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MindCare: Machine Learning based Personalized Mental Health Monitor

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***Abstract*—Mental health challenges are growing in recent years, emphasizing the need for effective monitoring and intervention systems. This paper presents a comprehensive approach to detect mental unstabilities by analyzing the text entered by the user. Utilizing a combination of sentiment analysis and machine learning techniques, the proposed system preprocesses text data to extract sentiment scores and other key features, which are then used to train models for accurate mental health assessments. The system also offers personalized recommendations based on the user's mental state. Experimental results demonstrate the effectiveness of the approach, with the model achieving accuracy of 82.31% for negative text classification. These results underscore the potential of the system to serve as a valuable tool in the early detection and management of mental health issues.**

***Index Terms*—Mental Health,Mental state, Monitoring, Personality, Well being**

I. Introduction

In recent years, mental health has gained increasing recognition as a critical component of overall well-being. Despite this growing awareness, many individuals still face barriers to accessing effective mental health support. These challenges often stem from the pressures to achieve professional success, accumulate wealth, and establish a reputation. The devastating impact of the COVID-19 pandemic and the subsequent extensive quarantines have profoundly affected everyone's lives, especially emotional well-being. This has created additional obstacles for individuals already struggling with mental health issues. Mental health refers to a psychological state in which an individual has a clear understanding of their own capabilities and limitations. Common manifestations of mental health problems include mood and personality changes, difficulty managing daily challenges or stress, and social withdrawal. Surviving with a mental disorder can impose significant physical, financial, and emotional burdens. Behavioral psychology, which focuses on understanding human behavior and emotions, provides valuable insights into these challenges. However, integrating these insights into accessible and user-friendly solutions remains a significant challenge.

Even though work generally promotes better health and well-being, some jobs may not be as beneficial as others [1]. Limited research has examined mental health across a broad range of occupations using large population samples. Despite the accessibility, affordability, and effectiveness of online therapies for common mental disorders, their uptake in the community remains low. A common reason cited for not pursuing mental health care is a lack of time. The study in [2] explored whether this excuse genuinely reflects a lack of time and how having more time influences the intention to use such interventions. According to [3], there appears to be a correlation between anxiety and depression and the duration of these interventions, with more time spent on them having a favorable effect on mental health.

To address this gap, the proposed system presents an innovative approach to mental health support by leveraging advanced machine learning techniques within a web-based platform. This system aims to serve as a comprehensive solution for individuals seeking to improve their mental well-being. The platform predicts and classifies mental health conditions through a combination of assessment tools, offering personalized recommendations to enhance psychological health. This study aims to leverage machine learning techniques to detect suicidal tendencies, predict burnout rates, and classify negative sentiments from user-generated content. These tasks are essential in understanding and improving mental health outcomes through timely interventions.

Upon accessing the platform, users can choose from various mental health assessments that evaluate their current emotional state. The system processes the responses to these assessments, predicting the user's mental health status. Based on the results, the platform suggests tailored activities and tasks designed to promote mental well-being. Additionally, the platform provides access to resources such as journals, yoga and exercise videos, motivational content, and literature on mental health, ensuring a holistic approach to mental wellness.

The contents of the paper are as follows: Section I provides the introduction to the topic and objectives of the work. Section II provides a discussion on the work done in the literature on the chosen topic. Section III describes the proposed methodology. Section IV provides the implementation details. Section V presents the results and discussion. The conclusion and future work are provided in Section VI.

II. LITERATURE SURVEY

People use mobile phone applications to assist with their mental health issues. The work in [4] checks to see if these apps are good at providing support and advice to individuals facing different mental health issues. They often do not do a great job of giving personalized advice or continuous support. In other words, they do not adapt to each person's specific needs and progress. Many of the apps reviewed lacked personalized recommendations and follow-up support, leaving users without a clear path for improvement. The review in [5] discusses the importance of mobile tools for monitoring and intervening in youth mental health issues. It highlights the use of ecological momentary assessments (EMAs) and digital phenotyping for daily monitoring. The review also discusses the results of the study, outlines the promises, limitations, and directions for future research, and evaluates the quality of the reviews using the AMSTAR checklist. Work in [6] examines mental health monitoring systems like virtual counseling, precision therapy, and diagnostic systems, analyzing their algorithms and parameters. It proposes a system that combines these systems for personalized mental care. AI technologies, such as chatbots and precision therapy, offer efficient services but may not replace one-on-one, individualized services.

