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Real-time Mental Health Monitoring: Multisensor Technology and Machine Learning

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Mental health disorders are a growing global concern, yet traditional diagnostic methods remain largely subjective and episodic, failing to account for real-time fluctuations in a patient's condition. However, recent advances in sensor technology and machine learning (ML) enable continuous and objective mental health monitoring. This study aims to develop and validate ML models that integrate different sensor data, including physiological, behavioral, and environmental signals, and ML algorithms to enhance the accuracy and robustness of real-time mental health monitoring methods. Data were collected using wearable devices and smartphones, capturing health-related data such as heart rate variability and physical activity. ML models, including support vector machines, random forests, and neural networks, were trained to conduct data preprocessing, sensor data fusion, and hyperparameter optimization. Random forest outperformed other algorithms in terms of accuracy, precision, recall, and F1-scores of its prediction results. Adding regularization enhanced the performance of neural networks, and data fusion from multiple sensors is far more effective than using single-sensor data for diagnosing mental health disorders. By providing a scalable, real-time system that leverages multiple sensor data and ML optimization, challenges in mental health monitoring, such as data heterogeneity and missing values, are addressed, and the deployment of the diagnosis system in clinical and everyday life becomes easier. The developed system enables the continuous, accurate care and support for people with mental health disorders. By integrating additional datasets and privacy protection measures, the developed system further enhances its effectiveness and accessibility.

1. Introduction

Mental health disorders have affected many people as a significant global health issue. People with mental health disorders experience depression, anxiety, bipolar disorder, and post-traumatic stress disorder (PTSD). In diagnosing mental health disorders, the presence, duration, severity, timing, or frequency of the symptoms must be understood precisely. It is also important to monitor the timing of symptom assessment (Fig. 1).[1] The symptoms are complicated and often

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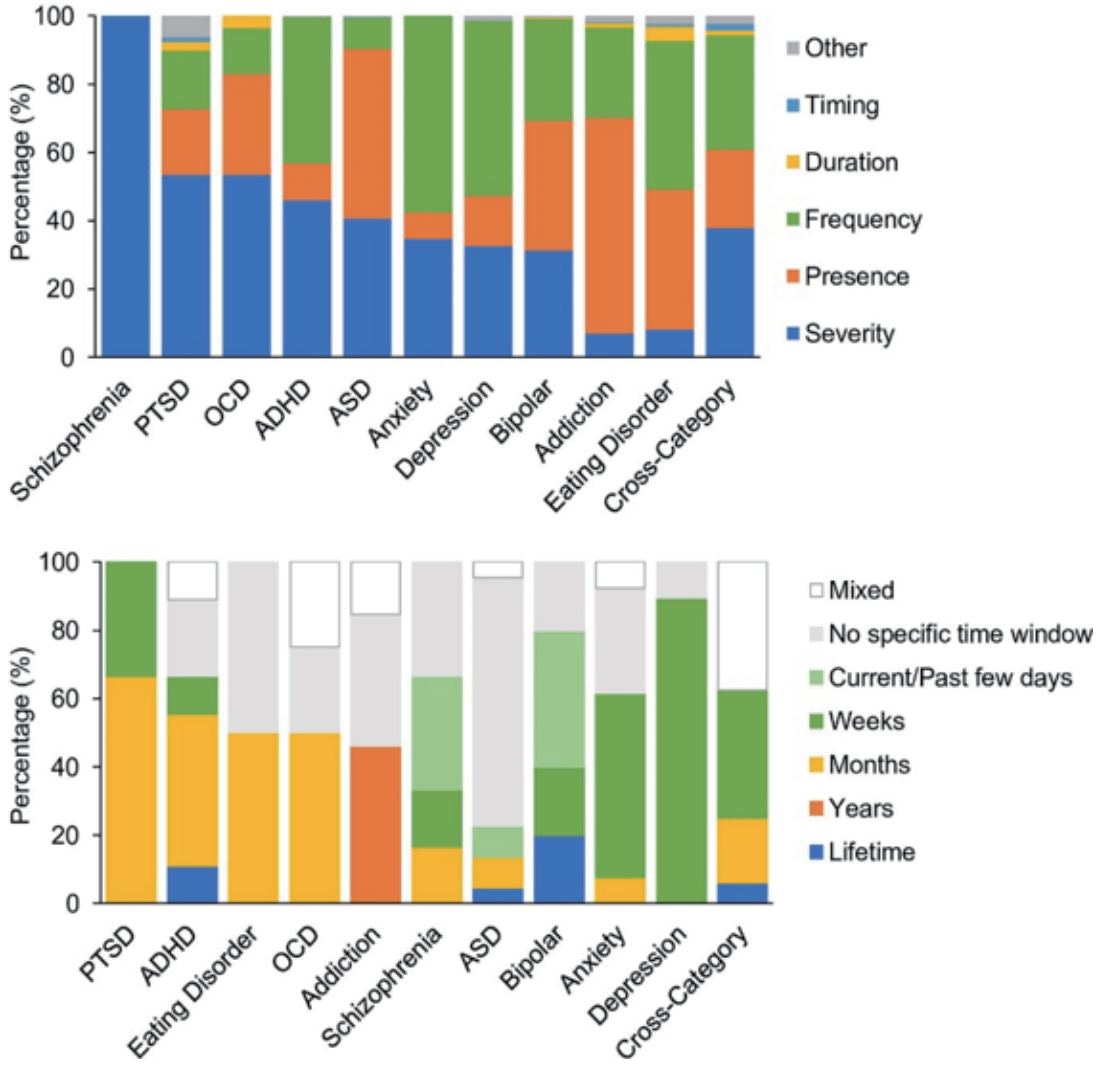


