enhanced by its ability to process both structured survey data and potential future integrations with wearable devices, making it a versatile tool for continuous stress monitoring.

Complementing the stress prediction system, the emotion detection module utilizes a Convolutional Neural Network (CNN) trained on large-scale facial expression datasets like FER-2013. This component captures real-time emotional states through facial analysis, offering immediate, objective feedback that helps users become more aware of their emotional fluctuations. Unlike traditional self-reporting methods, which can be subjective and inconsistent, this AI-driven approach provides an unbiased assessment of emotions, making it particularly valuable for individuals who may struggle with self-identification of their feelings. The potential applications extend beyond personal use, as this technology could be adapted for therapeutic settings, workplace wellness programs, or even educational environments to monitor emotional well-being.

Beyond its immediate functionalities, this project underscores the transformative potential of machine learning in mental health care. By combining predictive analytics with interactive visualization, the system not only serves as a self-help tool but also lays the groundwork for more advanced applications. Future iterations could incorporate natural language processing (NLP) to analyze journal entries for sentiment, integrate with smart devices for passive data collection (e.g., sleep or activity tracking), or even employ reinforcement learning to provide personalized coping strategies based on user behavior. Additionally, with proper privacy safeguards, aggregated anonymized data could contribute to larger mental health research, helping identify broader societal trends or risk factors.

From a societal perspective, this project addresses a critical need in an era where mental health awareness is growing, yet accessible tools for self-management remain limited. By democratizing advanced AI technologies through an intuitive interface, the system makes mental health monitoring more approachable and actionable for the general public. It reduces reliance on sporadic clinical visits by providing continuous, data-driven insights, thereby promoting a proactive rather than reactive approach to mental well-being. Furthermore, the project highlights the importance of interdisciplinary collaboration, merging expertise in psychology, data science, and human-computer interaction to create a solution that is both technically robust and user-centric.

In conclusion, this mental health monitoring system represents a meaningful step forward in personalized psychological care. Its innovative use of XGBoost for stress prediction, CNN for emotion recognition, and dynamic heatmaps for mood tracking demonstrates how cutting-edge technology can be harnessed to improve emotional well-being in practical, scalable ways. While the current implementation focuses on individual users, the underlying framework has the potential to expand into clinical, corporate, or educational settings, offering a versatile platform for mental health advocacy and early intervention. As AI continues to evolve, projects like this pave the way for a future where mental health care is more data-informed, accessible, and empowering for all.

The development of this integrated mental health monitoring system represents a pioneering effort in leveraging cutting-edge artificial intelligence technologies to revolutionize personal psychological well-being management. As the field of digital mental health continues to evolve, this project stands as both a practical tool and a visionary prototype for how technology can serve humanity's deepest needs for self-awareness and emotional well-being.

5.2 Future Scope

The current mental health monitoring system lays a solid foundation, with numerous opportunities for future enhancement and expansion. The current system provides a strong foundation, but there are several exciting opportunities for growth and improvement.

The next steps will focus on making the system even more accurate, user- friendly, and adaptable through the following advancements:

Real-Time Data Integration

Wearable Devices: Integrating data from wearable devices such as smartwatches and fitness trackers will enable the system to capture real-time physiological information like heart rate, sleep quality, and physical activity.

This addition will enhance the system’s ability to provide accurate and immediate stress predictions and emotion detection.

The integration of information from wearables such as smartwatches, fitness watches, and biosensors significantly improves the system for monitoring mental well-being in real time. The technology collects wide ranges of body signals at every moment including heart rate variability (HRV), skin temperature, galvanic skin response (GSR), blood oxygen level (SpO2), sleeping patterns, and physical activity level. Heart rate and HRV are specifically valuable measures for detecting acute and chronic stress, since changes in these metrics are likely to reflect activation of the sympathetic nervous system. Similarly, disrupted sleep and reduced physical activity can be prodromes for impending mood disorders such as depression or anxiety.