Analysis of mental health-related apps in the Google Play Store from 2016 to 2020, focusing on symptoms like depression, anxiety, and stress, is analyzed in [7]. Apps offer relaxation, stress management, and symptom tracking, but their trustworthiness is difficult to predict based on ratings and user feedback. The work in [8] talks about how technology can change how one cares for mental health. It is said that digital tools, like apps or websites, should be easy to use and fit into daily routines to help with mental well-being. It is also mentioned that a few tools lack the user-friendly feature, making them less helpful. Scoping review in [9] examines the clinical evidence base of mental health apps for children and young people, categorizing features, and analyzing technical mechanisms. It highlights the ecological dimensions of life, health, and emotional experience, emphasizing the need for bioethics and neuroethics examination.

A study that assesses the quality of evidence on mental health apps in [10], focusing on anxiety and depression. It is noted that stand-alone apps have better empirical quality. However, meta-analyses and quality studies are needed for other mental health issues or specific populations. The survey in [11] revised existing research on mental health issues using wearable sensors, revealing promising results. Off-the-shelf wearable devices measure physiological data, including HR, sleep, and breathing patterns, and can identify and monitor panic attacks in real time. It is highlighted that advances in computational power and high-quality biosensors make this area of active research. And also include integrating wearable devices with virtual reality or telehealth for comprehensive support. A study of 106 mental health apps [12] found that understanding user opinions is crucial for app design. Key themes identified include usability, security, and customer service. To improve the user experience, developers should focus on rich content, personalization, security, and regular updates. Design recommendations include engaging users and promoting mental health. The study focuses on mental health app reviews, capturing diverse opinions. However, it lacks information on user preferences and app usage duration. The authors suggest adding app developer expertise information to descriptions in Google Play and App Store, aligning with the Persuasive System Design Model. This approach fails to capture all the needs and preferences of users. [13] explores mobile application innovation in mental health, including chatbot-based therapy, VR/AR, wearable technology, and ethical considerations, highlighting its potential to improve accessibility and effectiveness. The study in [14] introduces a method for predicting mental health status by utilizing sentiment analysis and facial expression results. The system employs emotion detection and textual analysis to accurately predict mental health states by simulating a one-on-one conversation between the user and the chatbot. Using a variety of inputs, the chatbot provides recommendations for regulating the user's mood.

The study in [15] looks at how a mobile app can help improve the quality of life for people with Type 2 diabetes. It shows that using a mobile app for mental support can be helpful, especially for people with long-term health problems. [16] talks about using technology, specifically machine learning, to figure out if someone has a mental health issue by listening to how they talk. This app can be useful to take the initial step in figuring out one's status of mind. The use of speech-based diagnosis may not capture the full spectrum of mental health concerns and may lack user engagement.

The study in [17] looks at a bunch of mobile apps that help people make healthier lifestyle choices, which can also benefit their mental health. It finds that these apps can be useful in helping people change their habits for the better. It is also mentioned that the app could struggle to provide personalized help for the long term. This will limit the long-term effectiveness of the app.

III. PROPOSED SYSTEM

The proposed system has a web interface that aims to act as a one-stop solution to address behavioral psychology and mental health challenges. Machine learning techniques are used to predict and classify mental health through assessment. After signing in to the platform, the user can select the assessment. The proposed methodology involves preprocessing user-generated text, which is then analyzed to extract sentiment scores and other relevant features. These features are used to train a model capable of detecting suicide, predicting burnout rates, and classifying negative text. Based on these predictions, the interface will suggest activities or tasks to improve mental health.

