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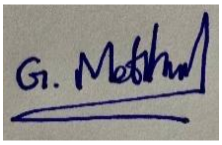
Signed: 

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1. Introduction

Mental health is an increasingly important aspect of overall human well-being, and still, it remains not addressed due to social stigma, lack of awareness, and access to professional help is limited. This problem is especially evident in Sri Lanka, where mental health services are not accessible to many people and the cultural barriers prevent people from having open conversations regarding their emotions (Attygalle, Perera & Jayamanne, 2020), as a solution to all these challenges, this project - MoodSync targets to develop a mental health monitoring system powered by machine learning providing a solution to bridge the gap between those who are in need and professionals that are ready to support.

This project was inspired by the growing digital tools in promoting mental health (Wijekoon Mudiyanselage et al., 2024), also this project was inspired to eliminate deaths by suicide which has globally increased recently. By using the advancements in Natural Language Processing (NLP) and sentiment analysis, this system looks forward to allowing users to monitor mental health effectively and access personalized guidance. The inclusion of features like mood prediction, coping strategies, motivational content, and real-time alerts for critical situations addresses the needs of users, especially in low-resource communities.

The anticipated impact of this project extends beyond the users, mainly targeting to reduce mental health stigma and provide timely interference to save lives (Deivanayagam et al., 2024). This software is mainly tailored to Sri Lankan users, but it can be used globally as well, also this software will be designed to be easily accessible, culturally favored, and user-friendly. By encouraging users with a motivated approach to mental health, this project seeks to make a meaningful contribution to users' and societal well-being.

2. Business Case

2.1. Business Need

Mental health problems have reached higher levels in Sri Lanka, according to World Health Organization (WHO) 2022 report, it is stated where one in five in the world and 20% of the population in Sri Lanka experience mental health disorders such as depression and anxiety during their lifetime (World Health Organization, 2022). Although there's a growing awareness and recognition of mental health importance, getting access to professional help is challenging because of the cultural stigmas, especially less resource availability in rural areas, around 60% in rural areas, 85% in urban areas and economic barriers making it unaffordable (Sri Lanka Ministry of Health, 2023). The current mental health applications like (Calm, Headspace, and Moodfit) have failed to provide unique guidance based on a person's mental health status which lacks sociocultural needs globally as well as for Sri Lankan users where 70% of users has reported that existing apps do not address the needs or provide guidance (Mental Health App Usage Study, 2023), leaving gaps in support provided. The lack of cultural relevancy and proper accessible mental health tools makes this issue much worse, as people are hesitant to seek in-person consultations mainly due to societal judgment. Further, there is an immediate need for a real-time monitoring system to identify worsening health conditions and provide timely interference to prevent suicide and life-threatening activities as 10% of increase in suicide rates for the last two years (Sri Lanka Suicide Prevention Annual Report, 2023). The need for an application like this is not only evident but essential to provide these solutions.

2.2. Business Objectives

Project MoodSync targets to achieve the following objectives that align with the need to improve mental health care accessibility and effectiveness in Sri Lanka.

1. **Personalization Enhancement**

- Implement advanced sentiment analysis and mood-tracking features that are made specifically for Sri Lankan and global contexts. Unlike other platforms generic responses will not be displayed, every output will be unique and personalized.

- Offers unique recommendations and coping methods based on users' behavioral patterns or by the user inputs (social media etc.).

2. **Improved Emergency Response**

- Integrate real real-time alert system that notifies the emergency contact, when the user displays worsening mental health, preventing self-harm to the user.

3. **Provide Professional Connections**

- Provide users with a directory of licensed mental health professionals, including details like hospital information, location, and appointment schedules for e-channeling.

4. **Promote Awareness**

- By using motivational content based on user health data, visualizing mental health trends, and personalized feedback to encourage daily engagement and self-awareness.

5. **Increased Accessibility**

- Develop user-friendly software that allows people from all regions, including rural areas, to access mental health support with less limits.

By addressing these above-mentioned objectives, this project looks forward to transforming the mental health landscape in Sri Lanka, making the support systems more impactful and personalized. Further, the platform’s adaptability ensures that it can be used to address global mental health challenges, increasing the platform’s relevance and value.

3. Project Objectives

Project MoodSync is designed to address the gaps in the current mental health support using advanced technologies to provide users with easily accessible and personalized solutions. This project aims to achieve the following objectives.

1. Sentiment Analysis Implementation

- To develop a good machine learning model with at least 95% accuracy to analyze the text inputs provided by the user (ex: social media posts) and evaluate their emotional and mental states accurately by the end of the development.

2. Personalized Mental Health Recommendations

- Create an intelligent guidance model that provides the users with coping methods, mental health tips, and motivational quotes specified to their recorded mental state and long-term data.

3. Anonymous Communication

- Design a secure and user-friendly web application to anonymously chat, making sure that users can express themselves freely without judgment, fear, and cultural stigma.

4. **Develop a Real-Time Alert System**

- Integrate a real-time monitoring system that identifies emotions and sends alert messages to loved ones and health professionals in serious situations.

5. **Mental Health Trends Visualization**

- Develop an interactive, graphical representation of the user's mood patterns throughout time, making them monitor their mental health journey and identify triggers and improvements.

6. **Integrate Support Channels**

- Connect the users to verify mental health professionals and provide information on the availability of health services and hospitals that are readily available to offer support.

7. **Promote Accessibility and Inclusivity**

- Ensure that the system is sensitive and inclusive to all Sri Lankan users while maintaining good adaptability to global audiences as well.

8. **Ensure Data Security and Privacy**

- Implement data encryption and strict authentication methods to safeguard users' data and maintain privacy.

4. Literature Review

This research paper explores the recent upgradation of machine learning and natural language processing (NLP) that has improved capacity in mental health monitoring through sentiment analysis on social media platforms such as X. The usage of X's large and complex datasets provides valuable insights into public sentiments facilitating timely responses to health crises. Within mental health, it has been seen that sentiment analysis has become a critical tool. This paper shows that traditional machine learning techniques like SVM and Naïve Bayes efficiently analyze user sentiments in real time though there have been challenges with slang and informal languages which is relatively common in a social media platform like X. Recent studies have clearly shown that deep learning models like Long Short Term Memory networks, which improve sentiment analysis by complex feature extraction. Although advancements have been made, according to this research paper there are gaps in research of sentiment analysis. The framework proposed by the authors shows the importance of historical tweets but hasn't done an in-depth analysis though they highlight more significant predictions regarding users' mental health. As a solution to in-depth analysis and to fill this gap, we could get the tweets data from users who are mentally suffering state and come up with identifying more accurate patterns to predict effectively. Finally, this research paper underscores the need for user driven data collection methods to improve data reliability and to provide cloud-based solutions for mental health monitoring. (Hinduja et al., 2022)

