Machine Learning Based Personalised Mental Health Monitoring and Recommendation for Better Life

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Abstract- Mental illness impacts 970 million individuals worldwide, with the most prevalent disorders being depression and anxiety. Even though the need for mental health care is increasing, there are vast inequalities particularly in low- and middle-income nations where 70% of those afflicted have no access to treatment. To fill this gap, the suggested Mental Health Monitoring App assists users in their management of mental health by monitoring physical activity habits, sleep patterns, and daily activities. These include wake-up times, meals, and physical exercise. Driven by machine learning algorithms, the app examines data like activity levels, steps, sleep quality, and daily rhythms to identify early warning signs of mental health conditions, sends notifications, tips, and prompts to encourage healthier habits like improved sleep, consistent exercise, and awareness. Customized advice guides users in creating healthy habits, which strive to avert mental health decline. Developed on secure foundations such as MongoDB, the application ensures that data is protected and kept confidential. Wearable devices and healthcare APIs are integrated to provide real-time data collection for enhancing user understanding while preserving confidentiality. This personalized, nurturing approach bridges gaps in mental health services, promotes resilience, and enables users to track and enhance wellness with confidence.

Keywords: Mental health, Machine learning, Personalized monitoring, Wearable devices, Recommendation system, Artificial Intelligence (AI) in healthcare, Behavioural analysis.

1. Introduction

Mental well-being is a crucial factor in overall health, affecting emotions, thoughts, and behaviour. It determines the capacity to deal with stress, sustain relationships, and make decisions. Difficulties like anxiety, depression, and stress disorders are on the rise because of demands of modern living, overuse of technology, and socio-economic demands. Vigilant care for mental well-being is imperative to construct a healthier society.

Amid increasing complexity in daily living, it is often hard to detect early warning signs of mental distress. Conventional interventions psychotherapy and psychiatric consultations are effective but not consistently available, especially in low-resource settings. Growing integration of digital technologies has provided the ability to deploy AI-based mental health interventions that provide constant monitoring and early treatment. Such interventions use machine learning for monitoring behaviour patterns, emotional states' assessment, and providing tailored recommendations.

Machine learning features prominently in mental health monitoring through the analysis of wearables, smartphones, and self-reported data. This information reveals patterns of emotional distress, sleep interference, and lower levels of physical activity. This type of information facilitates early intervention to enhance mental well-being before symptoms worsen. AI-powered apps also have features like CBT exercises, mood monitoring, and real-time support to help manage mental health better.

Personalized tracking is one of the main advantages of AI-powered mental health applications. While generalized methods do not learn behaviour, machine learning forms habits to fit specific actions and provides personal recommendations. For example, prolonged inactivity can trigger gentle exercise or mindfulness reminders. Poor sleep quality can trigger suggestions towards good sleep hygiene, keeping users in balance with daily routines.

Privacy and data protection are essential aspects of AI mental health systems. Owing to the sensitive information of mental health, robust encryption, anonymization, and compliance with data protection regulations such as GDPR and HIPAA are vital in order to instil trust. In the absence of tight controls, user usage may be restricted due to fears of data exploitation.

Though AI-driven mental health systems hold great potential, there are ongoing challenges. These involve user compliance, bias in algorithms, and issues relating to ethics regarding automation in mental health. Future development must focus on improving algorithms, adding human review, and providing diverse and inclusive training data sets.

This article delves into the promise of machine learning-driven personalized mental health monitoring systems, noting their capacity for early issue detection, personalized advice, and enhanced overall mental health. Through the use of AI, this method works to fill gaps in care, promote self-care, and enable individuals to live healthier, more balanced lives.

The agenda is to create a personalized, real-time mental health intervention system that tracks physical aspects like sleep, activity, and daily habits. Utilizing pre-existing datasets or data gathered from wearable devices and health APIs, the system facilitates proactive intervention through regular monitoring. Preprocessing and analysis of behavioural data is done through machine learning methods, providing personalized and actionable suggestions that promote healthier behaviours. The system emphasizes early detection of mental health issues while ensuring data security and user privacy through robust feedback mechanisms and advanced privacy-preserving technologies.

