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Ethical Considerations in Utilizing Machine Learning for Depression and Anxiety Detection in College Students

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Abstract: Depression and Anxiety are two of the most common mental disorders that are happening nowadays worldwide. This systematic review paper investigates the application of neural network-based machine learning techniques in assessing, identifying, and diagnosing depression and anxiety, which are two worldwide mental health problems. These approaches can range from many different types of neural network architectures like classical supervised learning methods to unsupervised approaches with recent deep models; if a systematic literature review of studies conducted in the last five years is carried out using databases like Science Direct and PubMed, these approaches can show promising results in tasks like clinical data analysis, biomarker identification, and personalized treatment plan creation. This makes it possible to explain the 91.08% accuracy ratio that he reported in his study, which gave rise to a comprehensive confusion matrix and analysis of the classification report for the employed neural network model (Level 6). There are still difficulties in correctly identifying cases of depression (class 1) despite relatively high recall and precision in non-depressive cases (class 0). This raises possible areas for improvement, particularly with the current class imbalances. This review paper can serve as a valuable source of information for all interested in neural network-based machine learning and how it may be used to address depression and anxiety, thereby providing insight into the future that will likely change mental treatment models.

Keywords: Machine Learning; Depression, Anxiety; Supervised Learning; Biomarkers; Mental Health; Diafgnosis and Review.

1. Introduction

People are becoming increasingly driven in their pursuit of careers [1]. They pay attention to their mental well-being because they understand that it portends a prosperous future. A student represents the future that society is investing in. Their contribution to the general well-being of society, as well as their mental health and well-being, are equally significant. It has been observed that psychological issues might affect anywhere from 2 percent to 50 percent of students. Mental illness has numerous causes (depression and anxiety) [2]. According to research, the main causes of anxiety and depression are thought to be familial circumstances, work position, and academic achievement [3]. Furthermore, appropriate mental health diagnosis and treatment lower the incidence of anxiety and depression [4].

Concern is growing over the high rate of depression among college students in the country. Depression is regarded as a multifaceted illness that interferes with social, professional, and interpersonal interactions. The fundamental feature of depression is a loss of positive affect, which can show itself as a variety of symptoms such as worry, poor concentration, sleep disturbance, neglect of oneself, and disinterest in day-to-day activities. Compared to 9% of the general population, research indicates that around50 one-third of college students have depression symptoms [5]. The World Health Organization (WHO) estimates that depression is the most predominant mental disorder, distressing over 300 million people worldwide. Because of its seriousness, numerous health researchers have directed their study efforts towards this field [6]. Late adolescence, a period of significant social stress and transition, especially adjusting to college life, seems to be when symptoms of depression peak. Numerous health issues have been connected to depression among college students, such as substance and alcohol misuse, increased tobacco use, anxiety and related mental health issues, weakened immune systems, and a higher risk of suicide [7].

A high prevalence of depression symptoms is seen among young people who have disabilities, cognitive impairment, or long-term medical conditions. Depression not only causes personal anguish and family strife, but it also exacerbates disability and the results of numerous physical conditions. Young patients' depression is always the result of a pathological process [8]. However, because of circumstances like late onset, co-morbid medical diseases, dementia, and grief, it may be challenging to detect in young people. Research has indicated that even in industrialized nations, there is still a deficiency in both diagnosis and treatment. Few comparable research have been conducted in the developing world, compared to the numerous studies conducted in affluent nations to regulate the incidence and threat aspects of depression between young individuals. The frequency and risk variables for depression varied significantly across all of these investigations [9].

Figure.1 illustrates the relationships between health risk behaviors and depression as well as how they relate to the findings of our study. All things considered, we discovered that poor choices made in life, traumatic experiences, lack of preparation for the future, and dissatisfied lives can effect in the improvement of dangerous performances associated to health, which ultimately, preferably or future, can outcome in depression [10]. Harmful outcomes such as low life satisfaction, depression, subpar theoretical routine, moderated sympathy, and diminished capability abilities might result from attending educational institutions.

