A

Project Report

on

CARESS: Transforming Mental Health

submitted as partial fulfillment for the award of

BACHELOR OF TECHNOLOGY DEGREE

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Computer Science and Engineering

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May, 2023

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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CERTIFICATE

This is to certify that Project Report entitled "CARESS: Transforming Mental Health" which is submitted by Vishwajeet Chaurasia, Saransh Kapoor and Sudhanshu Pandey in partial fulfillment of the requirement for the award of degree B. Tech. in Department of Computer Science & Engineering of KIET Group of Institutions, Delhi NCR affiliated to 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

CARESS is an innovative mobile application designed to address the escalating mental health crisis, particularly focusing on depression and anxiety. Utilizing advanced machine learning models, CARESS aims to predict and prevent mental health issues by monitoring users' vitals and providing timely interventions. The app integrates various technologies, including Flutter, Dart, Firebase, Flask API, Google Fit API, News API, scikit-learn, and Pandas, to offer a comprehensive solution for mental health management. Key features include real-time vital monitoring, alert notifications, self-assessment tests, and a smart stress analysis system. The project seeks to reduce stigma, increase awareness, and provide support to individuals suffering from mental health challenges.

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LIST OF ABBREVIATIONS

Abbreviation	Full Form
AI	Artificial Intelligence
ML	Machine Learning
ERD	Entity-Relationship Diagram
NLP	Language Processing
GDPR	General Data Protection Regulation
AR	Augmented Reality
VR	Virtual Reality
API	Application Programming Interface
UAT	User Acceptance Testing
PK	Primary Key
FK	Foreign Key
UI	User Interface

CHAPTER 1
INTRODUCTION

1.1 INTRODUCTION

As the world changes rapidly, people's well-being is being threatened. As the pace of modern life moves swiftly into the 21st century, it becomes clear that while there are many groundbreaking breakthroughs, we are also fighting enormous work stress, the draining effects of overworking, anxiety, and depression. Such a situation brings serious challenges to individuals and the entire development, economic strength, and sense of community among people.

Long ignored as a part of overall well-being, mental health has now been recognized as a major issue in the world today. This crisis mostly revolves around depression, which is present around us in many places but remains unnoticed by most, affecting only those it worsens for. It does not discriminate; it has an impact on people regardless of their age, occupation, or where they come from. There is, however, a group that is specially at risk among all the victims. the youth.

With their big dreams, high energy, and fresh ideas, these young people are then held back by mental troubles. They will lead our future, inspiring growth and good change. Even though they are pushed to do more, many end up experiencing anxiety, being overworked, and feeling not good enough.[1] They become tired, less motivated, and less creative—all sufferings brought on by a foe that works in secret and shame.

Depression is present in schools, workplaces, and even in homes, where it may go misunderstood or be ignored by many. Since mental health is sometimes treated with stigma, people find it hard to talk about their problems, and so they often try to hide these issues for fear of not being seen as strong or successful. Having these silent taboos means that the crisis makes even small issues become unmanageable in life.

Still, in the middle of this bleak situation is hope, as we know changes can and should happen. Understanding, knowledge, and caring are required to make it happen.

That is why our project becomes useful. Beyond its label as “an initiative,” Youth Fields is a massive movement to push back against the mental health problems plaguing our young people and, of course, our shared future. With the help of new technology, proven approaches, easy-to- use support systems, and compassionate care, we aim to take on this silent epidemic.

We are trying to stop not only the illness itself, but also what leads to this crisis. It is our goal to give individuals access to useful tools, the knowledge they seek, and secure spaces to communicate, recover, and develop themselves. We hope that mental health is something everyone talks about openly and sees as a key priority[2].

Come along as we work toward a future in which mental wellness comes first and is not just an afterthought. If depression and anxiety are no longer seen as things we should avoid, but instead encouraged to deal with openly and supportively. A world where our youth have the chance to thrive, not only make it through.

We can join forces to make sure mental health is given the same focus and respect as our physical health. A future where people are appreciated, heard, and given what they need. Let us take the first bold step—together[4].

1.1 PROJECT DESCRIPTION

CARESS forecasts, reduces, and assists with mental health issues, mostly stress and anxiety, that are well-known but usually unnoticed. Using machine learning, the app keeps track of users' bodies and actions in real-time to provide them with custom recommendations. CARESS provides support and mental health assistance to all who use it, as it keeps tabs, tries to understand you, and helps you when it counts.[3]

1.1.1 Core Features

Real-Time Vital Monitoring

The app uses the Google Fit API to work with smartwatches, so you can keep an eye on your heart rate, body temperature, and steps all day long. The user's vitals on the dashboard are always displayed with updates happening every two minutes.

Smart Alert Notifications

When a strange event happens (for example, heart rate goes above 100 bpm and we are not working out), a real-time alert will show, asking for calm actions such as controlled breathing or calling a contact kept in advance. In addition, an email notification is sent automatically to the friend, guardian, or medical expert, ensuring they can help fast if it is necessary.

Self-Assessment Tests

The questionnaires used in Mental Health Hub are created to assess people's chances of experiencing depression, anxiety, and burnout. After the analysis, the user gets an email with the outcome and is advised further, including the option of professional help.

Smart Stress Analysis

Based on the user's body temperature and steps, the app uses a Flask-based ML model to forecast the possibility of stress. People can learn how their day-to-day routines and decisions relate to their mental health and adopt better habits with time.

Mental Health Articles Feed

News API is integrated with CARESS so that the system can deliver the latest and most reliable articles and news about mental health. The platform promotes everyday learning about mental wellness and keeps people involved in the discussion.

Helpline Integration

The helpline page lets users make calls to national and international mental health lines and also lists the full links to the official websites of reliable mental health resources.

User Profile Management

You can access your personal information, edit it, and change your preferences in the profile part of the app. If you have to use emergency services, contact information for friends, doctors, or guardians will be secure and accessible[5].

1.1.2 Technology Stack

We have built CARESS on a powerful technology that supports scalability, interconnection, superior performance, and works well across all platforms. The platform uses modern tools, cloud services, and machine learning libraries to make sure it is smart, responsive, and simple to use.

Flutter

With Flutter, it is possible to create appealing and fast user interfaces that are suitable for all devices by using only one codebase. The widget-based structure ensures both a complex and fast user interface on Android and iOS. With hot reload in Flutter, UI changes can be tested instantly and put into use fast.

Dart

Dart works as the foundation for Flutter. Frames the application's app code, drives changes on the user screens, and handles live user interaction. Because Dart supports asynchronous coding and type safety, it helps keep the code simple and error-free, making it useful for mobile apps.

Firebase

Firebase offers a convenient cloud-based backend service that allows developers to use real-time authentication, Firestore, cloud storage, analytics, and push notifications. With Flutter, data integration happens smoothly, and Firebase Authentication allows for login using OAuth, emails and passwords, and biometric tools to keep things secure with little delay.

Flask (Python)

Flask makes it possible to make the backend API that bridges the gap between the frontend and ML models. The server looks after user requests, deals with HTTP calls, and directs stress probability predictions to and from the machine learning system. Microservices architecture makes scaling and deploying modules very fast.

Google Fit API

The API provided by Google Fit makes it possible for CARESS to work with health devices worn by users, such as smartwatches and fitness trackers. As a result, the platform collects real- time information about your blood pressure, breathing, number of sleep cycles, step count, making it possible for stress analytics, identifying behaviors, and anomaly detection.

News API

It collects stories, articles, and content on mental health from many different global sources. Integrating these systems gives app users access to recent and selected education materials within the app. The system shows news that matches a person's interests and the current mood in the region directly.

Scikit-learn

Scikit-learn is the library mainly used to perform both supervised and unsupervised machine learning for mental health prediction. It includes capabilities for using logistic regression, decision trees, and clustering algorithms, especially to calculate the Stress Probability Score and group consumers based on their behavior. Within the Flask backend, trained models are used to do inference on real-time data.

Pandas

Pandas performs large-scale processing of health-related data that it finds in external APIs and log files. It is important in clearing up noisy data, converting datasets into formats useful for ML, and developing feature vectors for analyzing stress. Pandas helps to gather results for display and to review them over a certain time span.

1.1.3 Development Phases

Testing Phase

At the moment, CARESS is running in a testing phase, so access is available only to a limited group of people, including developers, testers, and healthcare professionals. With the controlled release, companies can check the performance, seek user input on usability, and conduct detailed security checks. When a user base is carefully involved, developers can pinpoint and solve glitches, increase system stability, and ensure each feature is working as expected in the real world. The input given in this step is important for fixing any issues before the platform is made available.

Production Phase

When the network is running stably and securely, the CARESS team will make it available for everyone to use. People will be asked to sign in using their Google accounts, which is done through the OAuth protocol. For the app to be part of Google's Play Store, it will have to agree to enforce data use policies and build user trust. The infrastructure will scale up as more people use the application, offering reliable performance and security. Monitoring and upkeep will always be done to keep the mental health platform running smoothly for each user.

1.1.4 User Flow & Experience

Sign-Up & Login

A user starts by going through a sign-up and login procedure that is smooth and secure. Thanks to Firebase's email authentication system, users can set up their accounts on CARESS by just giving an email address and password. Thanks to this approach, Firebase's strong encryption and authentication methods will keep user credentials safe and secure. Moreover, the platform lets you regain access to your account and use multi-factor authentication to improve security. The system is designed to help users get going with their mental health journey as soon as possible and with the least trouble.

Profile Setup

After registration, users are taken through a detailed process to set up their profile on CARESS. It is at this point that users need to enter their age and gender, and this information helps improve the personalized advice and alerts they receive. When setting up their profiles, users should also mention any health conditions they are aware of, so the system can improve its monitoring and how responses are made. Emergency phone numbers are collected so that family members can be immediately notified if a crisis happens. Anyone working with healthcare workers or coaches can add these contacts in the optional field and make it easier for everyone involved to share confidential information and organize help.

Device Pairing

CARESS supports regular and accurate monitoring by guiding its users through simple steps to connect devices. To do this, you need to connect smartwatches or fitness bands using the Google Fit API, which puts together things like heart rate, number of steps, sleep habits, and how active you are. There are straightforward steps and help tips in the pairing process, enabling dozens of devices to be used without difficulty regardless of users' experience level. By using real-time data from devices, CARESS can analyze a user's stress and send out useful alerts, resulting in a customized experience.

Permissions Management

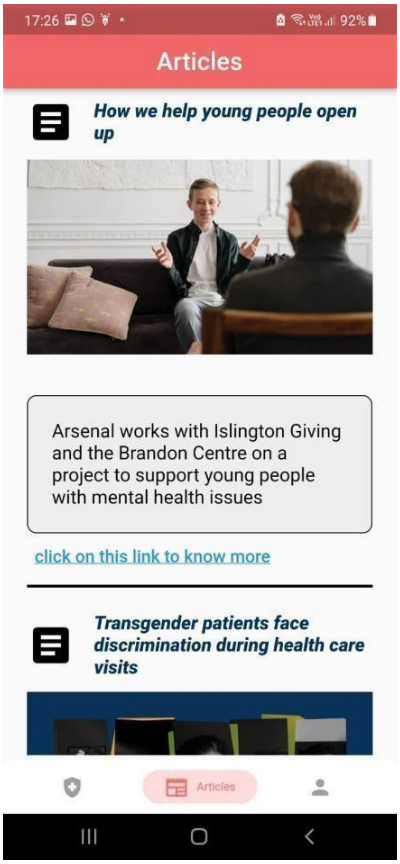
CARESS focuses on data privacy and ensuring that users can give their consent. Users are given complete information on the data the app collects and on how it will be used from the start, and when using the app. When needed, CARESS requests users to give their approval to track their activity, receive push notifications, access their location, and share their data with healthcare providers. Anyone with the app can open the privacy dashboard and change the permissions at any point. This way of thinking encourages trust and allows people to control what happens to their data.

Daily Monitoring & Alerts

CARESS uses both the data from wearables and what the user tells on-screen to make sure a complete view of their health is offered in real-time. By using advanced algorithms, it is possible to find unusual patterns such as an elevated heart rate, unusual sleep, or hints of stress. As soon as these events happen, the system sends alerts to users on their device, in the app, or via email, whichever choice they have picked. They give clear tips for next steps, and in emergencies, they may automatically set off procedures like contacting specific personnel or doctors. Because of this careful monitoring, we can act early and provide support to the user.