Figure 1 provides the system architecture of the proposed method. Once users enter the introductory page, they are presented with options to either login or register. Users can register by setting up or providing log-in credentials. Upon successful authentication, the user is automatically redirected to the home page. The homepage displays various categories, such as mental health assessments, journal records, and resources. The mental health assessments include a set of questionnaires that users need to answer. The journal record entries include the user interaction records. These entries, classified by mental state and the challenges faced, are stored in the database and can be viewed under the records tab. The resources include journal entries, yoga and exercise videos, motivational videos, and books on mental health.

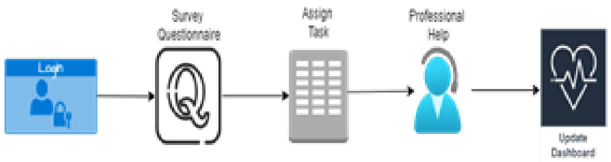

Fig. 1. Proposed Mental Health Monitor

Figure 2 provides the flow of training the model to predict the mental state of the user, based on their response to the questionnaire. Initially, the dataset is gathered, and then the preprocessing of the data is done. Consequently, the data is split into a training set and a testing set.

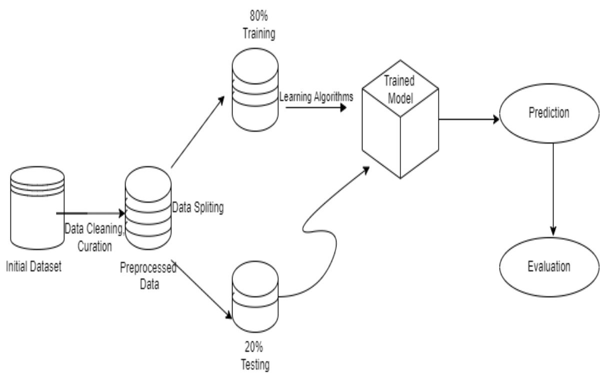

Fig. 2. Model Training

The initial stage involves gathering a dataset comprising textual data, which includes the classification of the text into categories such as suicidal, non-suicidal, and negative emotions. The datasets are divided into training datasets and testing datasets, respectively. The data is preprocessed to meet specific requirements before training. To train the mental health prediction module, a label encoder is used to encode textual columns. For the journal modules, superfluous columns are eliminated, the output columns are encoded using a label encoder, and the posts (texts) are cleaned by removing emojis, non-alphabetic characters, capital letters, and stop words. Subsequently, the purified text is subjected to lemmatization to discern a coherent and significant arrangement of the words. The lemmatized texts are then measured using methods such as TF-IDF and CountVectorizer.

IV. Methodology and Implementation

The combined approach for feature extraction and prediction involves a series of steps designed to integrate various types of data and enhance the predictive capabilities of the model. The first step is to gather the attributes of the dataset, which include things like years worked for the company, years of experience, years of evaluation, number of projects, average monthly hours, work accidents, turnover, promotions, department, and salary range. These features provide critical information about the individual's job profile and performance. The satisfaction levels are categorized based on predefined thresholds, converting raw scores into categorical labels to facilitate more straightforward analysis.

In parallel, sentiment analysis is performed using VADER (Valence Aware Dictionary and sentiment Reasoner). VADER analyzes text to produce sentiment scores, including positive, negative, neutral, and a compound score. The compound score, in particular, reflects the overall sentiment of the text, which is useful for understanding the emotional tone of the user's input. The next step involves combining these two sets of features. The sentiment scores from VADER are integrated with the dataset features to form a comprehensive feature set. This combined feature set is crucial for training the model, as it captures both the quantitative job-related metrics and the qualitative sentiment expressed by the user. Feature engineering is applied to ensure that all features are in a suitable format for model training. This includes converting satisfaction scores into categorical labels and normalizing or scaling features as needed to maintain consistency. The steps of execution are provided in Algorithm 1. Once the features are prepared, the model is trained using this enriched feature set. This training process allows the model to learn from both the dataset features and sentiment scores, improving its ability to make accurate predictions.