Figure 1. Association b/w depression & health risk behaviors

We found that students who felt dissatisfied with their life, were informally remote, needed difficulty snoozing, had little regulator finished their circumstances, and depended on others for their future were more likely to experience depression [11]. Research has revealed that among Pakistani [44] medical students, the prevalence of depression is correlated with physical activity, sleeping patterns, lifestyle choices, recent trauma, and coping strategies [12]. Four broad categories can be used to group relevant aspects: lifestyle, college experience, psychological and personality traits, and biological components. Table 1 [13] presents the individual risk variables categorized into four groups based on the literature review.

Table 1. Factors related to depression in college students.

Sr. No	Type	Precise variable	Factors that exhibit a robust positive correlation with elevated depression levels
1	Biological Aspects	Nationality	International students and members of ethnic minorities
2		Family	Low socioeconomic position of the family Too many siblings and a non-only child Divorced parents, parents with mental health issues, and dysfunctional families
3	Character and psychological ceremonial		Being neurotic Existence of mental illness elevated psychological stress (aspiration, deprivation, coping, or value). Insufficient self-efficacy
4	College involvement	Year of revision	Indecisive
		Academic presentation	Deprived academic recital
		Financial sustenance	Absence of financial incomes and care
		College consummation	Low fulfilment with teachers and little approval with college
5	Life style	Physical keep fit	Want of Physical workout
		Stuff exploitation	Smoking and drinking
		Snooze	Daytime stupor, meagre sleep worth,
		Food	Unhealthy food eating, gluttony, gamboling breakfast

Numerous socio demographic characteristics, such as age, gender, examination criteria, dissatisfaction, and an interminable test schedule, have been identified in studies from Pakistan as significant threat issues for depression, anxiety, and strain, particularly in medical students [14].Anxiety is a complex and multidimensional term. Six features include negative feelings, thoughts of anxiety or fear, and bodily signs like high blood pressure. Anxiety is the expectation of a threat that might materialize in the future, as opposed to dread, which is the sense of helplessness over an actual, present threat. Anxiety is a natural reaction to stressful life events such as major decisions, employment reviews, job interviews, and possible job loss [15].

Anxiety is considered natural when it is balanced to the stressful state. It is called neurotic anxiety or scientific anxiety when a person's reply is tired available and available of amount to a supposed risk and the incapability to handle develops independent (i.e., self-perceived failure). A realization and conflict with essential human anxieties, such as the self-determination and responsibility to give life meaning, the progress of a determination, impending death, and the hunt of living truly, can spring upsurge to existential anxiety, a third grouping of anxiety that also grants as worry, dread, and panic [16]. However, no published study from Lahore, Pakistan, has examined the degree of anxiety and depression among students enrolled in degree programs offered on an annual and semester basis. Determining the incidence of stress, anxiety, and depression among students enrolled in semester and annual examination systems at several public and private universities in Lahore, Pakistan, is the aim of the current study [20].

Our study's goal was to look into the phenomenon of career anxiety, which is the uneasiness that college students feel when they are working on their professional development. Giving reasons for these encounters can help place the phenomenon in a broader context than its association with reluctance alone. Future research and creative measuring techniques that successfully capture the essence of career anxiety can also be guided by broadening the phenomena and offering theoretical underpinnings [21]. Furthermore, our research can assist practitioners in comprehending the actual professional experiences of college students as well as the societal forces that currently influence employment. This perspective can be used by counselors to assist college students in establishing their careers in the rapidly evolving job market of the twenty-first century [22].

Organic influences such as age and gender, especially being female, financial strain, academic pressure from exams and workload, lack of free time, competition, concerns about not meeting parental expectations, establishing new relationships, and moving to a new location can all contribute to anxiety during college [23]. Research conducted worldwide on a variety of undergraduate student samples has revealed that anxiety and depression are slightly to highly prevalent in this demographic. Early identification and treatment of psychological distress lead to better patient outcomes and management. Therefore, it is essential to identify college students who are more likely to experience mental health issues [24].

