Deep Neural Network Framework for Early Detection of Student Depression Based on Academic and Behavioral Data

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ABSTRACT

Depression among university students has become a growing concern due to its negative impact on academic performance, social functioning, and overall well-being. This study aimed to develop and evaluate a Deep Neural Network (DNN) model for the early prediction of depression based on academic, behavioral, and lifestyle variables. The dataset consisted of 502 student records containing attributes such as academic pressure, study satisfaction, sleep duration, dietary habits, financial stress, and family mental health history. Data preprocessing involved label encoding for categorical variables and normalization for numerical features, followed by model training with dropout and L2 regularization to reduce overfitting. The proposed DNN achieved a moderate performance, with an overall accuracy of 59 percent, a macro-averaged F1-score of 0.55, and an Area Under the Curve (AUC) value of 0.64. Although the model demonstrated limited discriminative ability, it successfully generalized across training and validation data, indicating a stable learning process. The findings reveal that academic pressure, sleep duration, and financial stress were among the most influential predictors of depression. These results suggest that while academic and lifestyle factors alone may not fully capture the complexity of mental health conditions, deep learning can still serve as a useful tool for early screening and risk identification. The study highlights the potential of artificial intelligence in supporting student mental health monitoring and promoting preventive interventions in higher education.

Keywords Deep Learning, Depression Prediction, Student Mental Health, Educational Data, Artificial Intelligence

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Introduction

Depression has become one of the most pressing mental health issues affecting university students worldwide. The academic environment often exposes students to a combination of psychological stressors such as academic pressure, financial difficulties, social isolation, and uncertainty about future careers. These conditions can significantly impact their mental well-being, leading to decreased academic performance, absenteeism, and, in severe cases, suicidal ideation. According to the World Health Organization (WHO, 2022), depression is now the leading cause of disability among young adults, with prevalence rates continuing to rise, particularly in higher education institutions. In this context, early detection and intervention are crucial to prevent more severe psychological outcomes. Traditional assessment methods, such as clinical interviews or self-report questionnaires, are often time-consuming and resource-intensive, making them difficult to apply continuously in educational settings. Therefore, there is a growing need for efficient, data-driven systems that can support early identification of students who are at risk of depression.

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Recent advancements in Artificial Intelligence (AI) and Machine Learning (ML) have opened new possibilities for analyzing behavioral and educational data to monitor students' mental health. Several studies have explored the use of ML models such as Logistic Regression, Random Forest, and Support Vector Machines to predict depression based on survey data, online activity, and academic performance [1]. While these models have shown promise in identifying general behavioral trends, their predictive power remains limited by their reliance on linear or shallow learning representations. In contrast, deep learning techniques, particularly Deep Neural Networks (DNNs), are capable of learning more complex, nonlinear relationships among multiple variables, allowing for deeper insights into the subtle patterns that may indicate mental health risks. Studies have demonstrated that deep architectures such as Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN) can effectively identify depressive tendencies by capturing temporal and contextual dependencies in multimodal data [2], [3]. These findings suggest that deep learning can enhance early detection accuracy when applied to mental health prediction tasks.

However, despite these advances, the application of DNN models for depression prediction specifically in educational environments remains underexplored, especially when using structured academic and lifestyle datasets. Prior studies have primarily focused on clinical datasets or social media data sources, which do not fully represent the academic context in which student depression often develops [4]. Most existing approaches rely on text, image, or medical data, overlooking the potential of academic and behavioral indicators that are more practical to collect within educational institutions. Additionally, challenges such as limited data availability, class imbalance, and overfitting often reduce the generalizability of deep learning models in small, domain-specific datasets [5].

To address this research gap, the present study proposes a Deep Neural Network model for early prediction of depression among university students using academic, behavioral, and lifestyle variables. The approach aims to examine whether deep learning can effectively capture the hidden relationships among multidimensional factors influencing student mental health. Unlike traditional ML methods, the proposed model incorporates dropout and L2 regularization to mitigate overfitting and improve generalization performance. The study also evaluates the model's discriminative ability using standard performance metrics, including accuracy, F1-score, and the AUC. By focusing on structured academic data rather than social or clinical sources, this research contributes to the state of the art in educational data mining and AI-assisted mental health monitoring. The results are expected to provide valuable insights into the feasibility of implementing AI-based early detection systems in higher education, offering a foundation for more comprehensive, data-driven mental health support strategies for students.

