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POST-COVID-19 PANDEMIC MENTAL DISORDERS PREDICTION USING PHOTOPLETHYSMOGRAM

(*Ramalan Gangguan Mental Selepas Pandemik COVID-19 Menggunakan Fotopletismogram*)

[1]AZWANI AWANG
[1,2]NAZRUL ANUAR NAYAN*
[3]NIK RUZYANEI NIK JAAFAR
[1]MOHD ZUBIR SUBOH
[4]KHAIRUL ANUAR A RAHMAN

[1]Department of Electrical Electronics and Systems, Faculty of Engineering and Built Environment, Universiti Kebangsaan Malaysia, UKM, Selangor, 43600, Bangi, Malaysia

[2]Institut Islam Hadhari, Universiti Kebangsaan Malaysia, 43600 UKM Bangi, Selangor, Malaysia

[3]Department of Psychiatry, Hospital Canselor Tuanku Muhriz, (HCTM), 56000, Cheras, Wilayah Persekutuan Kuala Lumpur, Malaysia

[4]Department of Electronics & Computer Engineering Technology, Technical, University of Malaysia Malacca, Durian Tunggal, 76100, Malacca, Malaysia

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ABSTRACT

Mental disorders interfere with functioning and affect a person's quality of life. The COVID-19 pandemic has caused an increase in the number of people who are suffering from mental disorders, including suicide. Many people are unaware of their mental health status because the signs might not be readily apparent. In this study, a machine learning (ML) approach that differentiates between case groups, i.e., patients diagnosed with mental disorders and control groups, was developed using

**Corresponding author: Nazrul Anuar Nayan, Department of Electrical Electronics and Systems, Faculty of Engineering and Built Environment, Universiti Kebangsaan Malaysia, UKM, Selangor, 43600, Bangi, Malaysia, email: nazrul@ukm.edu.my*
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photoplethysmogram (PPG) morphology. The subjects consisted of 92 volunteers, who were divided equally into case and control groups, matched in gender and age. PPG signals were collected individually in a 5-min experiment in a relaxation mode. Out of 13 morphological features of PPG, eight features were extracted using the pulse rate variability method and five features were extracted using the fiducial point detection method. Statistical and correlation analyses have verified eight features as inputs to five types of ML algorithms. The results showed that the kNN model achieved the best performance of 92.86%, 99.10%, and 96.43% for sensitivity, specificity, and accuracy. The value of error in prediction, or mean squared error for kNN, was the lowest at 0.036. In terms of model robustness, the area under the curve of the receiver operating characteristic curve for kNN (0.964) was higher than the other models. A mental disorder model has been developed using Machine Learning (ML) from PPG extraction. In conclusion, mental disorders can be detected by PPG based on the obtained results. This development also respects Islamic ethical values, emphasising the importance of upholding individuals' privacy and dignity, especially when collecting and analysing sensitive health data like PPG signals.

Keywords: Photoplethysmogram; statistical analysis; correlation analysis; machine learning

ABSTRAK

Gangguan mental mengganggu fungsi dan mempengaruhi kualiti hidup seseorang. Pandemik COVID-19 telah menyebabkan peningkatan bilangan individu yang mengalami gangguan mental, termasuk peningkatan kes bunuh diri. Ramai yang tidak sedar dengan status kesihatan mental mereka kerana tanda-tanda mungkin tidak jelas. Dalam kajian ini, pendekatan pembelajaran mesin (ML) yang membezakan antara kumpulan kes, iaitu pesakit yang disahkan mengalami gangguan mental, dan kumpulan kawalan, telah dibangunkan dengan menggunakan morfologi fotopletismogram (PPG). Subjek terdiri daripada 92 peserta, dibahagikan kepada kumpulan kes dan kumpulan kawalan, dengan pertimbangan jantina dan umur yang seimbang. Isyarat PPG dikumpul secara individu dalam eksperimen 5 minit dalam keadaan rehat. Daripada 13 ciri morfologi PPG, lapan ciri diekstrak menggunakan kaedah variasi kadar nadi dan lima ciri diekstrak menggunakan kaedah penentuan titik fidusial. Analisis statistik dan korelasi telah mengesahkan lapan ciri sebagai input kepada lima jenis algoritma ML. Hasil menunjukkan bahawa model k-Nearest neighbour (kNN) mencapai prestasi terbaik pada 92.86%, 99.10%, dan 96.43% untuk kepekaan, kekhususan, dan ketepatan. Nilai ralat dalam ramalan, atau purata ralat kuasa dua bagi kNN, adalah yang terendah pada 0.036. Dari segi kebolehterimaan model, kawasan di bawah lengkung penerimaan ciri untuk kNN