Both members of certain communities and the general population in Pakistan suffer from mental health matters. On the other hand, little is unspoken about college students' mental health. However, little is known about the mental health of college students. Although the study's sample size was small and stress was not evaluated, previous research has shown that anxiety and depression are rather common in this group [25]. Predictive factors were also not disclosed because psychological health status was not the primary research variable. Based on the aforementioned information, we aim to ascertain the prevalence of stress, anxiety, and depression in a sample of college students from Pakistan as well as the factors that affect them. Anxiety attacks [47] are one of the physical manifestations of anxiety. Figure 2 illustrates the symptoms of an anxiety episode include headaches, nausea, lightheadedness, and fast breathing [26].

Figure 2. Anxiety attack symptoms

2. Related Work

ML-based solutions within the domain of mental health utilize promising capabilities to achieve differentiation in a number of aspects, including early detection, increased accessibility, and efficiency. ML algorithms used by these applications allow for the analysis [45] of digital footprints, detecting subtle variations in language and behavior suggesting possible mental issues. Early identification sets the stage for timely intervention and assistance, which is an important factor in combating mental health issues among college students [27, 28].

A critical strength of ML technologies is their potential for addressing large student populations despite some logistical and geographical challenges often associated with treatment settings in traditional mental health. This enhanced accessibility makes it possible for more people to enjoy mental help, regardless of geographical borders or lack thereof [29]. Moreover, ML enables mental health professionals to allocate resources more effectively by focusing on higher-risk students, thereby increasing the effectiveness of these interventions [30].

Although these possible gains are noteworthy, the implementation of ML into mental health software applications raises ethical issues that need to be approached with caution. Data security and privacy are two of the key issues. It is especially freshmen college students who have higher concerns about the safety of their personal information. The assemblage and examination of huge volumes of personal data for ML uses present such challenges as informed consent, transparency in the use of data, and control over private information. If unauthorized access and data breaches occur, it could lead to serious consequences, worsening students' existing mental health conditions [31].

Another ethical issue is the possibility of discrimination and bias in ML models. However, if these models are created using biased data, then they will unintentionally continue to deepen the social disadvantages. Algorithmic bias can disproportionately affect underrepresented groups, causing misdiagnoses and increasing the susceptibility of certain populations [32]. This aggravates the existing mental health care disparities, throwing ethical questions at ML implementations in such a scenario.

The problem of detecting mental health problems using ML models is an ever-present difficulty. Though ML has opened opportunities, especially in early detection, its accuracy is still in the infant stage of development [33]. Misclassification of mental health issues as false positives causes unnecessary anxiety and stigma and, at worst, could compromise an individual's well-being. On the other hand, false negatives where a model fails to assess real mental health challenges may lead to late or no help being provided for students in need at all [34]. The proper balance of sensitivity and specificity in ML models is essential for ethical and effective implementation in mental health applications.

The psychological effect is also of great concern. This overreliance on ML tools for diagnosing mental health problems may unintentionally cause people to undervalue their autonomy and responsibility. If people only depend on automated solutions, this may lead to a delay in seeking additional help from humans and, in turn, result in addiction to artificial interventions. Furthermore, continuous monitoring and possible misdiagnoses may negatively affect students' mental health on the whole, which hinges on artificial systems devoid of the empathy inherent in human relations [35, 36].

A concern worth mentioning is the possibility of replacing psychological specialists with ML tools. The ML's function in mental health should be supportive, meant to enhance the capacities of mental health counselors instead of replacing them. Although ML provides valuable information, human knowledge does not lose its importance in terms of diagnosis, treatment, and support. Also, the definite separation of roles and limits related to application is necessary for ethical practice with ML in mental health [37].

To deal with these ethical challenges and promote the appropriate application of ML in mental health, several suggestions have been proposed. Data security and privacy must be given the utmost importance. Measures should include the acquisition of informed consent, transparency in data use, and stringent safety mechanisms to protect student

In ML models, eliminating bias and ensuring fairness are essential. This can be done through the use of different training datasets that involve multiple ethnic groups. Monitoring and progressively correcting algorithms for bias identification is a central measure in tackling algorithmic prejudice [38].

Transparency and accuracy should be highlighted at all times during the building of ML models for mental health applications. This includes focusing on building strong and reliable models, regularly assessing their performance levels, and making it a point to identify these limitations for mental health professionals as well as students. Transparency strengthens trust and enables people to base their decision-making on making an informed choice about mental health care management [39].