2. Literature Survey

Olawade D.Be et.,al[1] conducts a narrative review to explore the application of Artificial Intelligence in mental healthcare, focusing on peer-reviewed journals and reputable databases from January 2019 to December 2023. The methodology includes a three-stage screening process: title screening, abstract screening, and full-text eligibility assessment, with specific inclusion and exclusion criteria to ensure relevance and quality. The review aims to analyze trends, examples, and ethical considerations surrounding AI's integration into mental health services, highlighting its potential to enhance early detection and personalized treatment.

Bakker,D et.,al[2] investigates the effectiveness of the MoodPrism app in improving mental health and wellbeing, particularly focusing on its relationship with emotional self-awareness (ESA). A total of 234 participants (73% female, average age 34.8 years) completed baseline and final assessments over 30 days. They used the app, provided informed consent, and completed a baseline assessment, receiving feedback based on their responses while reporting their mood daily. The study utilized the PHQ-9 for depression, GAD-7 for anxiety, and WEMWBS for mental wellbeing, with app engagement measured through a custom App Engagement Scale demonstrating good internal reliability (Cronbach's $\alpha = .839$). Mediated regression analyses were conducted using the PROCESS plug-in for SPSS, employing bootstrapping to assess indirect effects. Findings revealed that increased app engagement was significantly associated with reductions in depression and anxiety, with ESA serving as a mediating factor, particularly in clinically depressed and anxious individuals.

Karizat,N et.,al[3] paper analyzes 58 U.S. patent applications related to emotion AI technologies for mental health, focusing on the sociotechnical imaginaries these inventions propose. The authors employed an open-coding approach using qualitative data analysis software (Dedoose) to extract and categorize themes from the patent texts, identifying how inventors justify their technologies by claiming improvements in data accuracy, care provision, and patient-provider communication. The findings reveal that while these technologies promise enhanced mental health monitoring and support, they also raise ethical concerns regarding privacy, stigmatization, and the potential for invasive surveillance, emphasizing the need for a nuanced understanding of the implications of emotion AI in mental health contexts.

Wasil AR et.,al[4] paper examines the challenges of retention in online therapy and education, particularly in the context of the COVID-19 pandemic, which has accelerated the shift to remote delivery of mental health services and education. It highlights the historically low completion rates of massive open online courses (MOOCs) and digitally-enabled self-help interventions, with studies showing completion rates as low as 0.5% to 18%. The authors emphasize the need for improved user engagement and retention strategies, drawing on insights from both online therapy and education fields. Methodologically, the study involved analyzing existing literature on retention rates in online platforms, as well as collecting monthly active user (MAU) data from mobile app marketplaces to characterize the usage patterns of mental health apps during the pandemic. The research advocates for the development of novel metrics, such as the market share index-n (MSI-n) and the number needed to reach-p (NNR-p), to better understand the distribution and impact of mHealth apps on real-world users.

Alqahtani F et.,al[5] paper explores the co-design of a mobile app aimed at enhancing mental health support by engaging participants who have experienced mental health issues. The methodology involved three phases: first, focus group sessions were conducted to gather qualitative data on participants' personal strategies for managing mental health, leading to the identification of ten core themes. In the second phase, participants evaluated existing mental health apps, sharing their perceptions and preferences. Finally, in the third phase, participants were invited to design their ideal mental health app through sketches and discussions, allowing for user-generated insights. Data collection included audio recordings and thematic analysis, which helped uncover patterns and inform the app's design based on user needs and preferences. The study emphasizes the importance of user involvement in creating effective mental health interventions.

Schueller S et.,al[6] paper explores the motivations and experiences of individuals using mood-tracking applications in real-world contexts. The study involved 22 participants who were interviewed using a semi-structured format, complemented by a card sorting task that assessed their preferences regarding data entry and review features of these apps. The methodology included extensive training for the research team, which comprised members with diverse expertise, including clinical psychology and human-computer interaction. The interviews were recorded, transcribed, and analyzed using thematic analysis, leading to the development of a codebook with 13 codes and 37 subcodes to capture various themes related to user experiences and app functionalities. Key findings revealed that users were primarily motivated by negative life events and sought to enhance their self-awareness through mood tracking. Participants expressed a preference for visual representations of their mood data and highlighted a gap in the apps' ability to provide actionable recommendations for mood improvement. Overall, the study underscores the importance of understanding user experiences to inform the design and functionality of mood-tracking application.