(0.964) lebih tinggi berbanding model-model lain. Model ramalan gangguan mental telah dibangunkan menggunakan Pembelajaran Mesin (ML) daripada ekstraksi PPG. Secara kesimpulannya, gangguan mental boleh dikesan dengan menggunakan PPG berdasarkan hasil yang diperoleh. Pembangunan model ramalan ini juga menghormati nilai-nilai etika Islam dengan menekankan kepentingan perlindungan privasi dan kerahsiaan individu, terutamanya semasa mengumpul dan menganalisis data kesihatan yang diperolehi melalui isyarat PPG.

Kata kunci: *Fotopletismogram; analisis statistik; analisis korelasi; pembelajaran mesin*

INTRODUCTION

The COVID-19 pandemic has raised awareness in all countries, especially in the medical sector. The uncontrollable spread of the COVID-19 epidemic has led to the implementation of social restrictions around the world. Social restrictions or quarantines have significantly impacted the world community's mental health. According to a scientific summary published by the World Health Organization (WHO), in the first year of the COVID-19 pandemic, the global prevalence of mental disorders such as anxiety and depression increased by 25%. The most affected by this epidemic is the availability of mental health services. Many countries have reported major disruptions in lifesaving services, including suicide prevention. For example, too many people with mental disorders (MD) are not receiving the care and support they need. From an Islamic perspective, there is a strong emphasis on self-awareness and introspection. Individuals are encouraged to evaluate their mental well-being and to seek assistance if they encounter symptoms of mental distress. Since each person experiences symptoms differently, it can be challenging to diagnose mental problems from their outward manifestations (National Institute for Health and Care Excellence 2016). When a pandemic strikes, there are often gaps in medical care and assessment. The restrictions and social boundaries that exist make it difficult for the community to conduct a face-to-face examination of mental health conditions in a clinic or hospital. Hospital facilities also devote extra attention to COVID-19-infected patients. Regarding mental health assessment, there are two types: self-assessment and professional assessment. According to the research by (Garb 2021), the self-assessment by participants is more open to prejudice, and the subjects may be attempting to defend themselves rather than being classified as mentally ill. A professional assessment is too challenging to distinguish between mental health in general and clinical problems because it is heavily based on the subject's memories (Lane 2020).

The photoplethysmogram (PPG) is one of the biosignal methods used to assess autonomic nervous system dysfunction (ANS) in MD. Signals are closely related to vital signs, including heart rate, breathing rate, and blood pressure, which can be used to measure cardiac output, measure oxygen saturation, and evaluate autonomic function (Kalra and Sharma 2020). PPG uses infrared light to estimate the movement of blood under the skin, and a signal is divided into two main points: systolic and diastolic (Chowdhury et al. 2020). According to recent studies, PPG signals can identify a person's level of stress, anxiety, and major depressive disorder (MDD) by measuring pulse rate variability (PRV) (Madhan Mohan, Nagarajan, and Das 2016; Perpetuini et al. 2021; Rinkevičius et al. 2019). In a study (Stautland et al. 2022), patients with bipolar disorder were found to have lower PRV in the manic state than in the euthymic state. There is a strong theoretical correlation between the pulse waveform of the PPG and mental well-being (Liu, Ni, and Peng 2020). According to the preliminary results of the study, PPG can be a useful tool for emotion identification and is appropriate for applications that involve human-machine interaction (Perpetuini et al. 2021). At-risk individuals must be sent to a psychiatrist or psychologist for additional therapy, which necessitates the creation of quick and accurate automated screening techniques. Healthcare uses machine learning (ML) extensively, especially when adopting the Internet of Things (Ghazal, Hasan, et al. 2021). As demonstrated in research, pattern recognition algorithms can create predictive models for some diseases and help with prompt diagnosis (Ghazal, Anam, et al. 2021). Discriminant analysis (DA), k-nearest neighbors (kNN), decision trees (DTs), support vector machines (SVMs), and artificial neural networks (ANNs) are common techniques used in machine learning (ML), which predict and categorise future events. Using the mentioned ML methods, we examined a case-control group based on the reactivity of ANSs to predict MD from PPG signals.