There is an important need to foster personal initiative and reasonable use of ML equipment. However, mental health professionals should maintain professional accountability by spearheading the development and use of ML systems. This guarantees that these tools meet ethical criteria and are easily applied to current therapeutic settings. Supervision by humans is required to preserve the ethical and compassionate elements of mental health care [40].

3. Proposed Methodology

With the highest accuracy of 90.33% for depression, 92 % for anxiety, and 90.33 % for stress, the evaluation of depression, stress, and anxiety utilizing various machine learning techniques and logistic regression was determined to be the most effective [34]. New medication discovery, radiography analysis [49], epidemic outbreak prediction, and disease diagnosis have all benefited from the application of machine learning algorithms. Generally, machine learning algorithms are tools to analyze massive medical data sets. They are utilized as tools in assisting with medical diagnosis as they become more reliable in their performance. From time to time, machine learning and data mining approaches continue to develop rapidly. To address more complex medical diagnosis issues, strong algorithms and more sophisticated neural networks, decision trees, gradient boosting, and others were developed and used [35].

By utilizing urbane arithmetical and chancy systems, machine learning pursues to shape systems that can get healthier with usage. It is believed to be an actual helpful tool for mental health prediction. In addition to developing automated intelligent systems and delivering individualized experiences, it enables several researchers to extract valuable information from the data [33]. Future events have been predicted and categorized by means of machine learning techniques like random forests, support vector machines, and artificial neural networks. Five machine learning (ML) prediction models—artificial neural network (ANN), RF, SVM, NB, and DT—were employed in this study, and their predictive performance on the provided data set was evaluated in comparison with one another. Based on the degree of severity, this predicted the symptoms of nervousness and downheartedness in college students. Training, testing, and validation were represented by the ratio of 70:20:10 in the data set [30]. For optimizing parameters, the grid search method in conjunction with cross-validation was employed. The following settings were made for the parameters of several algorithms:

Based on the logistic activation function, the hidden layer of the ANN model contained five hundred neurons, with five hundred being the maximum number of iterations possible.

There were five maximum depth trees and 1000 trees in the RF model. The highest bias error control issue was set to 1 and the number of samples at 0.001 [31].

