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Prediction of Medical Students' Mental Health in Palestine During Covid-19 Using Deep and Machine Learning

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ABSTRACT

Introduction: The COVID-19 outbreak has nearly brought the globe to a standstill, and it has had both immediate and long-term effects on mental health university's students. The current study aims to forecast changes in a few mental health indicators, including depression anxiety, social dysfunction, and loss of confidence among Palestinian medical students. **Methods:** The 300 students completed a General Health Questionnaire (GHQ) with a score of 15 or above. Afterward, the survey data was analyzed and sanitized. The survey data was examined, and a comparative prediction of the probabilistic changes of the mental health variables was carried out using common deep and machine learning techniques, such as deep Artificial Neural Network (DNN), Support Vector Machine (SVM), and Random Forest (RF). **Results:** The findings of these algorithms were reviewed using four commonly used statistical indicators to provide a better comparison between real and predicted data in terms of Coefficient of Determination (R^2), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE). The DNN results were the best, with a coefficient of determination (R^2) of 99% and the other error measures being 0.00002, 0.0046, and 0.0035 for MSE, RMSE, and MAE, respectively. The determination coefficient R^2 for SVM and RF were 92.1% and 89.5%, respectively. **Conclusion:** This study highlights the importance of using machine learning tools for mental health prognosis.

Keywords: Mental Health, Medical Students, Deep Learning, Machine Learning.

INTRODUCTION

Wuhan, China, emerged as the epicenter of the first coronavirus disease (COVID-19) outbreak in December 2019, following the identification of the first case of coronavirus disease in November 2018, notwithstanding earlier occurrences of the disease in China [1]. The initial confirmed case of SARS-CoV-2 in Palestine was reported on March 5, 2020, subsequent to positive test results from a group of Greek visitors who had stayed at the Ba hotel in late February. By May 20, 2021, Palestine had documented 3,720 deaths and 333,810 cases, as reported by the Palestinian Health Minister [2]. The highly contagious nature of the virus necessitated immediate implementation of lockdowns and quarantines, significantly impacting students of all ages worldwide [3]. Consequently, all schools and universities in Palestine transitioned to remote instruction after the Palestinian National Authority declared a state of emergency on March 5, 2020, in efforts to mitigate the spread of COVID-19. Many students and professors were unprepared for this swift transition, resulting in inadequate access to necessary resources and facilities. This unforeseen shift posed unexpected challenges for many students, severely disrupting the educational process for some [2, 4]. The majority of learners were compelled to complete coursework independently from home, with limited access to educational aids. A smaller proportion of students lacked the means to communicate with their professors or peers, exacerbating feelings of uncertainty, sadness, anxiety, and isolation. Studies suggest that the lockdown measures implemented to contain the virus contributed to heightened feelings of despair, anxiety, and social isolation [5], with potentially adverse effects on mental health [6]. While the COVID-19 pandemic has taken a toll on all segments of society, its impact on students, particularly those in medical school, is profound [7]. Medical students, who regularly engage with COVID-19 patients, have seen their academic, social, personal, and recreational lives disrupted. These disruptions have led to feelings of detachment, ennui, frustration, anxiety, and apprehension [8].

This study primarily focuses on medical students. Medical education is inherently stressful and demanding, with students expected to navigate not only the typical stressors of life but also the complexities of medical science, post-graduation job prospects, and mounting debt [9]. While first-year medical students experience mental health issues at levels similar to their non-medical peers and the general population [10,11], these issues tend to intensify as they progress through their studies [12]. Globally, one-third of medical students' report experiencing depression or depressive symptoms [13,14], with depression, psychosomatic conditions, and anxiety being prevalent mental health concerns [15]. Additionally, medical students are at an increased risk of developing eating disorders [16]. Research suggests that female medical students experience higher levels of stress compared to their male counterparts [17], although some studies have found no correlation between race and psychological distress among medical students [18,19]. Marital status has also been linked to the mental health of medical students, with married students exhibiting lower rates of psychological distress [20]. Furthermore, psychological distress has been associated with poorer academic performance [21,22].