METHODOLOGY

The experimental paradigm consisted of five phases (see Figure 1). The five major phases are as follows: (1) data and PPG signal acquisition; (2) signal pre-processing and selection; (3) fiducial point detection from PPG signal followed by feature extraction; (4) feature selection based on statistical analysis and correlation analysis; and (5) input of the most significant features to the ML process for model prediction using a classifier with the best performance in terms of sensitivity (SN), specificity (SP), and accuracy (ACC).

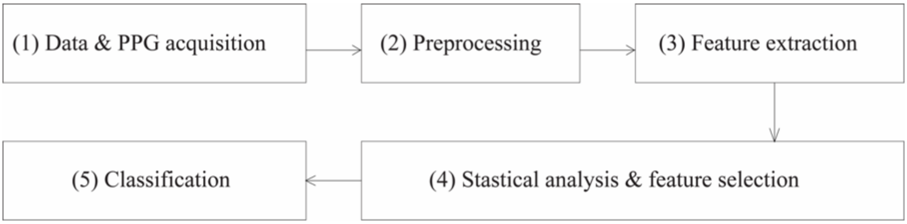

FIGURE 1 Five Phases in an Experimental Paradigm

Data Acquisition

Data acquisition for this study included demographic information from participants and recordings of PPG signals. The sample size was calculated with the nomogram proposed by Gore and Altman, and the estimated prevalence rate of stress among Malaysians during the COVID-19 pandemic was 29% (P) (Woon et al. 2020). With a confidence interval (W) of 0.083, this study aimed for 95.5% SN. As shown in Equations (1) and (2), the estimated total number of samples was 92, so 46 subjects were included in each case and control group.

$$TP + FN = \frac{Z^2\big(SN(1 - SN)\big)}{W^2} = \frac{1.96^2\big(0.95(1 - 0.95)\big)}{0.083^2} = 26.49 \tag{1}$$

$$Sample\ Size, N = \frac{TP + FN}{P} = \frac{26.49}{0.29} \approx \mathbf{92\ Samples} \tag{2}$$

where TP = true positive, FN = false negative, Z = standard score, SN = sensitivity, W = confidence interval, P = prevalence.

A total of 46 individuals met the criteria for the case group, that is, currently having MDs, and were recruited for this study. Their mean age was 24.76 years (SD = 5.43). All were patients admitted to the psychiatry clinic of the Canselor Tuanku Muhriz Hospital (HCTM), Kuala Lumpur. Subjects were not assessed using DASS-21 as they had been clinically diagnosed. Then, 46 gender and age-matched normal subjects with a mean age of 23.80 (SD = 6.02) as the control participants were recruited from university students and members of the public who passed pre-screening through DASS-21. The age range for inclusion was 18–40 years. All subjects provided their informed written consent after being screened for a history of chronic medical problems through verbal questions. The exclusion criteria included cardiovascular illness and smoking, both of which could interfere with PPG signals. A pulse oximeter (CMS50E, Contec Medical Systems Co., Ltd., China) with a sampling frequency of 100 Hz was placed on the index finger of each subject's left hand for the recording of the PPG signal. In the recording session, the subject was under-rested and in relaxed conditions. The total time for data recording was 5 min. Once PPG signal recording was completed, data was stored using the Smart Device Assistant, SpO_2 software, for further analysis.

Pre-processing

During PPG recording, the signal was influenced by various types of sounds and motion artefacts. High-frequency and smoothing techniques, as well as baseline or low-frequency removal techniques, were used in the filtering process. The first-order Butterworth low-pass with a cut-off frequency of 6 Hz and the second-order Butterworth high-pass with a cut-off frequency of 0.5 Hz were utilised (Pakdamanian, Sheng, and Baee 2021). After that, reliable signal stability was established using signal quality indexing (SQI). The SQI process determined how long a quality PPG signal segment should be. The SQI method used a template matching technique as suggested in previous work and was based on the raw signal quality of the PPG signal (Li and Clifford 2012; Ab Hamid and Nayan 2020). Three requirements must be met for the SQI process to work: extrapolated 10-second PPG signal must have a beat-to-beat interval of less than 2.2, the PPG pulse-peak gap must not be longer than 3 seconds, and the extrapolated 10-second PPG signal must have a pulse rate between 40 and 180 beats per minute. The tool used for this procedure was MATLAB (Mathworks Inc., USA).