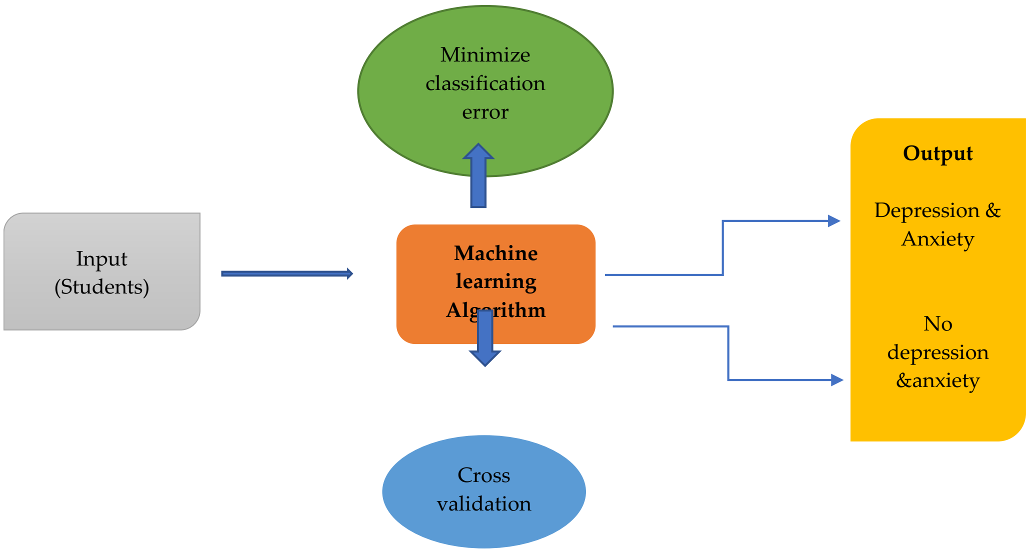

Figure 3. Proposed Machine Learning Model

All things considered, machine learning has shown to be a useful technique for determining and forecasting the related variables that affect student anxiety and depression. Figure 3 shows the implementation of machine learning within college information systems may make it easier to since the methods seem to be an effective model for predicting abnormal depression and anxiety symptoms among college students, which arises health prevention and intervention programs that will enhance students' mental health and cognitive development [32].A meticulously created dataset serves as the major focus point of my suggested method, which provides a comprehensive overview of how college students' mental wellness can be investigated. The factors create a comprehensive picture that encompasses all aspects of mental health, ranging from psychological indications to demographic statistics. In the search for the intricacy of mental health amongst college students, a range of machine learning algorithms have emerged as contenders. These algorithms include classic Naïve Bayes, robust Random Forest, the decision-making power of Decision Trees, and the sophistication of SVM (Support Vector Machine), which formed the basis. Finally, towering in front was the Neural Network algorithm, a guiding light into exploring predictive possibilities for mental health conditions [41].

Various machine learning algorithms have surfaced as potential candidates in the quest to understand the intricacy of mental health among university students. Classic Naïve Bayes, resilient Random Forest, the decision-making power of Decision Trees, and sophisticated SVM (Support Vector Machine), which served as the foundation, are some of these algorithms. Ultimately, the Neural Network algorithm stood tall in front, serving as a beacon for investigating potential predictors of mental health issues.

3.1. Data Preprocessing

The dataset [42] preparation for modeling is the main topic of this section. Blazing encoding and label encoding are the two methods used to encode categorical information. Boolean values are transformed to a numeric (0 or 1) format, and irrelevant columns are eliminated.

3.2. Train-Test Split

The train test split function in scikit-learn is used to divide the dataset into training and testing sets. This is a crucial step in machine learning to assess how effectively the model generalizes to new data.

3.3. Feature Scaling

Standard Scaler from scikit-learn is used for feature scaling. Neural networks benefit from standardization since it guarantees that all features have a standard deviation of 1 and a mean of 0.

3.4. Build Neural Network Model

Three layers were employed in the proposed ECMDADCS artificial [48] neural network: an input layer, a hidden layer, an output layer with 32 units and ReLU activation, and an input layer with 64 units and ReLU activation. Since the problem is binary classification [43], the model is compiled using the Adam optimizer and binary cross-entropy loss. The backpropagation method involves numerous processes, such as initializing weight, feedforward, backpropagation of error, and updating weight and bias. Each buried level neuron has an activation function such as f(x) =Sigmoid(x). The suggested ECMDADCS-ABPNN's input and hidden layer sigmoid functions can be expressed as

$$\gamma_\chi = \mathfrak{b}_1 + \sum_{j=1}^{m} \left(\omega_{j\chi} * \mathfrak{r}_j \right) \tag{1}$$

$$\mathfrak{f}_j = \frac{1}{1+\boldsymbol{e}^{-\gamma_\chi}} \; where \; \boldsymbol{\chi} = 1,2,3 \ldots n \tag{2}$$

From the output layer, the input is

$$\gamma_k = \mathfrak{b}_2 + \sum_{\chi=1}^{n} \left(\mathfrak{v}_{\chi k} * \mathfrak{f}_\chi \right) \tag{3}$$

Below is the output layer activation function.

$$\mathfrak{f}_k = \frac{1}{1+e^{-\gamma_k}} \quad where \; k = 1,2,3 \ldots r \tag{4}$$

$$\mathbb{E} = \frac{1}{2} \sum_{k} \left(\mathrm{t}_k - \mathfrak{f}_k \right)^2 \tag{5}$$

The back propagation error is represented by the equation above, where $t_k \& out_k$ stand for the intended and estimated outputs, respectively.