Fig. 1. (Color online) Symptom assessment characteristics (OCD: obsessive-compulsive disorder, ADHD: attention-deficit/hyperactivity disorder, ASD: autism spectrum disorder).

unnoticed because of societal stigma surrounding mental health. In a traditional mental health assessment, doctors interview individuals who report their feelings from their memory. However, this leads to an irregular subjective diagnosis. With conventional psychological methods, several mental illnesses cannot be detected for a long time, leading to ineffective treatment.[2] Therefore, reliable, constant, and scalable means to monitor mental health are required to provide a timely diagnosis and treatment of mental problems.

Technology advancement enables the tracking of mental health through the passive monitoring of past data. In passive monitoring, nonintrusive methods are used to monitor behavior and physical/physiological functions using smartphones, sensors, and other devices. It is possible to repeatedly gather data in life that indicates fluctuations in mental health, which might be related to mood and anxiety disorders, depending on the length of sleep, physical

exercise, interactions with others, and the characteristics of one's voice. Therefore, multisource data are required for a better diagnosis of mental health problems.[3,4] Despite the development of new diagnostic methods, difficulties still exist in monitoring mental health. Using multisource data requires robust privacy measures and reliable labels; however, it is challenging to design a reliable and accurate monitoring system using such data. As mental health affects people's lives, effective diagnosis methods must be tailored to each individual's needs. Because mental health disorders are complex, advanced computing technology is necessary to discover patterns from various forms of high-dimensional data, and it is vital to address challenges in accurate diagnosis and monitoring by utilizing data from multiple sources.[3]

After the COVID-19 pandemic, the benefit of remote and real-time mental health monitoring became widely recognized. Social struggles, financial problems, and health concerns have significantly affected mental well-being, placing excessive strain on healthcare systems and limiting access to quality treatment. This leads to an increase in the use of mobile health applications and telepsychiatry for monitoring and assisting people with mental health issues. For such applications, the sensor data processed by machine learning (ML) algorithms have contributed to the remote and large-scale management and detection of mental health problems.[4] Moreover, the daily behavior data collected from such devices are considered important in maintaining mental health. On the basis of digital phenotyping, behavioral and physiological characteristics linked to mental health are assessed to enable timely actions by health professionals. Data from different sensors and their fusion enable the improvement of the detection, treatment, and recovery from mental health problems. Such data play an important role in precision medicine and digital health, personalized therapies tailored to individual needs.

Various sensors are combined to assess the different features of a person's mental state.[1] Data, including heart rate, electrical skin reactions, phone and location habits, and environmental parameters, are collected from different devices to assess the mental health status and detect specific symptoms.[5] Sensor data contribute to the accuracy of mental health assessment. For instance, speech analysis with facial expression recognition and physiological signals is used to detect depression and anxiety (Fig. 2).[6] By using different data, emotions and actions linked to mental disorders can be detected. In such methods, data from multiple sources are utilized to improve the reliability of diagnosis, even with missing or noisy data.[7]

ML is applied to the analysis of data from sensors. ML algorithms determine important details, address complex relationships between data, and discover important patterns in big data. Convolutional neural networks (CNNs) and recurrent neural networks (RNNs), transformer models, and graph neural networks (GNNs) are widely used for the accurate diagnosis of depression, PTSD, and bipolar disorder.[8] ML models fuse various types of data, which enhances the accuracy of the mental illness diagnosis.[9] ML methods facilitate accurate and timely mental health monitoring based on the collected data. However, privacy and algorithmic biases must be addressed for transparent and secure applications, and datasets need to be expanded.[10] However, sensor data and smart algorithms provide effective methods to monitor mental health over time and notify users of signs of mental health issues.

In this study, the effectiveness of sensor technology in capturing physiological, behavioral, and environmental data was examined for real-time mental health monitoring. An efficient

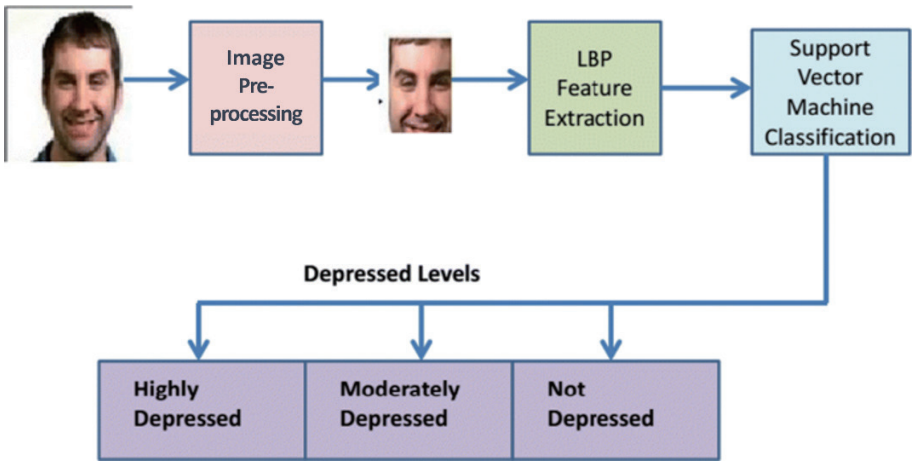


Fig. 2. (Color online) Emotion classification based on facial expression and physiological signals using deep learning (LBP: local binary pattern).

process and data fusion method were identified to detect and predict mental health status through the optimization of ML algorithms. The impact of the sensor data and ML algorithms on the early detection, personalized intervention, and continuous monitoring of mental illnesses has also been explored in real-world settings. The results provide a reference for the development of precision and personalized medicine and corresponding sensor technology.

