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ML-Driven Health Prediction using Smartphone Screen Time

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Abstract. In recent years, research has shown a direct link between how much time we use our smartphones and our mental well-being, our sleep quality, and our productivity, ultimately leading to an increase in mental illnesses. Therefore, this paper presents an ML-based digital health decision support system that utilizes one's daily/weekly/monthly smartphone screen time as well as one's behavioral data to predict the likelihood of suffering from a mental illness. Using user behavior analysis via machine learning and a digital twin–based prediction mechanism, our framework can analyze an individual's current behavior to predict how this behavior may affect future mental health risk progression. The system will use varying metrics of daily behaviors (e.g., daily screen time, hours of sleep, stress levels, productivity levels, and well-being index) in conjunction with multiple classification models (e.g., KNN, SVM, Decision Tree, and Ensemble) to classify a user's risk of developing a mental disorder. The ensemble model has achieved 90% accuracy and shown greater than 94% confidence in correctly classifying a case as high risk. The system will also provide a visual and quantitative assessment of 12 months of digital twin risk predictions, enabling individuals to proactively address and reduce the risk of developing a mental disorder. Finally, our digital health decision support system will generate automated clinical recommendations and prepare personalized health reports to help with early detection, increased awareness of digital well-being issues, and ongoing preventive mental health monitoring.

Keywords: Machine Learning, Digital Twin, Mental Health Prediction, Smartphone Screen Time, Decision Support System.

1. INTRODUCTION

Smartphones have become an essential tool for modern day to day activities such as communication, working, having fun, and following deadlines. They provide many benefits however, overusing and not monitoring how much time you spend on your smartphone has been linked to an increased number of issues related to health such as trouble sleeping, increased stress, decreased productivity, and negative impacts on mental health. As we continue to increase our use of digital devices it

is clear we need developed smart systems that work to analyze behavior to detect mental health concerns early on.

Recent advances in machine learning have made it possible to accurately predict health outcomes from large behavioral data sets. Analyzing smartphone use along with sleep patterns, stress levels, and activity data has been especially beneficial; however, existing solutions provide very little in the way of continuous monitoring or long-term decision support. The purpose of this paper is to describe Mind Fusion, a machine learning-based mental health decision support system that uses machine learning algorithms such as KNN, SVM, and decision tree to analyze behavioral factors like time spent on screen, amount of sleep, level of stress, productivity, and wellness scores through an ensemble approach for improved accuracy and reliability.

One innovative feature of this system is the inclusion of a digital twin that represents a user's mental health over a projected 12-month period and generates visual and numerical forecasts for future risk trends. In addition to providing visual forecasts, this system also includes a clinical decision support (CDS) component that produces and provides users with confidence scores, health recommendations, and individual reports for the purpose of awareness and screening, but not for the purpose of making a clinical diagnosis.

The predictive accuracy of the proposed ensemble model (90%) validates the capacity of the model to consistently identify high-risk behaviour through machine learning combined with digital prototyping (twins) and interactive visualisation, in order to support timely interventions and early, preventative mental health monitoring. It is difficult to identify when excessive use of technology occurs in the absence of direct impact on daily life; however, by identifying these behaviours early enough, it would prevent long-lived behaviours. A lack of accessible, evidence-based tools for continuous monitoring makes it challenging to have access to a preventative, evidence-based approach to monitoring one's behaviour. This creates an opportunity to develop intelligent systems based on machine learning and digital twin methodologies, which apply to extended environments beyond those typically seen in clinical settings, to provide a user with interpretable feed-back in a timely manner. By combining the aforementioned technologies, the proposed framework will provide a bridge between short-term assessments of mental health with the long-term monitoring of behaviours, with the use of automated decision support and interactive visualisation enabling users to better understand their own well-being while increasing the transparency and insightfulness of their ability to make informed decisions to manage their mental health in a more proactive manner.

2. BACKGROUND AND MOTIVATION

A smartphone is now an integral part of our daily exis-tence, providing ways to communicate, educate, work, and entertain ourselves. Though the advantages of these devices are apparent, the negative influence of increased screen time and irregular habits of use can adversely affect sleep quality, level of mental acuity, degree of stress, and overall well-being. Many are unaware of how their daily digital habits have a cumulative effect on their mental health until they start experiencing symptoms indicating that this has happened.

The traditional approach to tracking one's mental health or digital fatigue typically consists of self-reporting via survey or through intermittent visits to a clinician. Self-assessment surveys often lack validity and do not reflect what is truly happening. Additionally, the majority of tools currently avail-able analyze only the past, therefore, are incapable of indi-cating how one's current habits may influence future health outcomes. Consequently, opportunities for early intervention and preventative care are often lost.