Denecke K et.,al[7] explores how cognitive behavioral therapy (CBT) techniques are integrated into mobile health (mHealth) apps for mental health. A systematic review of 34 studies revealed that these apps predominantly utilize CBT techniques such as cognitive restructuring, behavioral activation, and problem-solving, but rarely exposure. The apps integrate technologies like chatbots, gamification, and social networks to enhance user engagement, adherence, and therapeutic effects. Methodologically, the authors followed PRISMA guidelines, screening three databases (PubMed, IEEE Xplore, ACM Digital Library) for studies from 2007-2020. Two reviewers independently extracted data, analyzing apps' functionalities, CBT techniques, and technical implementations. The study highlights gaps in efficacy research, ethical implications, and the need for evidence-based app recommendations.

Smith AC et.,al[8] investigates the impact of digital overload on college students' engagement with mental health apps. The study used semi-structured interviews with 12 diverse participants to gather data on phone usage, notification behaviors, and app engagement. Thematic analysis was applied to identify patterns in participants' experiences and preferences, highlighting that while digital overload was not a significant barrier, factors such as app design, usability, and user motivation strongly influenced engagement. Key themes included the need for customizable features, integration with existing routines, and addressing motivational barriers. Recommendations emphasize user-driven design approaches to improve app adoption and retention among college students.

Chawla S et.al[9] explores the perceptions, needs, and preferences of psychology students regarding the design of mental health applications (MHapps) to enhance resilience, employing Reflexive Thematic Analysis (RTA) as its methodology. Data was collected through six focus group discussions (FGDs) with 30 psychology students from universities in the Delhi-NCR region, utilizing a semi-structured topic guide and snowball sampling for recruitment. The analysis followed Clarke's six-step process, which included familiarization with the data, inductive coding, theme development, and iterative discussions among researchers to ensure coherence and validity of the identified themes, ultimately aiming to inform the design of culturally sensitive MHapps that address the specific needs of Indian students.

Wang K et.,al[10] reviews the effectiveness of mobile apps in monitoring and managing mental health symptoms or disorders, analyzing 58 U.S. patents on emotion AI in mental health through thematic and ethical coding. The findings highlight that emotion AI enhances data accuracy, communication, personalized treatment, and real-time emotional monitoring, offering significant potential in mental health care. However, critical concerns are identified, including risks to privacy, the potential for stigma, oversimplification of complex emotional states, and over-reliance on automated systems. The study underscores the importance of balancing technological advancements with ethical considerations to ensure safe and effective mental health interventions.

2.1 Problem Definition

To develop and monitor Personalized Real-Time Support system for Mental Health Management by considering physical factors such as sleep and other daily activities.

Leveraging data from smartphone apps and wearables, it utilizes AI and machine learning to discover patterns of behaviour associated with mental health. The system real-time adapts to the individual's way of life and provides timely interventions like mindfulness practices or motivational quotes. It is also able to converse with medical professionals when required, to provide a balance of professional and customized advice. By maintaining close attention to privacy and data protection, the system assists individuals to enhance their mental health through enhanced self-knowledge and better daily habits.

3. Materials and Methods

This section describes the tools, technologies, and processes employed to design, build, and test the mental health monitoring system, giving a comprehensive overview of data sources, algorithms, and implementation strategies followed during the project.

The System architecture has a streamlined flow to convert raw data into useful health insights. Every box in the fig 3.1 signifies a key process in analysing and processing user data from wearable devices. The end-to-end flow guarantees correct monitoring, individualized suggestions, and ongoing user participation.

Data Collection from Wearables: The primary source of behaviour and physiology data is wearable technology, including smartwatches and activity trackers such as Fitbit.