The layer is expressed as the rate of change in weight for the output in equation (6).

$$\Delta \backslash \omega \propto -\frac{\partial' \mathrm{E}}{\partial \omega}$$

$$\Delta \mathfrak{v}_{\chi,\ell} = -\,\varepsilon \frac{\partial' \mathrm{E}}{\partial \nu_{\chi,\ell}} \tag{6}$$

After using the Chain Rule approach, the equation above can be expressed as

$$\Delta \mathfrak{v}_{\chi,\ell} = -\,\varepsilon \frac{\partial E}{\partial f_{\ell}} \times \frac{\partial f_{\ell}}{\partial \gamma_{\ell}} \times \frac{\partial \gamma_{\ell}}{\partial \nu_{\chi,\ell}} \tag{7}$$

Equation (8) displays the value of weight modified after the values in equation (7) have been substituted.

$$\Delta \mathfrak{v}_{\chi,\ell} = \varepsilon(\tau_{\ell} - f_{\ell}) \times f_{\ell}(1 - f_{\ell}) \times (f_{\chi})$$

$$\Delta \mathfrak{v}_{\chi,k} = \varepsilon \xi_k f_{\chi} \tag{8}$$

Where,

$$\xi_k = (\tau_{\ell} - f_{\ell}) \times f_{\ell}(1 - f_{\ell})$$

Use the chain rule to update the input and hidden layers' weights.

The equation above can be simplified and expressed as

$$\Delta \omega_{i,j} = \varepsilon \xi_{\chi} \alpha_j$$

Where,

$$\xi_{\chi} = \left[\sum_{\ell} \xi_k \left(\mathfrak{v}_{\chi,\ell}\right)\right] \times f_{\chi}(1 - f_{\chi})$$

$$\mathfrak{v}^{+}_{\chi,\ell} = \mathfrak{v}_{\chi,\ell} + \lambda_F \Delta \mathfrak{v}_{\chi,\ell} \tag{9}$$

The weights between the output and hidden layers are updated using the equation above.

$$\omega^{+}_{j,\chi} = \omega_{j,\chi} + \lambda_F \Delta \omega_{j,\chi} \tag{10}$$

The weights between the input and hidden layers are updated using the equation above.

3.5. Train the Model

Using the fit approach, the neural network model is trained on the training set of data. With a batch size of 32, the training is carried out over ten epochs, and 10% of the training set is used for validation.

3.6. Make Predictions and Evaluate

The test set is used for predictions, and probabilities are converted to binary predictions by applying a threshold of 0.5 (0 or 1). The classification report, accuracy, and confusion matrix are used to assess the model's performance.

4. Simulation and Results

The study aims to investigate mental health among college students by employing a dataset that comprises a diversity of mental health indicators. The import of necessary libraries, dataset loading, and painstaking preparatory scheduling [46] like encoding and scaling marks the beginning of the process. Next, we build and train a sequential neural network architecture with Keras. Next, forecasts are produced, and assessment measures are used to provide an in-depth examination. Figure 4 shows the confusion matrix, Table 2 shows the classification report, and accuracy of the model are included in the findings, which are presented below and provide important information about its effectiveness. In addition to a cursory review of accuracy, focus is placed on precision, recall, and F1-score metrics—all of which are very relevant when it comes to mental health forecasts. The method is centered on creating a neural network model to forecast depression and anxiety levels. The ensuing sections delve into the nuances of the code, offering a detailed conception of the model's results about the prediction of depression and anxiety in college students. To evaluate the performance of the model, the accuracy, confusion matrix, and classification report are printed. Although the accuracy in this particular instance is stated to be about 91%, the classification report and confusion matrix point to certain problems, such as the model's inability to precisely forecast occurrences of the marginal class.

The accuracy of the model is approximately 91%, indicating the proportion of correctly predicted instances, both true positive and negative, out of the total instances. While accuracy is a common metric, it may not be sufficient, especially in imbalanced datasets. In this case, it's crucial to investigate other metrics to gain a more comprehensive understanding of the model's effectiveness.

Here are the formulas and descriptions for each Evaluation metric:

Precision:

$$\frac{\mathrm{TP}}{\mathrm{TP+FP}} \tag{11}$$

Recall:

$$\frac{TP}{TP+FN} \tag{12}$$

F1_Score:

$$\frac{\mathrm{precision\ X\ Recall}}{Precision+\mathrm{Recall}} \tag{13}$$

Accuracy:

$$\frac{\mathrm{TP+TN}}{\mathrm{TP+FN+TN+FP}} \tag{14}$$

Here, TP represents as True Positive, FP as False Positive, FN as False Negative, and TN as True Negative.