Machine Learning (ML) and Deep Learning (DL) are computer techniques that autonomously determine approaches and parameters to arrive at optimal solutions to problems, rather than being programmed with predetermined solutions [23,24]. Situated within the domain of Artificial Intelligence (AI), this learning process mimics aspects of human intelligence and can be utilized for various intelligent objectives. Central to ML methodology is the selection of techniques for classification, regression, clustering, or prescriptive modeling. These techniques encompass both supervised and unsupervised strategies. In psychiatry, ML techniques aim to derive statistical relationships from multidimensional datasets to make generalized predictions about individuals. Translational psychiatry presents four primary challenges—diagnosis, prognosis, therapy prediction, and biomarker identification and monitoring—which can be effectively addressed using ML approaches [25].

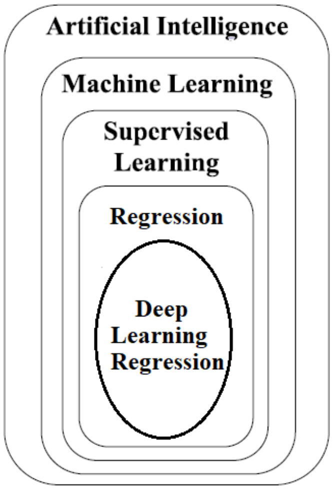

Figure (1): Artificial Intelligence & Machine learning.

Psychiatry relies on prognostic results to manage patients, provide psychoeducation, preventative psychotherapy, and prescribe medication and other treatments. According to [26,27], the most that can be done right now with objective evidence is to make the assumption that the person belongs in a diagnostic category based on their clinical symptoms and signs, and then use population averages to support that assumption. The number of people treated needlessly increases as a result of inaccurate stratification [28, 29, 30]. Thus, stratified prognostic forecasts would be helpful for treatment planning to pinpoint crucial turning points in the progression of an illness, such as changes in symptom severity, changes in daily functioning, and changes in quality of life [25].

To characterize depression trajectories over a two-year period, [31] combined magnetic resonance imaging with a focus on structural and functional tasks with ML techniques. They found that their predictive rates were comparable. Other research on depression has also used case records to categorize people based on their risk of suicide [32, 33] or self-reported clinical questionnaires to predict the course of the illness [34]. Individuals have also been stratified according to models that forecast future substance abuse using neuroimaging data [35] and a mix of demographic, clinical, cognitive, neuroimaging, and genetic data [36]. These studies demonstrate the ability to group people into categories to improve prognostic evaluations. For instance, Koutsouleris et al. used 189 questionnaire items gathered from 44 mental health facilities to predict the functional outcomes of people with a first episode of psychosis [37]. The analysis findings showed that outcomes can be anticipated with an accuracy of more than 70%. The study emphasizes how an ML technique might assess generalizability and generate condensed sets of features that may be used to create new questionnaires to evaluate patient outcomes.

In this study, machine learning and deep learning regression techniques were used to predict changes in various mental health characteristics of medical students, such as depression, anxiety, social dysfunction, and loss of confidence. First, the prevalence of mental health concerns and their associated factors was evaluated using the available data. Then, widely used medical and psychiatric ML techniques, such as Deep Artificial Neural Network (DNN), Random Forest (RF), and Support Vector Machine (SVM), were used to anticipate these three characteristics [38, 39]. Following that, certain important statistical metrics were used to discuss the algorithms' performances. The importance of the study lies in the use of AI through ML, which is widely used in medical field, prediction, and diagnosis. Additionally, the study's importance lies in the use of ML to predict the speed and accuracy of psychological problems, an important indicator for workers in the medical field, and it can be easily developed into a mobile application for use in primary medical care centers. Moreover, the significance of the study lies in examining the accuracy of predicting mental disorders through machine learning (ML), significantly contributing to overcoming the stigma crisis that prevents many people in need of psychological services and care. Therefore, the current study utilized machine learning and deep learning regression techniques to predict changes in various mental health characteristics among medical students, including depression, anxiety, social dysfunction, and loss of confidence.

METHODS

Study design

A cross-sectional study was conducted in two stages in March 20221. In the initial phase, a 12 item General Health Questionnaire (GHQ-12) was utilized to evaluate the prevalence of mental health issues and associated risk factors among a sample of medical students at An-Najah National University in Palestine. In the subsequent phase, predictive models for three mental health characteristics were developed using machine learning (ML) techniques. Figure 2 illustrates the flowchart of the study. This section provides comprehensive details on data collection, statistical analysis, data normalization, and ML techniques. Section 2.1 delineates data collection procedures, Section 2.2 elaborates on statistical analysis, Section 2.3 outlines data normalization techniques, and Section 2.4 elucidates the ML algorithms employed.