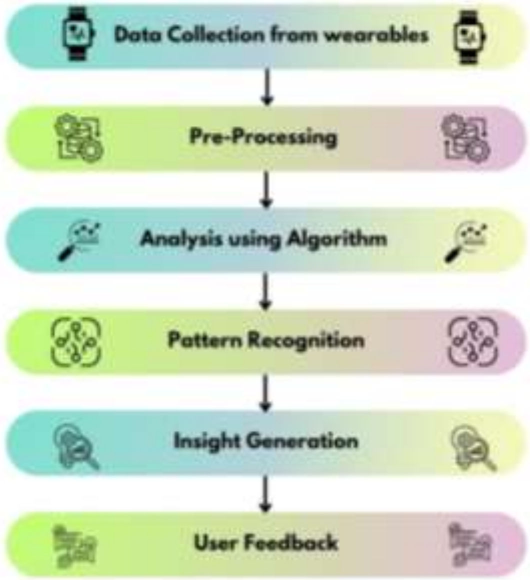

Fig 3.1 Block diagram

These devices monitor information in real time, such as heart rate, number of steps, calories burned, stress, and sleep scores. 43 subjects gave data for this research, aggregating over 215 distinct data points across significant health markers. Specifically, Fitbit wearables demonstrate a solid 80–85% accuracy in monitoring sleep and approximately 95% accuracy for steady-state monitoring of heart rate, providing a good foundation for analytics related to health. Regular, passive data gathering makes timely assessment of user wellness and comprehensive health monitoring possible.

Pre-Processing

Raw data is often noisy, incomplete, or inconsistent due to device limitations, human activity, or environmental conditions in raw data gathered from wearable sensors. To ensure data reliability, a robust pre-processing pipeline was developed. This involved filling in missing digits, smoothing fluctuations in values, and normalization of data through normalization methods like z-score scaling.

Categorical information such as gender and health status was properly encoded. The cleaned final dataset was consistent, providing strong input for machine learning algorithms. This process was very important to eliminate model bias and to ensure subsequent analyses yielded accurate and interpretable results.

Analysis using Algorithm

In the analysis step, a Random Forest classifier was employed to classify the pre-processed health data into health categories (e.g., Healthy, Moderate, At Risk). Random Forest, being an ensemble-based method, is particularly suited for handling both numeric and categorical data and for reducing overfitting. The model was trained and tested on 43 user samples and achieved an average accuracy of approximately 90.6%. Cross-validation showed stable performance across folds with a precision-recall ratio suitable for health monitoring tasks. This study allows subtle relationships and trends within the data to be discovered, establishing the groundwork for individualised health guidance.

Pattern Recognition

After classification, pattern recognition methods were applied to recognize recurring patterns in behaviour and physiology. The most important factors were detected using the Random Forest model's feature importance: Sleep Score (importance: 0.32), Heart Rate (0.28), and Steps (0.21). These parameters were used to detect trends like chronic sleep loss, elevated resting heart rates, and inactivity. For instance, individuals whose sleep score is less than 60 and high stress were often tagged "At Risk." These trends, if confirmed, help in identifying upcoming health issues and offer a proactive model for health management.

Insight Generation

With the observed trends, the system provided unambiguous, actionable insights regarding the users' physical and mental health. Examples would be identifying potential signs of burnout from suboptimal sleep and step rates and identifying patterns of fitness improvement from consistent activity levels. These findings were supported quantitatively, like a 20% drop in the performance of sleep over a week or a 15% increase in activity levels over the previous period. This information is necessary for users to make informed lifestyle choices or to consult a healthcare professional as necessary. It bridges the gap between raw data and actionable, user-friendly insight.

User Feedback

Providing insights to consumers through interactive dashboards, mobile notifications, or detailed health reports is the final step. Aside from giving consumers current health status details, this customized feedback loop allows them to act quickly. For instance, based on existing trends, alerts might recommend improved sleep hygiene or increased physical activity. The learning ability of the system can also be enhanced by feeding back user interactions and responses, ensuring that the health recommendations adjust and remain relevant over a period.

4. Algorithm and Implementation

The system proposed applies the Random Forest Model, an algorithm that is particularly effective in high-dimensional data handling and minimizing overfitting by aggregating decision trees. Its reliability in dealing with noisy real-world datasets guarantees resolute and solid predictions. With the use of this ensemble approach, the model improves on accuracy in identifying patterns and trends of mental health indicators. The system utilizes the Random Forest algorithm to construct decision trees from subsets of data and combine their predictions, analysing wearable device data and health API data to recognize trends in behaviour like abnormal sleep patterns and stress levels

Also, a Linear Regression model forecasts stress levels with 97% accuracy (R^2) and a minimal MAPE of 4%, validating accuracy. An intuitive dashboard presents visualizations of main mental health metrics, stress forecasts, and behavioural analysis, complemented by features for online therapy appointments, wellness services, and performance assessment tools such as ROC curves for real-time tracking and intervention.