2. Materials and Methods

The methodology of this study consisted of data collection, preprocessing, model training, and real-time deployment. The models and their parameters were refined based on the initial performance. To rapidly process data, small and light models powered by edge computing were used. To secure and protect the privacy of the participants, this study's procedure was approved by the Institutional Review Board of Shandong Women's University, China, for data collection and processing. The participants in this study signed informed consent after the study's goals, procedures, and possible risks were explained. All personal information was stripped out before the data was used. Health information was encrypted to restrict access. The participants were allowed to end their participation at any stage. The participants were provided with assistance in using the devices and advised to avoid high psychological risks and the disclosure of their emotions. All data were handled and shared transparently by everyone. The data and study results were utilized solely for specific purposes, avoiding any exaggeration. The system development process was carried out in strict adherence to ethical guidelines.

3. Data collection and processing

Sensors were employed to continuously record participants' physiological, emotional, and environmental parameters. Each participant was equipped with a research-grade wearable

device (Empatica E4; dimensions: 44 × 40 × 13 mm^3) and a custom-developed mobile application for real-time data synchronization. In Table 1, the sensors used for monitoring and their clinical applications to mental health are described. The participants wore the wristband device throughout the study period to capture heart rate variability (HRV), electrodermal activity (EDA), and physical activity levels (Fig. 3).[11] In parallel, smartphone-based sensors provided contextual information related to mobility, ambient environment, and vocal features.

Table 1
Sensors used in this study and their clinical applications.

Device	Sensor	Collected signal	Clinical application for mental health
Wristband	Photoplethysmography (PPG)	HR, R–R intervals (time duration between consecutive R-wave peaks in an electrocardiogram)	Autonomic nervous system balance (reduced HRV is a validated marker of stress and anxiety)
	EDA	Skin conductance level (SCL)	Sympathetic arousal (SCL spikes indicate acute emotional triggers or fight-or-flight responses)
	3-axis accelerometer	Movement magnitude (m/s^2)	Physical activity; low movement complexity often correlates with depressive lethargy
Smartphone	GPS	Longitude/latitude, radius of gyration	Digital phenotyping of mobility, travel distance, and locations to predict depressive episodes
	Ambient light sensor	Illuminance (lux)	Stress patterns in low-light indicate isolation, while bright-light suggests social exposure
	Microphone	Ambient noise (dB), audio prosody	Noise as an external stressor using speech tone and pitch reveal anxiety markers

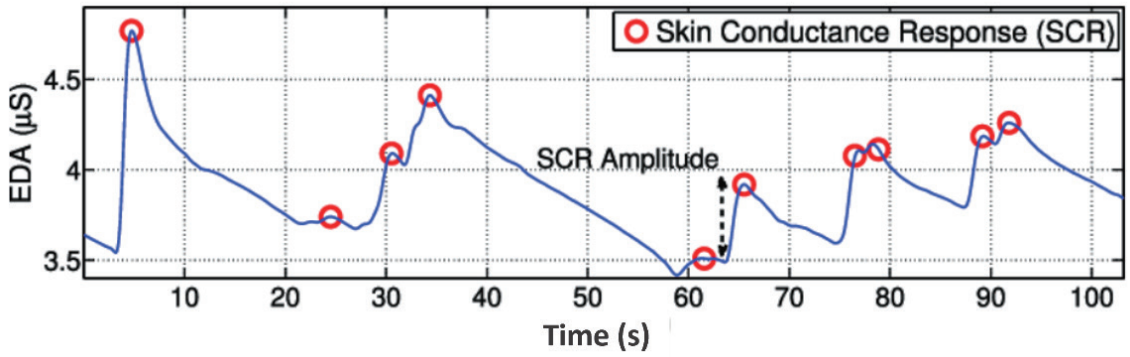


Fig. 3. (Color online) EDA of SCR is shown by red circles. An indicative notation of SCR amplitude is also shown.[12]

Smartphone applications were also used to record audio, GPS data, and emotional data. Environmental parameters, including brightness and ambient noise, were also collected using other wearable and portable devices. A GPS sensor was used to gather information on the digital phenotyping of the participant's social behavior.[13] In mental health monitoring, GPS data were used to calculate features such as location variance and circadian movement. A significant decrease in the variety of locations visited, or a shift in the timing of movement, such as late-night activity, provides an objective measure of social isolation and sleep–wake cycle disruption, which are important symptoms of clinical depression and PTSD that cannot be captured by physiological sensors alone (Table 1).