This advanced research study named "Machine Learning Techniques for Prediction of Mental Health" explores the way machine learning algorithms can be applied to predict current mental health status by gathering different attributes like financial and household data. Machine learning techniques have shown good results in detecting mental health issues earlier, the authors have used different datasets to identify the patterns that have been missed using the normal traditional methods. The authors have used many algorithms like Decision Tree, Random Forest, Support Vector Machine (SVM), Naive Bayes, Logistic Regression, XGBoost, Gradient Boosting Classifier, and Artificial Neural Networks to enhance the accuracy in predicting mental health. This dataset that has been used contains 76 attributes in total and the data has been split into a 70/30 ratio for training and testing. It included metrics like Precision, F1 Score, and false negative rate and accuracy. Among these algorithms, SVM has achieved a good overall accuracy of 87.38% whereas Gradient Boosting Classifier has obtained the highest F1 score showing a balanced precision. Naïve Bayes achieved a lesser accuracy of all algorithms which is 21.67% assuming that it has feature independence and is not suitable for big and complex datasets. This analysis clearly shows that SVM is the most ideal algorithm with high accuracy performed with data as no other algorithm has this level of accuracy. However, there are gaps identified in this research where there is no mention about imbalanced dataset which can be identified to improve model performances more. To fill this gap synthetic data can be used representing minority class for more balanced dataset. The findings from the research study indicate that machine learning techniques can be effectively used in mental health predictions though future research should aim more to improve the model to have a good performance. (Jain et al., 2021)

Another research study by Vidhi Mody highlights AI/ML-based approaches for identifying mental health issues, focusing on methods like multi-view clustering, expert systems, and wearable sensor integration. This paper shows how impactful physiological signals and smartphone data can be in detecting early mental issues such as stress, using techniques like fuzzy logic and multi-view bi-clustering. This paper showcases multi-view learning by combining perspectives like average activity, daily trends, and location variability resulting in an overall prediction of 87.1% accuracy. However, simpler classifiers like linear naïve Bayes were used in stress detection and achieved a lower accuracy of 80% which models can be improved more. The study highlights that current expert systems utilize rule-based reasoning and fuzzy genetic algorithms (fuzzy-GA) for identifying and planning treatments. These systems aim to mimic decision-making and provide personalized and therapeutic recommendations. This algorithm shows moderate accuracy and has limitations in boundary cases compared with the results obtained, where unreliability is often seen in the table of results. Although there is an algorithm upgrade, there is a gap in integrating multiple AI methodologies for diagnostic systems. The discussed existing methods have limitations in precision, which this proposed product will address with good precision and adaptability to evolving user states. My product will address this gap using an advanced machine learning model using traditional expert systems and to improve conditional handling well. This proposed product will be integrated with feedback and overall scores to deliver effective and personalized mental health recommendations. (Mody, 2019)

Another paper shows the progression made through machine learning algorithms and the way wearable devices help in detecting mental health disorders such as depression and anxiety, however there are gaps in these existing methods. This research study highlights a good accuracy rate in detecting health symptoms with the aid of KNN – K Nearest Neighbor, SVM – Support Vector Machines, and Naïve Bayes algorithms. However, most models are trained in controlled environments, making it overlook the real-world applicability of certain socio-economic conditions and cultural contexts, which affect the reliability of the product and mental health patterns, to fill this gap the proposed product will endorse the Sri Lankan local context. Additionally, the previous models have shown a limitation of scalability and practical issues when applied to resource-constrained settings which would have been better if continuous and real-time monitoring were used. However, the integration of these devices is challenging for low-income regions in Asia as the cost is high. This research shows how models and wearables can be utilized for impactful mental health detection. (Kumar et al., 2021)

Another research study conducted does a systematic review of examining machine learning applications in detecting mental health issues, with a focus on features, classifiers, and challenges faced with using these methods. This review shows the key techniques used in mental health detection such as feature extraction models like TF-IDF, Word2Vec, and N-Gram models as well as supervised machine learning techniques like SVM, logistic regression, and decision trees. The study shows a gap in handling data sparsity, multilingual content, and privacy constraints, especially for datasets sourced from Online Social Networks (OSNs). Though machine learning provides solutions to these concerns, there are issues like biased data, data preprocessing, generalizability, and model interpretation that remain significant obstacles. To address this gap, the proposed system will include localized data gathered from trusted government sources that eliminate biased data. Overall, the authors provide a review emphasizing the need for a good reliable model that addresses these challenges to improve health predictions. (Rahman et al., 2020)

This paper demonstrates the effectiveness of Machine Learning models, specifically SVM and XGBoost, in categorizing depression-related content from social media platforms. The authors show that SVM is highlighted above all other algorithms in terms of its high precision, making it the most reliable algorithm for mental health monitoring. However, the advancements gaps remain with the interpretability of ML models, especially concerning the language use of social media platforms which can lead to errors and misclassifications. Additionally, the class imbalance raises a challenge, which limits the generalization of the findings across user populations. Compared with previous research studies they have not shown a consideration in integrating a Large Language Model (LLM) which could've enhanced accuracy and understanding. To address these gaps as mentioned above the proposed system will be focused on an ML model ensuring a good performance in mental health detection indicators minimizing bias data. (Shatte, Hutchinson & Teague, 2019)

In this advanced study, the authors have emphasized the recent upgradation of Natural Language Processing (NLP) has made the way for innovative approaches to mental health analysis through social media. Traditional methods of mental health monitoring depend on face-to-face interviews which are not different from everyday emotional expressions found online. This paper has focused more on using ML techniques to classify emotions and states by user-generated content. For instance, the authors used a supervised algorithm to identify mental health indicators in social media posts and achieved good results. Similarly, it also demonstrated the effectiveness of deep learning models in identifying anxiety and depression-related content, highlighting the capability of automated systems in detecting real-time mental health status. Apart from these upgrades, gaps remain in interpretability of ML models and their generalizability from diverse populations. It is to be seen that these authors' main goal was to improve accuracy however they have missed addressing underlying reasons for misclassifications. This study aims to use LLM-large language models with SVM – Support Vector Machines to improve accuracy in stress-related posts. However, this is not the ideal solution as they lack generalizability of the findings though models accuracy is good, in the proposed project, it will closely align to cultural context. In addition, the model outputs will be analyzed to identify language indicators that cause mental distress thus completing the gap between accuracy and practical interpretation. This research carried out highlights the advanced technical possibilities in mental health analysis and contributes to a good system design before development. (Radwan et al., 2024)