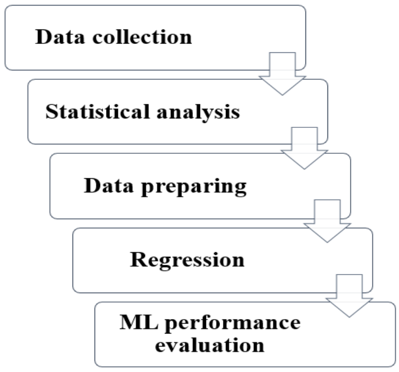

Figure (2): Study flow chart.

Data collection

Ethical approval for the study was granted by the Institutional Review Board (IRB) (Ref: Med. February.2021/9) of An-Najah National University in Nablus, Palestine, in accordance with the principles outlined in the Helsinki Declaration regarding human research. An online self-administered questionnaire was utilized for data collection, conducted between March and May 2021. Participants identified with a propensity for psychological issues (as indicated by a General Health Questionnaire (GHQ) score of 15 or higher) were selected and invited to complete the questionnaire. The collected data were numerical in nature. The questionnaire comprised 12 items, with responses ranging from 0 to 3. Total scores ranged from 0 to 36, with higher scores indicating a greater degree of disturbance in general health. A total score exceeding 15 points suggested a propensity for psychological issues. A total of 329 students participated in the questionnaire, with 300 students included in the subsequent data analysis.

Every participant received an overview of the study's objectives, as well as information on the kinds of data that will be gathered. An online questionnaire that participants self-administered was used to gather data. Additionally, prior to the study's start, each subject gave their written consent. Data were gathered in 2021 between March and May. Participants in the first phase of the study had to be at least eighteen years old, willing to participate, and able to supply all the necessary data. Individuals with a predisposition to psychological issues (general health questionnaire-12 score of 15 or higher). The study excluded students who were taking psychotropic or antidepressant medications.”

Data collection tool

The 12-item General Health Questionnaire (GHQ-12) was employed to assess mental health status [40]. The reliability and validity of the Arabic version have been confirmed [41]. GHQ scoring categorized responses as follows: 0 for better than usual, 1 for usual, 2 for less than usual, and 3 for much less than normal. Total scores ranged from 0 to 36, with higher scores indicating greater disruption in general health status. Participants scoring 15 or higher were considered predisposed to psychological problems [42,43]. GHQ scores ranged from 2 to 36 points, with a mean of 18.1 ± 7.7. The mean scores for depression and anxiety on the GHQ subscales were 7.0 ± 2.8 (range: 0–12), for social dysfunction 7.7 ± 3.4 (range: 0–15), and for loss of confidence 2.1 ± 2.0 (range: 0–6).

Statistical analysis

Data were analyzed using SPSS, version 21, with a statistical power of 80% and an alpha level of 5% for all tests. Means, standard deviations (SD), and percentages were estimated for continuous variables. The chi-square test assessed categorical variables related to depressive symptoms, while the independent sample t-test examined differences in means for continuous variables. To evaluate intervention impact on outcome variables, the percentage of mean change was calculated from pre- to post-intervention for each subject, followed by comparison of mean percentage differences between groups using an independent t-test.

Data preparation

GHQ-12 was utilized to collect data on factors influencing student mental health, resulting in a dataset with 12 columns and a total of 300 rows. Given differing units of quantification, normalization was necessary to address significant interquartile range and distribution in the dataset, a crucial preparatory step for machine learning (ML) algorithms. Failure to normalize can lead to dominance by larger-scale variables, compromising numerical stability in ML and deep learning (DL) techniques [44]. Minimum-maximum normalization was employed to enhance model fit to the data [45], treating all features equally in terms of magnitude [46]. This method linearly adjusts unnormalized data to a predefined lower and upper bound [47]. In this study, minimum-maximum normalization rescaled the data to a range of [0,1].