In this study, 1000 participants were recruited, reflecting the diversity of the general population. The participants from 18 to 65 years old who actively used smartphones and wearable devices were selected to gather their health data. Those who had taken medical substances for mental health issues or had had severe cognitive impairment within the past three months were not included. The detailed information on the participants is presented in Table 2. The participants' ages ranged from 18 to 65 years, with a mean of 42.3 years and a standard deviation of 13.8 years. Gender distribution was balanced with 52% female (n = 520) and 48% male (n = 480). 31% of the participants had had mental health diagnoses (n = 310), while 69% did not (n = 690). Among those with mental health diagnoses, 45% were diagnosed with depression, 35% with anxiety, 15% with PTSD, and 5% with other disorders. 60% lived in urban areas, 30% in suburban areas, and 10% in rural areas. 25% had graduated high school, 45% had a bachelor's degree, 20% had a master's degree, and 10% had a doctorate. 70% of the participants were employed, 15% were unemployed, and 5% were retired, while 10% were students.

The participants wore the devices and regularly used the smartphone application for two weeks from 8 to 22 May 2025. All the data collected from the sensors were stored in the cloud, and the sensors' connectivity and data transmission were monitored continuously. The participants submitted reports regularly for supervised learning. Their behavioral and mental conditions were assessed using the data and reports. Any data lost owing to disconnection or skipped reports were categorized as noncompliant data. The data collected were analyzed by ML algorithms.

Before data processing, noise reduction, missing data handling, and sensor data normalization were conducted to ensure consistency and accuracy. HRV and EDA data were corrected for movement and sensor glitches using adaptive Kalman filters. GPS and application data logs were

Table 2
Demographic composition of participants.

Demographic item	Description
Number of participants	1000
Age	18–65 years old [42.3 ± 13.8 years old (average age ± standard deviation)]
Gender	52% female (n = 520), 48% male (n = 480)
Mental health status	31% with mental health diagnoses (n = 310), 69% without (n = 690)
Mental health diagnoses	Depression (45%), anxiety (35%), PTSD (15%), and other disorders (5%)
Residential area	Urban (60%), suburban (30%), and rural (10%)
Educational attainment	High school (25%), bachelor's degree (45%), master's degree (20%), and doctorate (10%)
Employment status	Employed (70%), unemployed (15%), student (10%), and retired (5%)

processed to eliminate outliers and to set the timestamps on the same time scale. Device errors and abnormal environmental changes were excluded from environmental sensor data.

A K-nearest neighbors (KNN) algorithm was used to process vision and speech data for expectation maximization and efficient data imputation. Brief data interruptions were restored, and longer missing segments were omitted by the KNN algorithm. Features were extracted from the data, including sleep hours, movement complexity, and tones of speech. *Z*-score normalization was conducted for the data. SPSS software was used to analyze the data and identify factors affecting mental health. The processing of the data was automated for real-time monitoring.

Before analysis, data from multiple sensors were fused to polish and synchronize them. Then, the relationship among physical and behavioral factors was analyzed. Data fusion was conducted using

$$X_{fused} = \left[X_{physio} \| X_{behavioral} \| X_{environmental} \right], \tag{1}$$

where '||' denotes vector concatenation, and $X_{physiol}$, $X_{behavioral}$, and $X_{environmental}$ are physiological, behavioral, and environmental data. Physiological data, including HRV and EDA, represent internal biological processes. These signals are regulated by the autonomic nervous system and are generally beyond the participant's conscious control. Behavioral data are obtained from the accelerometer (movement), GPS (mobility), and audio recordings (speech and activity). These data are used to capture what participants do and how they interact with their surrounding environment.

4. ML algorithms

ML algorithms were utilized to organize the processed data and assess mental health. Radial basis function kernels were used in support vector machines (SVMs) to process complex and high-dimensional data. SVM models were designed to maximize the margin between data classes while effectively establishing the decision boundary. Ensemble learning methods using random forest (RF) were established to improve prediction accuracy. RF improves its performance on mixed and inconsistent input by combining decisions from decision trees with bootstrapped samples. From the importance metrics of RF, useful sensor data and their features were identified in this study. The sensor data were processed by CNNs and long short-term memory (LSTM) networks to explore the strategy-specific behavior of the participants. CNNs and LSTMs learned sequential patterns in the participants' behavior and mood, and extracted hierarchical features from physiology and speech data. The networks were refined using the Adam optimizer to avoid overfitting. An early late fusion model was designed to effectively use data from different sensors. At the low fusion level, all data were combined and then fed to the model, while at the high fusion level, the outputs of each distinct classifier were averaged using assigned weights. The model's resistance to errors or missing data was increased using adaptive fusion weights.

5. Evaluation metrics

The accuracy, precision, recall, and F1-score were used to evaluate model performance. Accuracy showed how correctly a model predicted, and precision demonstrated the ratio of actual positives out of all the positives. Recall was used to assess the impact of class imbalance on both metrics. The F1-score, which measures the balance between precision and recall, was computed using the following equation:

$$F1\text{-}Score = 2 \times \frac{Precision \times Recall}{Precision + Recall}. \tag{2}$$

Receiver operating characteristic curves and area under the curve (ROC-AUC) were used to measure how well the classification scores were balanced between sensitivity and specificity. The metrics were used to evaluate the effectiveness of the model in classifying the data into different classes. The confusion matrices were constructed to understand how errors occurred and minimize them. K-fold and leave-one-subject-out strategies were used so that the model still performed well with newly added data. Grid and randomized search techniques were used to find the best kernel coefficients in SVM and optimize the neural network's learning rate. The inference latency and memory consumption were measured to understand the appropriateness of the model. The accurate and fast models were used in the developed system.