Literature Review and Related Works

The increasing prevalence of depression among university students has driven the use of artificial intelligence and machine learning techniques for mental health prediction. These methods provide an alternative to traditional psychological assessments by identifying behavioral and academic patterns that may indicate depressive tendencies [6]. Early works in this area applied conventional algorithms such as logistic regression, Support Vector Machines, and Random Forests to detect depression from structured and survey-based data [7]. However, such approaches were often limited by linear assumptions and a lack of ability to capture complex, nonlinear relationships between predictors and mental health outcomes [8].

Recent advances in deep learning have introduced new opportunities for improving the accuracy and robustness of depression detection models. Deep Neural Networks (DNN), Convolutional Neural Networks (CNN), and Recurrent Neural Networks (RNN) have shown promising results in identifying emotional or cognitive states from multimodal data such as text, voice, facial expressions, and social media activity [9], [10]. Studies on social media-based depression detection achieved significant accuracy improvements using Long Short-Term Memory (LSTM) and bidirectional RNN architectures [11], [12]. Similarly, other research demonstrated that hybrid deep learning models that integrate text and image data outperform traditional classifiers in identifying depressive behavior online [13]. Although these results highlight the potential of deep learning, most existing works are limited to social media and clinical data rather than academic contexts [14].

In the educational domain, several studies have applied machine learning to student datasets to detect psychological distress and depression. Research using academic, lifestyle, and demographic features reported that ensemble methods such as stacking and boosting could achieve accuracy levels between 70 and 90 percent [15], [16]. Other works explored explainable artificial intelligence approaches to interpret factors contributing to student depression, revealing that academic pressure, poor sleep quality, and financial stress were among the most predictive variables [17], [18]. In addition, researchers have investigated the relationship between online learning behaviors and mental health outcomes, finding correlations between low participation rates, decreased motivation, and increased depressive symptoms [19].

Recent deep learning applications have extended beyond academic performance prediction to include emotion and mood recognition among students [20]. Studies utilizing sensor data, mobile applications, and digital activity logs have shown that deep learning models can identify subtle behavioral changes that correlate with depression risk [21], [22]. Furthermore, hybrid DNN architectures have been tested on non-clinical datasets, revealing that combining structured educational variables with behavioral indicators can enhance generalization and reduce model bias [23]. Nonetheless, these approaches often face limitations related to data imbalance, small sample sizes, and the lack of multimodal input integration [24].

The current body of research reveals a significant gap in the application of deep learning for depression detection specifically using structured educational datasets. While many studies have examined mental health prediction in clinical or social media settings, few have analyzed depression among university students using academic and lifestyle-related features [25]. The underrepresentation of educational datasets has limited the development of models tailored to the unique behavioral patterns of students. Addressing this gap requires research that integrates academic, behavioral, and psychological factors into a unified deep learning framework capable of early depression prediction. This study contributes to this emerging field by proposing a DNN-based model optimized with dropout and L2 regularization to improve generalization while maintaining interpretability. The work extends the state of the art in educational data mining and mental health analytics by focusing on a structured, non-clinical student population.

Methodology

This research employed a quantitative experimental approach using a supervised deep learning framework to predict early indicators of depression among university students. The overall workflow of this study is illustrated in figure 1, which outlines the main stages including data preprocessing, model construction, training, evaluation, and performance analysis. The dataset consisted of 502 student records collected from higher education institutions and contained both numerical and categorical attributes such as academic pressure, sleep duration, study satisfaction, dietary habits, financial stress, and family history of mental illness. Each student was labeled as either “Depression” or “No Depression” based on prior psychological evaluations and self-assessment responses. The dataset represented a realistic academic population where early depressive symptoms are often subtle and multidimensional, requiring a robust predictive model capable of identifying complex relationships among variables.