Feature Extraction

To assess ANS activity in response to a stimulus state, heart rate variability (HRV) is frequently used as a quantitative measure. The use of a PPG sensor to detect HR has been made possible by new technology and an effective algorithm. It has been proposed that PPG signals can be utilized instead of an electrocardiogram (ECG) to detect heart rate variability (HRV) (Elgendi 2012; Moraes et al. 2018). In this sense, the systolic peak served as the heartbeat reference point, and then the PRV of PPG was studied using the systolic-to-systolic intervals as the R-R intervals of HRV in the ECG (Lu et al. 2008). Two common measures of heart rate are the mean interbeat interval (IBI) and beats per minute (BPM). The HeartPy toolkit algorithms were applied to PRV features. According to the study (van Gent et al. 2019), this algorithm performed well compared to annotated data for four different metrics: the position of the identified peak, the mean peak-to-peak interval derived in the examined segment, the beats per minute (HR algorithm) and the normalized heart rate variability (HRV). For example, heart rate can be calculated using the time between two successive peaks, and PRV can be calculated using the standard deviation of sequential differences. While in the frequency domain, refers to the measurement of the frequency spectrum between 0.05 and 0.15 Hz (LF) and 0.15 and 0.5 Hz (HF). The power spectral density, which is determined using welch-based techniques, serves as the basis for the measures.

The relationship between other PPG waveform components was also investigated because of the signal's significant potential for developing new diagnostic features and improving MD comprehension. The delineator (Nan, Chui, and Vai 2010) and bp annotate (Alexandre Laurin n.d.) algorithms were used to find the fiducial points in the PPG signals. The zero-crossing position just before maximum diffraction was used to establish the pulse start, and the zero-crossing point right after diffraction was used to determine the systolic peak (Nan, Chui, and Vai 2010). MATLAB was used to detect these fiducial points in the PPG signal, where O is the onset, S is systolic, N is a notch, D is diastolic and i is the sequence of a cycle (see Figure 2).

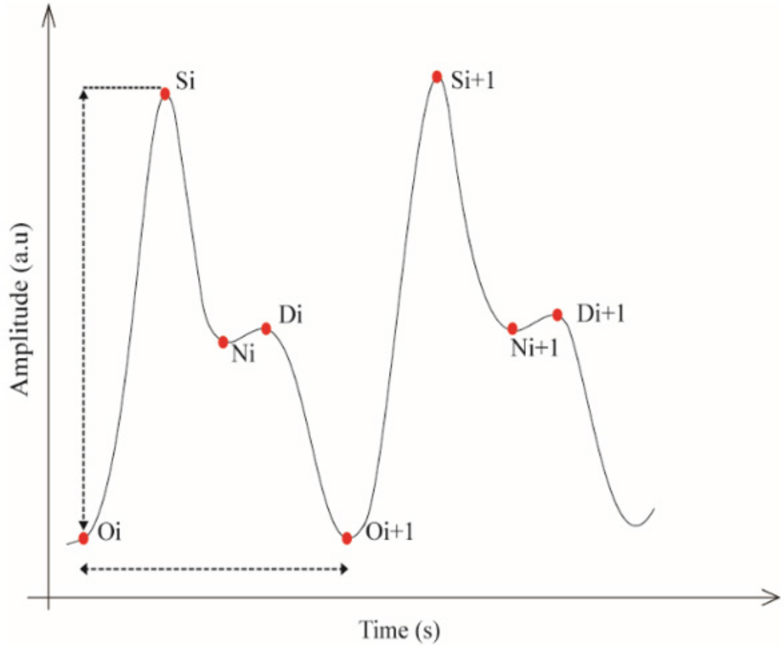

FIGURE 2 Fiducial Points in PPG are Identified on the Pulse Wave

In total, ten HR / PRV and 20 PPG pulse fiducial point detection features were obtained (see Table 1).