3. Algorithm Optimization

To enhance the mental health monitoring system's performance, accuracy, and durability, ML algorithms were optimized. Hyperparameter tuning was employed to systematically check the algorithm's process rates, strength levels, and complexities. By using grid and randomized search techniques, hyperparameters were identified. Bayesian optimization was used to swiftly identify the optimal hyperparameter by exploring probabilities.[14] Using Lasso and Ridge penalties, model complexity was maintained within preset limits to effectively fit newly added data. In training neural networks, the performance was continuously monitored using optimization methods to enhance accuracy and accelerate outcome generation.

3.1 Sensor data fusion

Sensor data fusion was employed to integrate information from multiple modalities into a unified dataset. The fused data were then processed by machine learning models capable of learning across modalities and extracting salient features through late fusion strategies.[15] In hybrid fusion frameworks, homogeneous modalities are typically combined via early fusion, while heterogeneous information streams are integrated through late fusion. This approach enriches the dataset by enabling the selection of optimal fusion levels, weights, and synchronization methods, thereby maximizing analytical effectiveness.

To merge the disparate data streams collected from wearable sensors and smartphone applications, a feature-level fusion (early fusion) strategy was implemented.[16] Raw signals from

the photoplethysmography, EDA, and GPS sensors were first synchronized using network time protocol timestamps to ensure temporal alignment across devices. Time- and frequency-domain features were extracted from each sensor, followed by normalization using *Z*-score scaling to account for differences in measurement units. These features were concatenated into a single, high-dimensional feature vector, which served as input to the machine learning classifiers. This method was used to simultaneously capture cross-correlations between physiological signals, such as increased skin conductance level, and behavioral signals, such as GPS-derived indicators of social isolation, consistent with the multimodal fusion framework.[15]

3.2 Real-time data processing

Monitoring systems must have real-time processing ability to generate outcomes effectively and minimize lags and workloads while ensuring excellent results. Processing data on devices by through edge computing reduces the need for data transmission to the server and shortens response time. It also enables faster inference on limited hardware resources since model compression, including quantization and pruning, demands a limited size and complexity of ML models. Incremental or online learning enables the model to continually adapt with new data and select important data for better efficiency.

3.3 Evaluation and feedback loop optimization

It is necessary to improve the feedback process and metrics to enhance the performance of the mental health monitoring system. Factors such as early detection sensitivity and reducing false alarms indicate that the system effectively fulfills its intended purpose. Various methods are used to prevent the overfitting of the training data and biased model predictions. The model was adjusted and improved on the basis of the reports of the participants. An adaptive thresholding method was also used to minimize the variability between the participants and provide personalized results.[17] The system provided visual explanations so that the participants could track their health improvements. The participants' feedback contributed to enhancing the system's accuracy, reliability, and overall usefulness.

4. Results

The dataset comprised 1000 samples across nine distinct categories of physiological and behavioral features. These categories represent the primary digital biomarkers used for mental health status classification. Table 3 provides the data for the mapping of these features.

The accuracy, precision, recall, F1-score, and ROC-AUC of the SVM, RF, and RNN models were analyzed using confusion matrices and ROC curves. Referring to the results, the advantages and disadvantages of the ML models were discussed as follows.

The data of 1000 cases and nine categories presented the behavior and physiology of the participants. 31% of the participants had mental health issues. When a small number of participants have mental health issues, the accurate prediction of their mental health status

Table 3
Categories of physiological and behavioral features.

Number	Feature category	Sensor	Description
1	HR	PPG (Wristband)	Average beats per minute
2	HRV	PPG (Wristband)	Root mean square of successive differences
3	SCL	EDA (Wristband)	Baseline level of electrodermal activity
4	SCR	EDA (Wristband)	Frequency of transient peaks in skin conductance
5	Physical activity intensity	Accelerometer	Mean magnitude of 3-axis movement
6	Social mobility	GPS (Smartphone)	Daily radius of gyration and location variance
7	Speech prosody	Microphone (Smartphone)	Mean vocal pitch and speech rate
8	Sleep duration	App/sensor fusion	Estimated hours of rest based on phone inactivity
9	App usage patterns	Smartphone logs	Total screen time and frequency of social app usage

becomes difficult for the model. Therefore, it was necessary to ensure the reliability of self-reports of the minority class. To prevent unexpected biases, the data were cleaned up, normalized, and imputed.

Figure 4 illustrates the relationship between the physiological and behavioral features in the pre-processed data. Most features showed low correlation, but HRV, EDA, behavioral patterns, and application usage patterns were interrelated. Individual sensor data exhibited minimal variation, making the mental health status difficult to determine. To address this, early fusion was applied to enhance feature interrelationships and improve assessment accuracy.

SVM, RF, and NN accurately predicted the mental health of the participants. Because it was difficult to distinguish between the classes, AUC was not high, ranging from 0.47 for RNN to 0.54 for RF (Fig. 5). The RF model performed better than the others as it combined decision trees, which are less affected by data noise. The RNN model's performance was similar to that of a simple model owing to a lack of adequate data and low network complexity. Low AUC was caused by the noise of sensor data. Such results indicated the necessity of continuous upgrading and the addition of data to improve diagnosis accuracy.