Algorithm 1 Preprocessing and Model Training

1: Clean the dataset by removing unnecessary characters such as links, non-alphabetic characters, and emojis.
2: Apply lemmatization to the cleaned text to standardize the words.
3: Use VADER to obtain sentiment scores (positive, negative, neutral, compound) from the text.
4: Extract additional text features using TF-IDF method.
5: Combine sentiment scores with other text features to create a comprehensive feature set.
6: Normalize the features if necessary.
7: Train the SVM model using the combined feature set.

For prediction, the same feature combination process is applied to new input data. The steps of execution are provided in Algorithm 2. The model uses the integrated feature set, which includes both dataset features and sentiment analysis results, to generate predictions. This approach ensures that the model can leverage all available information to provide a comprehensive assessment, enhancing its predictive accuracy and overall effectiveness.

The dataset for training the model is obtained from Kaggle [18]. This dataset is mainly used label the data as suicidal and non-suicidal cases. To analyze and train the model for employee emotions, the HR dataset is used [19]. This dataset contains attributes such as work satisfaction, sales performance, salary, average time spent in the office, and total time spent on work, based on which the mental health rate will be classified.

Algorithm 2 Prediction Process

if Survey is used **then**
    Collect responses from the user through a survey to gather relevant data.
else
    Allow the user to enter their thoughts or feelings in a text box, referred to as the journal.
end if
Clean the text by removing unnecessary characters such as links, non-alphabetic characters, and emojis.
Apply lemmatization to the cleaned text to standardize the words.
Use VADER to obtain sentiment scores from the preprocessed text.
Transform the preprocessed text into the same format used during training.
Combine the sentiment scores with other text features.
Input the combined features into the trained SVM model to make predictions.

Natural language is used for processing tasks, crucial for analyzing textual data, were facilitated by the Natural Language Toolkit (NLTK), enabling functionalities such as text cleaning and tokenization. Data visualization components were developed using Matplotlib, allowing for the graphical representation of findings and insights. TensorFlow was the backbone for building and training machine learning models, empowering the system to accurately predict mental health states. Scikit-learn complemented TensorFlow by offering a comprehensive suite of machine learning algorithms and tools for model evaluation and selection. Joblib was used for efficient model serialization and deserialization, optimizing deployment and scalability. Together, these packages formed the core infrastructure of the implementation, enabling the development of a robust and versatile system for mental health assessment and support. XAMPP [20] was used as the primary tool for data storage, managing crucial user information, including classifications and mail templates. This database plays a pivotal role in handling real-time application loads and facilitating comprehensive analysis of user interactions and data patterns.

V. Result

The mental health tracker web application developed in this project successfully enables users to register, complete a questionnaire, and receive personalized mental health suggestions based on their responses. The model demonstrates robust performance across various mental health-related tasks. For suicide detection, the model achieves an accuracy of 92.43%, effectively identifying instances with a high degree of precision. In predicting burnout rates, the model performs with an accuracy of 86.20%, showcasing its capability to assess the risk of burnout based on input data. Additionally, the model accurately classifies negative text with an accuracy of 82.31%, underscoring its effectiveness in detecting adverse sentiments or expressions within the text.

The screenshots illustrated provide the user interface, showcasing the intuitive design of the questionnaire and the delivery of tailored mental health recommendations. These results underscore the effectiveness of the system in providing meaningful and actionable mental health insights to users. Figure 3 provides the confusion heat map of the negative text classification model implemented using SVM. On the heat map, the diagonal represents the true positive (TP) and true negative (TN) values. It can be observed that the diagonal contains the highest values on all the rows, which indicates the model is providing accurate predictions.

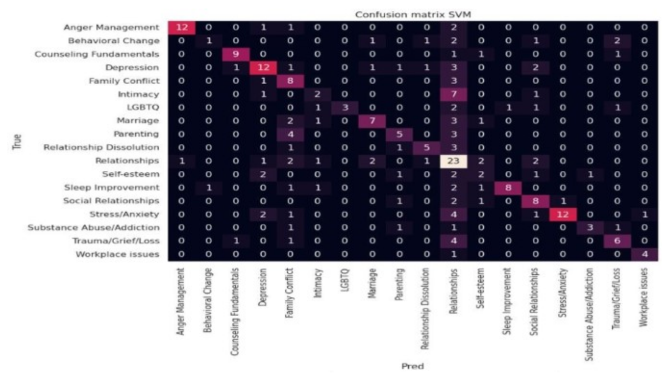

Fig. 3. Text classification model heat map

The mental health rate prediction module takes several inputs from users via form, as shown in Figure 4.