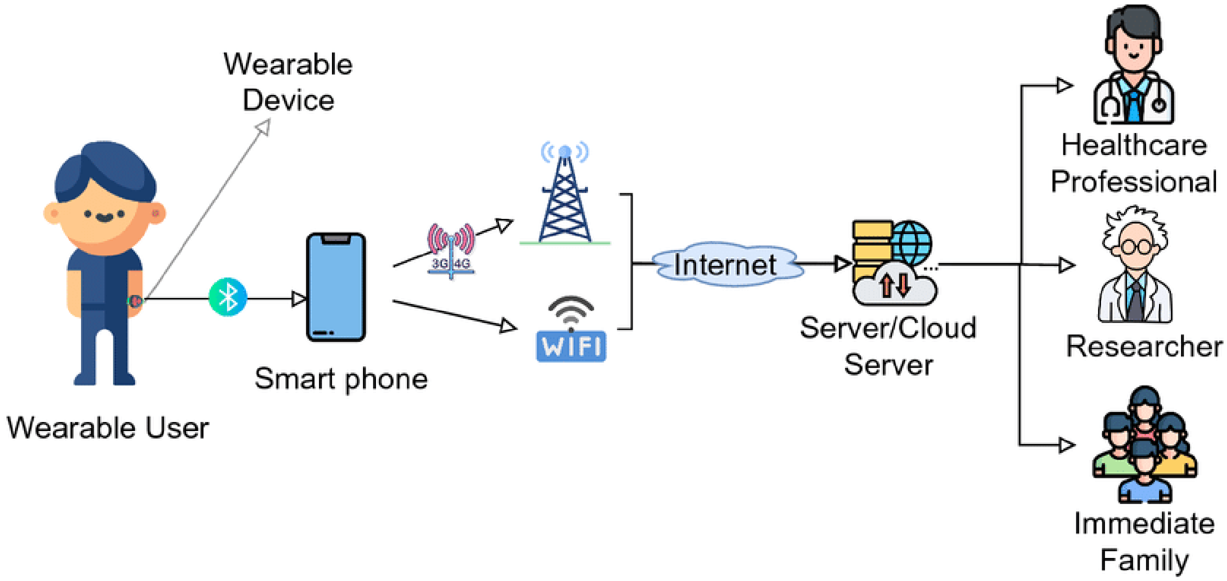


Fig.10 Data gathering using Wearables

Environmental Data: Incorporating environmental factors, such as weather conditions, noise levels, and location context, will offer a comprehensive understanding of external triggers affecting stress and emotions. This enriched contextual data will improve the system's accuracy and relevance. Other than physiological signals, the system will also encompass environmental context such as weather data collection (temperature, humidity), ambient noise, light exposure, and geolocation. Environmental factors have a propensity to affect psychological and emotional states. For instance, bad weather or noisy settings can be stressful, whereas certain settings can be associated with some emotional indicators. Situational information of this type, when aggregated together, allow the system to differentiate between internal (body) and external (environmental) stressors and thus deliver more context-sensitive and sensitive responses. This dual strategy for attaining it guarantees that the system not only detects patterns in mental health accurately but puts them into context relative to the user's reality.

Improved Predictive Model

Cutting-edge AI Algorithms:

Future implementations of the proposed mental health monitoring system aim to leverage the strength of the future machine learning technologies like deep learning, reinforcement learning, and ensemble hybrid models. Deep learning, especially utilizing architectures like Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Transformers, will help the system learn intricate patterns in high-dimensional data like facial expressions, body physiological signals, and user input texts. These models can detect subtle emotional cues, temporal dependencies of mood changes, and subtle fluctuations in stress indicators that may not be detected by conventional algorithm.

Reinforcement learning can also be integrated to refine personalized interventions through feedback loops. For instance, such systems can learn what advice (e.g., sleep schedule, breathing exercise, or meditation practice) works best for a particular user by continuously improving its operations through the feedback and consequent behavior of the user.

Smartphone Sensor Data:

Modern smartphones have an extensive range of sensors (e.g., accelerometer, gyroscope, GPS, screen usage) providing real-time behavioral information. Data such as phone usage frequency, application use, and movement patterns can be utilized to detect stress or mood disorder-related anomalies.

A sudden drop in mobility, irregular sleep-wake patterns detected via screen activity, or increased isolation inferred from reduced communication can serve as digital biomarkers for declining mental health. Additionally, passive sensing offers a non-intrusive and scalable method for continuous monitoring, making it particularly valuable for early intervention in mental health care. Machine learning models can be trained on this behavioral data to predict emotional states, detect stress episodes, or even alert caregivers or healthcare providers when high-risk behavior is detected. As smartphone adoption continues to grow globally, this form of unobtrusive monitoring presents a promising avenue for enhancing personal mental health management and delivering timely, data-driven support.