More and more people have access to smartphones today and are thus able to collect and analyze data on how they use their phone, including things like how long they spend looking at it, how well they sleep, how stressed out they are and how productive they are. While this has resulted in an increase in the number of systems available that can analyze these types of data, most of them rely on single-model predictions and are not equipped to make long-term predictions or provide good support for decision making. Therefore, this project will combine ensemble machine learning techniques with a digital twin-based approach to develop a forecasting system that provides immediate assessment of mental health risk to individuals and a 12-month forecast of future risk. The final system will also include interactive visualizations and provide automated recommendations to help users understand how their digital behavior impacts their mental wellness. By utilizing a transparent, interpretable, and continuously monitored system, the proposed solution will facilitate early detection, promote healthy digital habits and assist with the proactive management of mental health in non-traditional clinical settings.

3. RELATED WORK

Numerous studies have explored the influence of mobile phone usage and screen exposure on people's mental health and general wellness. Researchers have observed that in-creased screen exposure is related to increased levels of stress, sleep issues, anxiety, and lower overall mental well-ness through both experimental and longitudinal studies. One randomized controlled trial was particularly illustrative of the negative psychological effects of digital behaviours, as participants showed measurable improvements in multiple forms of mental health indicators after reducing their use of smartphones. This study was among many other long-term observational studies that have demonstrated the consistent na-ture of both positive and negative relationships between screen time and mental health outcomes, particularly in adolescents. Several broader literature reviews have reported similar find-ings in examining the relationship between prolonged digital screen exposure and cognitive performance, brain growth, and coupled behavioural outcomes. The existing literature highlights negative effects of excessive or prolonged digital screen time on learning, memory, brain growth, and psychiatric well-being across all ages. In contrast, other researchers have studied the risks and benefits of prolonged digital screen ex-posure but concluded that patterns and duration of use are the determining factors for the mental health outcome measures. In addition, evidence from emerging studies demonstrates smart-phone multitasking and ongoing smartphone usage among children and adolescents to be the most significant risk factors for mental health concerns in that age group.

Neuroimaging studies have also identified structural changes in the brain associated with problematic

Artificial Intelligence (AI) and Machine Learning (ML) is being increasingly applied in the field of mental health for use in early identifying, assessing and monitoring the onset of mental health issues. Integrative and systematic literature reviews have provided potential benefits related to AI and ML-based decision-making tools but also high-light challenges around things like interpretability, reliability and clinical deployment in real-world settings [1]. Human-Computer Interaction genre reviews emphasize that for mental health uses to be useful, they need to have explainable, user-centered and practical planning [2]. Data-driven approaches have been validated in multiple empirical studies across many disciplines and contexts for predicting mental health status through behavioral and lifestyle-based data [13]. Researchers are now looking into using continuous monitoring methodolo-gies to provide more accurate data than traditional episodic methods of mental health assessment. Using wearables as a means to overcome barriers with traditional methods to assess the presence of stressors, researchers have been able to demonstrate successfully the ability to provide continuous real-time detection and monitoring of individuals experiencing stress in their daily lives [14]. Digital Health Technology-based interventions can help scale access to mental health services especially for children and youth [15]. Lifestyle behaviours (daily routines and technology use) have been identified as contributors to both physical and mental health and should be considered in holistic health assessments [10]. Although significant progress has been made, most existing studies focus on static prediction models, isolated monitoring tasks, or short-term assessments. Limited attention has been given to long-term risk forecasting, behavioural simulation, and integrated decision support mechanisms. Few approaches combine multiple modelling techniques to provide insights into both current behavioural risks and future mental health trajectories. These limitations highlight the need for systems that integrate predictive modeling with forecasting and deci-sion support to enable proactive mental health monitoring and early intervention.

4. PROPOSED SYSTEM ARCHITECTURE

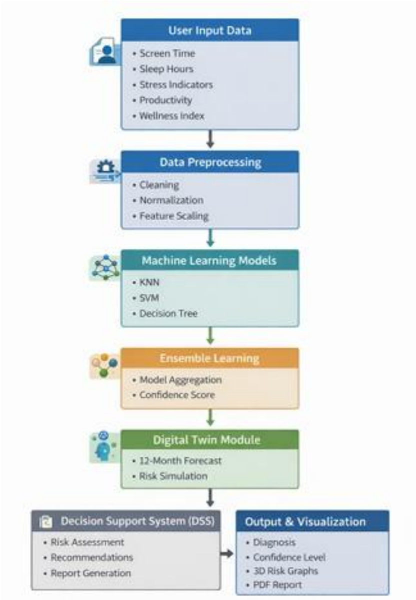

Fig. 1. Proposed system architecture of the ML-driven digital mental health decision support framework

The proposed system architecture offers a comprehensive approach to forecasting mental health by utilising both smart-phone display time and behavioural data, providing an inte-grated solution from data collection to machine learning-based forecasts to digital twin forecasting through machine supported decision-making. This allows for proactive and interpretable monitoring of mental health.