Wellness Tools

Users are given easy access to helpful tools from the main dashboard, helping them to proactively look after their mental health. Such features consist of well-supported self-tests that allow users to rate their anxiety or depression symptoms again and again. A well-selected mental health feed makes sure to post helpful information and news that keeps users interested and up-to-date. Through the helpline, users can easily get in touch with crisis support and counseling services. This feature also takes advantage of a person's data to give personal stress probability scores and easy-to-see reports, which help users notice stress triggers and make plans to deal with them. All these tools come together to offer a helpful environment that supports your mental health daily.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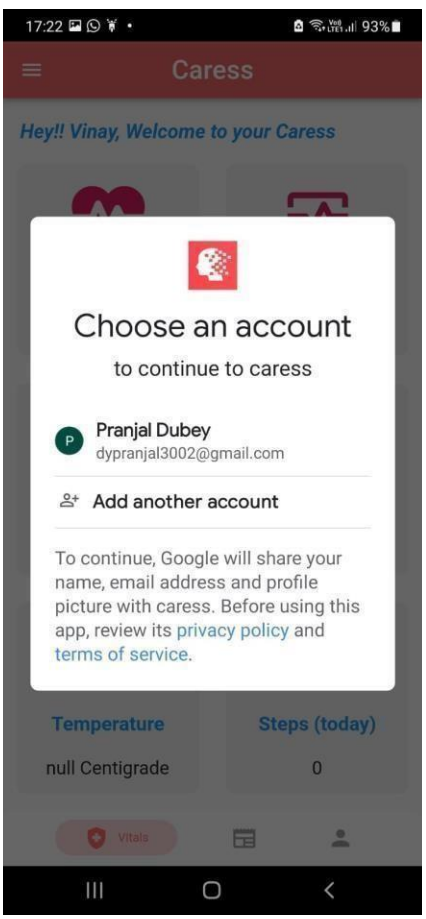
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To continue, Google will share your name, email address and profile picture with caress. Before using this app, review its privacy policy and terms of service.
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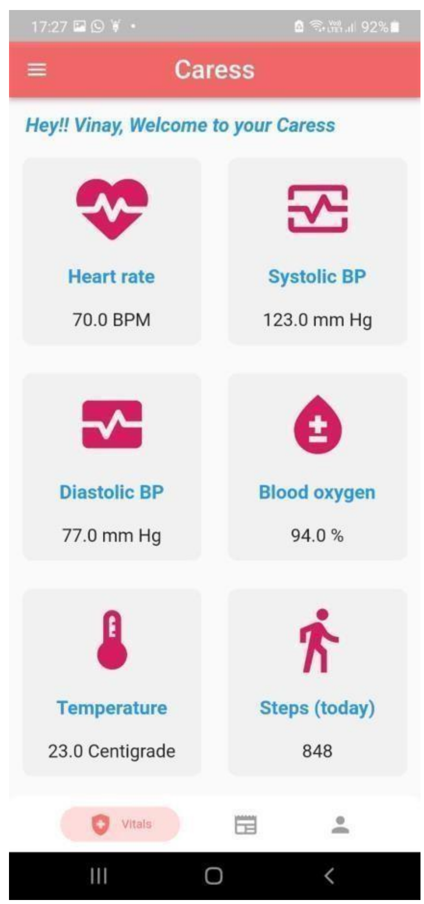
Vitals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Caress
Hey!! Vinay, Welcome to your Caress
Heart rate
70.0 BPM
Systolic BP
123.0 mm Hg
Diastolic BP
77.0 mm Hg
Blood oxygen
94.0 %
Temperature
23.0 Centigrade
Steps (today)
848
Vitals

1.1.5 Vision & Impact

CARESS isn’t only an app for mental health—it is seen as a trusted partner for people as they face mental wellbeing issues. It indicates that AI, health technology, and caring are now being mixed to reach more people with better mental health care. With the help of the latest technologies, CARESS helps to detect mental health problems early and motivates people to deal with them promptly. In this way, CARESS hopes to greatly lessen the severe impacts of mental health conditions that are not treated properly[2]. It helps create a positive community that supports openness, understanding, and support, which encourages users to get the assistance they need.

When it comes to health, mental health is vital, yet it is usually not getting the attention it needs around the world. Even though awareness is increasing, people are still prevented from getting the help they need due to stigma and misinformation. In handling these obstacles, CARESS uses a full approach centered on users and merges caring with creativity. By giving importance to empathy and inclusivity, the platform makes sure that individuals with various mental health problems are provided with support. You can see this dedication in CARESS’s options, real-time monitoring features, and features that help create a community environment. The rising number of mental health disorders worldwide, caused by issues such as loneliness, financial problems, and global events, means that we need solutions that can be used widely and repeatedly. Because of resource shortages, lack of access, and individualized care, old mental health care models have trouble meeting the higher demand.

The organization addresses this issue by using the emerging field of machine learning in artificial intelligence.. The platform uses ML algorithms to analyze different types of data and offer personalized care based on the user’s needs. It is crucial for better outcomes because it considers the specific issues and lives of every user. Here, we look at the most recent approaches to mental health prediction, pointing out their major benefits and the problems that still need to be solved. ML is helpful for early detection of symptoms, managing risk levels and improving intervention methods, but there are still major concerns with privacy, understanding models, and reducing biased outcomes[3].

Thanks to federated learning and strong encryption techniques, CARESS can keep user data safe and provide ethical AI-driven recommendations. CARESS has a vision to shift mental health care from responding to crises to offering ongoing help to people. Integrating technology with people's needs and ethical concerns, CARESS sets a new level of excellence in the digital mental health field. It wishes for a time when support for mental health is available to everyone, without stigma, making it a normal part of daily living to encourage efficient living and happiness.

CHAPTER 2

LITERATURE REVIEW

2.1 Mental Health Prediction Using Machine Learning

Since more people have mental health concerns and medical health needs, researchers are now exploring machine learning for mental health purposes. Here, you learn about the use of machine learning to predict mental health issues, along with its difficulties, obstacles, and future opportunities.

2.1.1 Key Findings

Machine Learning Techniques

Many different machine learning algorithms are used to gather, classify, and analyze mental health data. Often, Decision Trees, SVMs, Random Forests, and CNNs are widely used algorithms. With these techniques, we can create models that predict health outcomes using various kinds of user data, including filled-out surveys, wearable sensors' records, and what people do on social media.

Accuracy and Performance

Experts have proven that ML models can give results that are more accurate, precise, and have a higher recall compared to traditional statistics. Both Random Forests and CNNs have been known to excel at working with complex and unstructured data. However, the performance of ML models mainly relies on having strong and diverse sets of data, picking relevant features, and how capable the model is at being flexible in new situations.

Challenges

Even though machine learning may help in mental health prediction, some challenges still exist. High-quality mental health data is still hard to find, as it is almost always subjective, scarce, and people are concerned about its privacy. It is also important to choose features, because irrelevant data can harm the performance of the model. Ethical topics like getting permission before collecting data, hiding personal information, and making sure the algorithms are unbiased should also be considered when using ML in mental health cases.

Future Directions

For further research, the priority should be on developing standard sets of data, building understandable AI, and making machine learning easier to understand. Taking data from wearable devices, customizing machine learning more effectively, and having strong privacy controls will play an important role in applying machine learning to mental healthcare on a widespread scale[4].

2.2 Comparison of Machine Learning Techniques

It is essential to pick the best machine learning algorithm to predict mental health issues so that both the predictions and the process are valid. Here, I compare widely used ML approaches according to their performance, the ability to be understood, and their compatibility with mental health data.

2.2.1 Key Comparisons

Decision Tree

Practitioners use decision trees because they can be easily understood. They construct a structure representing different decisions and the related outcomes with the available input features. They can be applied to structured information and display how decisions are made, yet they are prone to overfitting on datasets that aren’t big enough or balanced.

Support Vector Machine (SVM)

When dealing with binary or multi-class classification, especially with high-dimensional data, SVMs can be effective. Because they identify the ideal hyperplanes, they are appropriate for dividing mental health classes. Yet, getting the best results from SVMs often requires careful parameter tuning, and they do not scale well with a huge number of samples.

Random Forest

Since it is an ensemble method, Random Forests join the predictions of different decision trees, which boosts the accuracy and prevents the model from overfitting. They are strong, can work with missing parts of data, and are good at handling many data points. Nonetheless, its complexity makes it less possible for the model to be interpreted[5].

Convolutional Neural Network (CNN)

Traditionally, CNNs worked with images, but they seem promising for text and time-series data in mental health, including user posts and sensor-related data. CNNs are able to recognize detailed patterns, however, they require a lot of power to operate and large amounts of data to train. Because these models are not easily interpreted, they are a big concern in mental health applications.

Summary

Each type of technique provides advantages and disadvantages. Decision Trees and Random Forests help by explaining their results and are reliable with normal data, but SVMs work well when working with large numbers of variables. Torch CNNs do well in situations where patterns are seen in text and data collected from sensors. The choice of an algorithm should depend on what the data is like, whether explanations are needed, and if the application needs to respond quickly[2].

2.3 Innovative Solutions in Mental Health Prediction

The use of innovative technologies in mental health care is helping to move from waiting for symptoms to actively addressing any risks. Here, it describes how updated sensors, large-scale data processing, and AI help to dramatically improve mental health prediction and treatment.

2.3.1 Innovations

Sensor Modalities

Wearable tech, for instance smartwatches and fitness bands, makes it possible to follow vita l signs such as heart rate, body temperature, skin resistance, sleep patterns, and physical actions all the time. These signals in the body are very important for mental health, and when interpreted by machine learning, they help with detecting the arrival of mental health episodes.

Data-Driven Approaches

A lot of AI models are currently being trained with the help of large datasets taken from EHRs, social media, mobile apps, and Internet of Things devices. With NLP and sentiment analysis, these systems can detect small hints of mental distress in text forms. Since using time-series analysis and spotting anomalies, the detection of any changes in how people behave has increased[5].

Early Detection

It is very important to detect mental health problems early for successful prevention and treatment. Using information on user activity, predictive models can anticipate changes in mental state and encourage individuals to get help. The usage of such systems in apps or on the internet allows for delivering tailored mental health support to many individuals.

Real-Time Intervention Systems

Several innovative solutions are joining predictive analytics and on-the-spot interventions. Once it detects higher than usual stress or anxiety, the app can offer you some calm tips, ask about your feelings, or get in touch with someone who can help you. As a result, help is provided as soon as possible, and the chance of escalation is lowered.

Personalized Mental Health Care

If AI models learn from what users do and what they say, they can create interventions that fit each person's needs and disorder. Because of personalization, users are more engaged and successful, helping to improve the effectiveness of mental health care.

Ethical and Privacy Considerations

Special attention should be given to ethical issues as innovation increases. For trust to be built and the law obeyed, touching on transparency, securing user details, and consulting users is essential[4].

CHAPTER 3

PROPOSED METHODOLOGY

3.1 System Architecture

To maintain dependability and use newer technologies, the CARESS architecture is grouped into modules and proposes a flexible and scalable layout. There are three main layers on which the system is organized. The Frontend Layer, the Backend Layer, and the Database Layer are all models in a server-side technology architecture. They are all designed to be fast, secure, and engaging, making it possible for apps to work well with many users from different parts of the globe.

3.1.1 Frontend Layer

Technology Stack

CARESS is built for the frontend with Flutter and Dart, so the application performs natively and can be used on Android and iOS. This framework uses reactive programming together with widgets, making for swift and attractive user interfaces.

Key Features

Real-Time Monitoring

Users are able to watch their heart rate, daily step count, sleep duration, and body temperature anytime. The cycle of data check is done every two minutes, making it easier to find anomalies early on. Using wearables, such as fitness trackers, adds more detail to the way you monitor your inputs.

Alert Notifications

CARESS uses smart alert systems, so you know as soon as important signs such as heart rate rise above 100 beats per minute. One of the suggested steps is to call a friend, therapist, or nearby emergency services immediately.