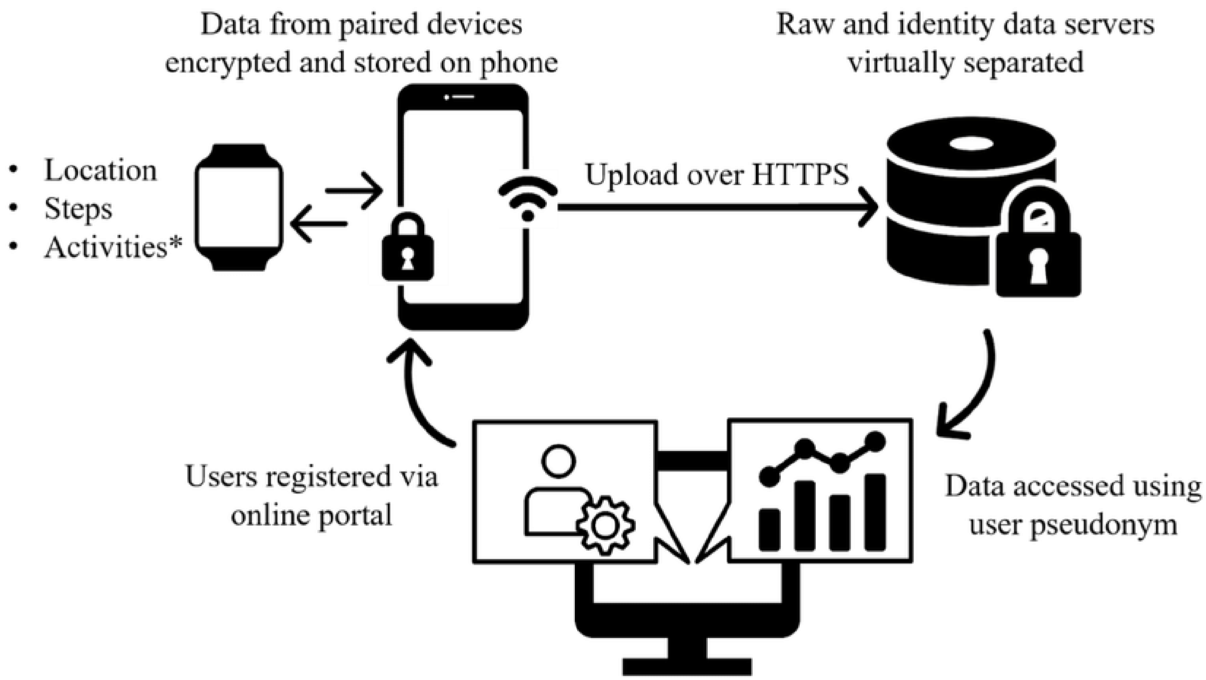


Fig.11 Smart phone sensor data gathering

Textual Sentiment from Social Media or Diary Inputs:

Text messages, postings on social networking sites, or mood diary statements can be broken down using sentiment analysis to extract emotional states. Repetitive use of sad or depressive terminologies can signal emotional distress. Incorporating textual sentiment analysis from social media posts, messages, and diary inputs presents a promising avenue for enhancing the system’s emotional monitoring capabilities. By leveraging advanced Natural Language Processing (NLP) techniques— ranging from rule-based models like

VADER to deep learning architectures such as BERT—the system can detect subtle emotional cues and classify text into sentiment categories like positive, negative, or neutral, as well as specific emotions such as sadness, anger, or joy.