An advanced study carried out by Ruba Skaik and Diana Inkpen from University of Ottawa shows the use of social media for real-time mental health surveillance and they explore the strategies to extract information using social media platforms. The authors discussed the growing trends of people using social media platforms such as X, Reddit, and Facebook capturing public user sentiment and identifying early warnings of related mental health issues such as anxiety, depression, and suicidal thoughts. This review shows the searches into different techniques used to extract and analyze obtained social media data, with a focus on techniques like Natural Language Processing (NLP) and Machine Learning. Further, these methods use sentiment analysis and modeling to break down topics to classify user-uploaded posts by mental health categories, which helps to detect the user's symptoms related to the disorder. The authors has considered more about detection speed in the approach which is a gap because it lacks longitudinal data analysis where in the proposed solution it will be addressed by using longitudinal analysis to get a understanding of crisis points and mental health trends more accurately. The authors further point out the advantages of using social media platforms for mental health detection. This is carried out by storing large amounts of data from the user over a period of time, which allows for the detection of disorders faster than traditional methods like surveys and clinical exercises. This research paper also discusses privacy concerns and the difficulty of ensuring the reliability of data to train the ML models, However there is gap of not considering how user respond to the model and there is no professional experience tailored in training the model, to address this gap constant user feedback will be taken in development of ML model making it more user centric backed by a professional. The authors seems more concerned about the ethical rules of collecting social media data and discuss other researchers to ensure the privacy protections of users and if data is collected responsibly. This review highlights how social media can be used to predict a user's mental health using techniques like NLP and ML models instead of old traditional methods. However, these authors suggest protecting privacy and checking the accuracy of the data obtained. (Skaik & Inkpen, 2021)

This research study highlights a review of existing approaches to mental health monitoring and shows a special importance on sentiment analysis and machine learning for mood tracking and predictions. This research paper shows the effectiveness of various ML models in understanding users emotional states by social media and other inputs. However, these solutions are mostly tailored to western user context limiting its applicability. While these models use sentiment analysis, very few integrate real time support system for user's needs, mostly in developing country like Sri Lanka. This research study lacks a approach of combining sentiment analysis and support mechanisms. By addressing the above-mentioned gaps could enhance the effectiveness of the proposed mental health monitoring system. By developing a cultural framework that has real time alerts and mental health advice can contribute to a better health care solution. (Alanazi et al., 2022). This research paper shows the use of machine learning and Arduino on mental health monitoring systems with important metrics like precision, accuracy, and sensitivity. The authors got a 96.6% higher accuracy rate in stress detection, showcasing the model's effectiveness with sensor integration with machine learning to obtain real-time health insights. However, there are gaps identified as there are different health conditions that are not limited to stress, where advanced machine learning and deep neural networks should be used. Additionally, integrating Natural Language Processing (NLP) could allow systems to interpret sentiments and interactions more deeply to offer personalized insights. By addressing these mentioned gaps, additional research would enhance monitoring systems facilitating early detection. Also, the models should be tested in a cultural context like in Sri Lanka, which would add depth where tools should be accurate and culturally sensitive to have a higher impact on the end product. (VENKATARAMANAIAH et al., 2024)

This research study showcases a different transfer learning framework being used for mental health monitoring and the importance of stress detection as a case study. The integration of transfer learning addresses gaps in existing mental health monitoring methods, which raises consideration of data privacy and insufficiency. Previously conducted research suggested that the use of federated learning techniques causes attacks and threats to vulnerability, limiting effectiveness for real-world scenarios. In addition, the existing models struggle with limited culture-specific training data leading to bad performance in models. The authors address issues by pre-training on large randomly picked datasets where it is obtained before getting tuned with user-specific data, if it is done therefore the model can be enhanced while protecting users' privacy. However, more exploration and tests should be conducted to ensure the scalability of this framework across diverse users and its various mental health conditions like depression to maximize utility in mental health monitoring practices. (Wang et al., 2024)

Machine learning (ML) becomes a reliable mechanism for mental health diagnosis when stable predictive trends emerge. From CNN to SVM to RF, the standard ML processes employed by researchers provide reliable diagnosis no matter the application of data collection—neuroimaging, transcribing, behavioral response scoring. For instance, CNNs achieve 94% reliable diagnosis of bipolar disorder and 91% reliable diagnosis of post-traumatic stress disorder (PTSD). Furthermore, Random Forests and Support Vector Machines provide reliable prediction of anxiety and depression diagnosis, respectively. In terms of prediction, many findings suggest success, yet many are based on specific cases. For example, with bipolar disorder, researchers have predicted using neuroimaging biomarkers and ML classifiers achieving over 90% accuracy for successful prediction with the potential for early detection and treatment. (Wijekoon Mudiyanselage et al., 2024)

Predictions also exist for schizophrenia with both ML and neuroimaging as well as genetic information, which shows promise with successful accuracy in finite efforts; however, finite efforts based on small sample sizes and the challenge of tracing the disorder miles down the line remain limitations for real-world implementation. The same can be said for PTSD, where ML efforts based on electrodermal activity signals, voice and speech characteristics, text-based elements, and passive tracking (i.e., GPS/location, cellphone information) yield clinically significant prediction accuracy. Furthermore, anxiety and depression apparently can be predicted as well through deep learning efforts like Long

Short-Term Memory (LSTM) networks through social media and speech-based efforts, opening yet another arena for detection potential. Finally, ADHD was found to have moderate to high detection accuracy using Decision Trees (DT) and Convolutional Neural Networks (CNN) with neuroimaging features. Yet gaps remain. Many studies utilize small, homogeneous sample populations limiting generalizability; privacy and ethical concerns require an extensive compliance protocol, which many studies do not undertake, plus certain predictive models like deep neural networks are too complex for explainability, rendering them inapplicable to a realistic clinical setting, etc. Furthermore, few studies utilize longitudinal or time series data due to time-relative predictors. This study will bridge these gaps with an emphasis on varied and diverse datasets, the use of longitudinal data, and an emphasis on greater explainability for future psychiatric applications. Ultimately, all three enhancements will lead to appropriate early detection, personalized interventions, and thus better mental health. (Madububambachu, Ukpebor & Ihezue, 2024)

4.1. Research Gap

The use of technology for mental health intervention has grown exponentially in recent years, resulting in many mental well-being applications. However, more needs to be done particularly with niche user groups in developing nations such as rural communities in Sri Lanka. Therefore, this chapter presents the solutions that have already been attempted, their failures, and the inadequacies in research this project intends to bridge.