The initial phase of the system focuses on the collection, cleansing and normalisation of user specific behavioural infor-mation such as daily screen time, hours of sleep, stress levels, productivity and wellness levels to serve as input features. The raw behavioural data are then processed using industry approved techniques to provide the machine learning models with the correct data to enable accurate machine learning. The raw data will be processed using feature scaling to reduce the potential for bias caused by the differences in the scales of the various features.

In the second stage, the processed data is fed into multiple machine learning models, including the K-Nearest Neigh-bor (KNN), Support Vector Machine (SVM), and Decision Tree classifiers. Each model independently learns behavioral patterns associated with different mental health risk levels. To improve robustness and prediction accuracy, an ensemble learning strategy is employed, combining the outputs of in-dividual models to generate a final prediction along with a confidence score.

A user's mood is predicted using a digital twin that creates an online representation of the user's digital behaviors through historical behavior data, machine learning predictions, and nu-merical and visual data. DSS outputs the actionable items that combine predictions, including confidence scoring and digital twin predictions, to produce health risk summaries, generate computerized recommendations, and generate personalized reports. The modular system allows the independent operation of separate components and a constant flow of information, permitting the continued addition and use of future data and algorithms. A combination of providing visual and quantitative information about a user's digital behavior will aid the user in interpreting the information and believing in the system, which will improve the user's ability to recognize potential mental health risks and to provide support to help create strong digital wellness.

5. METHODOLOGY

This section describes the methodology adopted to design and implement the proposed ML-driven digital mental health decision support system. The methodology consists of data acquisition, preprocessing, machine learning model training, ensemble-based prediction, digital twin forecasting, and decision support generation.

A. Data Collection and Feature Selection

Data from smartphone usage patterns (behavioral/lifestyle related) will be utilized to create predictive models to de-termine risk for developing mental illnesses, based on both previous research linking digital behavior/lifestyle habits to predictive measures of mental illness, and the collected data itself.

B. Data Preprocessing

The raw data will first undergo preprocessing to improve data quality and enable the use of predictive modelling al-gorithms. This stage will include data cleaning (removal of erroneous data) by identifying and first filling in any missing data, and then removing or normalizing the data that is not sufficiently complete. The resulting data structure is an appropriate example for how to use the same data to perform different types of predictive modelling.

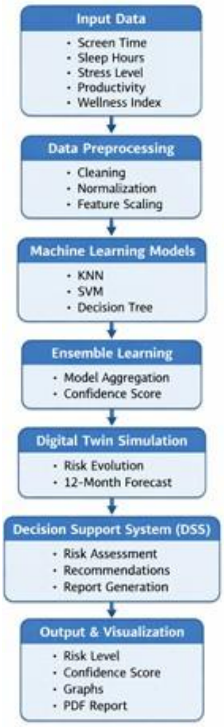

Fig. 2. Workflow of the proposed methodology for mental health risk prediction

C. Machine Learning Model Training

As part of the modelling process, different numbers of models will be trained to independently learn the various behavioral patterns of individuals with different levels of risk for developing a mental illness (as evidenced by their use of a smartphone). The algorithms selected for this study include Support Vector Machine (SVM) with a radial basis function kernel (RBF), K-Nearest Neighbour (KNN) and Decision Tree Classification (DTC). Each model will be trained on the preprocessed dataset and will be evaluated according to an accuracy metric.

D. Ensemble Learning Strategy

An ensemble approach is used to improve the robustness of predictions and decrease the model bias of predictions. The ensemble output is constructed by combining the predictions of individual classifiers through voting to produce a collective risk prediction. The output from the ensemble will be pre-sented as the predicted class and confidence value to provide a measure of the confidence in the ensemble output. In addition to improving the overall accuracy of the constructed system as compared to using only individual classifiers, the calculated ensemble outputs will be used to quantify how the long-term risk to a user's mental health may change as time progresses.