TABLE 1 PPG Features Covered by the Study

Features	Label	Details
HR	BPM, IBI	beats per minute, mean inter-beat interval
PRV	SDNN, SDSD, RMSSD, PNN20, PNN50, MAD, HF, LF	standard deviation of intervals between heartbeat, standard deviation of successive differences between neighboring heart beat intervals, the root mean square of successive differences between neighboring heart beat intervals, proportion of differences between successive heartbeat greater than 20ms, proportion of differences between successive heartbeat greater than 50ms, and median absolute deviation of intervals between heartbeat, high frequency, low frequency.
Onset	O_iO_{i+1}, O_iS_i, O_iN_i, O_iD_i, $O_i–S_i$, $O_i–N_i$, $O_i–D_i$	$Onset_i$ to $Onset_{i+1}$, $Onset_i$ to $Systolic_i$, $Onset_i$ to Notchi, $Onset_i$ to $Diastolic_i$, $Onset_i–Systolic_i$, $Onset_i–Notch_i$, $Onset_i–Diastolic_i$
Systolic	S_iS_{i+1}, S_iO_{i+1}, S_iN_i, S_iD_i, $Si–N_i$	$Systolic_i$ to $Systolic_{i+1}$, $Systolic_i$ to $Onset_{i+1}$, $Systolic_i$ to $Notch_i$, $Systolic_i$ to $Diastolic_i$ Systolic $–Notch_i$,
Notch	N_iN_{i+1}, N_iS_{i+1}, N_iO_{i+1}, N_iD_i	$Notch_i$ to $Notch_{i+1}$, $Notch_i$ to $Systolic_{i+1}$, $Notch_i$ to $Onset_{i+1}$, $Notch_i$ to $Diastolic_i$
Diastolic	D_iD_{i+1}, D_iO_{i+1}, D_iS_{i+1}, D_iN_{i+1}	$Diastolic_i$ to $Diastolic_{i+1}$, Diastolici to $Onset_{i+1}$, $Diastolic_i$ to $Systolic_{i+1}$, $Diastolic_i$ to $Notch_{i+1}$,

Statistical Analysis and Feature Selection

IBM SPSS Statistical Version 26 was used for the statistical analysis. Skewness and kurtosis ($2.0<p<2.0$), as well as the normality assumption test ($p>0.05$), were conducted (George and Mallery 2003). The abnormal distribution characteristic was assessed using a Mann-Whitney U test, whereas the normal distribution features were independently tested using a t-test. The features were then arranged from lowest to highest in terms of *p*-values, with a 95% confidence interval. Potential features were evaluated for isolated variability using the interquartile range. The next step was to use correlation analysis to identify features that were closely related to a goal and to confirm that there were no links between features. Feature selection aims to eliminate duplicate or ignorant predictions from a model (Kuhn and Johnson 2013).

Classification

The distinction between case and control group data has been achieved using five traditional ML models (DA, kNN, DT, SVM, and ANN). The linear and quadratic types of the DA algorithm were used because DA is fast and can provide accurate discrimination between groups (Uddin et al. 2019). A kNN algorithm can determine the minimum distance (euclidean) between test and training data and categorize features with different numbers of neighbors. The k value was set from 1 to 100. A DT classifier was used to produce 'true' or 'false' responses to training data with Gini's diversity index splitting criterion, and the number of splits was set from 1 to 100. An SVM algorithm was used to create decision boundaries (hyperplanes) that can differentiate two groups using the four different kernel functions of linear, radial basis, and third- and fourth-order polynomial functions. In ANNs, a multilayer perceptron network was developed with two hidden layers and one output layer. The number of hidden nodes varied from 1 node to 15 nodes in each hidden layer. The network was trained with the Levenberg-Marquardt training algorithm, the "log sig" transfer function (hidden layers), the "purelin" transfer function (output layer), and a training goal of 1 x 10-7 mean squared error (MSE).

$$Sensitivity, SN = \frac{TP}{(TP + FN)} \tag{3}$$

$$Specificity, SP = TN/(TN + FP) \tag{4}$$

$$Accuracy, ACC = \frac{(TP + TN)}{(TP + FP + FN + TN)} \tag{5}$$

where TP = number of MD accurately detected as the case group, TN = number of control subjects accurately identified as the control group, FN = number of MD inaccurately detected as the control group, and FP = number of control subjects inaccurately detected as the case group.

The AUC of the ROC curve can be measured by the following equation.

$$AUC = \int_0^1 ROC(t)dt \tag{6}$$

where t = (1 – specificity) and the ROC (t) is sensitivity.