Machine and Deep Learning Algorithms

Regression, classification, and decision-making procedures can be applied across various fields, from engineering to healthcare [48, 49, 50, 51]. Deep Learning (DL) and Machine Learning (ML) algorithms ensure highly satisfactory accuracy. In this study, three ML and DL algorithms Deep Neural Network (DNN), Support Vector Machine (SVM), and Random Forest (RF) were examined to forecast changes in various mental health metrics. The training phase of these algorithms utilized 12 inputs and 3 outputs (mental health parameters).

Deep Neural Network (DNN)

DNN, the most widely used AI algorithm, is inspired by biological neural networks in the brain and simplified versions thereof [52]. Essentially, this algorithm mimics the functioning of the biological nervous system, seeking to comprehend systems before generalizing findings. Due to its capacity for complex and nonlinear system prediction, it finds application in diverse fields. Technically, it adjusts weight values by focusing on the intricate intersection of input and output data. Typically, a backpropagation algorithm comprises several layers—input layer, hidden layers, and output layer and two stages: training and testing. In this study, a model structure with input, output, and two hidden layers of 12-12-10-3 (number of neurons) was obtained. The output layer comprised 3 mental health characteristics: anxiety, social dysfunction, and loss of confidence. Activation functions employed were Relu for hidden layers, Tanh for the output layer, and linear. Adam optimizer, early stopping modes, along with 200 training cycles, were specified.

Support Vector Machine (SVM)

A supervised learning technique, SVM can address problems involving regression and classification. It was introduced in 1992 [53] and has garnered increasing interest from researchers across various domains due to its efficacy and viability as a machine learning technique. One notable advantage of SVM is its adherence to statistical learning theory and the principles of structural risk minimization, aiming to reduce the upper bound of error in the generalization stage. To identify the ideal SVM model, Radial Basis Function (RBF), Linear, polynomial, and sigmoid kernel functions were examined, with RBF kernel selected for predicting the three mental health characteristics due to superior performance.

Random Forest (RF)

RF, a supervised learning algorithm, offers the benefit of applicability to both classification and regression problems, which are predominant in modern ML systems. It constructs an ensemble of Decision Trees (DT), typically trained using the "bagging" approach. Each internal node in a DT represents a test on an attribute, each branch reflects the test's result, and each leaf node represents a class label denoting a choice made after weighing available information. The bagging method combines learning models to enhance results. In the regression technique of RF, the performance of multiple DT algorithms is combined to categorize or predict the value of a variable. For this study, RF was utilized to predict the three mental health metrics with a maximum depth of 5.

RESULTS

In this study, regression techniques were applied to predict three mental health parameters: depression, anxiety, social dysfunction, and loss of confidence. The dataset was organized, and a total of 12 features (GHQ responses) were used for each input in DNN, SVM, and RF models. The tests were conducted using the Python programming language and its associated libraries: Keras, TensorFlow, and Scikit-learn. During the regression process, 60% (180 students) of the dataset was randomly assigned as training data, 20% (60 students) as validation data, and another 20% (60 students) as test data (see Figure 3). Statistical benchmarks, including the Determination Coefficient (R^2), Mean Square Error (MSE), Root Mean Square Error (RMSE), and Mean Absolute Error (MAE), were utilized as performance metrics to assess the regression models' efficacy in predicting the real data. An ideal model would exhibit a Coefficient of Determination (R^2) closer to one, while the other statistical indicators would tend towards zero.

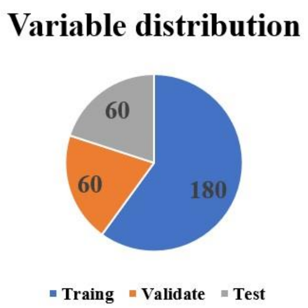

Figure (3): Variable distribution.

Figures 4 through 12 depict the actual and predicted results for the three mental health parameters using DNN, SVM, and RF. These visualizations illustrate the correspondence of predicted data to actual observations, with the x-axis representing the number of students (test data) and the y-axis indicating normalized health indicators. It is evident from the figures that DNN exhibits the highest accuracy compared to other models such as SVM and RF.