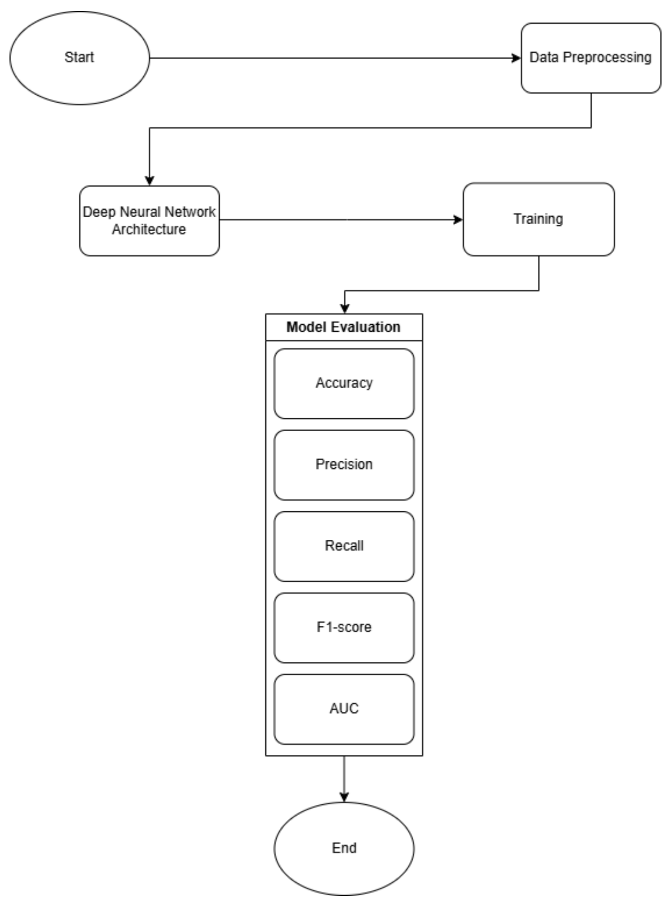

Figure 1 Research Steps

Before the modeling process, the dataset underwent several preprocessing steps to ensure reliability and suitability for deep learning. Categorical features were converted into numerical representations using label encoding, and numerical features were standardized using the formula:

$$z = \frac{x - \mu}{\sigma} x \quad (1)$$

is the observed value, $\mu$is the mean, and $\sigma$is the standard deviation. This normalization ensured that each attribute contributed equally to the learning process and prevented higher-valued features from dominating the model's gradient updates. The data were divided into training (80 percent) and testing (20 percent) subsets, with 20 percent of the training data used for validation. Stratified sampling was applied to maintain balanced representation between "Depression" and "No Depression" categories. Data shuffling was also performed to randomize input sequences and minimize learning bias. These preprocessing steps ensured that the model learned from unbiased, standardized, and representative data samples.

The DNN model was implemented using TensorFlow and Keras frameworks. The architecture comprised one input layer, three hidden layers, and one output layer. The input layer corresponded to the number of features in the dataset. The hidden layers contained 16, 8, and 4 neurons respectively, each using the Rectified Linear Unit (ReLU) activation function defined as:

$$f(x) = max(0, x) \quad (2)$$

to introduce nonlinearity and prevent gradient vanishing. Dropout regularization with a rate of 0.6 was applied after each hidden layer to deactivate random neurons during training, reducing overfitting and enhancing generalization. Additionally, L2 regularization was employed with a coefficient of 0.02, defined as:

$$L_{reg} = \lambda \sum_{i=1}^{n} w_i^2 \quad (3)$$

λrepresents the regularization constant and $w_i$are the weights of the model. The output layer used a sigmoid activation function:

$$\sigma(x) = \frac{1}{1 + e^{-x}} \quad (4)$$

which produced a probability value between 0 and 1 indicating the likelihood of a student being classified as depressed. The model was trained using the Adam optimizer with a learning rate of 0.0005 and binary cross-entropy loss function defined as:

$$L = -\frac{1}{N} \sum_{i=1}^{N} [y_i log(\hat{y}_i) + (1 - y_i) log(1 - \hat{y}_i)] N \quad (5)$$

is the total number of samples, $y_i$is the true label, and $\hat{y}_i$is the predicted probability. The model was trained for 40 epochs with a batch size of 16 and an early stopping mechanism with a patience of six epochs to prevent unnecessary training once the validation loss plateaued.