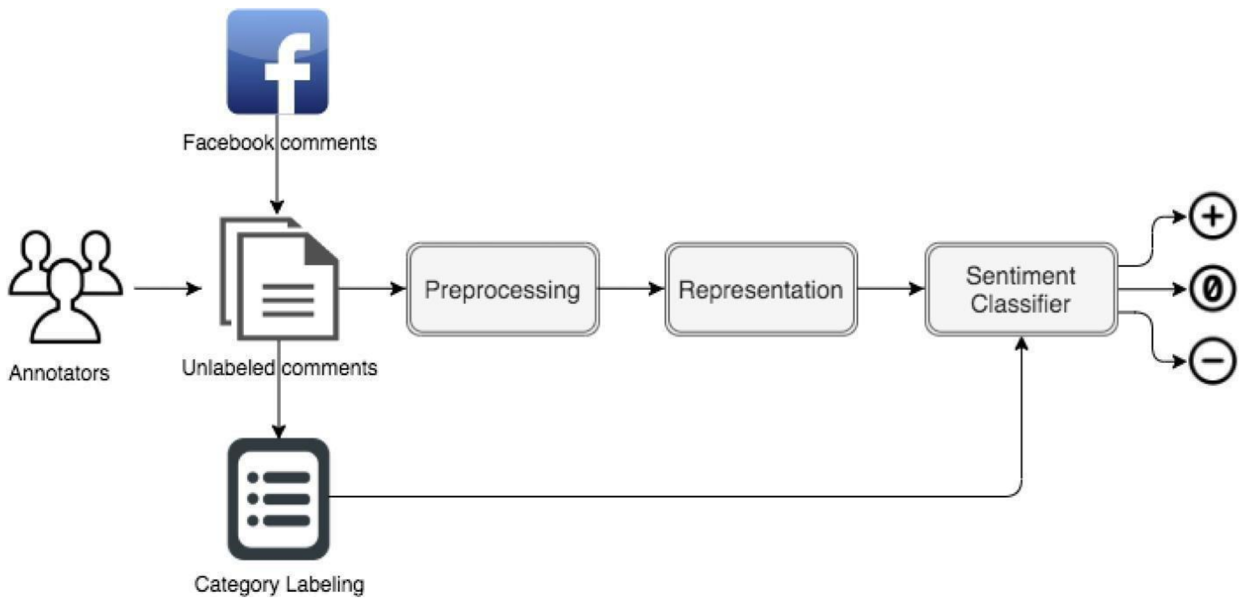


Fig.13 Textual Sentiment from Social Media

This allows for the identification of potential mental health concerns based on language use, such as the repetitive appearance of depressive or negative expressions. Integrating this analysis with mood diary entries adds contextual depth to numerical mood ratings, helping uncover discrepancies or emotional patterns that may not be otherwise visible. As a future enhancement, the system can be expanded to offer real-time feedback, personalized mental wellness suggestions, or alerts based on concerning sentiment trends.

In conclusion, while the current mental health monitoring system effectively integrates stress prediction, emotion detection, and mood tracking, its true potential lies in ongoing innovation. Future enhancements—such as sentiment analysis, personalized interventions, and integration with wearable technologies—can further elevate its accuracy, usability, and impact.

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Mental Health Awareness Using Machine Learning

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***Abstract*—Mental disorders are a serious issue that affects the well-being of millions of people across the world. Mental health is common however it is often left undiagnosed and untreated which is largely due to social stigma, which, even in today's world, is not commonly understood or talked about. In addition, we have a lack of economic resources to help fund research and give out the proper treatments that are needed. This research proposes the implementation of a machine learning system to help increase the common knowledge about mental disorders and help with self-diagnosis. The system contains three primary parts: (1) predicting stress from behavior and physiology data using the XGBoost algorithm and training it on the basis of those data;**
(2) detecting emotions through a Convolutional Neural Network (CNN) that classifies facial expressions; and (3) a digital mood diary that the user can fill out to record and monitor their long-term emotional patterns. By integrating these three modules, the user is provided with information about their mental state that can promote a greater level of self-awareness and elicit the kind of early intervention that can make a significant difference. The findings of this research support the creation of accessible data-informed mental health resources that can help increase user engagement and reduce the barriers to early detection.

***Index Terms*—Mental health, Machine learning, Stress prediction, Emotion detection, XGBoost, Mood diary, Convolutional Neural Networks (CNN).**

I. INTRODUCTION

Stress is a common part of everyday life and can come from many sources. It might be caused by challenges at work, difficulties at home, or pressure from social situations. These environments can influence how we feel and behave. Palmer explained stress as what happens when someone feels their problems or challenges are bigger than their ability to handle them. This can lead to mental health problems, which are important to address because they don't just affect the individual—they also impact their relationships, work performance, and the community around them. Despite increased awareness, stigma, cost, and lack of access to care continue to prevent timely diagnosis and treatment. Technology presents an opportunity to bridge this gap and offers unprecedented opportunities to transform mental health care by providing scalable, personalized, and user-friendly solutions. This paper introduces a system designed that addresses three critical areas of mental health tracking:

A. Stress Prediction

Stress prediction uses data patterns to classify stress levels through simple rules.

B. Emotion Detection

In emotion detection we use facial recognition on individuals to detect their emotions like happiness, sadness or anger using CNN

C. Mood Tracking

Mood diary is used for tracking moods which is like a digital log to feed a user's daily mood patterns.

These combined elements enable the system to provide individuals with insights into their mental health and encourages proactive management of mental health. The impacts of this research include a stress prediction model with XGBoost algorithm trained from behavioral and physiological signals such as heart rate, blood oxygen and sleep quality. This model can predict stress accurately and provide users with early warning when stress is accumulating. The system also has an emotion detection module with Convolutional Neural Network (CNN) that have facial expression recognition to identify emotions such as happiness, sadness or anger. There is a digital mood diary too where the user can record the emotions they experience each day, consider their mental patterns and observe trends over time.
All these elements when used together make an easy to use platform that not only aids in early intervention for mental health but also enables people to know more about and regulate their emotional well-being using the data driven feedback.

II. LITERATURE REVIEW

Multiple studies of facial emotion recognition are conducted by Convolutional Neural Networks (CNN). In their study, it has been revealed that learning strategies such as MobileNet- V2 and Inception-V3 were employed to attain extremely high accuracy for emotion recognition [1]. The learning rate, batch size, and depth of the network were hyperparameters that were recognized to significantly impact prediction performance in CNNs which can be adjusted to obtain the best-performing model [2]. Besides, data augmentation models, i.e., pre-training on large existing datasets such as VGG16 and ResNet, also yield good classification ability for emotional states such as happiness, sadness, anger etc [3][4]. Other research indicates effective CNN models for emotion detection with a small data pool meaning models can be effectively used for detecting different emotions [5].