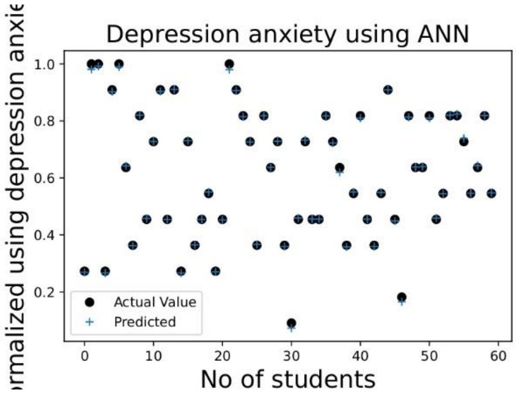

Figure (4): Actual & predicted results using ANN; depression anxiety.

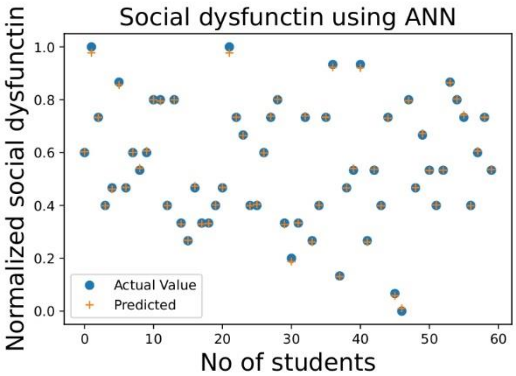

Figure (5): Actual & predicted results using ANN; social dysfunction.

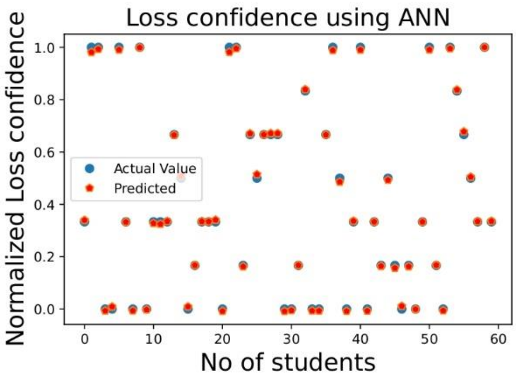

Figure (6): Actual & predicted results using ANN; loss confidence.

It is evident from Figures 4–6 that the estimated results from the deep ANN closely align with the actual values. When compared to the true values, the results exhibit a high determination coefficient across all dimensions, including loss of confidence, anxiety, sadness, and social dysfunction. This underscores the effectiveness of deep ANN models in accurately forecasting mental health indices.

The strong association observed between the ANN-estimated outcomes and the actual values not only validates the model's reliability but also underscores its potential to support clinical assessments and therapies effectively. By leveraging advanced computational approaches like deep learning, we can gain deeper insights into the complex dynamics of mental health issues. This, in turn, can pave the way for the development of more targeted and efficient treatment strategies.

The findings presented in Figures 4–6 underscore the significance of deep ANN in advancing our understanding and prediction of mental health indicators. This presents new avenues for enhancing clinical decision-making and, ultimately, enhancing patient outcomes.

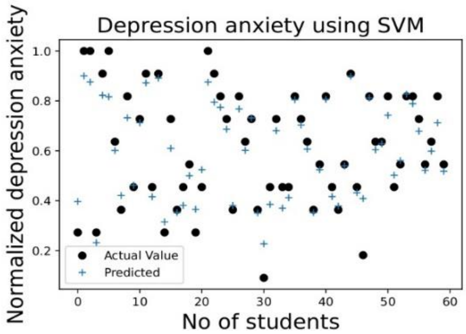

Figure (7): Actual & predicted results using SVM; depression anxiety.

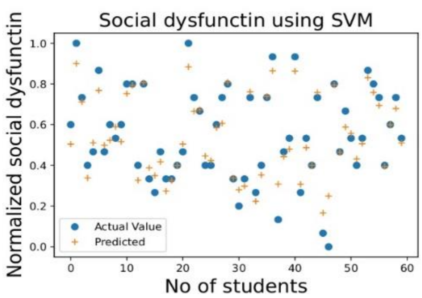

Figure (8): Actual & predicted results using SVM; social dysfunction.