The confusion matrices of SVM, RF, and RNN models are presented in Fig. 6. In the RF model, more true negatives were identified as false positives than in the other models. 59 false negatives were identified as positives. Even though RNN achieved the highest precision accuracy, it overfitted the majority class. The SVM model was inaccurate as it identified some positives as negatives. To minimize such errors, sensitivity and specificity must be balanced through cost-sensitive learning to ensure accurate detection and prediction.

Precision, recall, and F1-score were calculated to evaluate the effectiveness of the models. While the SVM model generated accurate predictions, many positives were not recognized. The RF model showed higher precision (Fig. 7). However, because of its lower recall, the RF model needs to be improved to prevent delayed treatment. The RNN model generated predictions with higher frequency. To enhance the model's performance, unequal class distribution must be addressed, loss functions need to be adjusted, and the number of minority samples must be effectively managed. Additional data are also required to enhance the model's performance.

Figures 8 and 9 display the training and validation accuracies, and losses over 20 training epochs for the RNN model, respectively. After training, the accuracy reached 70% while the validation accuracy was 67.5%. RNNs easily overfit the results. Therefore, the dropout method

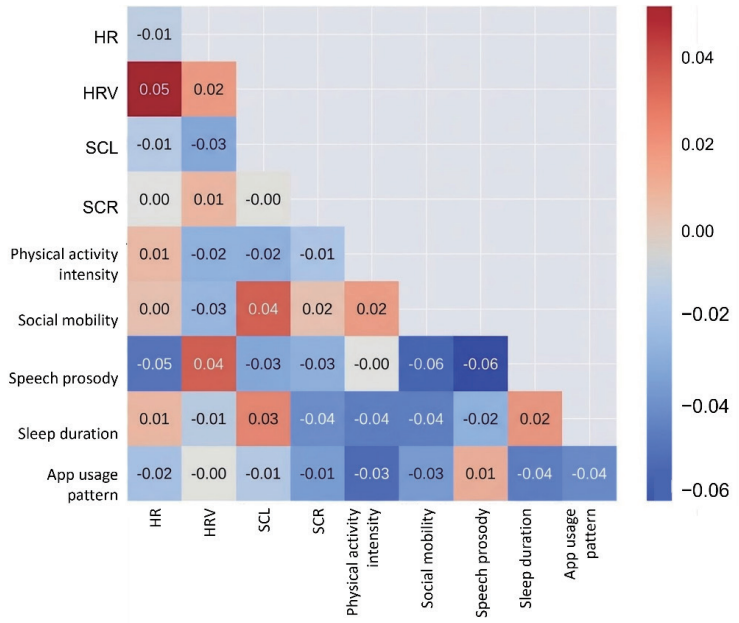


Fig. 4. (Color online) Correlation heat map of features in data.

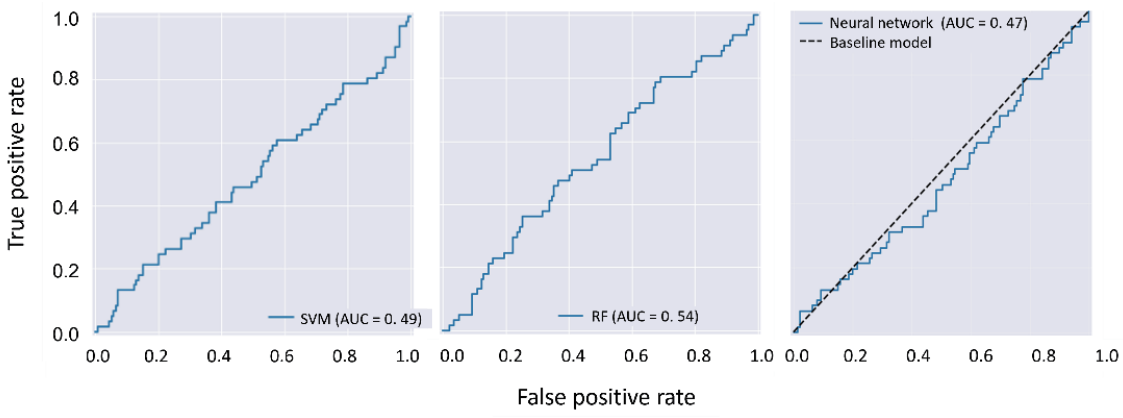
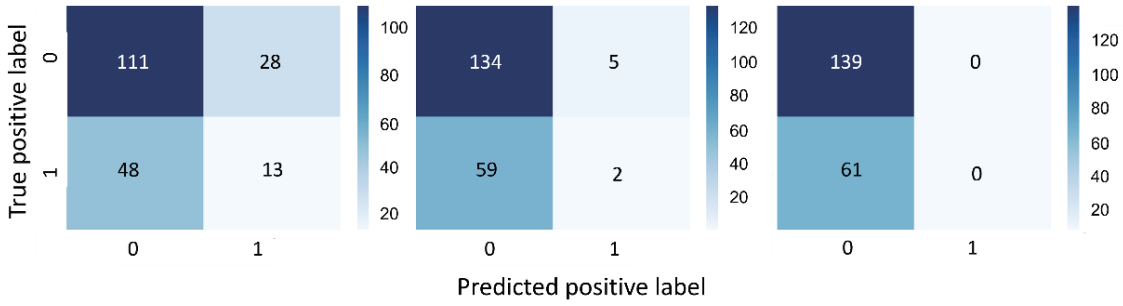


Fig. 5. (Color online) ROC curves of different models.