E. Digital Twin-Based Risk Forecasting

A digital twin module will be used to represent how a user's risk of developing a mental health disorder will change over time. Using the ensemble and historical behavioural patterns of the user, the digital twin will create a 12-month forecast of the user's risk of developing a mental health disorder, accounting for changes in risk based on the user's current behavioural pattern. The 12-month forecast will be presented numerically as well as visually in a 3-dimensional (3D) manner, providing an understanding of long-term risk as opposed to only static predictions.

F. Digitization and Knowledge Representation in Ayurveda

The last component of the methodology will utilize the prediction, confidence level, and digital twin forecasts results within a decision support system. The decision support system will produce a series of actionable recommendations, risk summaries, and reports similar to a medical report for the user. In addition to the reports, interactive graphical representation will be made available through the user interface to illustrate trends in user risk and the user's 3D health map. While the decision support system is designed to be an artificial intelligence (AI)-based screening and awareness tool, it does not serve as a replacement for clinical assessment.

G. Model Simulation Using Mathematical Formulation

This subsection presents the mathematical formulation used to simulate the behavior of the machine learning models employed in the proposed system. The models operate on behavioral attributes such as screen time, sleep duration, and stress level to predict mental health risk.

1. **K-Nearest Neighbors (KNN):** The KNN classifier determines the class of a test instance by computing the distance between the input feature vector and training samples. Given an input vector

$$X = (x_1, x_2, x_3),$$

the Euclidean distance between X and a training sample X_i is defined as

$$d(X, X_i) = \sqrt{\sum_{j=1}^{n} (x_j - x_{ij})^2},$$

where n represents the number of features. The final class label is assigned based on majority voting among the k nearest neighbors.

2. **Decision Tree Classifier:** The Decision Tree classifier performs prediction using a hierarchical structure of decision rules derived from feature thresholds. A generic decision rule can be expressed as

$$\text{If } x_i \leq \theta \Rightarrow C_1, \text{ else } C_2,$$

where x_i denotes a selected feature, θ represents the splitting threshold, and C_1, C_2 are the resulting class labels. The final prediction is obtained by traversing the tree from root to leaf.

3. **Support Vector Machine (SVM):** The SVM classifier separates data points by learning an optimal hyperplane that maximizes the margin between classes. The decision function is given by

$$f(X) = w^T X + b,$$

where w is the weight vector and b is the bias term. The class assignment is defined as

$$\text{Class} = \begin{cases} +1, & \text{if } f(X) \geq 0, \\ -1, & \text{if } f(X) < 0. \end{cases}$$

4. **Ensemble Prediction Strategy:** The ensemble model combines the predictions of individual classifiers to improve robustness. The final class label is determined using majority voting:

$$C_{final} = mode(C_{KNN}, C_{DT}, C_{SVM}),$$

where C_{KNN}, C_{DT}, and C_{SVM} denote the predictions of the respective models. The confidence score is computed based on the agreement among the classifiers.

H. Mathematical Formulation of the Prediction Models

In this portion of the document, there is a description of how the mathematical formula has been developed that will allow the machine learning models being used within the system to simulate the way that the models will operate. The models will make their predictions using a number of different behaviours including screen time, sleep time and stress levels, and this will allow each individual to have their mental health classified in terms of the different risk categories assigned to them.

1) **K-Nearest Neighbors (KNN):** is a classification tech-nique whereby a KNN Classifier determines what class to assign to a new point (the test instance) based upon the distance of that point from training points already present in the dataset. Therefore, given an input feature vector, e.g.,

$$X = (x_1, x_2, x_3)$$

where

- x_1= Screen Time
- x_2= Sleep Duration
- x_3= Stress Level

The Euclidean distance between the input vector $X$and a training sample X_i is calculated as

$$d(X, X_i) = \sqrt{\sum_{j=1}^{n} (x_j - x_{ij})^2},$$

Where n represents number of features.
The predicted class is obtained by selecting the majority class among k nearest neighbors.

2) Decision Tree Classifier: This classifier performs predic-tion through a hierarchical structure of decision rules derived from feature thresholds.

A general decision rule is defined as
If $x_i \leq \theta \Rightarrow C_1$
Else $\Rightarrow C_2$
where

- x_i= selected feature
- θ= decision threshold
- C_1, C_2= class labels

The final class prediction is obtained by traversing the tree from the root node to the leaf node.