AI-based mental health monitoring system demonstrated effective identification of emotional distress at the earliest. User engagement was increased with personalized suggestions and promoted healthier lifestyle choices.

Having multiple models integrated ensures interpretability while still achieving predictive performance, fitting the needs of different users. The most significant factors in mental health differences are sleep time, screen time, and physical activity, as identified by feature importance analysis. The system facilitates smooth integration with mobile health apps and institutional wellness software. Continuous model training, based on user feedback, enables responding to evolving behavioural patterns. Data privacy and ethical issues are handled through secure processing and anonymization. The system provides a holistic, data-based paradigm for proactive mental wellness.

Fig 4.1 shows the Linear Regression model predicts a stress level of 8.6/10 based on selected health and lifestyle parameters, demonstrating 97% accuracy (R^2) with a low error rate (MAPE: 4%, RMSE: 0.37)

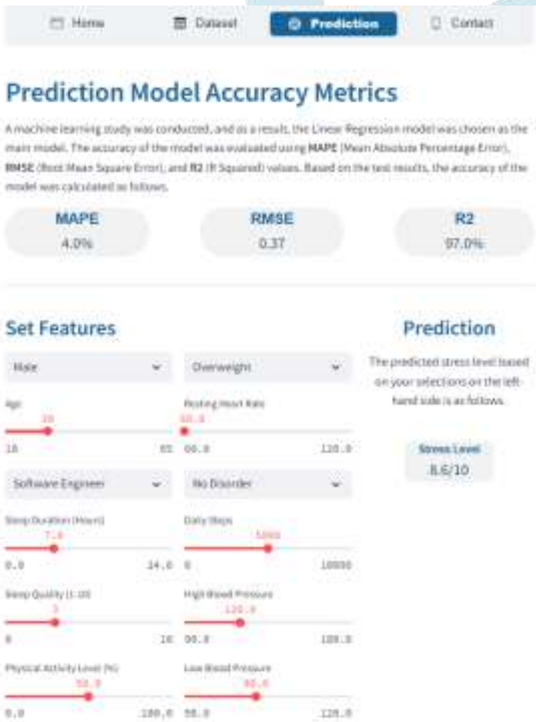

Fig 4.1 Mental Health results

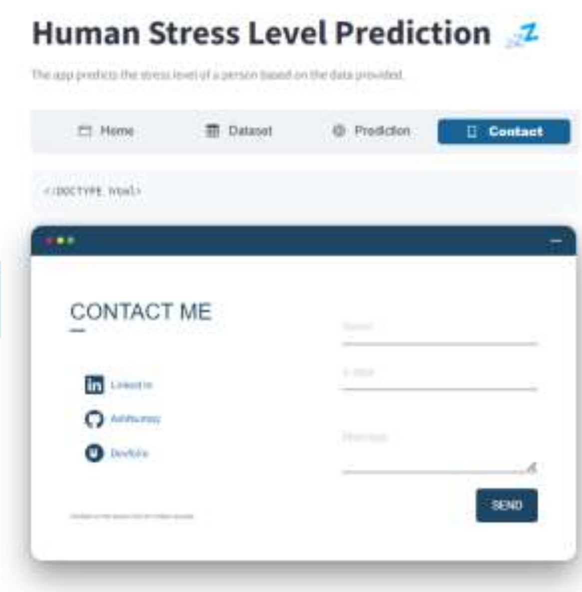

Fig 4.2 Staff Sign up

Fig 4.2 this is a web-based application for predicting human stress levels using provided data. The interface includes navigation options, a prediction feature, and a contact section for inquiries.

Fig 4.3 shows website, "Mind Matters" focused on mental health and therapy services, featuring images of counseling sessions. It includes options for booking online, emphasizing empowerment through psychological support.

Fig 4.3 Patient consultancy

Fig 4.4 Slot booking

Fig 4.4 shows this section showcases mental health services like relaxation techniques and crisis management, available for booking at an affordable price.