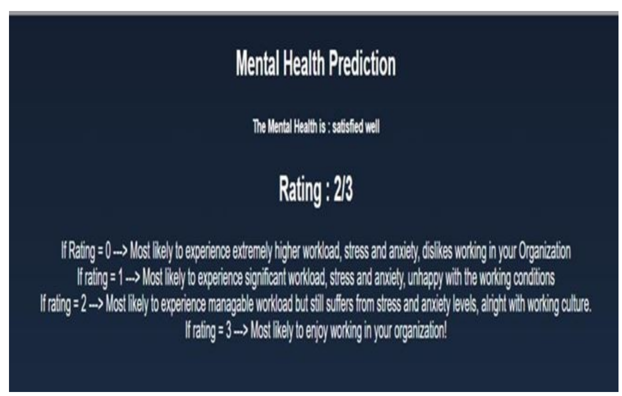

Fig. 4. Survey Questionnaire

The rating and the prediction value are showcased on the same page after processing user inputs via questionnaire, which will be displayed on the screen in Figure 5. Based on the state of mind of the user, it would suggest activities. One such activity is to advise users to read good books, play games, perform exercises, or listen to some soothing music. The same can be recorded in the journal to assess the user's mental status. The entry given by the user in the journal module is classified as a model performance table, and the confirmation is displayed to the user on the journal page as shown in Figure 6.

Fig. 5. Mental Health Status

Fig. 6. Journal page

After analyzing the mental health status of the user, the model provides suggestions and links to various activities for the user. Based on their interest, the user can select the link and participate in the emotion-boosting activities. The screenshot of the page is provided in Figure 7.

Fig. 7. Motivation – Techniques for better well-being

VI. Conclusion

The proposed system takes cognitive state-determining parameters from the user as input and decides the mental state or classifies the user's inferred emotional state and triggers alerts whenever critical. The database integrates several standalone modules to share data making it a self-sufficient, communicative application. The modules showcase an accuracy of 80% on average. The system enables the user to check whether one is suffering from a complex cognitive state and also assist them in dealing with those conditions.The main goal of this paper was to create a system that acts as a central platform. In this Application, mental health issues are addressed more precisely, leading to improved overall well-being. In addition to saving time, this application also removes the necessity for the user to navigate through numerous websites.

The resources or information page is simply a digest of several scientifically proven methodologies to improve mental well-being and critical counselor's contacts and helpline numbers presented as comprehensively as possible to make it readable by people of any age group and of any geographical background. A simple Instruction guide on how to use the web application is also listed on the homepage of the application to avoid any application usage difficulties. The system enables users to access the application without any additional complications. Deploying the application on the Internet allows users from different geographical locations and time zones to use the services, thereby eliminating location access barriers. Additionally, multilingual support can be added to the application to enable users to submit and view data in their local preferred languages as English might not be the preferred language for everyone and this can increase the interactions with the application as the users can find the data in a script they understand the most. Providing support features on-board counselors, and voice assistants can always be positive add-ons.

References

[1] F. Ferry, M. Rosato, E. Curran, and G. Leavey, "Occupation type, family demands and mental health: analysis of linked administrative data," *Journal of Mental Health*, vol. 33, no. 2, pp. 150–158, 2024.

[2] J. Busby Grant, A. Gulliver, A. L. Calear, L. M. Farrer, and P. J. Batterham, ""i don't have time": an exploration of the role of time pressures in acceptance of internet interventions for mental health," *Journal of Mental Health*, vol. 33, no. 2, pp. 169–176, 2024.

[3] F. Karim, A. A. Oyewande, L. F. Abdalla, R. C. Ehsanullah, and S. Khan, "Social media use and its connection to mental health: a systematic review," *Cureus*, vol. 12, no. 6, 2020.