3) Support Vector Machine (SVM): The SVM classifier determines the optimal separating hyperplane between classes.
The decision function is expressed as

$$f(X) = w^T X + b$$

where

- w= weight vector
- b= bias term

The predicted class is defined as

$$\text{Class} = \begin{cases} +1 & \text{if}\, f(X) \geq 0 \\ -1 & \text{if}\, f(X) < 0 \end{cases}$$

4) Ensemble Prediction Strategy: To improve prediction reliability, an ensemble approach combines the outputs of the individual classifiers.

The final predicted class is obtained using majority voting:

$$C_{final} = mode(C_{KNN}, C_{DT}, C_{SVM})$$

where

- C_{KNN}= prediction from KNN model
- C_{DT}= prediction from Decision Tree model
- C_{SVM}= prediction from SVM model

5) Example Prediction Scenario: Consider a user with the following behavioural attributes:

TABLE I
EXAMPLE BEHAVIOURAL INPUT.

Feature	Value
Screen Time	4 hours
Sleep Duration	7 hours
Stress Level	5

The feature vector is

$$X = (4, ,7\ 5)$$

Assume a training sample

$$X_i = (5, ,6\ 6)$$

The Euclidean distance becomes

$$d(X, X_i) = \sqrt{(4-5)^2 + (7-6)^2 + (5-6)^2}$$
$$d(X, X_i) = \sqrt{1+1+1}$$
$$d(X, X_i) = \sqrt{3}$$

Based on the nearest neighbours and ensemble voting, the final predicted class is

$$C_{final} = 1$$

where

- 0 = Stable
- 1 = Acute Digital Stress
- 2 = Chronic Digital Fatigue

This example demonstrates how behavioural attributes are mathematically processed to generate a mental health risk prediction.

6. EXPERIMENTAL RESULTS AND OUTPUT ANALYSIS

The behavioral dataset was analyzed to understand the relationships between key features such as screen time, sleep duration, and stress indicators. Visual exploration of the data helps identify clustering patterns and variations that contribute to mental health risk prediction.

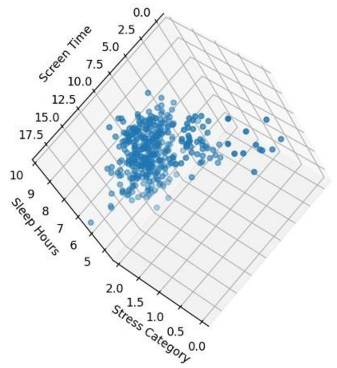

Fig. 3. 3D visualization of behavioral data distribution illus-trating the relationship between screen time, sleep duration, and stress category.

The observed clustering behavior indicates that variations in screen time and sleep duration are associated with different stress levels, which supports the selection of these features for machine learning–based mental health risk prediction.

A. Experimental Setup

Smartphone habits were used in the studies as a behavioral dataset. Data collected included: total screen time during a single day; sleep length; stress levels; productivity levels; overall wellness ratings. This dataset was pre-processed prior to splitting into training and testing datasets and training each machine learning program (KNN, SVM, and Decision Tree). Therefore, it is reasonable to compare the performance of each model against each others' model training datasets.

B. Evaluation Metrics

TStandard classification metrics were used to evaluate sys-tem performance. Specifically, accuracy was the primary mea-sure used to assess ML predictive model accuracy. The con-fusion matrix is one of the most accepted means of evaluating the performance of a machine learning model. The confusion matrix compares the number of correctly predicted samples to the number of incorrectly predicted samples for each class of a machine learning model (True Positives, True Negatives, False Positives, False Negatives). Additionally, using the confusion matrix provides a measure of the reliability and robustness of machine learning prediction models.

C. Model Performance Analysis

Fig. 4 provides a comparison of the accuracy of each classifier individually as well as the accuracy of the ensemble model collectively. The ensemble model has the highest overall accuracy, verifying that the strengths of individual classifiers can be effectively combined to produce better predictions.

The ROC curve shown in Fig. 5 illustrates an ROC (Re-ceiver Operating Characteristic) graphically, which is a way to show the relationship between the true positive rate and the false positive rate for various machine learning models. The more close a model is to the upper left corner of the ROC plot, the better the performance of the classification method is.

Fig. 6 shows how screen time, sleep time and stress con-tribute to predicting mental health risk.

Fig. 7 demonstrates the increase in both training and valida-tion accuracies as the size of the dataset increases. The gradual increase in the validation accuracy implies that the model's learning is stable, which helps prevent the model from being overfit.