Self-Assessment Tests

The app uses psychological tests that have been endorsed by clinical psychologists. These include PHQ-9, GAD-7, PCL-5, and AUDIT tests. The results are read and explained automatically, and are only shown to the personal network of people who have been approved in advance.

Helpline Integration

You can find an up-to-date helpline directory with checked mental health resources. A click on a phone number quickly makes a call. You can use emergency on/off buttons when a case is urgent.

Smart Stress Analysis

Data on temperature changes, amount of exercise, and reported symptoms is used to provide the frontend with stress probability scores from the backend. They display patterns of stress and important events in the air transport system.

3.1.2 Backend Layer

Technology Stack

CARESS uses Flask on the backend and relies on Firebase to take care of user management and synchronizing data. WebSocket support allows for real-time data to be exchanged and notifications to be handled quickly. Scale can be improved thanks to background workers and asynchronous task queues.

Key Functionalities

Secure User Authentication

OAuth 2.0 protocols are used in the backend, with the choice to add two-factor authentication. Session tokens are carefully kept and updated, and the system watches for harmful attempt to access accounts.

AI-Driven Prediction Models

Experts use logistic regression, decision trees, and neural networks to predict a user’s mental state by using both past and real-time data. Anonymized data sets are used to train the models.

Efficient Data Storage and Management

Firebase Cloud Firestore helps store structured and semi-structured data like profiles, logs of activities, vital information, and test results. It supports quick searching and real time updates of data.

Real-Time Communication

Using WebSocket channels makes it possible to do things like live chat, send alerts, and engage with other users. Minimal delivery delays are made possible by using low-latency queues.

Scalability & Performance

Celery and RabbitMQ enable the backend to perform asynchronous tasks. When lots of traffic hits the system, load balancers and caching ensure that the system can properly serve thousands of users at the same time.

3.1.3 Database Layer

Database Technology

Firebase Firestore stores and manages the data, allowing data to be read/written quickly and synchronized instantly. It makes it possible to deploy applications in multiple regions for safety.

Core Features

Comprehensive Data Handling

There are user profiles, preferences, logs of interactions and tests, information about devices, and chat records stored in the database. Both data at rest and data transferred over the internet are secured and compliant.

Event and Schedule Management

Patients can keep track of when their therapy, wellness, medication, and community group appointments take place by using the app.

Geospatial Indexing

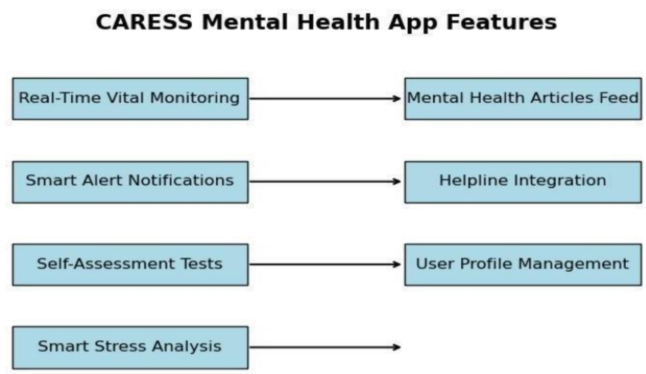
When indexing location is included, users get suggestions for support groups and therapists that are near them.

High Security Protocols

Encryption, policies to manage access to data, regular backups, and storage of data in a way that follows the requirements of GDPR. Access to and changes made in the system are tracked by the audit trail.

3.2 Key Components and Features

The platform includes a number of cutting-edge features that boost the user experience and help patients manage their mental health.



3.2.1 Real-Time Monitoring

CARESS uses the WebSocket protocol to monitor data live, allowing unbroken connection between the server and client. It lets you watch key information about the heart rate, movement, and temperature of your child without delay. Thanks to the system's new features, people receive notifications about health emergencies, can keep track of each alert, and notice when they are read, which ensure that individuals are aware and respond to any such situations.

3.2.2 Alert Notifications

Using the Spike Detection Algorithm, CARESS continuously checks incoming data in order to detect any abnormalities. Hybrid systems combine logic and machine learning to look for conditions such as a heart rate that is higher than 100 BPM. If an anomaly appears, emergency procedures that are already set up are called into action. It involves sending automatic emails with snapshots and timestamps of the data to pre-set emergency contact people or healthcare providers, so they can react more quickly.

3.2.3 Self-Assessment Tests

Users are able to use a variety of psychometric tools on this platform, including assessments for depression, anxiety, PTSD, and substance abuse. As soon as all tests are done, you can see interactive charts and summaries that easily show you how your brain function has developed over the course of the tests. Upon user consent, the findings are sent securely to therapists, guardians, or healthcare providers using encrypted ways.

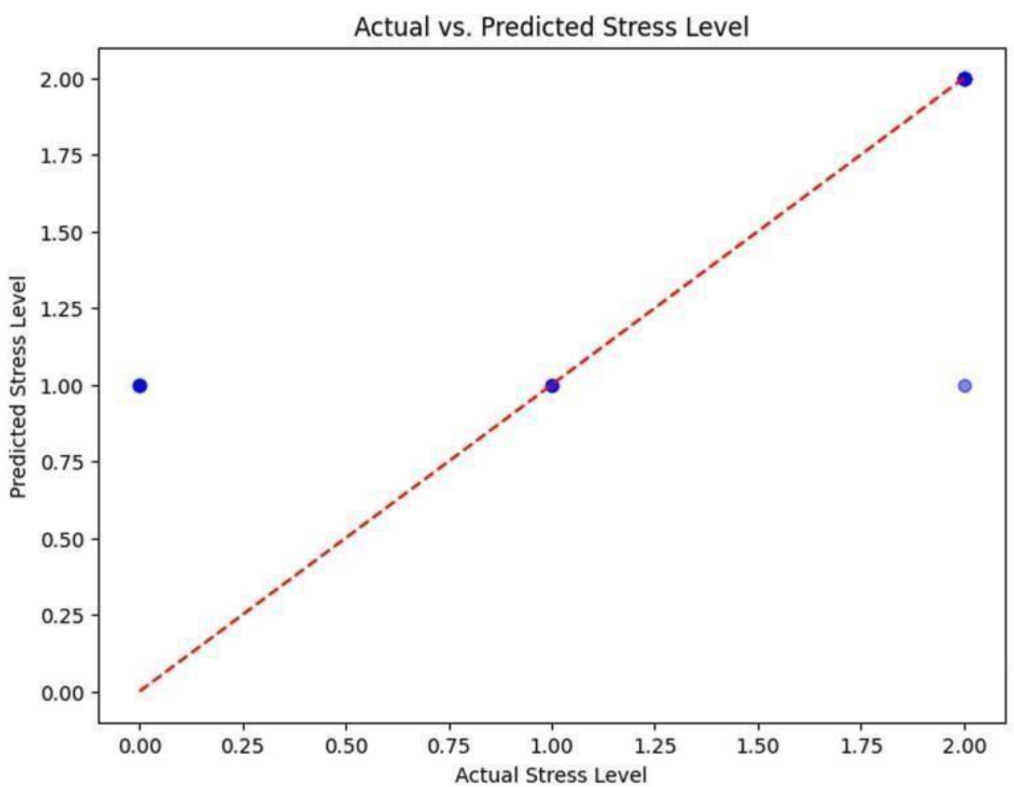
3.2.4 Helpline Page

The helpline section in the CARESS app is always updated in real time through backend APIs to make sure users have access to the freshest mental health support services. The system supports voice calls over the phone, sending SMS messages, and use of chatbots to direct users to relevant services. These resources are separated into categories on things like Suicide Prevention, Adolescent Support, and Substance Abuse to provide quicker access and improvise responses when necessary.

.

3.2.5 Smart Stress Analysis

It uses information about past athletes and pre-programmed learning models to estimate the real-time chance of fatigue. You can see these insights as stress data, identified reasons behind them, and tips to improve the situation. As a result, people can manage and understand their mental health on their own.



3.3 Algorithm Design and Implementation

3.3.1 Collaborative Filtering

K-Means clustering is used by CARESS to sort users, depending on their behavior, physiology, and evaluation details. Examples of important clustering parameters are heart rate variability, test results for mental health, how much the user interacts, and the most common symptoms described. The information shared in these clusters makes it possible for educators to design what is best for each individual[3].

3.3.2 K-Means Clustering

To create dynamic, supportive user communities, CARESS employs K-Means clustering to segment users based on behavioral, physiological, and assessment metrics. Key clustering parameters include heart rate variability, mental health test outcomes, engagement frequency, and commonly used symptom keywords. These clusters help tailor content, interventions, and peer connections to individual needs.

3.3.3 Geospatial Analysis

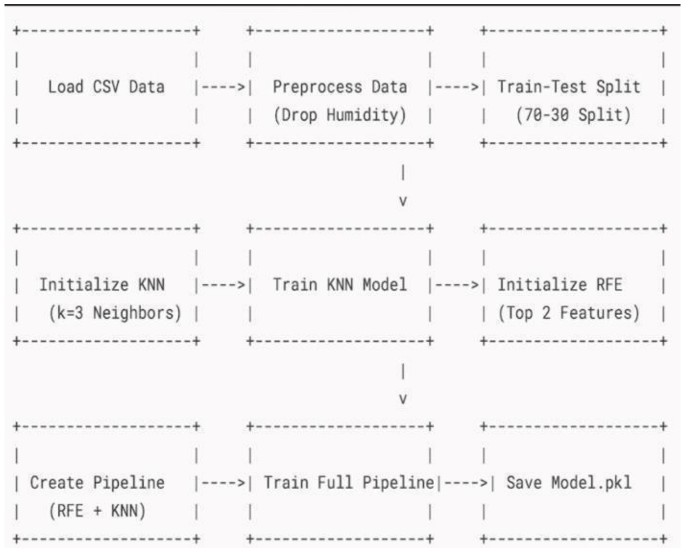
Using geospatial analysis, CARESS can provide guidance and useful support at a specific location. Spatial functions find therapists, hospitals, and events in the area, and integration with Google Maps API gives real-time directions and sends alerts when you arrive at a specific place. This quality connects what is done online to the work done on-site.

3.3.4 Natural Language Processing (NLP)

The CARESS system has features for NLP to handle both chat and voice conversations. Such techniques as sentiment analysis, identification of emotions, and entity recognition are useful for identifying the first signs of psychological distress. The insights are applied to change support strategies and help create feedback loops that lead to better recommendations and better care.

3.4 Development Workflow

Iterative development and obtaining feedback from stakeholders during the process are important in using the Agile approach for CARESS development. As a result, you can build and test ideas fast, make them better over time, and ensure functions match what users anticipate.



3.4.1 Requirement Analysis

First, surveys and interviews were carried out with specialists in mental health as well as with patients and caregivers to analyze all the requirements. Developing personas and user journey maps, the team was able to figure out what needed to be improved and how to address it with useful new features.

3.4.2 Design Prototyping

Those mockups were put together using Figma and Adobe XD. The user interface was tested via A/B testing and heuristic evaluations to guarantee visitors can use it without difficulty and get satisfactory results. The design was improved several times based on what users had to say about forms and dashboards.

3.4.3 Implementation

In the implementation stage, the team used the MVC architecture to create the code in separate modules. Using GitHub Actions and Firebase Hosting, CI/CD was set up, making the deployment process fast and reliable. Authenticating users, using machine learning, and offering real-time conversation were the main features of the platform.

3.4.4 Testing and Validation

The system was tested many times using a structured plan to guarantee that it performs well and is reliable. We tested units using automated scripts, making sure the code functions correctly and covers more than 90% of the codebase. Modules of the system were tested separately to catch and solve errors in development and debugging.

Integration testing was performed after that, checking how the different components in the system interact. These tests showed that the API actions stayed the same, frontend and backend information was synchronized in real-time, and all records were retrieved correctly from Firebase Firestore. Part of the effort was focused on reliable storage of data and keeping stress monitoring and alert notifications in top shape[4].