Existing Solutions and Limitations

There are many mental health apps Calm and Headspace to Moodfit that offer general possibilities for mood tracking and meditation. Yet, while these apps promote mental health awareness and assist multitudes, they function with a Western majority inclination and the global, culturally lingual assessment required for proper user engagement does not come easy cultural Relevance and Localization.

Cultural Relevance and Localization

Currently, many apps lack cultural relevance and localization, which are necessary for heightened engagement and successful mental health intervention. For example, Hinduja et al. (2022) assess the advancements in machine learning capabilities and natural language processing (NLP) features within social media spaces to assess mental health concerns. However, much of the training of such models comes from Westernized language tendencies; for example, if someone is depressed and makes a comment on social media and/or uses particular language tendencies, it's much different than how someone in Sri Lanka would be spelling or saying how they feel through language. Thus, an increasingly successful model is needed, trained on the socio-cultural forces at play with the Sri Lankan population.

Personalization and Sentiment Analysis

Some applications boast sentiment analysis features, such as Moodfit, but none personalize the reaction concerning culturally relevant factors and one's specific feelings. For example, according to Jain et al. (2021, 1), Support Vector Machines are pretty effective in assessing if an individual suffers from mental health issues but fail to acknowledge the potentially biased nature of some datasets. This is critical because it shows that more balanced, culturally trained, edited datasets would allow for equity and accuracy of assessments for this population in Sri Lanka. Real-Time Feedback & Professional Collaboration. Currently, most mental health apps fail to provide real-time feedback and professional collaboration. For instance, Mody (2019) reveals that many AI/ML-based solutions to stress detection rely on physiological signals and input using the smartphone very precisely. However, such precise outcomes produce rule-based expert systems that omit real-time interaction from the end-user or a professional—meaning such systems could never adapt over time based on end-user needs or affiliation with licensed mental health professionals. Furthermore, Skaik and Inkpen (2021) demonstrate how social media could be the vehicle for real-time assessment and research into mental health tracking, but it does not provide any means for longitudinal assessment with professional guidance. Thus, the findings are not practical for the long-term mental health support of persons from rural Sri Lanka.

Sentiment analysis as a form of medical diagnosis through trends in mental health via sentiment emerges as a common occurrence on social media. For example, Usmani et al. report that mental health issues can be predicted possibly even before people have them in real life. However, such features run into barriers. For example, employing a non-trained, non-domain, or field-specific dataset and the naturally complicated ways in which people talk about sarcasm, vagueness, etc. poses typical barriers. However, according to Reinert et al., sentiment analysis not trained through domain experience does not assess the status-in-context needed for mental health assessment. Learned relative to attempting to solve another issue, class imbalance within the trained data where "Normal" and "Depression" appear frequently but "Stress" and "Personality Disorders" do not. This restricts what machine learning might be able to discover with less frequently encountered mental illnesses. Similarly, however, learned as well. For example, Kim and Kaushik et al. created their own and adjusted models to circumvent the discrepancies while Hahad et al. suggest that the more variables from the data set, the more holistic understanding of the problem. Therefore, future research must make the algorithms more sensitive, expand the annotated corpora, and develop niche applications. Should such shortcomings be addressed, sentiment analysis could provide a powerful form of instantaneous evaluation of mental health with greater accessibility for a global mental health crisis. (Jain & Rathour, 2024)

Anonymity and User Privacy

Anonymity is another important requirement that many of the existing applications fail to satisfy. Where they offer private adjustments, they do not offer a secure way for people to access much-needed help for mental health problems without the fear of exposure. Rahman et al. (2020) note that privacy issues are one of the biggest obstacles to using online social networking for mental health monitoring. Therefore, applications are necessary that keep anonymity on the user's part but fulfill the support requirements for a culturally appropriate Sri Lankan application.

The following research gaps have been written based on the conducted literature reviews above:

1. **Personalized Support** – Most applications don't provide a unique response to users instead they provide a common generic response. To address this gap the proposed system aims to use advanced machine learning algorithms trained with localized datasets to offer unique personalized responses with an overall score.

2. **Real-Time Support** – Current applications don't have real time support/alerts to users' loved ones in immediate health needs. This proposed system will plan to include real-time alerts using SMS to get immediate support in need.

3. **Cultural Context** – There is a lack of mental health applications that represent users in the Sri Lankan context. The proposed system will address this gap by using local languages and cultural backgrounds in its design and functionalities. By engaging with a mental health professional, this application will be tailored and ensured for local users.

4. **Professional Support** – No application connects mental health professionals with their users; to address this gap the proposed system will showcase the directory list of professionals with times and locations that will be available for channeling.

5. **Anonymity** – Unlike other applications, this proposed system will have a feature to chat with a representative for quick support without exposing the user as it cuts off the user's fear of getting support.