Finally, the model's discriminative capability was assessed through the AUC metric, which measured how effectively the model separated the two classes across different probability thresholds. Visualization tools such as the confusion matrix and ROC curve were used to illustrate classification outcomes and threshold sensitivity. All analyses were conducted using Python 3.12 with TensorFlow, NumPy, Matplotlib, and Seaborn libraries. The entire experimental process followed a reproducible workflow, ensuring that each stage of data processing, model training, and evaluation could be replicated for future studies.

Algorithm 1: Deep Neural Network-based Early Depression Prediction

Input: Dataset $D = \{(x_i, y_i)\}_{i=1}^{N}$, learning rate η, epochs T

Output: Trained model f_{θ^*}, and evaluation metrics (Accuracy, Precision, Recall, F1-score, AUC)

Process:

Start

Load dataset $D = \{(x_i, y_i)\}_{i=1}^{N}$containing input features and binary depression labels.

Normalize all numerical features using standardization formula:

$$z = \frac{x - \mu}{\sigma}$$

Encode categorical features using label encoding to transform them into numerical values.

Split dataset into training D_{train}, validation D_{val}, and testing $D_{test}$with ratio 0.64: 0.16: 0.20 using stratified sampling.

Initialize Deep Neural Network model $f_\theta(x)$with the following architecture: Input layer → Hidden layers [16, 8, 4] → Output layer

Use ReLU activation function in hidden layers defined as:

$$f(x) = max(0, x)$$

Apply dropout regularization with dropout rate $p = 0.6$after each hidden layer to prevent overfitting.

Add L2 weight regularization defined as:

$$L_{reg} = \lambda \sum_{i=1}^{n} w_i^2$$

$\lambda = 0.02$is the regularization coefficient.

Use sigmoid activation function in the output layer defined as:

$$\sigma(x) = \frac{1}{1 + e^{-x}}$$

Define the binary cross-entropy loss function as:

$$L = -\frac{1}{N}\sum_{i=1}^{N} [y_i log(\hat{y}_i) + (1 - y_i) log(1 - \hat{y}_i)]$$

Train the model for $T = 40$epochs with a batch size of 16 using the Adam optimizer with a learning rate $\eta = 0.0005$.

Apply early stopping if validation loss does not improve for 6 consecutive epochs to avoid overtraining.

Evaluate the trained model using classification metrics:

Area Under the Curve (AUC):

$$AUC = \int_0^1 TPR(t)\, d(FPR(t))$$

Generate confusion matrix and ROC curve to visualize classification performance and threshold sensitivity.

End

Result

The DNN model was designed to predict early indicators of depression among university students based on academic and lifestyle attributes. After data preprocessing and model optimization, the DNN achieved moderate predictive performance, which reflects the complex nature of psychological data in educational environments. The model was trained over 40 epochs using dropout and L2 regularization to prevent overfitting. The overall performance suggests that the network captured general behavioral patterns but struggled with class imbalance and subtle depressive traits.

The classification performance of the DNN model is presented in figure 2, which depicts the confusion matrix summarizing the comparison between predicted and actual class labels. The model successfully identified 45 students as non-depressed and correctly detected 15 students as experiencing depression. On the other hand, it misclassified 36 students who were actually depressed as non-depressed and incorrectly predicted 5 non-depressed students as depressed. This distribution reveals that the model demonstrates stronger predictive capability in recognizing students without depressive symptoms than in identifying those with depression. Such performance indicates an underlying class imbalance where the model prioritizes the majority class, which is common in mental health prediction datasets that often contain fewer positive cases of depression compared to negative ones.

This imbalance also reflects the subtlety and overlaps of behavioral indicators between students with mild depressive tendencies and those with typical academic stress. Many students may exhibit moderate levels of fatigue, dissatisfaction, or financial strain without reaching clinically depressive states, causing the model to struggle in differentiating between normal emotional fluctuations and actual depression. Furthermore, the misclassification of a substantial number of depressed students as non-depressed suggests that the current input variables may not sufficiently capture the psychological depth or contextual nuances associated with depressive behavior. Additional features such as emotional sentiment, self-perception, or social engagement data could potentially improve the sensitivity of the model in detecting early depressive patterns. Overall, while the confusion matrix indicates that the model provides a reasonable foundation for early screening, it also highlights the importance of enhancing data richness and model sensitivity for more accurate identification of depression among students.