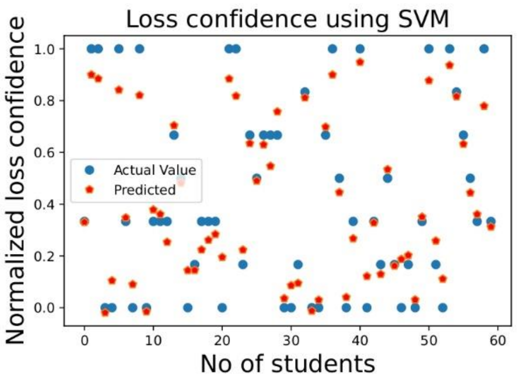

Figure (9): Actual & predicted results using SVM; loss confidence.

When compared to the actual values, the SVM method yields the lowest determination coefficient (0.921), as evidenced by the analysis of Figures 7–9. Nonetheless, the SVM model demonstrates a notable capability to approximate the actual values across various mental health indicators, including loss of confidence, anxiety, sadness, and social dysfunction, despite this reduced coefficient.

Although SVM exhibits the lowest determination coefficient among the models examined, a coefficient of 0.921 still signifies a substantial correlation between the estimated and actual values. This indicates that SVM remains a viable option for predicting mental health indicators reliably, even if it may not achieve the same level of accuracy as deep ANN or Random Forest.

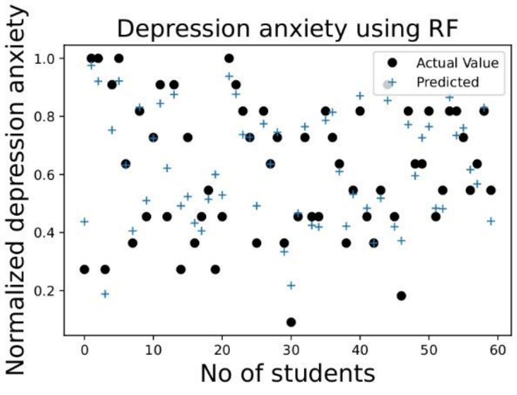

Figure (10): Actually & predicted results using RF; depression anxiety.

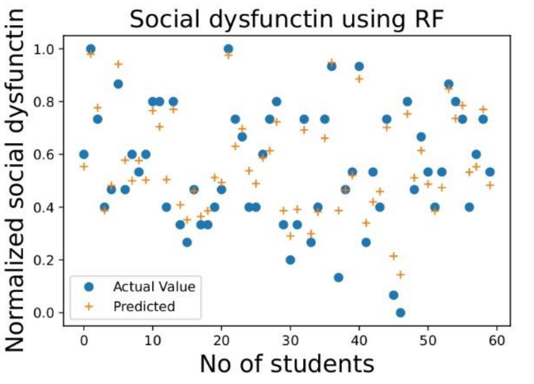

Figure (11): Actual & predicted results using RF; social dysfunction.

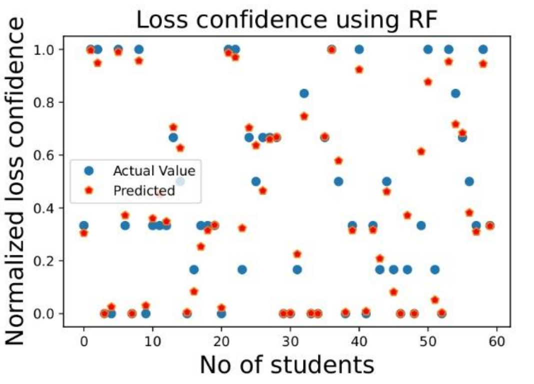

Figure (12): Actual & predicted results using RF; loss confidence.

Upon close examination of Figures 10–12, it becomes apparent that the estimated outcomes generated by the RF algorithm exhibit a significantly lower determination coefficient compared to the actual values. Nevertheless, the RF model demonstrates a notable ability to approximate the true values across various factors, including social dysfunction, melancholy, anxiety, and loss of confidence. While the determination coefficient may be somewhat lower than the results obtained from deep ANN models previously discussed, the RF method still offers valuable insights into mental health indicators. The performance of the RF model suggests its potential as an alternative method for forecasting these complex phenomena, albeit with potentially lower accuracy. Despite not achieving the same level of accuracy as deep ANN in this context, RF still holds promise in supporting mental health evaluation and intervention techniques, as indicated by the moderate correlation observed between the RF-estimated outcomes and the actual values.