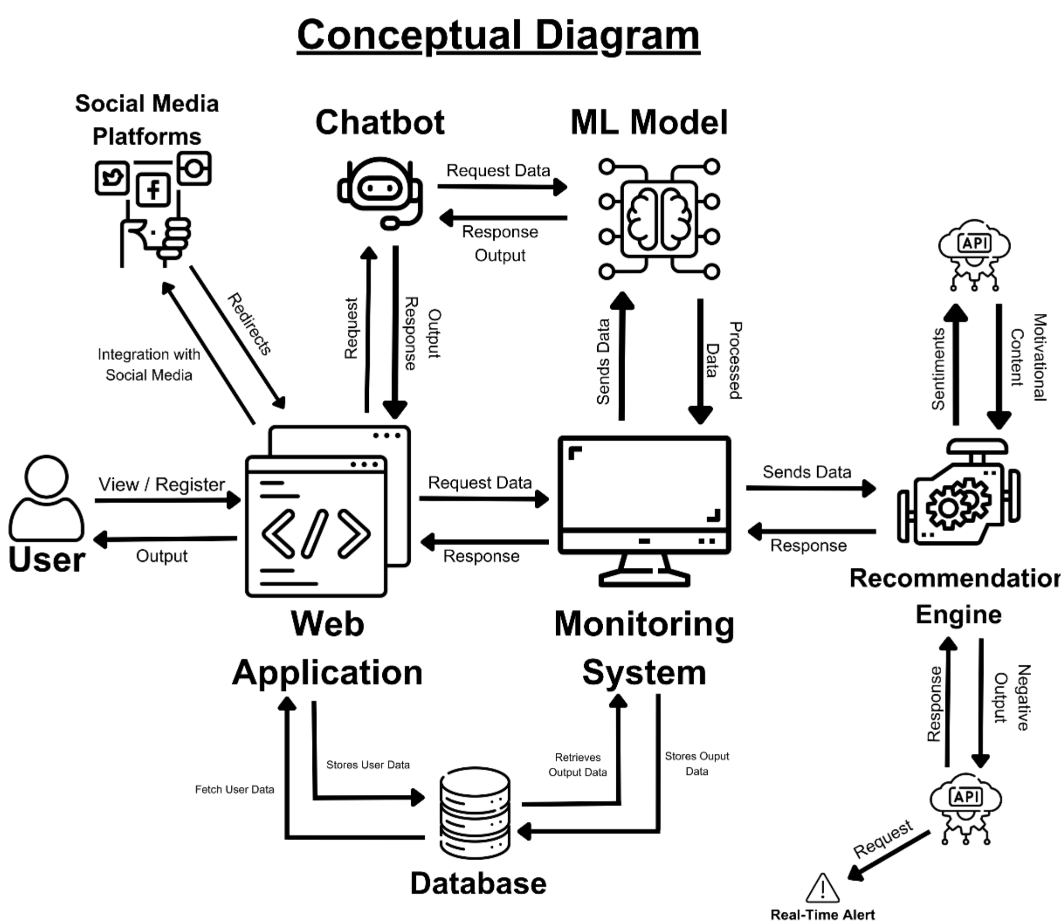


Figure 1 - Conceptual Diagram

5. Method of Approach

The development of project MoodSync will follow a structured approach, ensuring that the system is reliable, user-focused, and well-matched with the project objectives. This section shows the methodologies, tools, techniques, and frameworks that will be used in this project.

5.1. Technical Approach

Backend Development

- **Python** - will be the main language, and it is used for machine learning models and sentiment analysis algorithm development.

- **TypeScript** – For web development backends such as Node.js, Express.js, data visualization and, API requests, where logic will be handled.

NLP Libraries

- **NLTK** – For tokenization, sentiment analysis, and text processing.

- **spaCy** – For advanced NLP tasks, entity recognition, and parse dependencies.

- **scikit-learn** – For machine learning algorithms like Support vector machine (SVM) to predict user's moods by text inputs.

Database

- **MongoDB** - which is a NoSQL database, stores user information, mood logs, and analysis results for scalability and efficiency.

<u>Frontend Development, Tools, and Frameworks</u>

- **React.js** - for building responsive and modern user interfaces.

- **Vite** - Vite is a modern build tool that will ensure faster build times of the application than traditional react apps.

- **Tailwind CSS** – CSS framework for modern user interface development.

- **Flowbite** - UI library will be used alongside Tailwind CSS for easy and faster development.

- **TypeScript** – For frontend web, component development, and its logic. Will enhance code quality and maintainability.

- **Socket.io** – This will be used to implement real-time features like anonymous chat and sending alerts to loved ones when the condition is detected.

Data Visualization

- **Chart.js and D3.js** – For visualization of user sentiments and mood trends using charts and graphs.

API’s

- ***Twilio API*** – Third-party SMS sending API that will be integrated to send text messages to emergency contacts.
- **Quotable/Zen Quotes API** – To fetch motivational quotes for user inspiration.
- **Health data API** – to fetch additional mental health resources.

Development Tools and Platforms

- **IDE’s** – JetBrains PyCharm (Professional Edition) for backend machine learning models development and Visual Studio Code for frontend development.
- **Version Control** – Git and GitHub to manage my codebases.
- **CI/CD** – Docker to maintain environments with Jenkins CI/CD pipeline for automation of the application.

5.2. Project Management Approach

The agile methodology will be used to ensure flexibility and continuous improvement throughout the software development lifecycle. By using this approach it allows repetitive releases, integration of user feedback, and flexible planning, to ensure that the product meets user expectations and addresses the real-world challenges effectively.

Agile practices include:

- **Sprints** – Divide the development processes into short iterations according to the software development life cycle (SDLC) so that the complexity of the project is broken down as shown in the Project Gantt Chart.
- **Backlog Management** – Prioritizing features like sentiment analysis, mood tracking, and alerts based on users and their feedback so that project objectives are easily achievable.

5.3. Functional Components Approach

Sentiment Analysis and Mood Predictions

- User inputs (text and social media posts) will be analyzed using the NLP to detect the sentiment and the mood predictions.
- Machine learning models will be trained by using localized datasets to ensure good accuracy and reliability.

Real-Time Alerts

- Emergency contacts will be notified by SMS when the user's mental health score passes a certain level.

- Integrated with third-party SMS API (Twilio) for instant responses.

Professional Directory and Anonymous Chats

- The database of licensed and best professionals and channeling hospitals will be integrated into the web application.

- A secure and anonymous chat feature would be available with trained representatives for immediate user support.

Data visualization

- Graphs and charts will be used to display mood trends over time so users can get to know the insights.

5.4. System Architecture Approach

This system will be developed using the client-server architectural method with the following layers,

1. **User Interface (UI)** – Web application for the user to interact.

2. **Application Logic** – Backend services for data processing and recommendations.

3. **Data Storage** – MongoDB for storing user profiles, logs, and analytical data.

4. **Machine Learning** – Python-based ML models for sentiment analysis and mood predictions.

5. **APIs** – For motivational content and health resource implantation.

These above methods of approaches will ensure that the system is built efficiently adheres to the best practices and address the unique mental health challenges while adapting to the global audiences.