RESULT AND DISCUSSION

Data Acquisition

Table 2 provides a summary of participant data, including gender, age, height, weight, BMI, and accuracy of the Stroop test. The average age of the participants in the control group was 23.8 years and there were 16 men and 30 women (34.8% and 65.2%, respectively). 16 men and 30 women, with a mean age of 24.76 years, made up the case group. Levene's Test for Equality of Variances revealed no statistically significant differences between the two groups in terms of gender (p = 1.00), age (p = 0.491), BMI (p = 0.366), and the accuracy of the Stroop test (p = 0.640).

TABLE 2 Demographic and Characteristics of the Subject (N = 92)

Characteristics	Mean (SD)		*P*
	Control (*N* = 46)	Case (*N* = 46)	
Gender, male	16	16	1.00
Age	23.80(6.02)	24.76 (5.43)	0.491
BMI (kg/m^2)	23.49(5.29)	24.20 (7.79)	0.366
ST Accuracy	96.10(14.47)	93.99 (11.71)	0.640

Pre-processing

The PPG signal was first filtered and then an SQI approach was used to identify a reliable signal. The high-quality PPG signal is shown in blue, whereas the low-quality PPG signal is highlighted in red (see Figure 3).

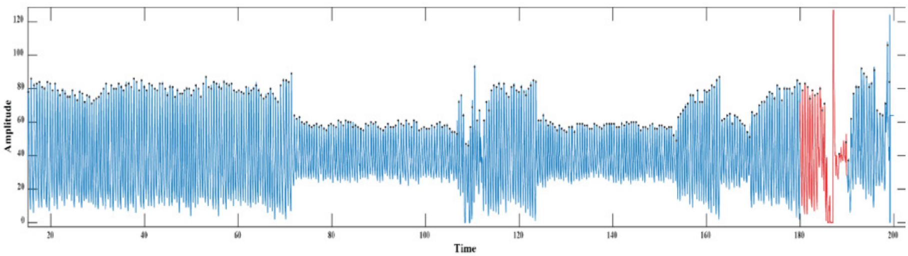

FIGURE 3 PPG Signals with low quality are red, while those with high quality are blue.

Feature Extraction

In this study, 30 features were extracted from the PPG signal. HR and PRV features were extracted using Python, while fiducial point detection (onset, systolic, notch, and diastolic) was extracted with MATLAB. These features were divided as follows: 20 from the time domain, two from the frequency domain, and four from the amplitude domain.

Statistical Analysis and Feature Selection

The rank of the *p*-value in descriptive statistics was applied by analyzing the mean values for each feature. Among the 30 features, 13 features with significant differences (*p*-values<0.05) were identified (see Table 3).

TABLE 3 Significant Features are Ranked by the *p*-value from Smallest to Largest

No.	Feature	*p*-value
1	N_iO_{i+1}	<0.05
2	HF	<0.05
3	MAD	<0.05
4	PNN50	<0.05
5	LF	<0.05
6	S_iO_{i+1}	<0.05
7	PNN20	<0.05
8	O_iO_{i+1}	<0.05
9	SDNN	<0.05
10	BPM	0.001
11	IBI	0.001
12	N_iN_{i+1}	0.003
13	N_iS_{i+1}	0.007

Then, the significant features were validated through correlation analysis. Figure 4 shows the heat map of the correlation matrix and the correlation strength (absolute value of the correlation coefficient, |r|). It also shows that some of the data points have a strong correlation and contained similar data points, meaning that they were more likely to be associated with each other. PNN20 was removed because it had a high correlation (correlation |r| > 0.8) with PNN50 and MAD. S_iO_{i+1}, BPM, IBI, and N_iS_{i+1} were highly correlated to one another given that most measurements were close to and consistent with a pulse measurement. S_iO_{i+1} was chosen because it had the least *p*-value and the highest correlation strength with respect to other measure related to S_iO_{i+1}, such as IBI, BPM, and O_iO_{i+1}. The strength of the correlation was determined by analyzing the lowest p-value. Upon reviewing the heatmap, it was observed that the correlation exhibited an average strength of 0.38 ± 0.0631. In this context, it could be inferred that a strong correlation existed, which was also statistically significant.