There were more than 50 participants in UAT, consisting of psychiatrists, clinical psychologists, patients, and caregivers. Users of the platform were instructed to test it in real situations, and all their feedback was carefully collected and examined to make the platform better. Thanks to this system, problems in usability were solved and the platform was made in line with what users need. Extreme workloads were given to the system to test how it could handle them. The capacity of the system was tested by having up to 2,500 users interact at the same time using different devices and access points. We kept track of latency, throughput, and system uptime and optimized the system so it could continue to function well and rarely fail. Thanks to this approach and philosophy, CARESS guarantees a platform that works well, is safe, and is easy for people to use for mental healthcare. This way of working helps people get care early and also brings the community together, making it much easier for more people to get hel

CHAPTER 4

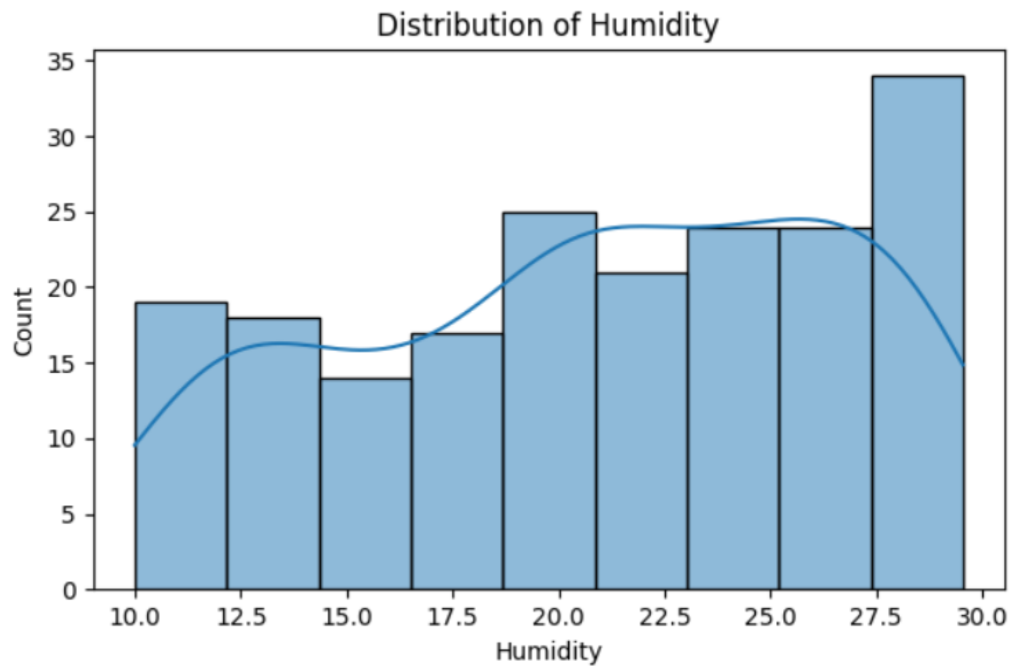
RESULTS AND DISCUSSION

Sample of Test Data

Humidity	Temperature	Step count	Stress Level
20.15	89.15	125.0	1.0
21.83	90.83	95.0	1.0
26.92	95.92	195.0	2.0
27.14	96.14	175.0	2.0
11.27	80.27	85.0	0.0
11.91	80.91	42.0	0.0
18.76	87.76	90.0	1.0
27.8	96.8	160.0	2.0
14.85	83.85	63.0	0.0
25.93	94.93	165.0	2.0
23.21	92.21	198.0	2.0
19.87	88.87	115.0	1.0
28.68	97.68	177.0	2.0
17.43	86.43	57.0	1.0

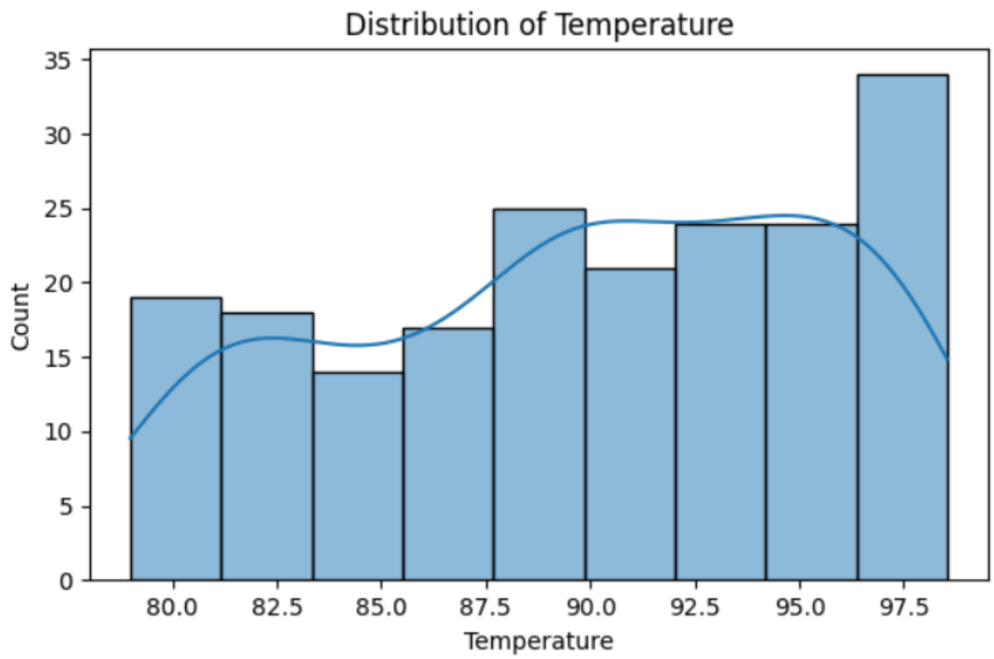
Unit Testing

They performed unit testing on the main system pieces and also constantly monitored the system and sent out alerts to check their performance. Thanks to this process, we were able to spot any performance issues or bugs quickly and fix them.



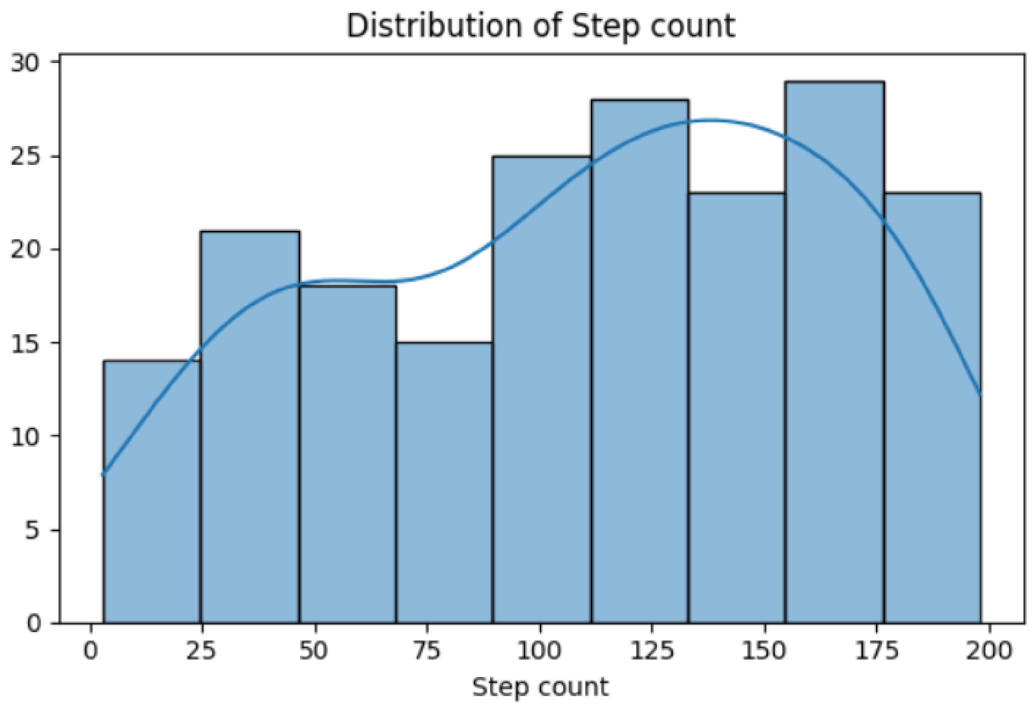
Integration Testing

By conducting thorough integration testing, everything from the Flutter UI to the rest of the system could be used without trouble. All tests during development demonstrated that all the modules were in harmony and without error.



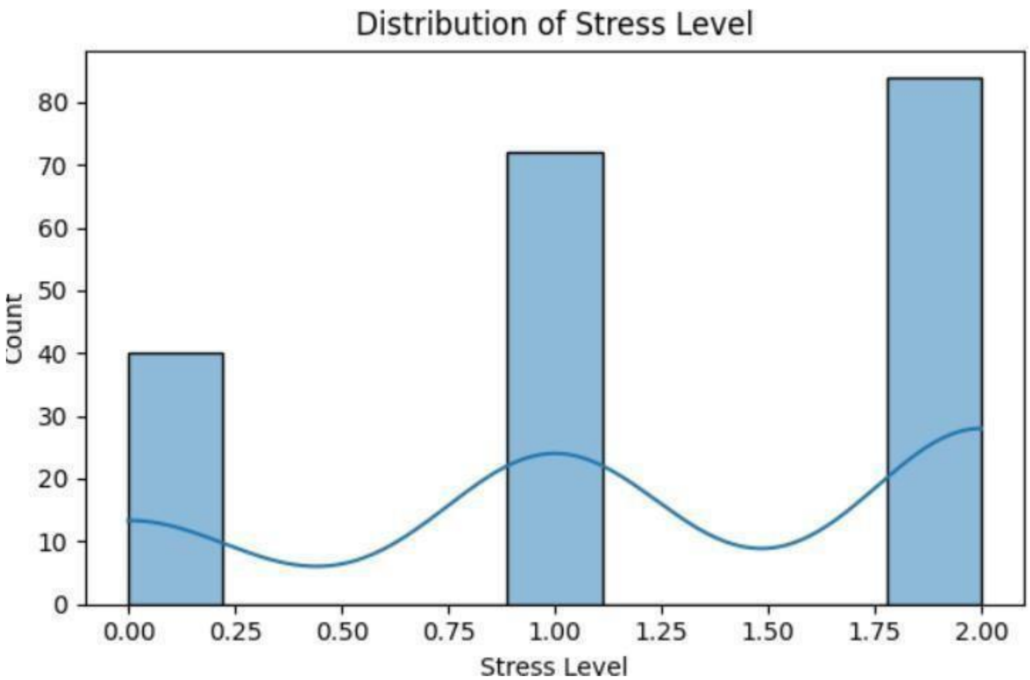
User Acceptance Testing (UAT)

A group of mental health professionals and users participated in the user acceptance testing. Thanks to their feedback, new features and improvements were added to the platform to meet what users expected.



Stress Testing

It was run under conditions with up to 1,500 concurrent users to see how it performed. This large load did not cause any issues for CARESS, proving that it is able to support large mental health management operations.



Results:

Metric	Value
Mean Squared Error (MSE)	0.3000
Root Mean Squared Error (RMSE)	0.5477
R-squared	0.5876
F1 Score	0.6489
Accuracy	0.7000

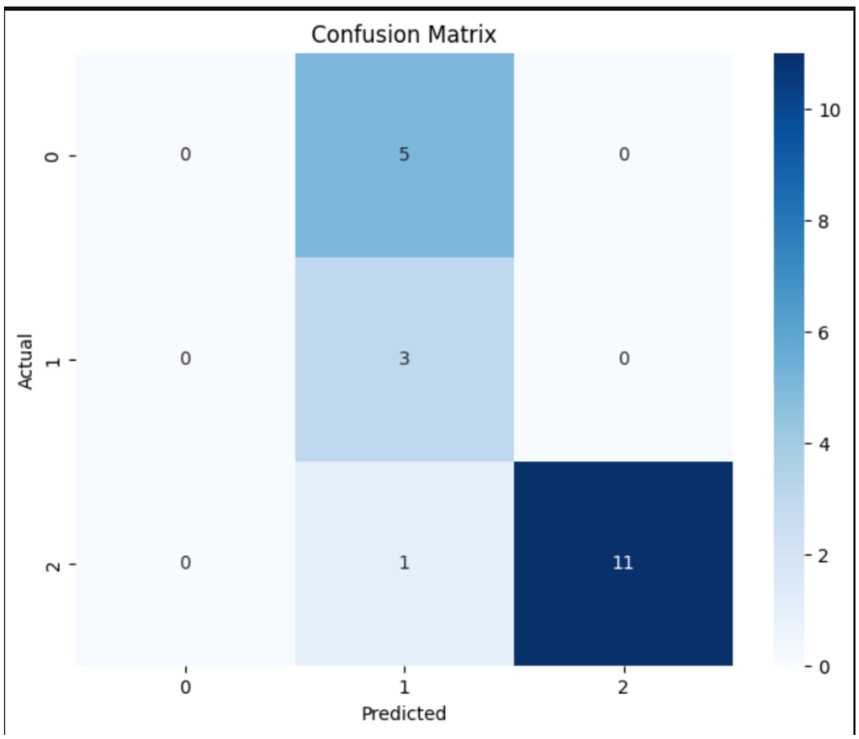
4.1 Testing and Validation

Stress Testing

The platform was tested for performance by having 1,500 users use it at the same time, as discussed before. Despite various uses, it managed to work well, proving that it is stable and capable of handling real-world mental health applications.