5. Results and discussion

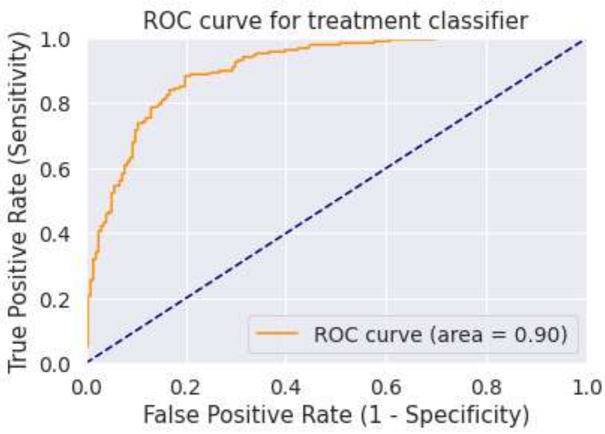

Fig 5.1 ROC Curve of the Treatment

Fig 5.1 shows the ROC curve representing the performance of a treatment classifier in distinguishing between positive and negative cases. The curve is well above the diagonal baseline, indicating that the classifier performs significantly better than random guessing. The area under the curve (AUC) is 0.90, suggesting a high level of accuracy in classification. A higher AUC value implies that the model has a strong ability to balance sensitivity and specificity. Overall, this classifier demonstrates good predictive performance, making it a reliable tool for treatment classification.

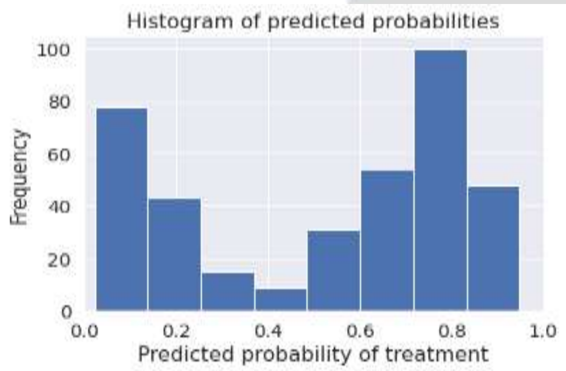

Fig 5.2 Frequency Prediction

Fig 5.2 shows histogram displays the distribution of predicted probabilities for receiving treatment. Most predictions fall near 0.1 and 0.8, indicating two strong clusters of low and high likelihoods

	Age	Gender	Country	self_employed	family_history	treatment	work_interfere
0	37	Female	United States	NaN	No	Yes	Often
1	44	M	United States	NaN	No	No	Rarely
2	32	Male	Canada	NaN	No	No	Rarely
3	31	Male	United Kingdom	NaN	Yes	Yes	Often
4	31	Male	United States	NaN	No	No	Never

5 rows × 24 columns

Table 5.3 Cleaning data

Table 5.3 shows dataset is being cleaned by dropping irrelevant columns (comments, state, Timestamp) and checking for missing values. The preview shows responses related to mental health in the workplace, with some missing entries in the self-employed and family history columns.

Fig 5.4 shows the age group distribution, where the majority of respondents fall within the 26–35 age range, indicating a younger demographic dominance. Fig 5.5 presents the country-wise distribution, with the United States comprising over 60% of the total responses, followed by the United Kingdom and Canada.