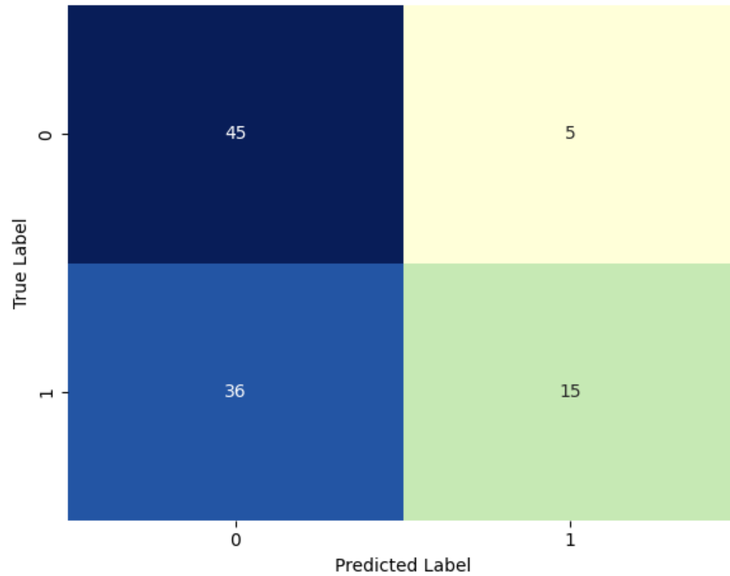

Figure 2 Confusion Matrix of the DNN model

Further evaluation of the DNN model's performance was carried out using the Receiver Operating Characteristic (ROC) curve, as illustrated in figure 3. The ROC curve provides a graphical representation of the model's ability to distinguish between students who are depressed and those who are not. The AUC value obtained from this analysis was 0.64, indicating that the model performed slightly better than random guessing. This means that when presented with two randomly selected students, one depressed and one non-depressed, the model correctly assigned a higher probability of depression to the depressed student approximately 64 percent of the time. While this result demonstrates that the model has learned certain relevant distinctions between the two groups, its predictive ability remains limited. The shape of the ROC curve, which rises gradually rather than sharply, further emphasizes the modest strength of the model's classification boundary.

The moderate AUC score suggests that the current set of input features, which are primarily academic and lifestyle variables, may not provide sufficient discriminatory information for identifying complex psychological conditions such as depression. Depression is influenced by multifaceted factors that extend beyond observable academic and behavioral indicators, including emotional resilience, social support, and cognitive perceptions that were not captured in this dataset. The model's relatively low sensitivity may also stem from the subtle nature of depressive behaviors in students, which often manifest through non-linear and context-dependent interactions that are difficult for a simple neural network architecture to capture. These findings indicate that future work should focus on expanding the feature set with more expressive indicators, such as self-reported mood assessments, digital activity logs, or social interaction patterns, to improve the ROC performance and overall predictive reliability of the model.