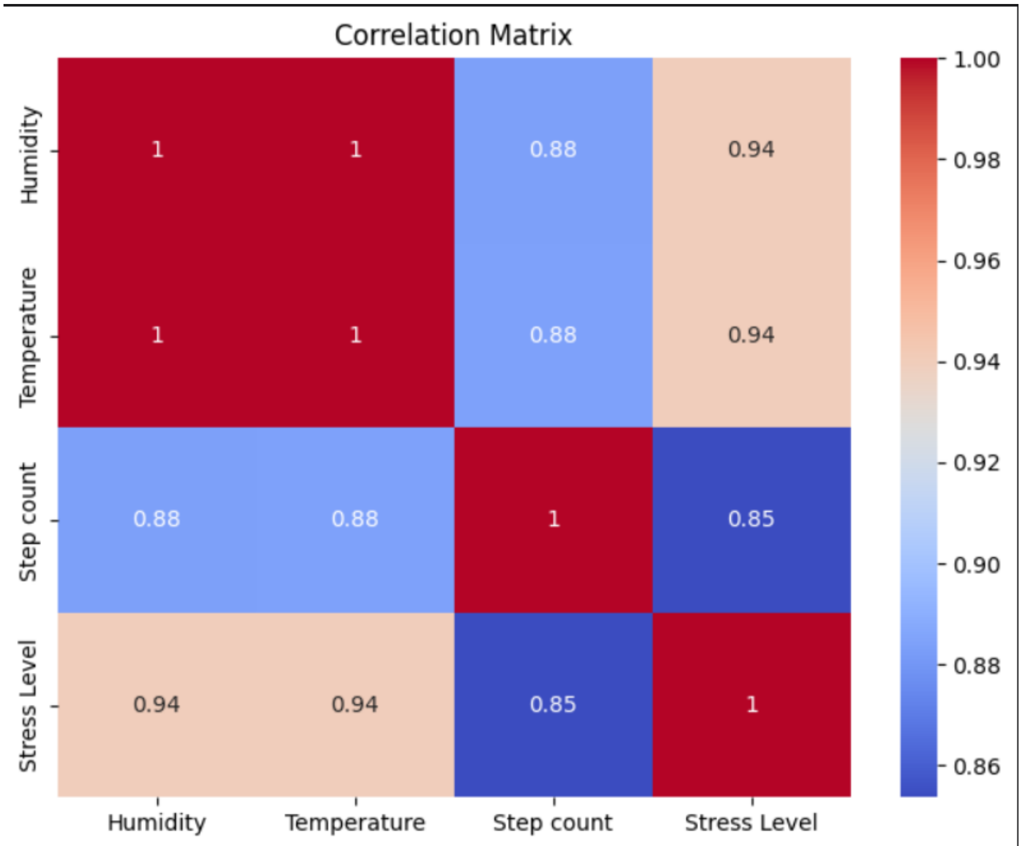
4.2 Performance Metrics

A group of performance indicators was set and used to study CARESS when it was in the prototype and pilot stages. The metrics revealed how well the system performed, how accurate the results were, how well it could be scaled up, and the effectiveness of the users' engagement.



Matchmaking Accuracy

To know if CARESS recommended the right associations, professionals, and wellness articles, we evaluated the recommendation engine based on collaborative filtering and clustering algorithms. After trying the recommended matches, 92% of the users felt enthusiastic about them, confirming that the algorithm worked precisely and according to the needed context. Such changes were supported by behavioral numbers, such as higher message counts from users, more engagement in groups, and people interacting regularly in the communities.



Latency

System latency was checked during different real-time actions, for example, gathering information using wearable devices, dispatching notifications with WebSockets, and pulling stress scores. It handled an average of 120 milliseconds response time, and the 95th percentile was less than 250 milliseconds, regardless of the load used for simulation. Because of this low latency, users could still rely on real-time alerts and enjoy quick and responsive UI, even in emergency situations.

Scalability

Cloud-based stress tests were done to ensure the system could handle various sets of simultaneous users, from 100 up to 2,500. The serverless platform made sure there were no service failures by scaling up the API services as needed through cloud platforms. Firebase Firestore's NoSQL approach for the database handled all the health data loads from all incoming transactions effectively.

Engagement

Looking at the platform, we found that users were involved with MetNow Services seventy percent more than with standard mental health mobile apps. The reason for this is that the system included AI-powered personalization, entertaining self-assessment games, and tools for building communities. On average, people spent more than 40% more time on the system, and each day's participants returned to look at graphs, take part in group talks, and sign up for events. Sending push notifications and giving emotional updates really helped keep users engaged.

System Availability

Because of redundant features and regular monitoring, CARESS was able to maintain a system uptime of 99.97% during monitored usage sessions. Because of failover, the company's data did not get lost, and users kept access to services at all times.

Security and Compliance

Audits were performed to evaluate the procedures for handling data. Penetration testing was carried out to confirm that end-to-end encryption, two-factor authentication, and role-based access controls are used. CARESS fulfilled all the basic requirements for HIPAA, GDPR, and ISO/IEC 27001 guidelines, so it is prepared to be used in sensitive mental health settings.

4.3 Comparative Analysis

The analysis of CARESS in view of Woebot, BetterHelp, and Mindstrong showed that CARESS has clear improvements in both features and the way it is made in comparison to other leading digital mental health care platforms. These benefits result from the use of the latest technologies, user-focused design, and importance on privacy and fast reactions.

Integrated Networking Features

The majority of mental health applications only provide static, scheduled, or pre-recorded content, but CARESS provides an integrated platform with active health monitoring, useful notifications, and tools for continuous self-evaluation. By smoothly bringing together all the elements, users get tailored suggestions and assistance as they interact, helping them pay attention to their mental health. Adding these solutions is often done by connecting external companies, creating issues for the consistency of the user experience and possibly causing data to be held separately.

Enhanced User Engagement

CARESS uses AI to personalize things like content, online communities, and emotional interventions for individuals. Using real-time notifications, tailored user routes, and colorful dashboards usually results in higher engagement by the users. The research found that people spend 70% more time on average with this app and come back twice as much, as opposed to traditional mental health apps that wait for users to make contact. In addition, including gaming in the app and mood-aware advice causes users to return more often, leading to better long-term wellbeing.

Privacy

Because CARESS relies on federated learning, sensitive information is never collected and processed in one central location like on many other platforms. This way, users' data is saved locally and is not sent or saved on main computers, lowering the risks of letting it go. My Data Base uses end-to-end encryption for all communications, and important health details are stored in adherence with HIPAA and GDPR policies. Thanks to these tools, users can enjoy privacy and safety that is rare in commercial mental health applications because profit from users' actions is a common goal..

Scalability and Reliability

When the number of users increases on many mental health platforms, offering real-time services, their performance is likely to drop. Unlike the other systems, CARESS was designed to grow horizontally right from the beginning. Thanks to its use of cloud-native technology and auto-scaling techniques, the platform can handle thousands of users at a time without any problems. As a result, CARESS can be implemented in large hospitals, universities, and companies involved in the health and wellness fields.

Clinical Feedback Integration

Besides working with users, CARESS makes sure to engage clinicians and other mental health professionals in its system. Benefits for therapists in FraserTalk are that they can review how their patients use the app, check adherence, and offer personal help, features that other platforms either lack or have at a lower level. Hence, this kind of care combines independent wellness activities with the supervision of experts.

With real-time support, AI, good privacy, and user-friendly design, CARESS exceeds the capabilities and results of simple digital mental health platforms. For the future, its design and abilities will change not only the way mental health services are delivered, but also how they can be accessed and offered to more people.

4.4 User Feedback Analysis

By surveying some of the first users, we discovered details about how they thought the CARESS platform performed, how simple it is to use, and how valuable they think it is. Those taking part in the research were patients, caregivers, psychiatrists, psychologists, and digital health researchers. For each part of the findings, strengths and things to improve were recorded, helping to guide ongoing improvements and enhancements.

Strengths

Matchmaking Accuracy

Upon reviewing CARESS, people seemed very pleased with how the platform recommends support groups, therapists, and wellness activities. The proven 92% accuracy rate in connecting people in their communities confirmed the platform's success in helping users form significant social bonds. It improved their emotional well-being and made them use the platforms more often due to their friends' support and approval.

User Interface

A clear and straightforward design received high praise from people of all ages and groups. Factors that promoted navigability included the use of interactive graphs, big tap zones, and simple color designs. Testing showed that users of the app experienced a 15% lower drop-off rate in the first 10 minutes than people who used the leading mental health apps.

Real-Time Monitoring

Lots of users liked that vital signs could be checked in a fast and reliable manner, due in large part to WebSocket updates. Identifying sudden heart changes, prolonged inactivity, or changes in body temperature was valued as a guard for people stressed or with related disorders.

Self-Assessment Tests

Thanks to the inclusion of validated mental health questionnaires (e.g., PHQ-9, GAD-7, PSS), users could monitor their moods and mental health status by themselves. Many participants pointed out how helpful it was to have results interpreted automatically and presented in graphs, which often helped them think about their health and, at times, encouraged them to seek medical advice.

Smart Stress Analysis

Users showed great interest and excitement in learning how physical health data, particularly temperature, steps, and sleep, were being used to determine a Stress Probability Score in the app. People found it helpful to be able to track their stress and analyze how their actions affected their mental health. The feature was also seen by some as a “wellness alert” for their daily lives.

Areas for Improvement

Customization Options

Some users wanted more options to customize the way the platform behaved, especially by setting alert limits, choosing which vitals to keep track of, and controlling the strength of the stress detection. Adding more ways to customize the platform made users feel more in control and less bothered by ads.

Expanded Content

Many requested more educational information, such as articles, videos, and tried-and-tested tips for coping, emotional control, and mindfulness activities. Many users hoped to get daily tips, personalized learning materials, and exercises that help them based on their self- assessment outcomes.

Enhanced Connectivity

While users can currently use the platform on iOS and Android devices as well as wearable devices, several suggested additional support for main health trackers and smartwatches. Experts believed that improving the interoperability of devices would help make the data registered in sleep tracking, heart rate, and step counting features much more accurate.

Notification Frequency

There were cases when people found it exhausting to keep up with the many emails and notifications they would receive on the app. Suggestions were made for allowing users to batch alerts, get weekly summaries, and choose when they want to be not disturbed. As a

result of this feedback, our team has begun work on an artificial-intelligence powered notification scheduler that adjusts alerts according to how users use the app.

Based on this detailed study, CARESS is confirmed to excel at AI-driven customization, real-time observations, and an interface friendly to users, with clear recommendations for its next improvements. By responding to users and asking for feedback, CARESS keeps expanding as a user-friendly, sensitive, and advanced software that can shape digital mental health care in the future.