(a) (b) (c)

Fig. 6. (Color online) Confusion matrices of different models. (a) SVM, (b) RF, and (c) RNN.

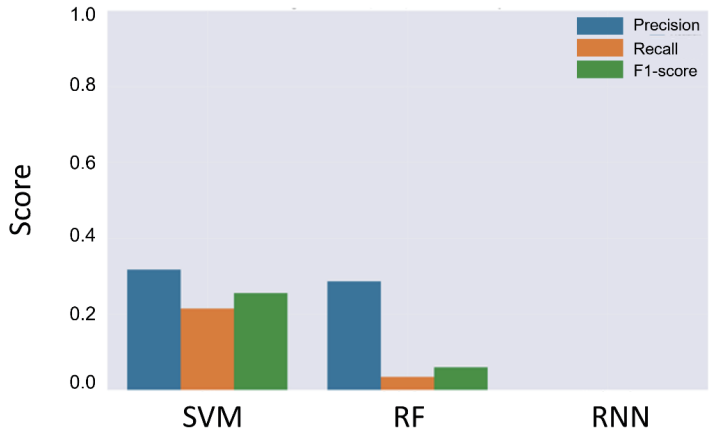


Fig. 7. (Color online) Precision, recall, and F1-score of different models (blue bar: precision, orange bar: recall, and green bar: F1-score).

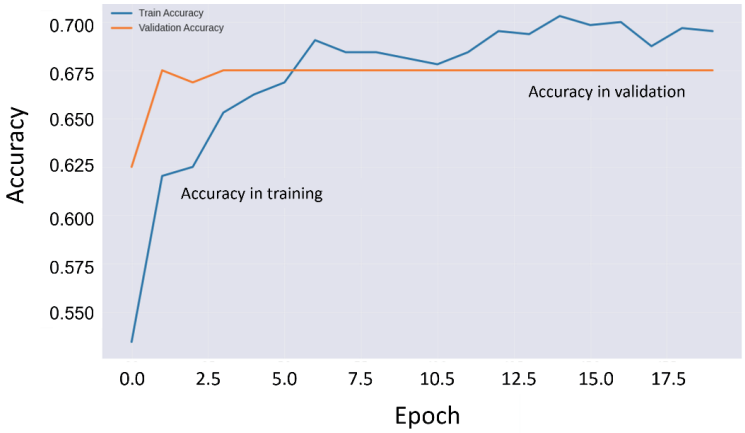


Fig. 8. (Color online) Training and validation accuracies of RNN model in epochs.

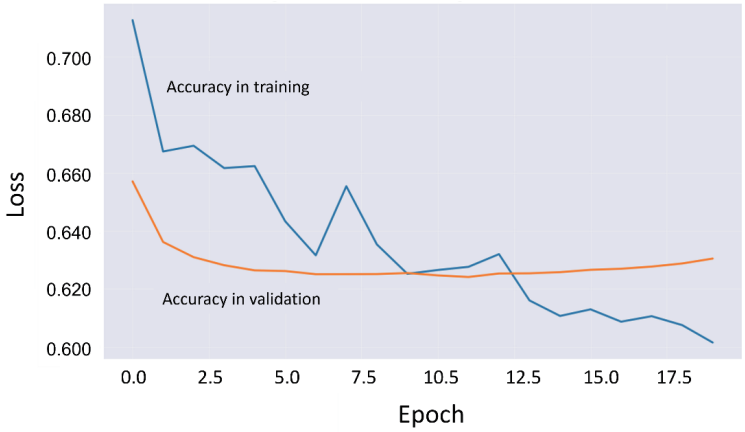


Fig. 9. (Color online) Training and validation losses of RNN model in epochs.

and the Adam optimizer were used to solve the problem instead of using a larger dataset. While the RNN model learns the trends of the data, it tends to miss the essential details of the minority classes. Therefore, it is essential to add different data samples.

The optimized ML models identified mental health status successfully. The RF model generated the best results in terms of sensitivity and specificity. The RF model classified cases into correct categories, with very few in the wrong category. In mental health monitoring, detecting individuals at risk is crucial owing to the possible severe repercussions of missing them. In mental health monitoring, models with high precision and recall are necessary because of the complexity of the data. Precision, recall, and F1-score enabled the understanding of the advantages and disadvantages of ML models. The hybrid model is necessary to identify mental illnesses at a low error rate and ensure prompt and appropriate care. The ML models need learning and validation to accurately identify mental health status.

In this study, the accuracy and loss of the RNN model were constantly improved in training without overfitting. This showed that the model could adapt to newly added data. Similar metric values for training and validation proved that preprocessing and limiting the number of features enabled the model to perform better. The ML models can provide helpful and accurate advice to detect, intervene, and monitor patients with mental health problems. Increasing the amount of data and advancing the technology are expected to improve the performance of ML models and effectively support mental health management.