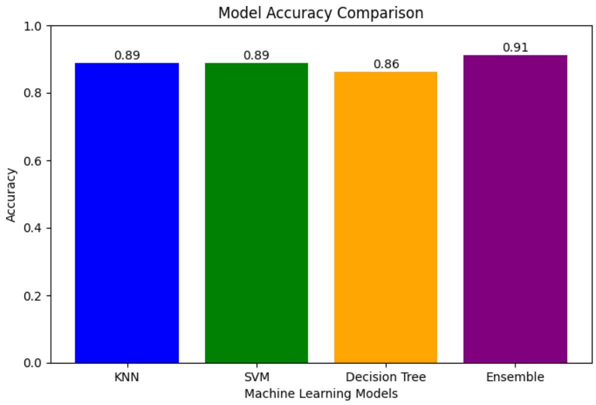

Fig. 4. Accuracy comparison of machine learning models.

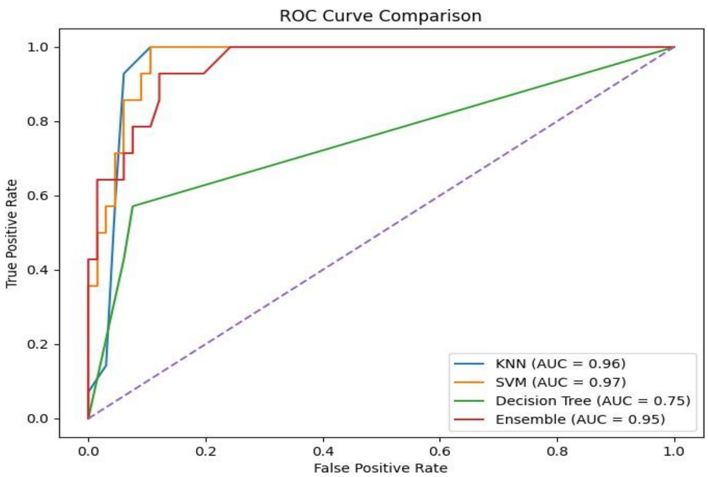

Fig. 5. ROC curve comparison of classifiers.

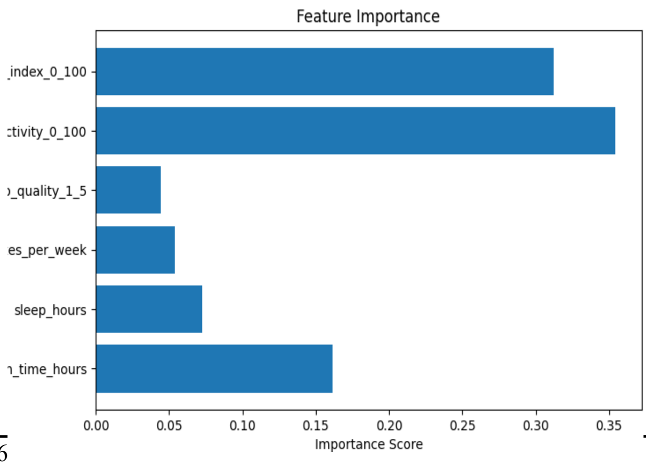

Fig. 6. Feature importance analysis of behavioral attributes.

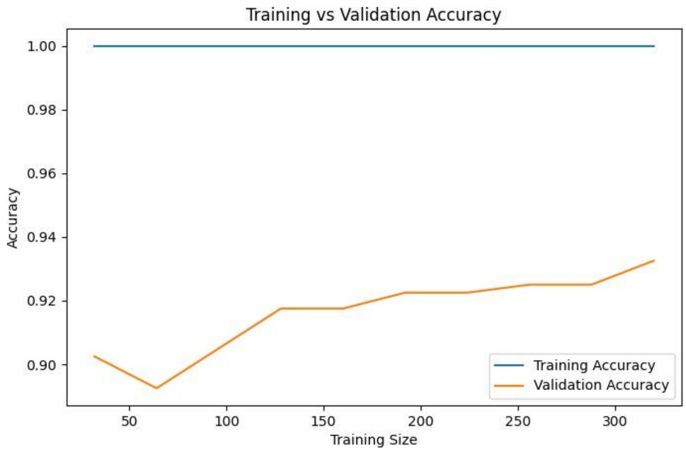

Fig. 7. Training versus validation accuracy.

D. Confusion Matrix Analysis

The confusion matrix for the KNN classifier can be found in Fig. 8. This matrix shows the relationship between the predicted class label and the actual class label; instances of correct classification are represented by the matrix' diagonal entries. The accuracy of the KNN classifier is high, as it can classify a significant majority of the instances correctly. However, there are some incorrect classifications that can be found away from the diagonal in the confusion matrix.