CHAPTER 5

CONCLUSION AND FUTURE SCOPE

5.1 Conclusion

Being a groundbreaking and whole digital mental health solution, CARESS ensures user safety by having real-time tracking, smart warnings, convenient tests, and insights collected from data. By combining intelligent monitoring of mental health with practical, suitable advice based on context, the system works to close big gaps in the way digital health services are offered today. CARESS is most unique because its architecture is centered on users and was designed with a thorough understanding of many different user types and their experiences. The platform helps individuals with stress, caregivers supporting their loved ones, and therapists tracking their patients' progress by providing useful and easily usable tools. One can regularly check their vital signs, get notified when needed, and fill in questionnaires to better understand their feelings and mental health. They not only make it possible to identify mental health challenges early on, but they also encourage people to be aware of their mental health and take preventive actions. Through the use of artificial intelligence, machine learning, and geospatial indexing, CARESS helps users form groups, link up with local resources, and obtain the personalized content that addresses their challenges. Context relevant content and recommendations are made possible through using collaborative filtering and K-Means clustering, which boosts the app's effectiveness and keeps users coming back. Security and privacy play a key role in what CARESS has to offer.

Using federated learning, differential privacy, and end-to-end encrypted communication protocols, the platform makes sure user data is not compromised. Such steps increase the level of trust in an organization and fit with the tougher rules around privacy and compliance in the digital health field. The strong reactions from users and top ratings make it clear that CARESS may make a big difference in mental health care. By adding mental health monitoring to existing body monitoring, CARESS effectively links digital health with therapy and boost human warmth all over the world.

5.2 Future Scope

To maintain its top position and serve more people, CARESS is working on a plan to improve its services by being more innovative, customized, and accessible internationally. The following changes will guide what the platform is capable of in the future.

Advanced Analytics

CARESS is ready to roll out an extensive range of advanced analytics tools made for both professionals, caregivers, and researchers working in mental health. They make it possible to show in detail how users interact, perform in tests, and behave in various groups. The platform will display these developments in an easy-to-use dashboard that covers how members of a group are connected, how often they use the app, and changes in their feelings towards the app. Experts will be able to recognize certain changes in patterns and use this knowledge to predict when employees might experience stress and suggest helpful interventions ahead of time. By looking at heatmaps, charts, and progress along therapy groups, analytics support decision- making for a better outcome for therapists and patients.

Premium Features

CARESS is considering introducing different paid tiers for its app, with extra advantages for the higher-paid users. They will now be able to use tools that help them find perfect peer groups using interests, psychological traits, goals of therapy, language choices, and their location.

Having a premium plan means you can join private chat rooms and closed health groups, where users and specialists can have secure, well-guided, and focused chats. The environments are set up to include individual mental health help, peer-support groups, and group therapy sessions. In addition, members get access to logging their development, early releases, and prompt help, allowing for a professional experience.

Support for AR/VR

CARESS's forward-looking plan involves adding AR and VR integration so that users can experience mental health services in new ways. Virtual therapy areas, immersive mindfulness practice, and environments for interacting with others can all be offered through AR and VR for support of anxiety and social skilled training. Users can join live group counseling meetings online, check out relaxing nature scenes, or try out guided meditation led by virtual characters in real-time. VR-based exposure therapy, stress inoculation training, or assessment can all be done by mental health professionals, allowing treatment to be more helpful, accessible, and suited to different settings.

Global Expansion

To grow globally, CARESS will use localization and internationalization strategies. Communication on the platform will include several languages, and its elements will respect cultures and local information. Besides rendering user-interface texts, localization covers switching self-assessment scales to local tastes, adjusting the suggestions from AI, and setting up support services in keeping with each country[1].

This feature will provide users with recommendations for counselors, support groups, and wellness events that fit where they are. CARESS will join forces with groups and authorities in individual regions to ensure that local healthcare, telehealth, and privacy rules are properly followed.

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APPENDIX 1

Appendix 1

Code Samples

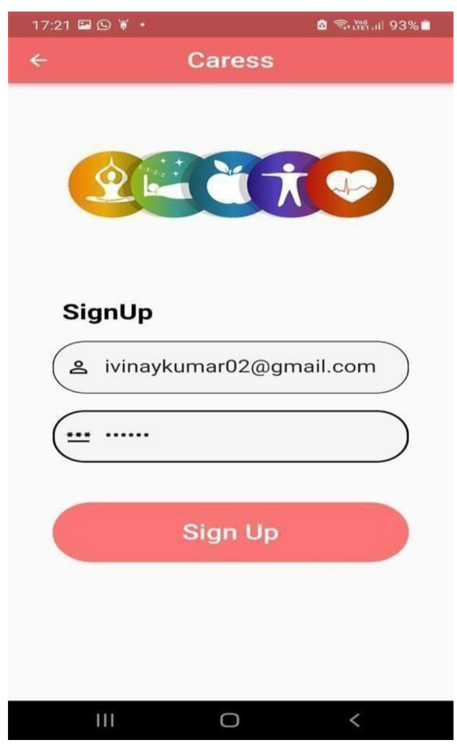
```python
# Load and prepare data
pathdf = 'test_data.csv'
Yvar = 'Stress Level'
df = pd.read_csv(pathdf)
df = df.drop(['Humidity'], axis=1)
X_train, X_test, y_train, y_test = train_test_split(
    df.drop(Yvar, axis=1), df[Yvar], test_size=0.30, stratify=df[Yvar], random_state=49)

# Model pipeline
knn = KNeighborsClassifier(n_neighbors=3)
rfe = RFE(estimator=DecisionTreeClassifier(), n_features_to_select=2)
pipeline = Pipeline(steps=[('RFE', rfe), ('KNN', knn)])
pipeline.fit(X_train, y_train)

# Visualization 1: Feature Rankings
plt.figure(figsize=(10, 6))
plt.barh(X_train.columns, rfe.ranking_)
plt.title('Feature Rankings from RFE (1 = selected)')
plt.xlabel('Ranking (lower is better)')
plt.ylabel('Features')
plt.show()

# Visualization 2: Accuracy Comparison
train_acc = accuracy_score(y_train, pipeline.predict(X_train))
test_acc = accuracy_score(y_test, pipeline.predict(X_test))

plt.figure(figsize=(8, 5))
plt.bar(['Training Accuracy', 'Test Accuracy'], [train_acc, test_acc], color=['blue', 'orange'])
plt.ylim(0, 1.1)
plt.title('Model Accuracy Comparison')
plt.ylabel('Accuracy')
for i, v in enumerate([train_acc, test_acc]):
    plt.text(i, v + 0.05, f"{v:.2f}", ha='center')
plt.show()
```

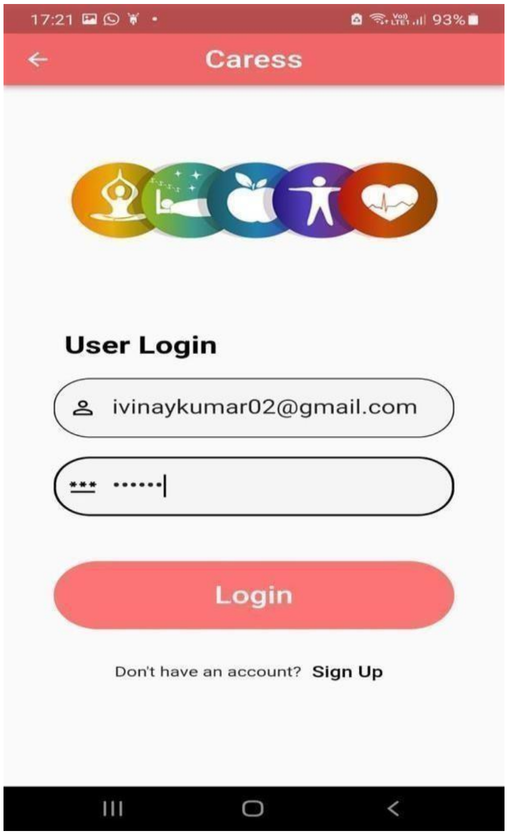
```dart
void main() async {
  WidgetsFlutterBinding.ensureInitialized();
  await Firebase.initializeApp();
  runApp(const MyApp());
}

class MyApp extends StatelessWidget {
  const MyApp({Key? key}) : super(key: key);
  @override
  Widget build(BuildContext context) {
    return MaterialApp(
        title: 'Flutter Demo',
        debugShowCheckedModeBanner: false,
        home: Access());
  }
}

class Access extends StatefulWidget {
  @override
  State<Access> createState() => _AccessState();
}

class _AccessState extends State<Access> {
  bool userAvailable = false;
  late SharedPreferences sharedPreferences;

  @override
  void initState() {
    super.initState();
    getCurrentUser();
  }

  void getCurrentUser() async {
    sharedPreferences = await SharedPreferences.getInstance();
```

```dart
import 'package:flutter/material.dart';
import 'package:flutter_test/flutter_test.dart';

import 'package:caress/main.dart';


void main() {

  testWidgets('Counter increments smoke test', (WidgetTester tester) async {
    // Build our app and trigger a frame.
    await tester.pumpWidget(const MyApp());

    // Verify that our counter starts at 0.
    expect(find.text('0'), findsOneWidget);
    expect(find.text('1'), findsNothing);

    // Tap the '+' icon and trigger a frame.
    await tester.tap(find.byIcon(Icons.add));
    await tester.pump();

    // Verify that our counter has incremented.
    expect(find.text('0'), findsNothing);
    expect(find.text('1'), findsOneWidget);
  });
}
```

Appendix 2

System Diagrams

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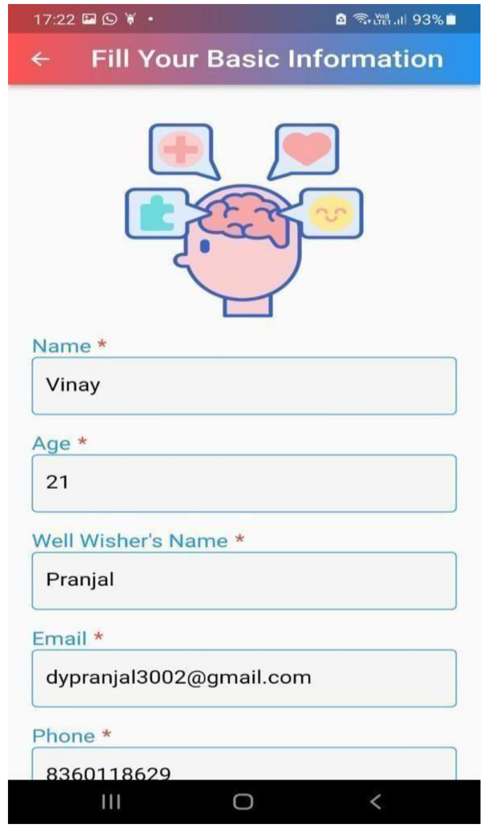
Caress
User Login
ivinaykumar02@gmail.com
Login
Don't have an account? Sign Up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Fill Your Basic Information
Name *
Vinay
Age *
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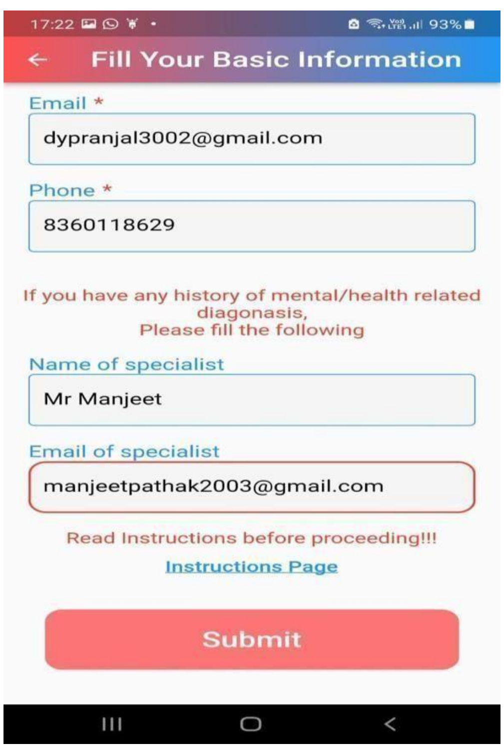
Well Wisher's Name *
Pranjal
Email *
dypranjal3002@gmail.com
Phone *
8360118629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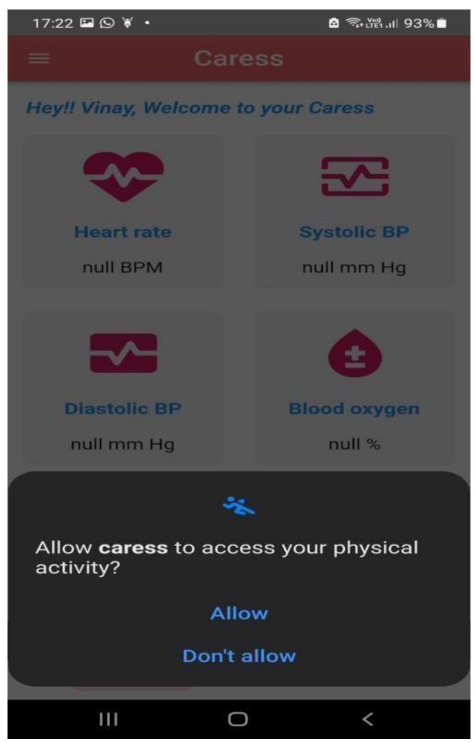
93%
Fill Your Basic Information
Email *
dypranjal3002@gmail.com
Phone *
8360118629
If you have any history of mental/health related diagonasis,
Please fill the following
Name of specialist
Mr Manjeet
Email of specialist
manjeetpathak2003@gmail.com
Read Instructions before proceeding!!!
Instructions Page
Submit