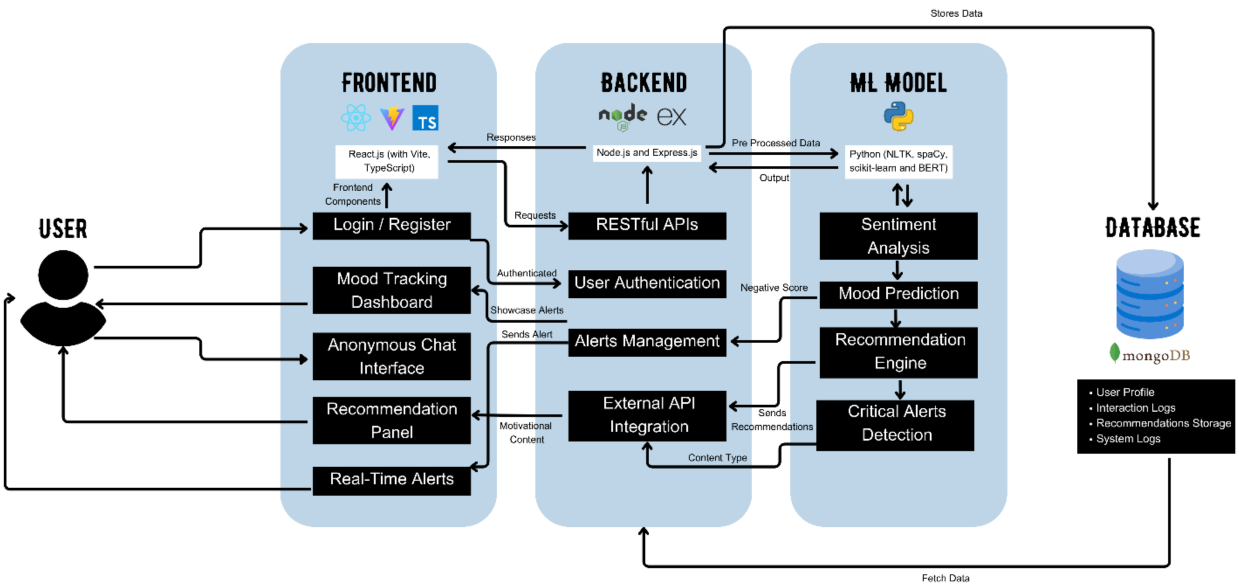


Figure 2 - High Level Architectural Diagram

6. Initial Project Plan

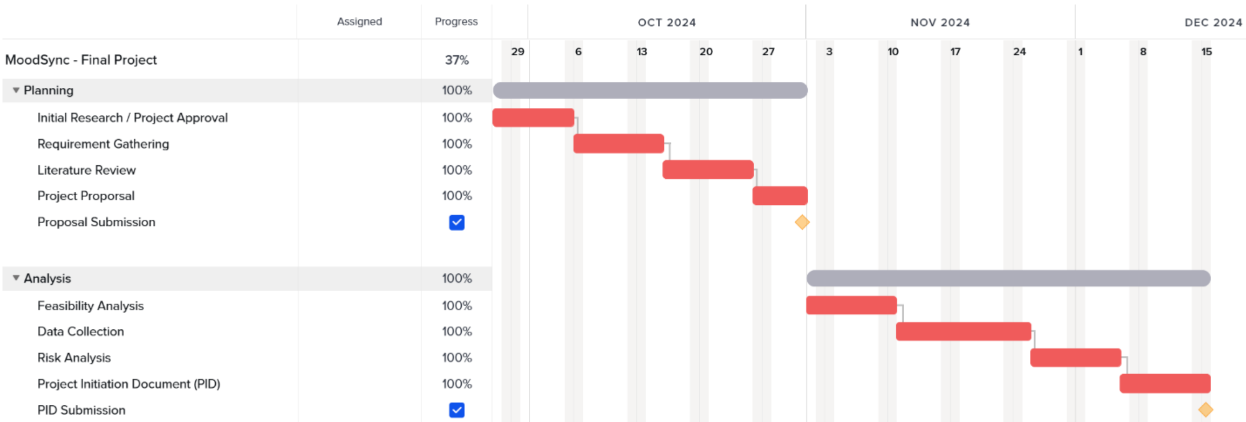
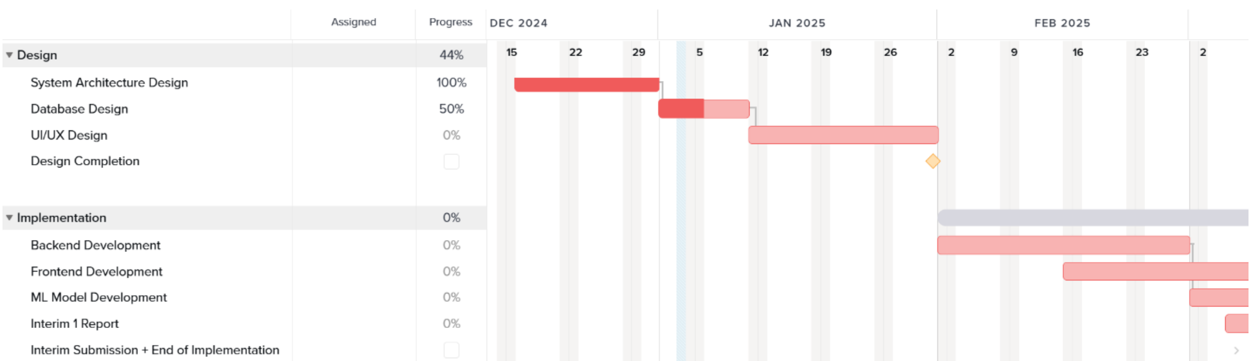
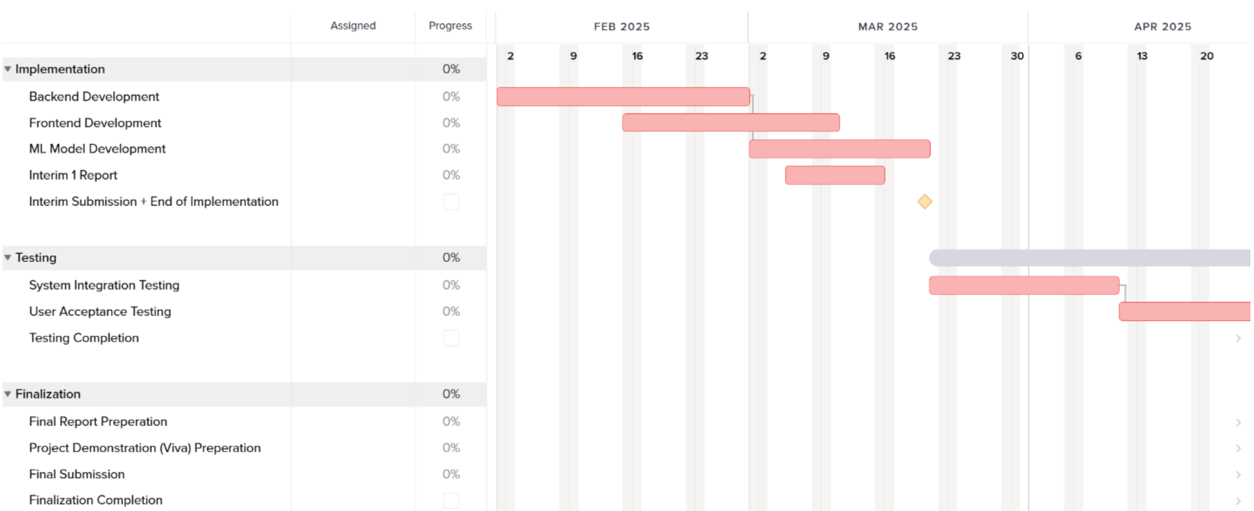
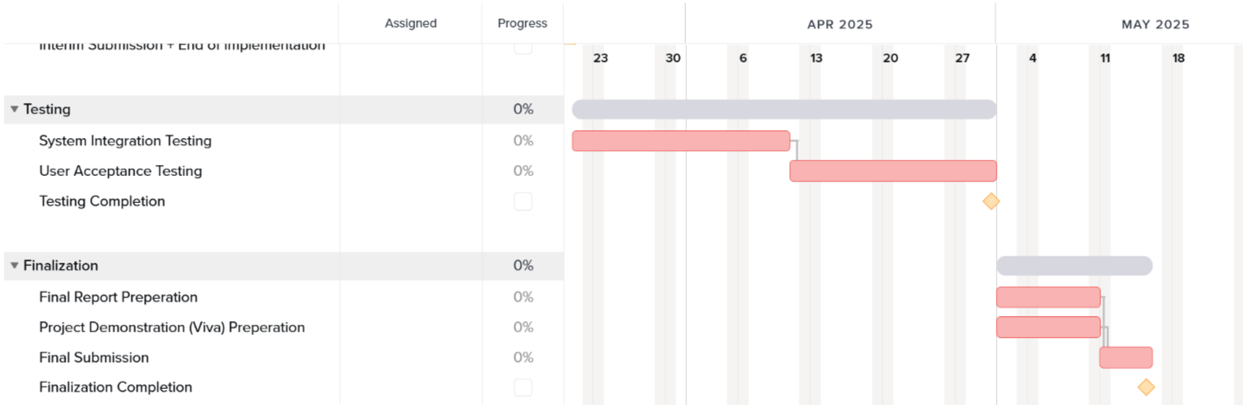