[4] S. Elbagir and J. Yang, "Twitter sentiment analysis using natural language toolkit and vader sentiment," in *Proceedings of the international multiconference of engineers and computer scientists*, vol. 122, no. 16. sn, 2019.

[5] L. Marciano, E. Vocaj, M. A. Bekalu, A. La Tona, G. Rocchi, and K. Viswanath, "The use of mobile assessments for monitoring mental health in youth: Umbrella review," *Journal of Medical Internet Research*, vol. 25, p. e45540, 2023.

[6] V. Mody and V. Mody, "Mental health monitoring system using artificial intelligence: a review," in *2019 IEEE 5th International Conference for Convergence in Technology (I2CT)*. IEEE, 2019, pp. 1–6.

[7] M. A. Islam and N. Choudhury, "Mobile apps for mental health: a content analysis," *Indian J Mental Health*, vol. 7, no. 3, pp. 222–229, 2020.

[8] J. K. Rout, K.-K. R. Choo, A. K. Dash, S. Bakshi, S. K. Jena, and K. L. Williams, "A model for sentiment and emotion analysis of unstructured social media text," *Electronic Commerce Research*, vol. 18, pp. 181–199, 2018.

[9] J. E. Williams and J. Pykett, "Mental health monitoring apps for depression and anxiety in children and young people: A scoping review and critical ecological analysis," *Social Science & Medicine*, vol. 297, p. 114802, 2022.

[10] T. Lecomte, S. Potvin, M. Corbie`re, S. Guay, C. Samson, B. Cloutier, A. Francoeur, A. Pennou, Y. Khazaal *et al.*, "Mobile apps for mental health issues: meta-review of meta-analyses," *JMIR mHealth and uHealth*, vol. 8, no. 5, p. e17458, 2020.

[11] N. Gomes, M. Pato, A. R. Lourenco, and N. Datia, "A survey on wearable sensors for mental health monitoring," *Sensors*, vol. 23, no. 3, p. 1330, 2023.

[12] F. Alqahtani and R. Orji, "Insights from user reviews to improve mental health apps," *Health informatics journal*, vol. 26, no. 3, pp. 2042–2066, 2020.

[13] S. Akbar, N. Andriani *et al.*, "Mobile app innovation in mental health monitoring," *Jurnal Kesehatan*, vol. 2, no. 4, pp. 253–261, 2024.

[14] A. Naik, P. Ushashree, K. Sooda, A. A. Munsur, H. Fathima, and J. V. Patil, "Carebot: A mental health chatbot," in *2024 5th International Conference on Innovative Trends in Information Technology (ICITIIT)*. IEEE, 2024, pp. 1–6.

[15] B. L. Cook, A. M. Progovac, P. Chen, B. Mullin, S. Hou, and E. Baca-Garcia, "Novel use of natural language processing (nlp) to predict suicidal ideation and psychiatric symptoms in a text-based mental health intervention in madrid," *Computational and mathematical methods in medicine*, vol. 2016, no. 1, p. 8708434, 2016.

[16] F. A. Acheampong, H. Nunoo-Mensah, and W. Chen, "Transformer models for text-based emotion detection: a review of bert-based approaches," *Artificial Intelligence Review*, vol. 54, no. 8, pp. 5789–5829, 2021.

[17] R. Alderslade, A. Fawcett-Henesy, and M. Ruseva, "On the perspectives of public health and what ihpa can contribute to its advancement in practice," *South Eastern European Journal of Public Health (SEEJPH)*, 2018.

[18] Kaggle.com, "Suicide and depression detection," https://www.kaggle.com/datasets/nikhileswarkomati/suicide-watch, 2021, [online] Available.

[19] Kaggle.com, "HR," https://www.kaggle.com/datasets/liujiaqi/hr-comma-sepcsv, 2018, [Online; accessed 13-May-2024].

[20] D. D. Dvorski, "Installing, configuring, and developing with xampp," *Skills Canada*, vol. 492, 2007.