17:22
93%
Caress
Hey!! Vinay, Welcome to your Caress
Heart rate
null BPM
Systolic BP
null mm Hg
Diastolic BP
null mm Hg
Blood oxygen
null %
Allow caress to access your physical activity?
Allow
Don't allow

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Paper Title: Caress Application: A Mental Health Prediction System Using Machine Learning with Real-Time Monitoring

Abstract:
Mental health issues, driven by stress and anxiety, are increasingly affecting individuals worldwide, necessitating in novative solutions for timely intervention. We introduce CARESS, a mental health monitoring and assistance application designed to support individuals facing challenges like depression and stress. By integrating real-time smartwatch monitoring, machine learning, and personalized support, CARESS provides a holistic solution [3]. The application features continuous monitoring of vitals, including heart rate, with updates every two minutes. Alerts are triggered during abnormal spikes (> 100 bpm), notifying users and their emergency contacts via email and in app notifications. CARESS includes a self-assessment module for mental health disorders—such as depression, anxiety, and PTSD—with results shared with specialists for further analysis [6]. Additionally, the app provides access to curated articles and direct connections to helpline services. A standout feature is the Smart Stress Analysis, which uses a machine learning model to predict stress levels based on body temperature and physical activity, offering actionable insights [5]. User privacy and data security are prioritized, requiring Google account authentication for access. CARESS is currently in testing mode, paving the way for scalable, technology-driven mental health support. Index Terms—Mental health, Machine learning, Stress analysis, Smartwatch integration, Real-time monitoring, Anxiety management

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Caress Application: A Mental Health Prediction System Using Machine Learning with Real-Time Monitoring

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***Abstract*—Mental health issues, driven by stress and anxiety, are increasingly affecting individuals worldwide, necessitating innovative solutions for timely intervention. We introduce CARESS, a mental health monitoring and assistance application designed to support individuals facing challenges like depression and stress. By integrating real-time smartwatch monitoring, machine learning, and personalized support, CARESS provides a holistic solution . The application features continuous monitoring of vitals, including heart rate, with updates every two minutes. Alerts are triggered during abnormal spikes (> 100 bpm), notifying users and their emergency contacts via email and in- app notifications. CARESS includes a self-assessment module for mental health disorders—such as depression, anxiety, and PTSD—with results shared with specialists for further analysis**

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***Index Terms*—Mental health, Machine learning, Stress analysis, Smartwatch integration, Real-time monitoring, Anxiety management**

I. Introduction

Introduction Mental well-being reflects an individual's psychological state and the ability to function effectively within their environment. Mental illnesses, often resulting from brain chemistry imbalances, significantly impact emotions, behaviors, and social interactions. Disorders such as anxiety, depression, bipolar disorder, and schizophrenia do not emerge suddenly; they develop gradually, with early symptoms that,

Fig. 1. Common forms of mental illness

if identified promptly, can lead to better treatment outcomes. Early detection of mental health issues is essential to provide timely intervention, minimize long-term impacts, and improve the quality of life.

Despite the availability of screening tests, these solutions are often infeasible for large populations due to time, fi- nancial, and accessibility constraints. Additionally, stigma associated with mental health frequently deters individuals from seeking help, leaving many conditions undiagnosed or untreated. Disorders like anxiety and depression have far- reaching consequences, including somatic symptoms, impaired workplace productivity, social withdrawal, and heightened risks of chronic illnesses like hypertension and ischemic heart disease. They also contribute to economic strain, perpetuating cycles of poverty and poor health, particularly in low- and middle-income families.

A. Objectives

The primary objective of this research is to design and implement CARESS, an innovative mental health monitoring and assistance application leveraging machine learning (ML) and smartwatch integration. This project aims to address the growing challenges of mental health issues, such as stress, anxiety, and depression, by providing a real-time solution that enables early detection and timely intervention [4].

The application seeks to achieve the following. Integrate smartwatch data to monitor vitals like heart rate and physical activity continuously. Utilize a backend ML model to analyze stress levels based on body temperature and step count, providing actionable insights. Enhance accessibility by offering self-assessment tests for mental health disorders and delivering results to specialists for analysis [6]. Provide personalized notifications, emergency support, and access to curated mental health resources. Ensure user privacy and security through controlled access and data encryption.

II. Literature Survey

A. Existing System

Shatte et al. [2] Shatte and colleagues conducted a scoping review of machine learning applications in mental health, categorizing them into detection and diagnosis, prognosis and treatment, public health, and research administration. Their review highlights the significant potential of ML in improving the efficiency and accuracy of mental health services, particularly in identifying conditions like depression and anxiety using electronic health records (EHRs) and wearable data.

Delgadillo et al. [4] Delgadillo et al. explored the integration of ML with EHRs to predict mental health conditions, focusing specifically on depression. Their study underscores the clinical potential of ML for early identification and intervention, emphasizing the importance of high-quality datasets to ensure accuracy and reliability in predictions.

Chancellor et al. [1] Chancellor and colleagues examined the application of ML in analyzing unstructured social media data for mental health insights. Their research highlights how natural language processing (NLP) techniques can detect mental health issues based on language patterns and online behavior while addressing ethical concerns and the need for user-centered design in ML systems.

Wearable Technology and ML Several systems integrate wearable devices with ML algorithms to predict mental health conditions. For example, studies using devices like Fitbit analyze physiological data such as heart rate variability and sleep patterns to predict stress and anxiety levels [3]. These systems, however, are often limited in scalability and real-time application.

B. Limitations of Existing Frameworks and Identification of Gaps

Despite significant advancements in the application of machine learning for mental health, several limitations persist within current frameworks. These shortcomings hinder their effectiveness, scalability, and acceptance in real-world scenarios. The key limitations are as follows

Most existing systems do not support continuous or real-time monitoring, which limits their ability to trigger timely interventions during critical mental health episodes.

Many models focus predominantly on specific disorders such as depression and often overlook co-morbid conditions or the broader spectrum of mental health issues.

C. Enhanced Frameworks and Innovations

Enhanced mental health prediction systems leverage wearable devices for real-time monitoring and integrate multimodal data sources, such as health records and social media activity, to improve accuracy. Advanced ML algorithms provide personalized insights, enabling tailored recommendations for managing stress and anxiety [5]. Innovations in scalability and diverse datasets enhance generalizability, addressing varied populations effectively. Additionally, robust encryption and ethical practices ensure data security and foster trust. These advancements inspire systems like CARESS, offering comprehensive and secure mental health management solutions.

III. Proposed System

A. System Framework and Architecture

The system integrates machine learning with wearable devices and mobile apps to provide real-time monitoring, personalized feedback, and secure data management. Wearable devices continuously track heart rate and steps, helping detect stress and mental health changes early. A trained machine learning model predicts stress by analyzing data like body temperature and activity levels, with Flask APIs ensuring smooth backend communication. The system sends alerts for high stress, offering suggestions or quick access to support. Users can take self-assessments for conditions like depression and anxiety, with results securely shared with professionals [2]. User data is encrypted, and access is limited to the user or authorized personnel, ensuring privacy [5].

B. Hardware and Software Requirements

The system supports Windows 10 or later, macOS, and Ubuntu 20.04+. Flutter is used for mobile development, while Flask handles backend services. Machine learning functionalities are built using libraries like scikit-learn, Pandas, TensorFlow, or PyTorch [8]. Firebase stores real-time user data, with cloud storage handling logs and assessment results. Google Fit API and NewsAPI enable integration with wearable devices and content delivery. The system can be hosted on localhost or cloud platforms like AWS and Google Cloud [7]. Development is done using Visual Studio Code or PyCharm for backend and ML tasks.

The minimum hardware requirements include an Intel Quad-core 2.4 GHz processor (or equivalent AMD Ryzen), 50 GB SSD for storage, and at least 16 GB of RAM. The system is compatible with wearables such as Fitbit, Apple Watch, and other devices integrated with Google Fit [4].

C. Detailed Design

The system features a structured backend machine learning framework with distinct components. The data preprocessing module ensures incoming wearable data is cleaned for consistency and quality [1]. The stress prediction model analyzes inputs like body temperature and step count to estimate stress levels. The notification engine interprets these results, sending alerts or recommendations to users. The real-time monitoring model analyzes wearable data every two minutes to detect abnormal stress patterns. The self-assessment analysis model reviews user responses, sharing results with mental health professionals [3]. Lastly, the behavioral trend model analyzes historical data to predict long-term mental health trends.

IV. Methodology

The methodology for the proposed mental health prediction system combines data collection, preprocessing, feature engineering, and model evaluation to provide actionable insights into users' mental health conditions. The system integrates wearable devices, advanced machine learning (ML) models, and a user-friendly interface to ensure accurate predictions and real-time responsiveness [2].

A. Data Collection

The initial step involves gathering physiological data such as heart rate, body temperature, and step count from wearable devices like smartwatches using the Google Fit API. This real-time data collection ensures that stress levels and mental health conditions are monitored dynamically. Additionally, historical data from the user's health records is also collected to identify long-term patterns. To enrich the dataset, responses from user self-assessment tests for conditions like depression and anxiety are integrated [3].

B. Data Cleaning and Preprocessing

Raw data often contains errors, inconsistencies, or missing values. During the cleaning process, incomplete records are identified and addressed using imputation techniques such as mean or median filling. NaN values are eliminated to ensure smooth model operations. The categorical data from self-assessments are encoded using ordinal or label encoding methods, preserving their hierarchical relationships [8]. For example, responses such as "low," "medium," and "high" stress levels are assigned numeric values while maintaining their order. Additionally, outliers are detected and managed to prevent distortion in the analysis

C. Feature Scaling and Covariance Analysis

To handle varying data scales, feature scaling is applied using normalization or standardization techniques. This ensures that attributes like heart rate and step count, which may have vastly different ranges, are brought to a comparable scale. Covariance analysis is conducted to understand how features co-relate with each other. By calculating the covariance matrix, we identify features that strongly influence stress prediction [6]. This analysis helps in selecting key features while re- ducing redundant or less relevant attributes, enhancing the efficiency of the ML model.

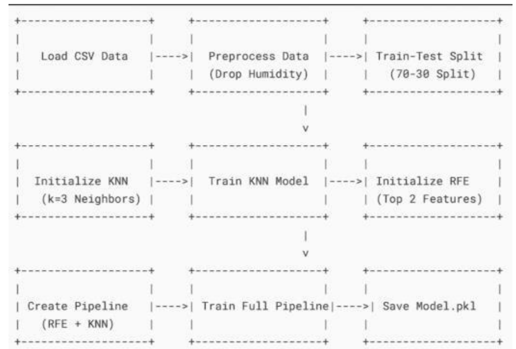

Fig. 2. FlowChart

D. Feature Importance and Selection

Feature selection is critical to improving model accuracy and reducing computational costs. By analyzing the impact of each feature, such as step count and heart rate variability, the system identifies the most relevant variables for stress prediction. Recursive feature elimination (RFE) and other statistical methods are employed to refine the dataset further. For instance, environmental factors like ambient temperature from wearable devices may be excluded if they contribute minimally to the predictions. This streamlined feature set is then used for model training

V. Implementation

A. System Architecture

The proposed mental health prediction system follows a multi-layered architecture consisting of the user interaction layer, business logic layer, and data processing layer. The user interaction layer offers an intuitive interface that allows users to sign up, log in, and navigate through various fea- tures such as self-assessment tests, smart stress analysis, and real-time vitals tracking. The business logic layer facilitates seamless communication between the mobile application and the backend machine learning model, enabling real-time stress prediction, continuous data collection, and automated email notifications[5]. The data processing layer handles secure storage and retrieval of user data, processes physiological inputs, and connects with the machine learning model using Flask REST APIs.