5. Discussion

Sensor data and ML models enable effective mental health monitoring. Integrating multiple models ensures the accurate and reliable monitoring and detection of mental health problems.[1,18] Data, including heart rate and skin responses, collected from smartphone applications, were essential for such models.[1,3] The RF model provides a reliable solution for monitoring mental health when sensor data are consistent and standardized. Its ability to process missing data and mitigate class imbalance is essential, especially when the collected data is not consistent.[3] The RF model showed the highest F1-score and recall compared with the SVM and RF models in this study. Its stable training and validation results showed that the model ensured shortened training time and consistent outcomes.[19]

Digital phenotyping improves mental healthcare. ML models can be used for mental health care through real-time monitoring. Constant monitoring with appropriate devices and smartphones enables personalized care and prompt treatment.[3] Because of high accuracy and low delay, ML models overcome the existing challenges of previous clinical practice.[20]

To use ML models, data privacy, ethics, and the user acceptance of professionals and clinicians are mandatory, as they are significant barriers to the widespread use of the technology. Well-labeled multimodal datasets are still required,[1] and it is essential to share data to develop better models and compare the results.[20] Different models and various sensor data need to be integrated to improve the accuracy of mental illness diagnosis. Speech, facial expressions, and physiological signals need to be included in the dataset for more reliable results in assessing medical and mental conditions,[20] enabling doctors to understand the patient's status better and

provide successful treatment. Sensor data and ML have become inevitable in health monitoring as a result of their effectiveness, stability, and real-time capability. It is necessary to expand and diversify datasets, considering users' and clinicians' feedback, to build better personalized health monitoring systems.

The developed multisensor system in daily healthcare contributes to the transition from episodic to continuous care. In conventional clinical practice, a patient's mental state is assessed during infrequent visits, which are less reliable because of recall bias and may fail to capture dynamic changes. By contrast, the developed system provides a clinical dashboard that visualizes real-time risk scores generated by the RF model, enabling clinicians to monitor patients continuously and intervene proactively.

For individuals diagnosed with major depressive disorder or generalized anxiety disorder, the system operates through the following stages: (1) continuous baseline monitoring by establishing each patient's normative physiological and behavioral patterns during periods of stability, (2) early warning alerts by using the system to detect a sustained combination of decreased social mobility (GPS-derived) and heightened sympathetic arousal (EDA) window,[21] and (3) just-in-time adaptive interventions using the smartphone application for immediate micro-interventions, such as guided breathing exercises or cognitive reframing prompts. This mechanism effectively extends therapeutic support into the patient's daily environment.[22]

However, challenges, such as the difficulty in collecting data, must be addressed. For example, electroencephalography provides valuable information on the brain and emotions, but specialists with appropriate devices can obtain the data. Collecting facial expressions raises privacy concerns and issues, limiting the use of the data.[19] This necessitates sensors that do not interfere with people but still provide valuable data.

A single method and a limited amount of data are not adequate to monitor mental health effectively. For reliable or accurate solutions, data on mind, body, and the environment, including speech, gestures, eye movements, and bodily signals, are required.[3,23] As integrating different types of data into a single model is not plausible, multiple algorithms must be used for effective and accurate monitoring.[3] Developing reliable algorithms is also critical to effectively utilize various kinds of sensor data and fuse them.[24] Creating easy-to-use interfaces is also necessary, although it is complex.[23] Technologies must be adopted through discussion and agreement between patients and doctors for achieving prompt and supportive outcomes.[24]

As mental health data are private, data privacy, security, and ethics must be wellregulated to avoid data leakage and improper use. Users share their data when they trust in privacy. Personal health information must be shared in a regulated and authorized system. Sensors for mental health monitoring need to be developed to enhance connectivity, reduce power consumption, and improve data storage and transmission. Related applications on smart devices must be user-friendly and allow users to promptly provide feedback.[23] Sensors used for clinical purposes and mental health management must be standardized to provide normalized sensor data.

Such challenges must be addressed to increase the user acceptance of sensors and devices, and develop accurate and reliable ML models that effectively perform data fusion and processing. For the widespread use of sensor data and ML models, effective communication between patients and doctors is mandatory. Ethical practices, data governance, and compliance

with regulations also need to be formulated to solve privacy and security issues. Collaboration among stakeholders is essential to increase the amount of data, develop ML models, and share results.

6. Conclusions

In this study, the applications of sensor technology and ML learning algorithms are examined to monitor mental health in real time. Using the data of physical responses, behaviors, and environmental parameters, the system with ML algorithms accurately and reliably detects different mental health conditions. The experiment results in this study showed that the RF model performed better than other ML models. The RNN model generated accurate predictions with early stopping and dropout to avoid overfitting. By using sensor data, issues associated with traditional mental health assessment methods, focusing on an individual's opinions and memory, were addressed. Data collection from various sensors enabled the rapid assessment of mental health. The low latency and high reliability of the RNN model are wellsuited for continuous monitoring. The ML model ensures digital phenotyping and precision psychiatry based on sensor data, enabling the provision of personalized treatment and care. By addressing the challenges, such as data privacy and ethical use, ML models enable users and medical practitioners to understand and address mental issues. The developed system fuses and processes diverse sensor data to provide valuable information about mental health management. By comparing different ML algorithms, the developed system enables the effective and efficient monitoring of mental health. Following ethical procedures and respecting users' privacy are critical in managing and regulating data. On the basis of the results of this study, user acceptance can be increased and clinicians can employ the system for better healthcare management.

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