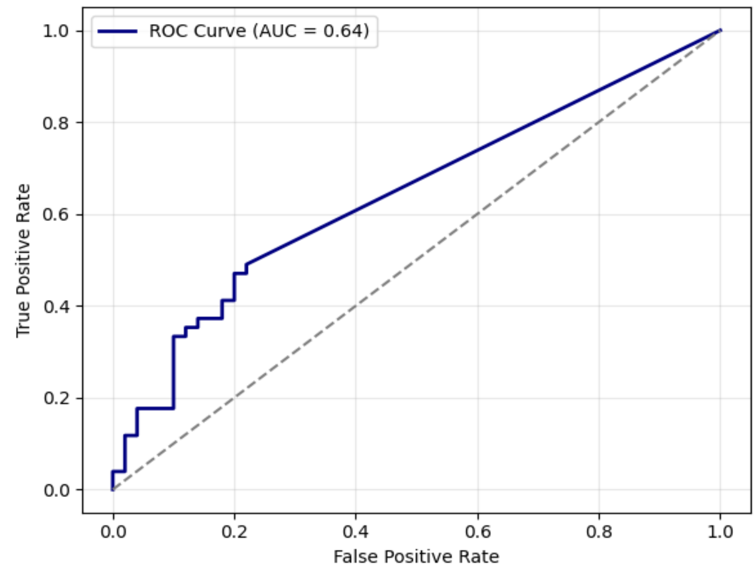

Figure 3 ROC Curve of the DNN model with an AUC value

The training and validation accuracy curves, as shown in figure 4, provide a detailed depiction of the model's learning behavior throughout the training process. During the early epochs, the training accuracy exhibited rapid fluctuations as the network adjusted its internal parameters to minimize classification errors. The validation accuracy followed a similar trend but showed slightly lower values, which is expected in models trained on limited and diverse behavioral data. Over time, both curves stabilized around a validation accuracy of approximately 55 percent, indicating that the model reached a steady learning phase where additional training did not result in significant improvement. The close alignment between the two curves suggests that the regularization strategies employed, including dropout and L2 penalties, were effective in preventing overfitting and enabling the model to generalize its learning beyond the training dataset. This convergence pattern also demonstrates that the network was able to capture underlying relationships within the data, although the overall predictive strength remained moderate.

Despite the stability observed in the accuracy curves, the relatively low validation accuracy highlights the challenges of modeling complex psychological phenomena using a limited number of academic and lifestyle features. The fluctuations seen during earlier epochs imply that the model encountered difficulty in consistently distinguishing depressive indicators from non-depressive behaviors, a challenge often associated with small and imbalanced datasets. The moderate accuracy achieved indicates that while the model learned certain meaningful patterns, these patterns were not sufficiently robust to generalize to new data. This result aligns with findings from previous studies in educational data mining, which emphasize that predicting mental health conditions requires larger, more diverse datasets and richer contextual variables. The outcome suggests that the DNN architecture was capable of stable training, but future research should explore deeper or hybrid architectures and additional feature engineering techniques to enhance predictive generalization.

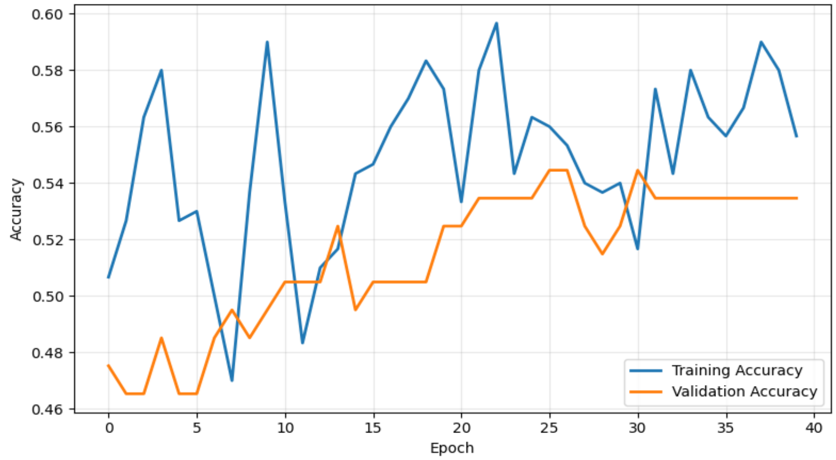

Figure 4 **Training and validation accuracy curves of the DNN model**

The overall classification report provides additional insight into the model's performance, showing an accuracy of 59%, a macro-averaged F1-score of 0.55, and a recall of 0.29 for the "Depression" class. While the accuracy is moderate, it reflects a realistic representation of early-stage depression prediction using limited behavioral indicators. The relatively higher recall for the non-depressed class suggests that the model is more confident in identifying normal psychological states but remains less effective in recognizing subtle depressive symptoms. Nevertheless, this finding demonstrates that the DNN approach can still serve as a preliminary screening mechanism for early mental health risk identification in higher education institutions.