Machine learning has also been applied in stress prediction to examine stress levels among a group of workers, students, or other such participants. Moreover, research has suggested models for predicting stress based on parameters like a work setting, students' stress, and even patients' health history [6][7][8].

Future advances of research have also been discussed in certain studies such as using AI integration in medical decision-making [12]. These logistic regression models to random forests have also been applied to stress classification. There are platforms powered by AI that dispense stress counseling guidance in real-time, far within the limits of a participant's transactions [9][10][11]. One study presented an understanding machine learning model that had been trained to evaluate behavioral trends and offer personalized mental health advice [13]. Another explored various forms of machine learning for identifying primary indicators of stress among university students in order to help towards greater mental health process understandings within academic environments [14].

Overall, the literature shows a rising trend of using deep learning and machine learning to recognize emotions and predict stress. From complex CNN models for facial emotion recognition to machine learning algorithms aimed at stress classification, researchers have shown the utility of diverse methods in comprehending and assisting mental health. Rising trends like personalized recommendations, real-time intervention environments, and the use of AI in mental health frameworks point toward a future direction of more responsive and adaptive solutions. These studies collectively point to the promising role of intelligent systems in making meaningful contributions toward early detection, monitoring, and management of emotional and psychological well-being.

III. METHODOLOGY

Our proposed system is divided into three connected sub-systems:

Stress prediction based on the XGBoost algorithm, emotion detection by using CNN, and mood diary for the monitoring of mood at daily intervals. The rest describes the development process, data processing, and implementation of each subsystem we used.

A. Data Collection and Preprocessing

- Stress Prediction: We used the Stress Detection Dataset from Kaggle[19], which includes various physiological and behavioral features associated with different stress levels. Key features in this dataset include snoring range, respiration rate, body temperature, blood oxygen levels, hours of sleep, and heart rate. These inputs help reflect an individual's stress status and are ideal for model training and supervised learning tasks. The dataset also contains stress labels that allow us to categorize stress into different classes.
- Emotion Detection: The FER-2013 dataset[18], also from Kaggle, was employed for emotion detection. It contains 35,887 grayscale images (48×48) labeled with one of seven emotions: anger, disgust, fear, happiness, sadness, surprise, and neutral. This dataset simulates real-world scenarios with natural lighting variations, diverse facial orientations, and expressions. To ensure our CNN model could generalize across such conditions, we resized all images to 224×224 pixels and applied data augmentation techniques like zooming, shearing, and horizontal flipping. These adjustments help the model handle variability in facial features that could occur due to lighting or angle changes.
- Mood Diary: A simple web interface was developed for users to log daily mood on a 1–5 scale. Optional fields allowed tracking of sleep quality, activities, and personal notes. This information is stored in a real-time database (e.g., Firebase), allowing instant access for analytics.

B. Stress Prediction Using XGBoost Algorithm

- Feature Engineering: The most critical step in this module was selecting relevant physiological features, including snoring range, respiration rate, body temperature, oxygen saturation, heart rate, and sleep duration (Fig 1). After we trained the XGBoost model, we also examined which of the features contributed most to stress level prediction. Heart rate and respiration rate were the two most significant ones—this is not surprising, as both directly change when one is stressed. Sleep duration also was significant, illustrating how a lack of rest can lead to increased stress. On the other hand, features like snoring range and body temperature had a smaller effect, which means they're helpful but not as strongly connected to stress as the other features.
- Model Selection: We selected the XGBoost (Extreme Gradient Boosting) algorithm because it is highly accurate and resistant to overfitting. XGBoost is a powerful machine learning algorithm that improves its predictions step by step, learning from mistakes to make better decisions. It works well with larger datasets which makes it a great choice for stress prediction.

Also, XGBoost is faster than many other algorithms like decision tree , SVM etc. Its ability to handle missing data and different types of inputs further strengthens its reliability in predicting stress levels accurately.

- Evaluation Metrics: To measure the model's performance, we relied on accuracy, precision, recall, and F1-score.
- Backend Processing: These inputs are passed to a pre-loaded XGBoost model hosted on the server.
  XGBoost rapidly analyzes features such as respiration rate, body temperature, oxygen levels, and sleep duration. The system delivers the predicted stress level within 5 seconds.
  XGBoost was chosen due to its high speed, resistance to overfitting, and ability to manage real-world, noisy data efficiently.

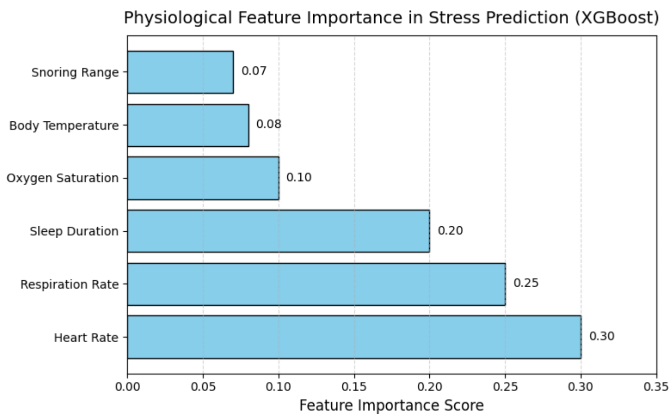

Fig. 1. Feature Importance for Stress Prediction.