RF models offer an alternative perspective to deep learning techniques, leveraging the advantages of decision trees and ensemble learning to provide fresh insights into the dynamics of mental health.

Tables 1 through 3 provide a summary of the evaluation of the three algorithms utilized in this experiment across the three datasets (train, validate, and test). R2, MSE, RMSE, and MAE are four commonly employed statistical metrics utilized to assess the accuracy of the three models employed.

Table (1): Train data performance evaluation.

Algorithm	MSE	RMSE	MAE	R^2
DNN	0.000452	0.0046	0.0035	0.99
SVM	0.003	0.073	0.048	0.94
RF	0.001	0.033	0.024	0.98

Table (2): Val data performance evaluation.

Algorithm	MSE	RMSE	MAE	R^2
DNN	0.00000487	0.00698	0.005	0.99
SVM	0.004	0.066	0.052	0.935
RF	0.008	0.089	0.068	0.876

Table (3): Test data performance evaluation.

Algorithm	MSE	RMSE	MAE	R^2
DNN	0.00004587	0.006777	0.00492	0.998
SVM	0.005	0.074	0.056	0.921
RF	0.006	0.081	0.059	0.895

The R2 value of the Deep ANN model (R2 = 0.998) approached 1, indicating high precision, while other statistical error measures (MSE, RMSE, and MAE) were close to zero. In the SVM regression case, the R2 value was 0.921, with corresponding error measures of MSE = 0.005, RMSE = 0.074, and MAE = 0.056. Comparatively, RF's statistical metrics were lower, featuring an R2 of 0.895, and MSE, RMSE, and MAE values of 0.006, 0.081, and 0.895, respectively.

Figure 14 displays the ML correlation results for the three ML algorithms investigated, while Figure 15 illustrates the associated statistical metrics. It is evident that the ANN outperformed other methods in predicting mental health parameters, achieving the highest accuracy among them.

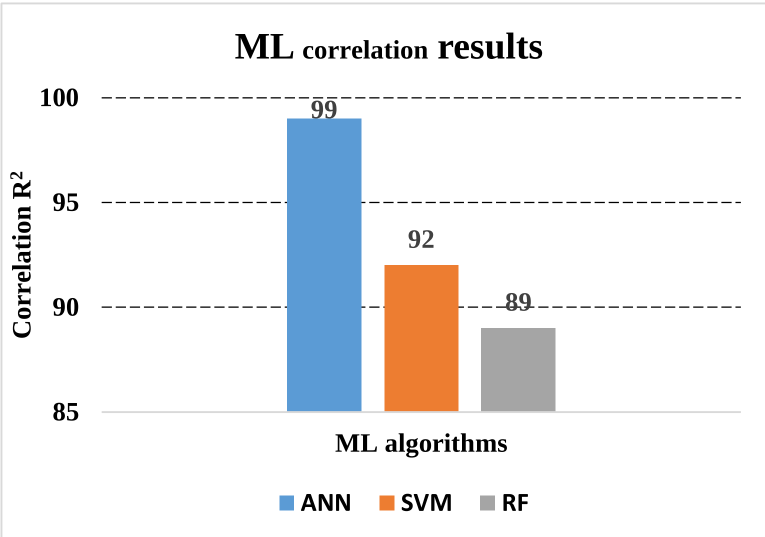

Figure (13): ML correlation results.