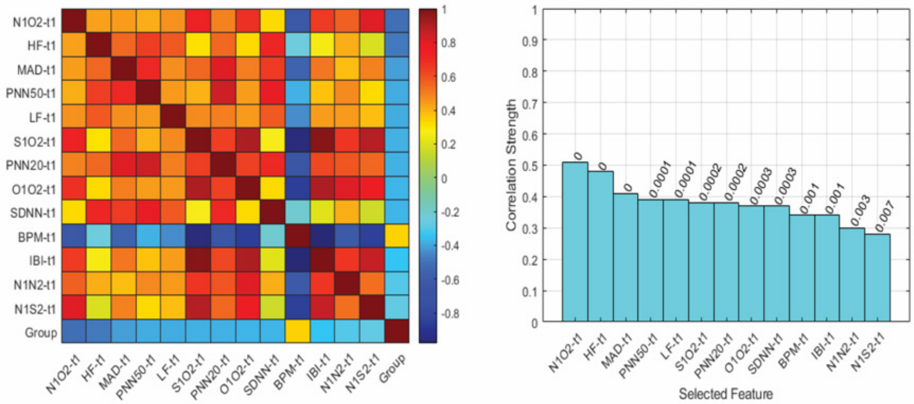

FIGURE 4 The Correlation Matrix and Correlation Strength

Classification

To classify case and control individuals using the chosen attributes, five distinct ML models are created. The models used in this study were randomly split into training and test data, and they were trained using increasing input numbers beginning with the lowest *p*-value. For each task, the same random values were chosen to give each model identical training and testing data. The accuracy of the best-trained models for each ML with different numbers of features is shown in Figure 5. kNN produced the highest accuracy (96.43%) in classification using four features: N_iO_{i+1}, HF, MAD, and PNN50.

In terms of model robustness, the best metric to measure is the AUC (area under the curve) of a ROC curve (receiver operating characteristics). This metric is polyvalent as it measures the ability to accurately predict a particular class. The AUC score is the area under the ROC curve and is a useful measure for measuring the performance of a classifier. The ROC curves and performance of the best-trained model for each ML are shown in Figure 6. In this study, the AUC-ROC for kNN (0.964) was higher than in other models.

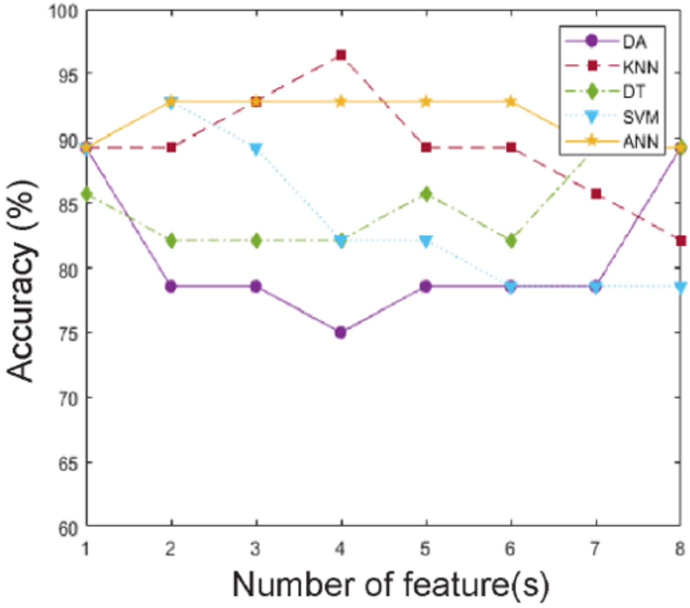

FIGURE 5 ML Classification Performance with an Increasing Number of Features

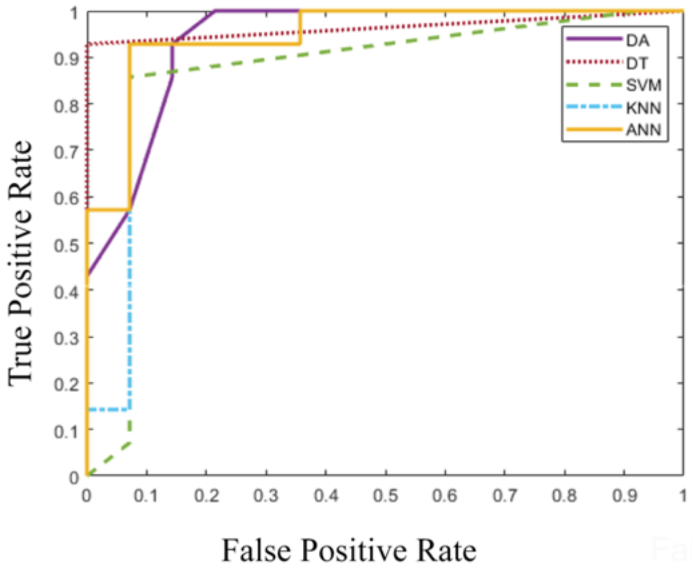

FIGURE 6 The Best-trained ML Model's AUC-ROC Curve

The best performance of the ML model in this study was observed in kNN with SN of 92.86%, SP of 99.10%, and ACC of 96.43%. The detailed performance of the five ML models is shown in Table 4.