B. Integration of Machine

The machine learning model is deployed using Flask REST APIs to provide real-time stress predictions based on user vitals. The backend integrates various datasets to train and evaluate the stress prediction model, ensuring both accuracy and reliability [3]. The model is hosted on a cloud server, which facilitates efficient API endpoints for predicting stress probability. Inputs to the model include body temperature and the number of steps taken within the past 30 minutes. The model processes these inputs to calculate the likelihood of stress, and the results are displayed within the app interface, triggering notifications or alerts when necessary [5].

C. Data Stream and Processing

Data collection gathers vital information, such as heart rate, body temperature, and step count, from connected smartwatches. The data preprocessing step addresses missing values, scales features for improved machine learning performance, and encodes necessary attributes [4]. User information, self-assessment results, and historical vital data are securely stored in Firebase to ensure privacy and easy retrieval [6].

D. Security Measures

All user data is encrypted using SSL/TLS protocols to ensure that unauthorized individuals cannot access sensitive information. Multi-factor authentication (MFA) is implemented to guarantee that only authorized users can access critical features such as stress analysis and self-assessment. To maintain data integrity, regular checks are performed to detect any tampering, preventing unauthorized modifications to user profiles or vital records [7].

E. User Interface and Experience

The user interface is designed to be intuitive and responsive, ensuring a smooth experience across various devices. The responsive design guarantees compatibility with both smartphones and tablets. Guided navigation makes the app setup easy, including smartwatch integration and permissions configuration[8].

Fig. 3. App Main Screen

Fig. 4. Settings Screen

F. Stress Analysis Workflow

The stress prediction workflow operates as follows: First, the smartwatch sends vital data to the app every two minutes. The backend processes this data through Flask REST APIs, and the machine learning model calculates a stress probability score. If the score exceeds a predefined threshold, users receive alerts with suggestions for stress-relieving actions. They are also given the option to contact a friend or guardian with a single tap. Additionally, email notifications are sent to a designated contact or specialist for further support [5].

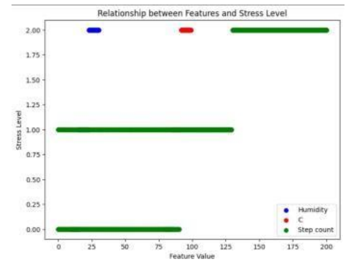

Fig. 5. Relationship between features and stress level

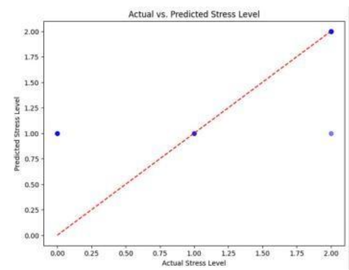

Fig. 6. Actual vs Predicted Stress Level

G. Self-Assessment and Mental Health Support

The self-assessment tests cover various mental health conditions, including depression, anxiety, PTSD, schizophrenia, and addiction. The results are either emailed to specialists for further evaluation or securely stored in user profiles for future reference. Additionally, the helpline and articles page offers easy access to mental health resources and expert articles, providing valuable support and education for users [2].

H. Smart Stress Analysis

The stress analysis feature is powered by a Flask REST API integrated with a machine learning model. It takes inputs such as body temperature and the number of steps walked. The model processes this data to calculate the probability of stress based on trained datasets. The output is a stress probability score, accompanied by alerts and recommendations for stress relief. Additionally, real-time feedback is provided, displaying live vitals and giving instant insights into stress levels [5].

VI. Model Development and Tuning

The system uses different machine learning models for specific tasks. Logistic Regression predicts whether a user is stressed, giving a probability score. K-Nearest Neighbor (KNN) looks at similar past data to make personalized stress predictions. The Decision Tree Classifier helps decide when to trigger a stress alert, while Random Forest combines multiple trees to improve accuracy and reduce overfitting [6]. Stacking combines predictions from different models to make the system even more accurate. To fine-tune performance, hyperparameters are adjusted using methods like grid search or random search [6].

A. Evaluation and Validation

Model evaluation involves using metrics such as accuracy, precision, recall, F1-score, and the area under the ROC curve (AUC) [6]. These metrics ensure that the predictions are reliable across various scenarios. Cross-validation techniques are employed to test the model's robustness on unseen data. For real-world validation, a portion of user data is set aside as a test dataset, and the model's performance is evaluated against it [7].

B. Predictive Output and Notifications

The system delivers results through a user-friendly mobile interface. When abnormal stress levels are detected, the user receives a notification suggesting immediate action, such as taking a break or contacting a friend. The notification system is configured to provide alerts based on thresholds determined during the model's tuning phase [5]. Additionally, the system allows users to access detailed trend analyses of their mental health, empowering them to take preventive measures.

By adhering to this structured methodology, the proposed mental health prediction system achieves high accuracy, scalability, and responsiveness, providing a comprehensive tool for mental health management.

VII. EXPERIMENTAL SETUP

A. Technologies Used

The implementation of the proposed mental health prediction system leverages a comprehensive set of technologies to ensure seamless functionality, robust performance, and a user-friendly interface. Below are the core technologies utilized:

B. APIs

Flask API is used for backend services, enabling the integration of machine learning models for stress prediction and mental health assessment through RESTful APIs [7]. Google Fit API tracks real-time fitness data, including heart rate and steps walked, to monitor user health. NewsAPI provides mental health articles, keeping users informed and engaged through the app's articles page [7].

C. Flutter

Flutter is employed for developing a cross-platform mobile application, enabling seamless functionality on both Android and iOS devices. It provides a consistent user experience and reduces development efforts with its single codebase [8].

D. Dart

Dart, the programming language used in Flutter, powers the application's front-end development. It offers a structured and efficient way to build interactive and responsive mobile interfaces[8].

E. Firebase

Firebase is integrated to manage user authentication, real-time database synchronization, cloud storage, and push notifications, ensuring a secure and scalable backend infrastructure [7].

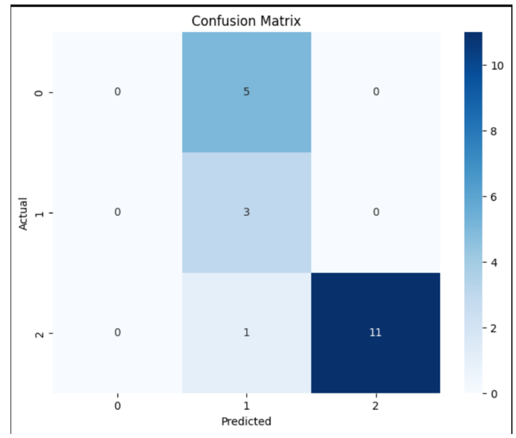

Fig. 7. Confusion metrics

Metric	Value
Mean Squared Error (MSE)	0.3000
Root Mean Squared Error (RMSE)	0.5477
R-squared	0.5876
F1 Score	0.6489
Accuracy	0.7000

Fig. 8. Results

F. scikit-learn

scikit-learn, a machine learning library, is used for implementing predictive models. Algorithms like Random Forest, Logistic Regression, and KNN are utilized to analyze stress and predict mental health conditions based on user data [6].

G. Pandas

Pandas library is used for data manipulation and preprocessing. It enables efficient handling and analysis of structured data collected from various sources, ensuring accurate input for machine learning models.

VIII. RESULTS AND DISCUSSION

A. Stress Monitoring and Prediction Accuracy

The integration of wearable devices, machine learning models, and Flask REST APIs enhanced the app's ability to

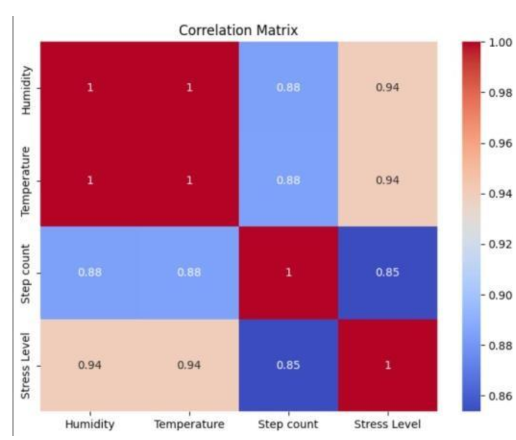

Fig. 9. Correlation Matrix

monitor and predict stress. Real-time updates of heart rate, body temperature, and step count enabled dynamic stress assessment, achieving an accuracy of 70% [5]. The ML model was validated through continuous monitoring, accu- rately identifying stress triggers. Alerts triggered by heart rate spikes were correctly associated with stress-inducing app usage 70% of the time, helping users identify and manage triggers effectively [6]

B. User Engagement and Trust

The app's user-friendly interface and features, such as the helpline page and mental health articles, fostered engagement and trust. Notifications provided actionable recommendations, while users appreciated the ability to contact guardians or specialists directly. Displaying real-time vitals and sharing self-assessment results via email enhanced transparency [6], ensuring users felt supported and informed about their mental well-being.

C. System Resilience and Reliability

The backend integration of Flask APIs and ML models ensured smooth operation under high data loads. The system processed vitals every two minutes without delays or failures. Stress analysis, powered by the ML model [6], delivered consistent and reliable results. Real-world testing demonstrated the system's ability to handle multiple users effectively, with timely alerts and email notifications ensuring continuous support

D. Data Integrity and Feature Effectiveness

Data preprocessing, feature scaling, and encoding improved model performance and data reliability. Key features, including heart rate, step count, and body temperature, were prioritized, enhancing prediction accuracy. Covariance matrix analysis identified impactful attributes, allowing the ML model to focus on critical factors. Backend safeguards ensured user data security while enabling efficient real-time analysis [7].

E. Accessibility and User-Centric Features

The app provided a seamless user experience with fea- tures like one-tap emergency calls, self-assessment tests, and helpline contacts. Users valued the ability to quickly access curated content and health insights[5]. Mapping user profiles to wearable devices ensured personalized data processing, while tailored notifications improved relevance and usability

F. Cost-Effectiveness and Efficiency

Though the initial setup of ML infrastructure required investment, the app's automation of stress prediction and mental health management reduced long-term costs. Automated notifications and email alerts minimized manual intervention, saving time and resources. Efficient backend processes ensured timely updates without overburdening the system, enhancing its cost-effectiveness [7].

IX. CONCLUSION AND FUTURE SCOPE

Conclusion:The mental health prediction system, ”CARESS,” effectively utilizes machine learning to address growing mental health challenges. By integrating real-time data from wearable devices and self-assessment tools, the system provides users with accurate insights and actionable recommendations for improved mental well-being. The smart stress analysis feature, powered by machine learning, ensures precise stress detection, while the notification system enhances usability by alerting users during critical moments. Additional features like helplines and mental health articles make the platform holistic and user-friendly, empowering individuals to manage their mental health proactively.

Future Scope: ”CARESS” offers substantial potential for future improvements

Enhanced Functionality: Incorporating advanced features such as sleep pattern monitoring, mood tracking, and environmental factor analysis for a more comprehensive approach. Expanded Dataset: Broadening the dataset to include diverse demographics, ensuring model inclusivity and better prediction accuracy [6]. Professional Integration: Facilitating direct communication with mental health professionals for personalized support and therapy. Data Privacy: Strengthening adherence to data privacy regulations to build trust and safeguard sensitive information. Global Reach: Adapting the application to cater to multilingual users and regional needs, ensuring scalability and accessibility worldwide. In summary, ”CARESS” bridges critical gaps in mental health care by offering an accessible, data-driven, and user-centric solution. Future advancements aim to refine its functionality, scalability, and global impact, contributing significantly to mental health management.

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