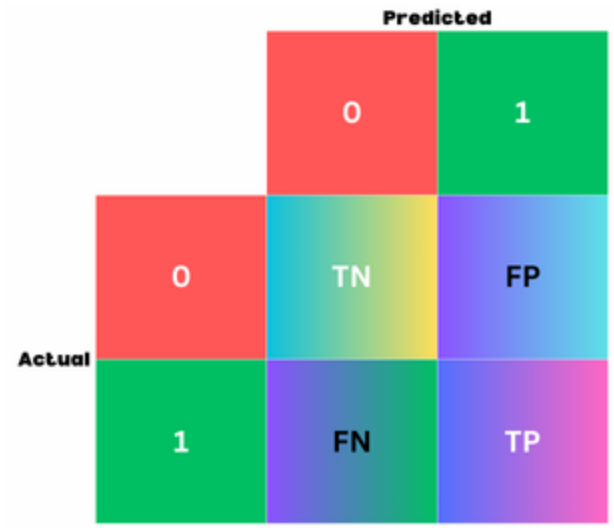

Figure 4. Confusion Matrix

The confusion matrix shows an unsettling trend: the model predicts no instances of the minority class but accurately detects instances of the majority class (0). (1). Understanding this disparity is essential to appreciating the model's limitations, particularly when the minority class plays a major role.

4.1. Classification Report

The classification report provides additional metrics for each class, including precision, recall, and F1-score. In this case, it is as follows:

Table 2. Classification Report of Neural Network

	Precision	Recall	F1-score	Support
Class 0 (Negative)	0.91	1.00	0.95	143
Class 1 (Positive)	0.00	0.00	0.00	14

Accuracy	-	-	0.91	157
Macro Avg	0.46	0.50	0.48	157
Weighted Avg	0.83	0.91	0.87	157

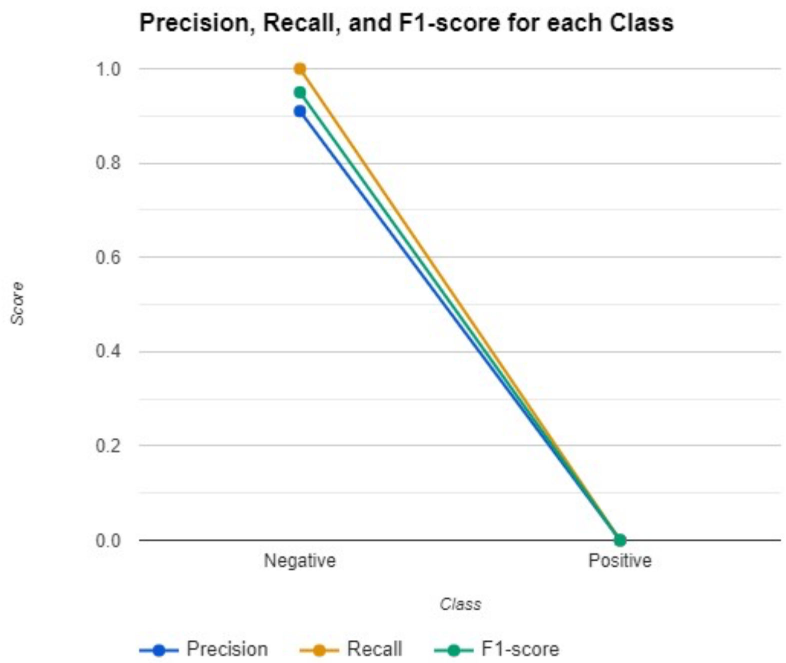

Figure 5. Classification Graph

Figure 5 shows that Precision can be defined as the percentage of all positive forecasts that are true positive predictions. It is 0.91 for class 0, suggesting a high degree of precision, but it is 0.00 for class 1, suggesting that the model's optimistic forecasts for class 1 are not trustworthy.