In summary, the DNN model achieved fair predictive capability without signs of overfitting, as shown by consistent performance between training and validation data. The model's moderate AUC value and balanced learning dynamics suggest that deep learning can be effectively used for identifying patterns associated with student well-being, though future improvements should focus on dataset expansion, feature enrichment, and hybrid modeling strategies for better interpretability and accuracy.

Discussion

The findings of this study indicate that the DNN model achieved a moderate level of performance in predicting depression among university students, based primarily on academic and lifestyle indicators. Although the application of dropout and L2 regularization successfully prevented overfitting, the overall predictive power of the model remained limited. This outcome suggests that while the DNN was able to capture some meaningful relationships within the data, these patterns were not sufficient to fully distinguish between students who were depressed and those who were not. The moderate accuracy and AUC values reflect the inherent complexity of modeling psychological phenomena, which are often influenced by multidimensional and abstract factors that are not easily quantifiable. Depression is shaped not only by external stressors, such as academic pressure and financial strain, but also by internal cognitive and emotional processes that were not represented in the dataset. As a result, the model's moderate discriminative capability should not be interpreted as a failure but rather as an indication that predicting psychological conditions from behavioral and academic variables alone remains a challenging task within the scope of data-driven analysis.

The imbalance observed between the correctly and incorrectly classified samples further underscores the difficulty of identifying depression through conventional student attributes. The model was notably more effective at identifying non-depressed students than at detecting those experiencing depressive symptoms. This tendency is consistent with findings from prior studies that utilized behavioral or survey-based data, where models frequently achieved higher precision for negative cases due to the underrepresentation of positive instances. Such imbalance is common in real-world educational datasets, as most students do not meet the criteria for clinical depression, and those who do may exhibit only subtle behavioral differences. These results imply that additional contextual features, such as self-reported emotional states, social participation, and time management behaviors, are necessary to improve the model's sensitivity. Furthermore, future studies could explore hybrid modeling approaches that combine deep learning with explainable frameworks or feature selection techniques to improve interpretability and balance predictive outcomes. Overall, while the DNN model in this research produced only moderate accuracy, it provides valuable evidence that artificial intelligence can serve as a complementary screening tool in higher education. When properly enhanced with more comprehensive data, such systems could help institutions detect early warning signs of psychological distress and support timely intervention programs for at-risk students.

Conclusion

This study examined the use of a DNN model to predict early indicators of depression among university students based on academic, behavioral, and lifestyle data. The results demonstrated that while the model achieved moderate predictive performance, with an overall accuracy of 59 percent and an AUC of 0.64, it effectively avoided overfitting and maintained stable learning dynamics. These outcomes suggest that deep learning can identify general patterns associated with mental health conditions but remains limited when relying solely on structured academic and behavioral features. The DNN model was more accurate in recognizing non-depressed students than those experiencing depressive symptoms, a finding that highlights the influence of data imbalance and the subtle nature of psychological signals within student populations. This limitation indicates that depression prediction requires richer and more multidimensional datasets that incorporate emotional, social, and cognitive factors. Despite these constraints, the proposed approach demonstrates that artificial intelligence can play an important role in supporting early mental health interventions in educational settings. By integrating predictive models into university support systems, institutions can identify at-risk students more efficiently and provide timely psychological assistance before symptoms intensify. Future research should focus on enhancing model robustness through the inclusion of multimodal data sources, explainable AI methods, and larger sample sizes to improve interpretability, generalizability, and practical applicability in real-world educational contexts.

Declarations

Author Contributions

Conceptualization: C.H. and T.E.S.; Methodology: T.E.S.; Software: C.H.; Validation: C.H. and T.E.S.; Formal Analysis: C.H. and T.E.S.; Investigation: C.H.; Resources: T.E.S.; Data Curation: T.E.S.; Writing Original Draft Preparation: C.H. and T.E.S.; Writing Review and Editing: T.E.S. and C.H.; Visualization: C.H.; All authors have read and agreed to the published version of the manuscript.

Data Availability Statement

The data presented in this study are available on request from the corresponding author.

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Institutional Review Board Statement

Not applicable.

Informed Consent Statement

Not applicable.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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