TABLE 4 The Best-trained Model Classification Performance

ML	DA	*kNN	DT	SVM	ANN
Task			(N=8)		
Trained features	1	4	7	2	2
ML Setting	Type=Linear	k=1	Split=1	Kernel=3rd order Polynomial	HN1=5 HN2=8
Val MSE	0.250	0.308	0.231	0.154	0.154
Val ACC	75.00	69.23	76.92	84.62	84.62
Test MSE	0.107	0.036	0.108	0.071	0.071
%Test SN	92.86	92.86	85.71	92.86	92.86
%Test SP	85.71	99.10	92.86	92.86	92.86
%Test ACC	89.29	96.43	89.29	92.86	92.86
AUC	0.941	0.964	0.870	0.918	0.949

The current study discovered that PPG features differentiated patients with MD from control subjects, implying that PPG features are biomarkers for MD. The correlation matrix showed that four out of the 13 features selected from a PPG signal had high significance. The classification group consisted of N_iO_{i+1}, MAD, and PNN50 from the time domain and HF from the frequency domain, which had the lowest *p*-value and the highest correlation strength. Additionally, all these features had lower mean values in the case group than in the control group. These results were consistent with previous studies (Hartmann et al. 2019), in which the PRV features of depressed patients were lower than those of nondepressed patients. N_iO_{i+1} could be used to assess stress as a result of changes in cardiovascular properties (Charlton 2018). Furthermore, PRV features (MAD, PNN50, and HF) are related to ANS and respiration and may be used to identify pathological conditions in mental health (Dillen et al. 2020; Liu, Ni, and Peng 2020; Firth et al. 2017; Nardelli et al. 2017).

These findings hold promise for improving mental health care in societies affected by COVID-19, in alignment with ethical principles and Islamic values. The integration of such scientific advancements with ethical and Islamic perspectives can contribute to a holistic approach to mental health care within Islamic civilisations. This includes providing easily accessible and inclusive mental health services that cater to the diverse needs of individuals within the Islamic civilisation, adopting culturally sensitive approaches through research involving diverse populations while respecting the values and norms of different communities within the Islamic civilisation, promoting education and awareness about mental health within Islamic communities, fostering understanding and reducing stigma surrounding mental health in line with Islamic ethical principles such as empathy and compassion, integrating Islamic counseling approaches, and conducting research ethically based on Islamic principles such as justice and the protection of human dignity. However, further research with larger sample sizes and diverse populations is needed to solidify the practical applications of these findings. Besides this concern, there are also other potential biases in data obtained by the use of this ML. Cultural Bias: The way mental health data is collected and interpreted may be influenced by individuals' cultural backgrounds. For instance, certain mental health symptoms or expressions may be culturally specific and not easily recognized by a model that lacks cultural diversity in its training data. Algorithmic Bias: If the ML algorithm is not designed to account for cultural, gender, or age-related variations in mental health, it may make inaccurate predictions or recommendations for specific groups. Privacy and Data Security: In the process of collecting and utilizing mental health data, concerns about privacy and data security must be taken into consideration. If sensitive mental health information is not adequately protected, it can lead to ethical and legal issues.

CONCLUSION

This study has shown that the ML performance model, kNN provided 92.86% sensitivity, 99.10% specificity, and 96.43% accuracy compared to other ML models. Therefore, an MD prediction model was developed using machine learning techniques from PPG morphological extraction. While the kNN model has shown promising outcomes in this study, future research should prioritize strengthening its reliability and feasibility. This can be achieved through thorough validation, enhancing model interpretability, conducting comparative analyses with alternative models, and addressing scalability considerations. Taking this comprehensive approach will enable a more accurate assessment of the kNN model's potential for predicting mental disorders in practical healthcare applications.

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