Table 2. Accuracy of classification Algorithms

Algorithm	Accuracy
Decision Trees	71.05%
Naïve Bayes	71.05%
Random Forest	78.9%
Support Vector Machine	75.55%
Neural Network	91%

In order to address a particular problem, table 3 trained with machine learning techniques in this research work, focusing on the algorithms being used. Of the approaches investigated, decision trees and naïve Bayes classifiers achieved accuracies of 71.05%, which shows average predictive ability. The Random Forest method demonstrated that it was capable of achieving enhanced predictive accuracy in the realm of ensemble learning, as indicated by its increased precision score of 78.9%. Despite the fact that it captured intricate relationships within data, the Support Vector Machine (SVM) model worked with an accuracy of 75. The neural network that was used had the most sensational result, with an unbelievable accuracy of 91%. This shows how neural networks can learn complicated correlations and patterns that are attractive alternatives for instances where accuracy is vital. Research into these machine learning algorithms resulted in highly informative results regarding their benefits and drawbacks, emphasizing the importance of selecting an algorithm appropriate to the exact features of the data set and the goalmouths of the study.

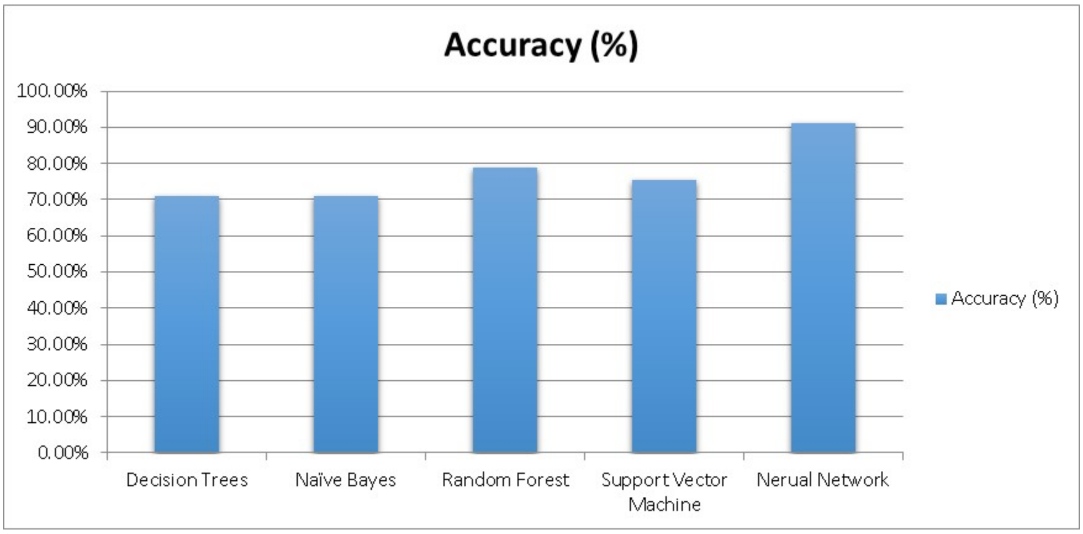

Figure 6. Accuracy rates of Algorithms.

The percentage of actual positives is divided by the number of true positive predictions. It is 0.00 for class 1, showing the model's inability to find any examples of class 1, but 1.00 for class 0, suggesting the model captures all occurrences of class 0. The harmonic mean of recall and precision is the F1-score. It is 0.95 for class 0, indicating a balance between recall and precision. On the other hand, class 1's F1-score of 0.00 highlights how difficult it is integrate [50] to anticipate the minority class.

5. Conclusion

Finally, this study carefully researched the mental well-being of college students using structured data that captured a wide array of variables, from demographics to measures of psychological and physical health. Interpreting the complex problems that relate to mental health in this population has become a lot more sophisticated and nuanced with the introduction of machine learning approaches, especially neural networks. The data were thoroughly preprocessed, while the model development phase took into account a wide variety of features that mirror the diversity of elements that influence mental health. The utilization of neural network layers with non-linear transformations proved to be an effective method for discovering complex patterns in mental health trends that would otherwise remain undetected by traditional linear models. The evaluation process, including accuracy, precision, recall, and the F1-score, helped in a comprehensive assessment of the model's effectiveness in detecting mental health problems among college students. This research not only provides a consolidated review of previous mental health research but also stresses that further studies and the continued refinement of models of the human mind are inevitable to solve the complexities involved in it.

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