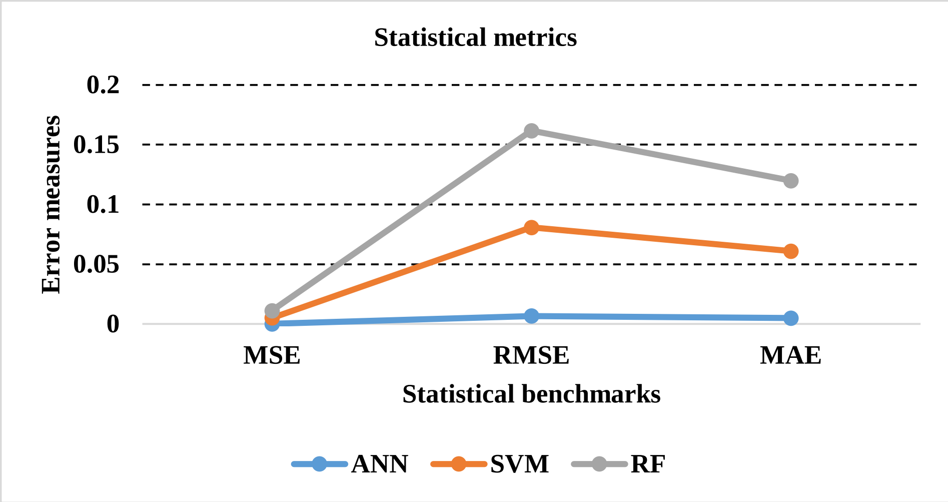

Figure (14): Statistical metrics where x axis is related to error metrices, and y axis is related to error quantity.

DISCUSSION

The findings of this study align with previous research, indicating that approximately one-third of medical students experience depression or depressive symptoms [13,14,57,58]. Psychosomatic illness, anxiety, and depression are recognized to coalesce into a significant mental health challenge [15]. The efficacy of machine learning models in forecasting changes in various mental health attributes was assessed by measuring MSE, RMSE, MAE, and R2. The DNN model exhibited superior correlation performance and lower values for RMSE, MSE, and MAE compared to other models applied. These results are consistent with prior studies evaluating the effectiveness of ML regression in predicting changes in diverse mental health parameters, where the SVM model demonstrated an overall precision of 82.75.

In a study by Koutsouleris et al. [37], ML models achieved an accuracy level above 70% in predicting the functional outcomes of individuals experiencing a first episode of psychosis. Similarly, Arbabshirani et al. [38] reported at least 27 neuroimaging studies predicting the progression from moderate cognitive impairment to Alzheimer's disease with an average prediction accuracy exceeding 70%. Saha et al. predicted changes in various mental health characteristics, including education, behavior, and mood of young individuals in West Bengal, India, using SVM with precisions of 82.75%, 72.41%, 65.51%, 58.62%, and 72.41% [56]. Comparing our study with other similar ML prediction studies, we found that ours had higher accuracy performance measures with accuracies of 70% and 82% [56]. Our study revealed an accuracy of 99%, demonstrating the effectiveness of machine learning models in predicting mental health parameters.

A notable finding of this study is the high accuracy performance measures achieved by the selected ML models. According to our research, employing ML approaches to screen medical students will aid in identifying those most at risk of developing depression through regression analysis, subsequently facilitating the development of successful preventive measures. Moreover, due to the multinational dataset used in this study, it also evaluates the predictive potential of various ML algorithms among students while addressing the integration of novel technologies for detecting and treating anxiety and depression in medical students.

CONCLUSION

In this study, we assessed the mental health of medical students and predicted several mental health characteristics, including anxiety, social dysfunction, and loss of confidence. Data was collected using the GHQ, and three machine learning and deep learning algorithms were employed to predict these characteristics. Our results demonstrated that the DNN model achieved a correlation R2 of 99.8% and low error metrics of 0.000045, 0.0067, and 0.00492 for MSE, RMSE, and MAE, respectively. These findings underscore the importance of utilizing ML and DL methods for mental health prognosis. The significant outcome of high predictability for psychological problems such as depression, anxiety, low confidence, and social dysfunction in the current study may motivate individuals to seek mental health services without fear of stigma by utilizing artificial intelligence applications.

Ethics approval and consent to participate

The An-Najah National University in Nablus, Palestine, Institutional Review Board "IRB" granted ethical approval, and the study complied with the Helsinki Declaration for research involving human subjects. All the student's Informed consent was taken for participation in the study.

Consent for publication

Not applicable

Availability of data and materials

The datasets used and/or analyzed during the current study are available from the corresponding author upon reasonable request.

Author's contribution

All authors listed have contributed to the work and approved it for publication. The authors have worked in an organized manner. Ahmad Hanani & Mohammed Mansour Conceptualized, supervised, and designed the study and wrote the manuscript. Mohammed Mansour did the software preparing. Manal Badrasawi collected the data. Ahmad Hanani has reviewed the data and the final manuscript for approval. The authors read and approved the final manuscript.

Competing interest

The authors declare that they have no competing interests.

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