Figure 4 - Gantt Chart







Click to see the images and diagrams if unclear HERE!

7. Risk Analysis

7.1. Technical Risks

1. Sentiment Models Accuracy

- **Risk** – The NLP model may not identify user inputs to slang and cultural nuances.
- **Chance** – Medium.
- **Impact** - High.
- **Mitigation** – Using a localized dataset to train the machine learning model, test users' input samples, and tune the algorithm based on results and user feedback.

2. API Integration

- **Risk** – Delays and Failures in API responses in health data and motivational content.
- **Chance** – Medium.
- **Impact** – Medium.
- **Mitigation** – By using the fallback method and cache data in the browser to handle the API unavailability.

3. Real-Time Alert System Reliability

- **Risk** – Delayed and failed to notify emergency contacts in peak situations.
- **Chance** – Low.
- **Impact** – High.

- **Mitigation** – Using a reliable third-party SMS generator, and also to monitor how the performance works out regularly.

7.2. Project Management Risks

1. Timeline Delays

- **Risk** – Missing deadlines due to technical issues and other unexpected problems.
- **Chance** – Medium.
- **Impact** – Medium.
- **Mitigation** – By using agile methodology as mentioned above to track progress in sprints and allocate resources as needed.

2. Skills Gap

- **Risk** – Lack of expertise in technologies like Natural Language Processing and Machine Learning.
- **Chance** – Medium.
- **Impact** – Medium.
- **Mitigation** – By allocating time to learning, meeting with the project supervisor to get information, and the use of online resources as guidance for correct integrations.

7.3. Financial and Resource Risks

1. Budget Constraints

- **Risk** – Additional costs for data gathering from health professionals, use of IDE's professional versions, and support that may be unplanned.
- **Chance** - Low
- **Impact** - Low
- **Mitigation** - Use of premium software services provided by the university free, use of open-source software tools, and preparing for additional expenses.

2. Resources Availability

- **Risk** – Limited access to tools and health professionals.
- **Chance** - Medium
- **Impact** - Low
- **Mitigation** - Maintain a regular connection with the professionals till the application is built.

7.4. Data Privacy and Security Risks

1. Data Breaches

- **Risk** – Unauthorized access to users' sensitive data like mood logs and emergency contact details.
- **Chance** – Low.

- **Impact** – High.
- **Mitigation** – By using end-to-end encryption, the latest authentication mechanisms like OAuth 2.0, and data protection regulations (ex: GDPR).

2. Anonymity Concern

- **Risk** – Users' identities could be exposed in anonymous chats.
- **Chance** – Low.
- **Impact** – High.
- **Mitigation** – By ensuring that the chats are encrypted and accessed securely with strict access controls.

7.5. User Adoption Risk

1. User Resistance

- **Risk** – Users may hesitate to use this system due to cultural stigma and lack of familiarity with the application.
- **Chance** – Medium.
- **Impact** – High.
- **Mitigation** – By designing a user-friendly interface and giving tutorials inside the web application for navigation.

2. **Cultural Relevance**

- **Risk** – Failure to detect language nuances by the ML model.
- **Chance** – Medium.
- **Impact** – High.
- **Mitigation** – Testing with people during the development and adjusting the model.

7.6. Ethical Risks

1. **User Trust and Consent**

- **Risk** – Users may not fully trust the application to give their sensitive information of themselves.
- **Chance** - Low
- **Impact** - High
- **Mitigation** – Clear communication of data usage of the application getting user consent and ensuring data transparency while handling users' data.

2. **Model Algorithm Biases**

- **Risk** – ML models may give biases that give inaccurate results and unfair results to users.
- **Chance** – Medium.
- **Impact** – High.
- **Mitigation** – Train models on different datasets and regularly check for biases.

By addressing these risks, Project – MoodSync ensures the development is culturally relevant and meets user expectations. Frequent reviews and adjustments will be made to tackle these risks and come up with a quality product.

8. Additional Sections

8.1. Stakeholder Analysis

The successful development of Project MoodSync depends on effectively identifying and engaging the stakeholders. I have classified the stakeholders into two sections,

Primary Stakeholder

- **Normal Users** – People who look out for mental health support. They are the direct beneficiaries of this system developed, who expect feedback and strategies to continuously improve their mental health.

- **Mental Health Doctors** – Therapists, counselors, and psychiatrists who will use this platform to connect with the users and offer their service with ease and track historical data.

Secondary Stakeholder

- **Families and Loved Ones** – They will receive an alert in situations where the connect user's mental health would get worse and the potential chance of getting self-harmed so families can be attentive to prevent such conditions.

- **Hospital Organizations**– Hospitals may integrate this application externally to extend their mental health services, generating good revenue for the good service.

- **Government and NGOs** – Stakeholders that focus on mental health awareness and suicide prevention as volunteers.

More Details of Data Collection in Stakeholders

Sri Lanka Sumithrayo / Sri Lankan Mental Health Foundation – Planning to get localized data from these government organizations. These organizations work to promote mental health care and provide support to people suffering from mental health illnesses.