Fig. 9 presents the confusion matrix of the SVM classifier. The concentration of values along the diagonal demonstrates that the SVM classifier can achieve high levels of predictive accuracy. However, some of the off-diagonal values reflect some small amounts of incorrect predictions on the basis of the class.

The confusion matrix for the Decision Tree classifier can be seen in Fig. 10. The confusion matrix provides evidence that this classifier is capable of classifying a large number of instances correctly. However, there are some instances that have been misclassified due to the limitations of a single decision tree structure.

The confusion matrix of the Ensemble classifier can be found in Fig. 11. In contrast to the confusion matrices of the individual classifiers, the confusion matrix of the ensemble classifier has a significantly greater number of instances cor-rectly classified, as well as a significantly lower number of instances misclassified. This demonstrates that the Ensemble classifier provides higher levels of predictive accuracy and greater overall model stability than the individual classifiers.

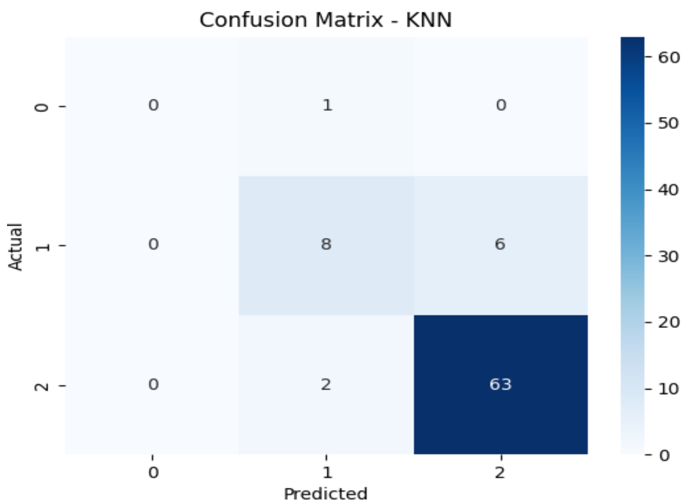

Fig. 8. Confusion Matrix of the KNN Classifier.

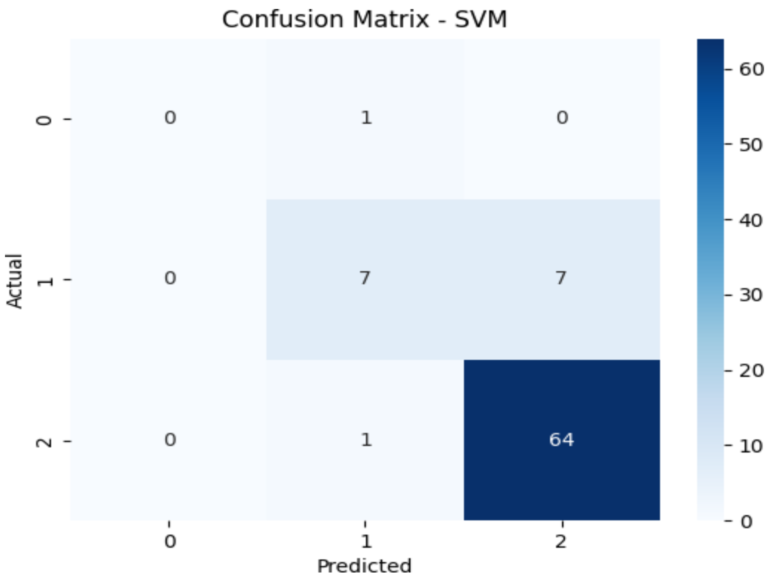

Fig. 9. Confusion matrix of the SVM classifier.

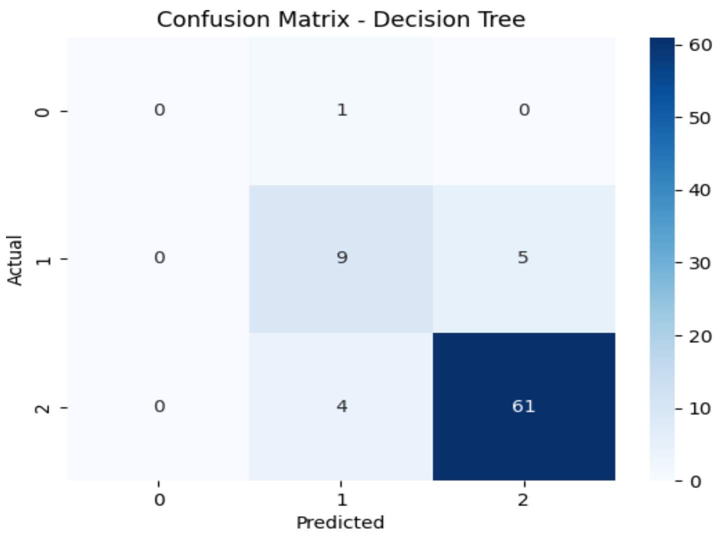

Fig. 10. Confusion matrix of the Decision Tree classifier.