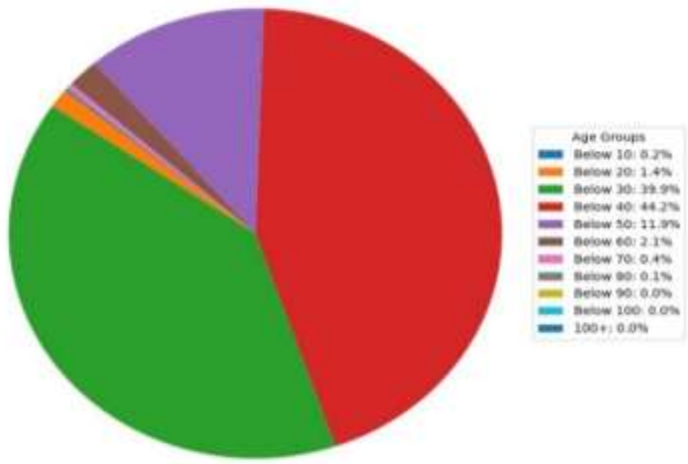

Fig 5.4 Age Group Distribution

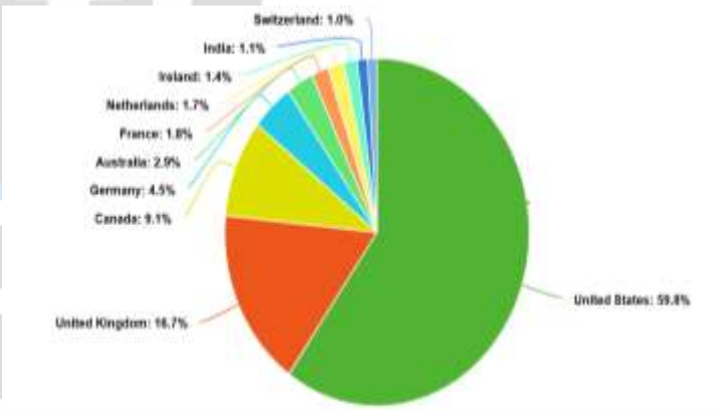

Fig 5.5 Country Based Distribution

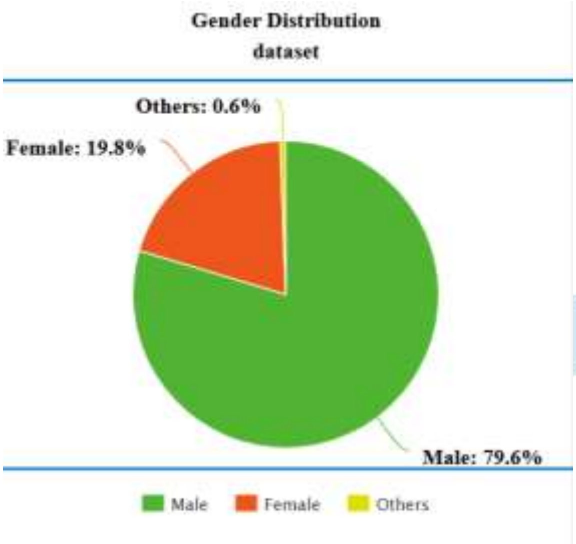

Table 5.6 Gender Distribution

This highlights a strong representation from Western countries. Fig 5.6 illustrates the gender distribution, where males represent the majority, with females and other gender identities forming a smaller portion of the dataset. These distributions provide important context for interpreting mental health trends in the tech industry.

	Age	Gender	self_employed	family_history	treatment	work_interfere	no_employees	remote_work
0	19	0	0	0	1	2	4	0
1	26	1	0	0	0	3	5	0
2	14	1	0	0	0	3	4	0
3	13	1	0	1	1	2	2	0
4	13	1	0	0	0	1	1	1

5 rows × 24 columns

Table 5.7 Cleaning NaN

The first five rows in table 5.7 shows of a mental health survey dataset after cleaning. It includes information like age, gender, work conditions, and responses about mental health treatment and awareness, with some missing data still visible.

5. Conclusion and Future Work

The Mental Health Monitoring App provides secure data protection with secure storage options such as MongoDB while providing real-time user feedback. Ongoing monitoring of physical activity levels, sleep cycles, and daily habits facilitates early detection of mental health issues. Customized recommendations motivate healthier behaviours such as better sleep, more physical activity, and mindfulness exercises. Sophisticated machine learning methods, such as Random Forest and LSTM algorithms, process user behaviour and produce actionable knowledge. Users take charge of their mental well-being through the method. User-centric design gives simple access to the information and support that matters most. The app fills gaps in mental health care accessibility, encouraging active self-management of mental well-being. Future releases will include adding support for other wearable devices to increase the number of data inputs. Predictive algorithms will be honed to be more accurate, providing finer granularity insights into trends in mental health. More types of mental health indicators will be added for users to see how well they are doing overall. More emphasis will be placed on bringing more sophisticated analytics and artificial intelligence to bear on further tailored recommendations. Greater third-party wellness app and service integration will be emphasized. Continuing feedback from users will be used to shape the app to meet changing needs and desires. These enhancements seek to create a comprehensive and effective solution for managing mental health.

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