Psychiatrist Information (Confirmed):

- Dr. Saman Weerawardhane – (MBBS) Psychiatrist / Mental Health Specialist.
  National Institute of Mental Health (NIMH)
  NIMH, Mulleriyawa New Town, Angoda
  Details of the Local Hospital (Data Collection):

- Mana Suwa Piyasa (මනසුව පියස) – Mental Health Clinic
  Colombo South Teaching Hospital – Kalubowila
  B229 Hospital Rd, Dehiwala-Mount Lavinia 10350

8.2. Ethical Considerations

Following ethical considerations plays a major role in Project MoodSync as much user group data has been handled by this application.

- **Data Privacy** - Strict restrictions will be applied to the system to ensure data privacy. (ex: OAuth 2.0, GDPR, etc.).

- **Biases in the ML Models** – Regular testing in machine learning algorithms to prevent inaccuracies of mood predictions and guidance's with stakeholders (Psychiatrist).

- **Transparency** – This will ensure that users can interact with the web application with consent and will provide 100% transparency in retrieving personal details.

8.3. Communication Plan

Constantly will be in touch with the confirmed stakeholder (Psychiatrist) to check the quality of the product, mainly results as if they abide by the health standards.

Bibliography

- Attygalle, U.R., Perera, H. & Jayamanne, B.D.W. (2020) Stigma related to mental health issues – a study among adolescents in Sri Lanka. *Sri Lanka Journal of Psychiatry*. 11 (1), 8–13. doi:10.4038/sljpsyc.v11i1.8243.

- Deivanayagam, T.A., Ní Chobhthaigh, S., Devakumar, D., Patel, K. & Rannan-Eliya, R.P. (2024) Mental health prevalence, healthcare use and access between 2018 and 2022 in Sri Lanka: an analysis of survey data. *Global Health Research*. 1–16. doi:10.3310/hjwa5078.

- Hinduja, S., Afrin, M., Mistry, S. & Krishna, A. (2022) Machine learning-based proactive social-sensor service for mental health monitoring using twitter data. *International Journal of Information Management Data Insights*. 2 (2). doi:10.1016/j.jjimei.2022.100113.

- Jain, E. & Rathour, A. (2024) Understanding Mental Health through Sentiment Analysis: using Machine Learning to Analyze Social Media for Emotional Insights. In: *2024 5th International Conference on Data Intelligence and Cognitive Informatics (ICDICI)*. 18 November 2024 IEEE. pp. 782–786. doi:10.1109/ICDICI62993.2024.10810855.

- Jain, T., Jain, A., Hada, P.S., Kumar, H., Verma, V.K. & Patni, A. (2021) Machine Learning Techniques for Prediction of Mental Health. In: *Proceedings of the 3rd International Conference on Inventive Research in Computing Applications, ICIRCA 2021*. 2 September 2021 Institute of Electrical and Electronics Engineers Inc. pp. 1606–1613. doi:10.1109/ICIRCA51532.2021.9545061.

- Kumar, P., Chauhan, R., Stephan, T., Shankar, A. & Thakur, S. (2021) A machine learning implementation for mental health care. Application: Smart watch for depression detection. In: *Proceedings of the Confluence 2021: 11th International Conference on Cloud Computing, Data Science and Engineering*. 28 January 2021 Institute of Electrical and Electronics Engineers Inc. pp. 568–574. doi:10.1109/Confluence51648.2021.9377199.

- Madububambachu, U., Ukpebor, A. & Ihezue, U. (2024) Machine Learning Techniques to Predict Mental Health Diagnoses: A Systematic Literature Review. *Clinical Practice & Epidemiology in Mental Health*. 20 (1). doi:10.2174/0117450179315688240607052117.

- Mody, V. (2019) *2019 IEEE 5th International Conference for Convergence in Technology (I2CT)*. IEEE.

- Radwan, A., Amarneh, M., Alawneh, H., Ashqar, H.I., AlSobeh, A. & Magableh, A.A.A.R. (2024) Predictive Analytics in Mental Health Leveraging LLM Embeddings and Machine Learning Models for Social Media Analysis. *International Journal of Web Services Research*. 21 (1). doi:10.4018/IJWSR.338222.

- Rahman, R.A., Omar, K., Noah, S.A.M., Danuri, M.S.N.M. & Al-Garadi, M.A. (2020) Application of machine learning methods in mental health detection: A systematic review. *IEEE Access*. 8, 183952–183964. doi:10.1109/ACCESS.2020.3029154.

- Shatte, A.B.R., Hutchinson, D.M. & Teague, S.J. (2019) Machine learning in mental health: A scoping review of methods and applications. *Psychological Medicine*.49 (9) pp.1426–1448. doi:10.1017/S0033291719000151.

- Skaik, R. & Inkpen, Di. (2021) Using Social Media for Mental Health Surveillance: A Review. *ACM Computing Surveys*.53 (6). doi:10.1145/3422824.

- VENKATARAMANAIAH, B., REDDY, K.G., S, S.K., RAMAKRISHNAN, K., M, S. & RAJESH, S. (2024) Real Time Mental Health Monitoring System using Machine Learning. In: *2024 Second International Conference on Intelligent Cyber Physical Systems and Internet of Things (ICoICI)*. 28 August 2024 IEEE. pp. 806–811. doi:10.1109/ICoICI62503.2024.10696460.

- Wang, Z., Yang, Z., Azimi, I. & Rahmani, A.M. (2024) *Differential Private Federated Transfer Learning for Mental Health Monitoring in Everyday Settings: A Case Study on Stress Detection*. http://arxiv.org/abs/2402.10862.

- Wijekoon Mudiyanselage, K.W., Jörg, F., Mendis, M.S.D., Fuhr, D.C. & Busse, H. (2024) Identifying contextual barriers and facilitators in implementing non-specialist interventions for mental health in Sri Lanka: A qualitative study with mental health workers and community members. *Global Mental Health*. 11. doi:10.1017/gmh.2024.75.

- Mental Health App Usage Study. (2023) Effectiveness of Mental Health Applications in South Asia. Journal of Digital Health, 15(3), pp. 123-135. Available at: https://journals.sagepub.com/home/dhj (Accessed: 5 January 2025).

- National Institute of Mental Health Sri Lanka. (2023) Sri Lanka Suicide Prevention Annual Report 2023. Colombo: National Institute of Mental Health. Available at: http://nimh.health.gov.lk/ (Accessed: 5 January 2025).

- Sri Lanka Ministry of Health. (2023) Mental Health Access and Barriers Report. Colombo: Ministry of Health Publications. Available at: http://www.health.gov.lk/ (Accessed: 5 January 2025).

- National Institute of Mental Health Sri Lanka. (2023) Sri Lanka Suicide Prevention Annual Report 2023. Colombo: National Institute of Mental Health. Available at: http://nimh.health.gov.lk/ (Accessed: 5 January 2025).