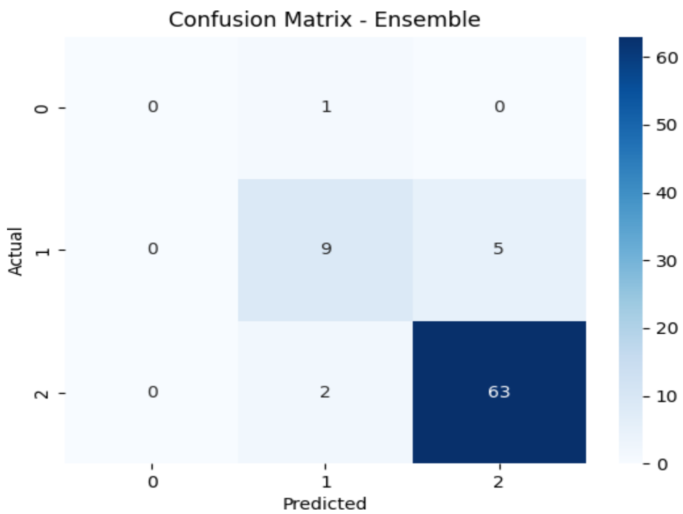

Fig. 11. Confusion matrix of the Ensemble classifier.

E. Decision Support Output Analysis

The final output(s) from the system will be presented to users via Decision Support Interfaces (DSIs) with risk classifi-cation, confidence level, and individualized recommendations. Understanding the user's risk will be further enhanced through the use of different forms of interactive visualizations such as trend graphs or three-dimensional (3D) representations of risk. The medical reports generated by the system will promote awareness of and facilitate screening for individuals at risk of developing mental health issues as they clearly indicate to the user that the system is designed for non-clinical use.

7. FUTURE WORK

The future upgrades planned will involve connecting smart-phones and wearable technology to pull continuous data for real-time adaptive mental health monitoring. In addition to all current physiological factors (heart rate variability), more factors (i.e. physical activity level), and sleep quality (by hour). The additional benefit of including context (i.e. the subject's patterns of movement throughout the day) will provide greater insight into how environmental factors interact with individual behaviour. This provides more accuracy in predicting user behaviour through more accurate models. Many possibilities for advanced modelling approaches using the techniques of advanced deep neural networks exist: designing a recurrent neural network; using attention-based architecture. Modelling user behaviour over time can benefit from advanced ensemble learning methods that will dynamically change the weights assigned to models, making the prediction more reliable as the user's behaviour changes. The digital twin portion of the system would someday be able to provide real-time feed-back in addition to creating new predicted user behaviour paths. Other enhancements will include improving the sys-tem's interpretability to the user, which will enhance user confidence, thus increasing predictive capabilities, through the use of explainable AI (XAI) methods for communicating risk predictions and recommendations to users. Furthermore, the system would need to be clinically validated and employed on a broader scale with health care providers to validate the system's accuracy, reliability, and ethical implications for utilising the system for real-time preventative mental health and digital wellness applications.

8. CONCLUSION

usage behavior and screen time data to assess mental health risk. The proposed deci-sion support system utilizes an ensemble learning technique enabling higher reliability in predicting risk and addressing lack of accuracy using a single classifier. A digital twin-based predictive system that relies on historical and real-time data rather than just static evaluations will also be part of the ma-chine learning-based solution to predict future mental health risks. Using the behavioural factors of screen use, sleep patterns and stress-related characteristics, research demonstrates that behavioural factors are very predictive of mental health conditions. The ensemble prediction model consistently outperformed the other individual predictors in predicting mental health conditions.In addition to the behavioral predictive models to gauge risk, decision support features will also be incorporated into the machine learning-based predictive model related to digital well-being such as confidence scoring, visual analytics and personalized recommendations. The architecture of the proposed decision support system is modular and consists of data preprocessing, model training, ensemble prediction, digital twin simulation and decision support, allowing the system to be scalable and flexible to add new algorithms and behavioral predictors making the proposed framework a proactive and scalable solution for the monitoring of preventive digital mental health.

Conflict of Interest

The authors declare no conflicts of interest regarding the current research.

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