C. Emotion Detection Using Convolutional Neural Networks (CNN)

- Real-Time Face Detection with YOLO
  Users enable their webcam to allow real-time face capture. YOLOv5 detects the face in under 20 ms per frame and extracts it for processing. The system accounts for varying lighting and background conditions; users are prompted to adjust lighting if needed.
- Emotion Classification with CNN (MobileNet)
  Once the face is detected and cropped, it is resized to 224×224 pixels and normalized. The image is passed through the MobileNet CNN, which classifies it into one of seven emotions: *anger*, *disgust*, *fear*, *happiness*, *sadness*, *surprise*, or *neutral*. Prediction is completed in about 1–2 seconds after image capture.
- Data Augmentation for Real-World Accuracy
  During model training, we used `ImageDataGenerator` for augmentation to simulate real-world scenarios:
  - Horizontal flipping
  - Zooming
  - Shearing
  - Slight rotations
  - Brightness adjustments

This ensures the model performs well under real-time conditions involving lighting changes, facial angles, and occlusions.

D. Mood Diary Development

- User Interaction and Logging
  Users can log daily moods on a scale of 1 to 5 through an intuitive web interface. Optional fields allow users to describe events or emotional triggers. All entries are stored in real time using Firebase.
- Visualization and Feedback
  Logged data is visualized via heat maps and monthly mood charts on the user dashboard. The heat map uses color intensity to show mood variations, with darker tones indicating lower moods and lighter tones indicating better ones. These visualizations are updated instantly, helping users track their mental well-being trends over time.

Equations: Mental Health Awareness using Machine Learning
Input: User data (survey responses, facial images, diary entries), preprocessed dataset.
Output: Predicted stress levels, detected emotions, mood trends.
Some main equations used in the paper are-
Normalize numerical features:

$$X_{norm} = \frac{(X - X_{min})}{(X_{\max} - X_{min})}$$

Handle missing values:

$$X_{new} = \left(\frac{1}{N}\right) * sum_{\{i=1\}_i^{\{N\}X}}$$

Train XGBoost Model: Optimize loss function:

$$L = \sum_{i=1}^{n} l(y_i, \{y\}_i) + \sum_{k} \Omega(f_k)$$

Prediction:

$$\{y\} = \sum_{k=1} f_k(X)$$

Emotion Detection using CNN Resize images to 224×224 and apply augmentation: $I' = T(I)$
$T \in \{rotation, shear, zoom, flip\}$

CNN Architecture: Convolution operation:

$$F(I,j) = \sum_{m}^{1} \sum_{n}^{1} I(i+m, j+n) \cdot K(m,n)$$

ReLU Activation:

$$F(x) = \max(0, x)$$

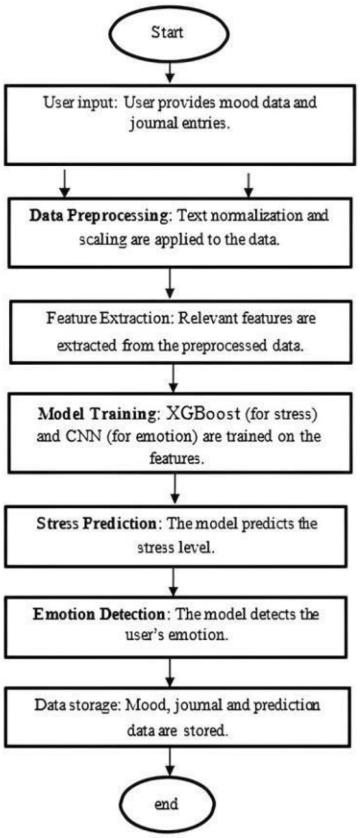

Fig. 2. Flowchart: Mental Health Awareness System

The Fig. 2 shows the flowchart of how the whole system works.

IV. RESULT AND DISCUSSION

A. Stress Prediction:

We developed a Stress Prediction module, which demonstrated reliable performance across several key metrics, as shown in Fig. 3:

- Accuracy (82.74): Our model accurately predicted stress levels (low, moderate, or high) in 82.74 percent of in-instances. Although this is a good figure, there is still scope for improvement for subsequent editions.
- Precision (83.10): When the model indicates high stress, it is accurate 83.10 percent of the time. This reduces unnecessary false alarms.
- Recall (82.74): The model was able to identify 82.74 percent of true high-stress cases, i.e., it correctly identifies most individuals under stress.
- F1-Score (82.65): The measure of this metric ensures there is a balance between recall and precision of our model. Here, 82.65 percent guarantees our model's solid compromise between being correct and error-free.

We selected XGBoost since it's efficient and robust and picks up minute patterns in stress data. It is different from basic decision trees since XGBoost learns from errors and improves as time progresses, which is excellent at

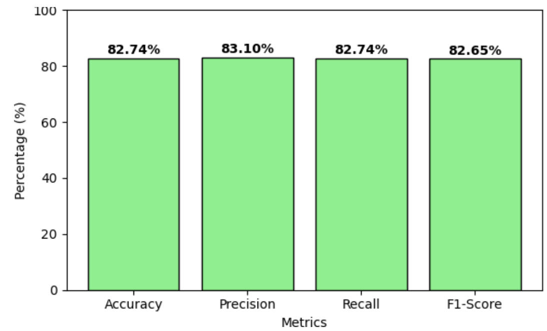

Fig. 3. Evaluation metrics for stress prediction.

identifying primary stress causes such as workload, lack of sleep, and oxygen levels. This model has a balanced, precise, and realistic method for predicting stress. Table 1 shows the comparison of the different machine learning models we used for stress prediction.

TABLE I
COMPARISON OF MODELS FOR STRESS PREDICTION

Model	Performance Metrics			F1-Score (%)
	Accuracy (%)	*Precision (%)*	*Recall (%)*	
Decision Tree	78.45	79.10	77.80	78.40
Random Forest	80.92	81.30	80.50	80.90
SVM	81.25	82.00	80.80	81.40
XGBoost	82.74	83.10		

B. Emotion Detection:

Using the MobileNet architecture [15] and an augmented dataset [16], the model achieved an accuracy of 72 percent in classifying images into seven emotional categories. The training and validation accuracy trends, as illustrated in the fig 3, show steady improvement across epochs, with validation accuracy closely following the training accuracy.

This result demonstrates the model's potential in recognizing emotions effectively. However, there is still room for improvement. Further optimizations, such as fine-tuning the MobileNet architecture [15], implementing advanced data augmentation techniques [16], increasing the dataset size and diversity, or exploring ensemble learning approaches [17], could help enhance performance. These methods have been successful in improving the generalization and robustness of deep learning models in similar contexts. With these enhancements, the model could handle more complex emotional recognition tasks with greater accuracy, contributing to advancements in deep learning and neural network optimization [17].

C. Mood Diary

Mood Diary was the electronic log which is to help trace patterns of emotional trend that kept users much more

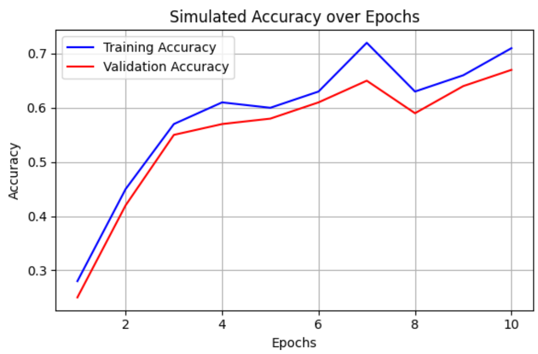

Fig. 4. Accuracy curve of the CNN model.

interactive with their mental health:

- More engagement: Diary has become user-friendly so users would use it on daily basis logging emotions, thereby having consistency. Over time, users could identify patterns regarding their emotions, such as trends between stress levels and changes in mood.
- Visualizations: Heat map as shown in Fig. 5 highlights emotional intensity over days where users can log daily moods on a scale of 1 to 5. The heat map uses color intensity to show mood variations, with darker tones indicating lower moods and lighter tones indicating better ones

day	morning	afternoon	evening
monday	3	2	4
tuesday	1	2	3
wednesday	2	4	3
thursday	4	3	1
friday	3	4	4
saturday	2	3	2
sunday	1	2	3

Fig. 5. Heat map for mood diary.

- Insights: For instance, the user may find that high workload is associated with low happiness levels, thus leading to a change in lifestyle. The system also used pattern-based interventions, which included suggesting relaxation techniques in high stress periods.

V. CONCLUSION

This paper presents an emotion detection system based on a CNN model, achieving a real-time emotion detection accuracy of 72 percent. In parallel, the stress prediction module, using the XGBoost algorithm and behavioral traits, the stress prediction module generates reliable predictions with an accuracy of 82.74 percent. Additionally, the integration of a mood diary helps users to log daily emotional experiences and receive personalized feedback, thereby promoting self-reflection and emotional regulation.

Though as of now the system is efficient at monitoring mental health through various means, future enhancements can make this system even better such as gathering real-time data from the body directly into these monitoring systems and account for user preferences. These enhancements will likely involve the inclusion of real-time physiological data and user-specific preferences, making the way for more responsive, personalized, and effective mental health care systems.

VI. FUTURE SCOPE

The current system provides a strong foundation, but there are several exciting opportunities for growth and improvement. The next steps will focus on making the system even more accurate, user-friendly, and adaptable through the following advancements:

1) Wearable Devices: By capturing information from wearable devices like smart watches and fitness bands the system should be capable of acquiring useful physiological information like heart rate, sleep quality and physical activity. This will make the system able to forecast stress and sense emotions in real-time and make the system more responsive and effective.

2) Personalization: It ought to give more personalized feedback since the system learns more with time. The system will also consider the behavior and physiological reactions of the individual, so that it gives more situational and useful advice that is more effective in stress and emotional management.

Integrating block chain with ML-based mental health systems could improve data protection and privacy. Block chain secures sensitive records and addresses anxiety about ethical issues with AI-powered diagnosis of mental health conditions, [20]. All of these advances will create a more intuitive and adaptable system that personalizes to the needs of the person, enabling users to understand their stress and emotions better and eventually improve their mental well-being.

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Appendix A: Dataset

Sources Stress Detection

Dataset – Kaggle

This data set includes different physiological and behavioral indicators such as heart rate, skin temperature, and other biometric measurements recorded at different levels of stress. This data set is utilized to train machine learning models for detecting stress levels from real-world inputs. The data set includes labeled data that is needed for stress prediction supervised learning.

FER-2013 Dataset – Kaggle

The Facial Expression Recognition 2013 (FER-2013) dataset is made up of 35,887 grayscale 48x48 pixel images divided into seven emotional categories: anger, disgust, fear, happiness, sadness, surprise, and neutral. The dataset is primarily applied to emotion detection and is a standard benchmark to train deep models like CNNs to identify facial emotions.

Appendix B: Tools and Technologies Used

- Programming Language: Python
- Libraries: TensorFlow, Keras, scikit-learn, OpenCV
- Frameworks: MobileNet, Decision Tree Algorithm
- Development Environment: Jupyter Notebook, Google Colab

Appendix C: Performance Metrics Formulae

Accuracy = (TP + TN) / (TP + TN + FP + FN)

Precision = TP / (TP

+ FP) Recall = TP /

(TP + FN)

F1-Score = 2 × (Precision × Recall) / (Precision + Recall)

Model building of the XGBoost model

```
import pandas as pd
from xgboost import XGBClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score

# Load dataset (replace 'your_dataset.csv' with actual path)
data = pd.read_csv('your_dataset.csv')

# Assume 'label' is the target column, and others are features
X = data.drop('label', axis=1)
y = data['label']

# Train-test split
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=42)

# Initialize and train XGBoost model
model = XGBClassifier()
model.fit(X_train, y_train)

# Predict and evaluate
y_pred = model.predict(X_test)
accuracy = accuracy_score(y_test, y_pred)
print("Accuracy:", accuracy)
```

Model building of the CNN model

```
from tensorflow.keras import layers, models, regularizers

def build_emotion_model(input_shape=(48, 48, 1), num_classes=7):
    model = models.Sequential([
        layers.Input(shape=input_shape),

        layers.Conv2D(32, (3, 3), activation='relu', padding='same',
kernel_regularizer=regularizers.l2(0.001)),
        layers.BatchNormalization(),
        layers.Conv2D(32, (3, 3), activation='relu', padding='same',
kernel_regularizer=regularizers.l2(0.001)),
        layers.BatchNormalization(),
        layers.MaxPooling2D((2, 2)),
        layers.Dropout(0.25),

        layers.Conv2D(64, (3, 3), activation='relu', padding='same',
kernel_regularizer=regularizers.l2(0.001)),
        layers.BatchNormalization(),
        layers.Conv2D(64, (3, 3), activation='relu', padding='same',
kernel_regularizer=regularizers.l2(0.001)),
        layers.BatchNormalization(),
        layers.MaxPooling2D((2, 2)),
        layers.Dropout(0.25),

        layers.Conv2D(128, (3, 3), activation='relu', padding='same',
kernel_regularizer=regularizers.l2(0.001)),
        layers.BatchNormalization(),
        layers.Conv2D(128, (3, 3), activation='relu', padding='same',
kernel_regularizer=regularizers.l2(0.001)),
        layers.BatchNormalization(),
        layers.MaxPooling2D((2, 2)),
        layers.Dropout(0.25),

        layers.Flatten(),
        layers.Dense(256, activation='relu',
kernel_regularizer=regularizers.l2(0.001)),
        layers.BatchNormalization(),
        layers.Dropout(0.5),
        layers.Dense(num_classes, activation='softmax')
    ])

    return model
```