DESIGN OF AN IMPROVED MODEL USING XGBOOST, LIGHTGBM, AND LSTM FOR PREDICTING GRADUATION AND STRESS RATES IN COLLEGE STUDENTS

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Abstract: The understanding and mitigation of the level of stress in college students are very critical since it bears on them both in their academic performance and general well-being. Most literature focuses on specific causes of stress and graduation rate—a non-comprehensive approach to identify rather multifaceted issues. Traditional models may obscure complex interactions that take place with the variables and also fail to optimally use sequential data samples. The paper presents an integrated, multi-method framework for analyzing the effects of independent variables that influence graduation and stress rates in colleges. In the model proposed herein, advanced feature engineering, robust machine learning algorithms, and sequence models have been embedded to ensure elaborate analysis for accurate predictions. For this to be achieved, begin with an automated feature engineering in Featuretools, followed by recursive feature elimination with cross Validation. This combination not only automated the process of generating new features but also efficiently selected the most relevant ones, reducing the feature dimensionality from more than 100 raw features to 20-30 optimized ones, thus improving model accuracy or F1-score by 5-10%. Then Gradient Boosting Machines, including XGBoost and LightGBM, were used because they were efficient and accurate in the presence of large data sets and complex interactions between features. They could achieve classifying accuracy to the range of 85-90% with an AUC-ROC of 0.88-0.92, which showed their strong predictive capability. Another attempt at improving performance would be the stacking method with a meta-learner, such as Logistic Regression, in order to combine XGBoost, LightGBM, and Random Forest models. This increased the accuracy by another 3-5% and improved AUC-ROC by another 0.02-0.05. Long Short-Term Memory (LSTM) networks and Bidirectional LSTMs captured the temporal dependencies of student behavior, yielding an accuracy of 80-85% in the prediction of future stress levels, with an RMSE of 0.15-0.2 for academic performance. It employs methods for exploratory data analysis, including t-Distributed Stochastic Neighbor Embedding and Principal Component Analysis to achieve the visualization of data structure and relationships. In this instance, PCA explained a range from 90% to 95% of the variance, while t-SNE clearly marked the clusters of stressed versus non-stressed students. The impact of the work has been enormous in providing a robust framework for identifying learners who are stressed, along with educational outcomes of targeted interventions in different use case scenarios. This paper applies state-of-the-art techniques of machine learning and deep learning in a comprehensive and practical manner to a very relevant question in higher education scenarios.

Keywords: Machine Learning, Feature Engineering, Gradient Boosting, LSTM, Student Stress

1. Introduction

This wide and increased prevalence of stress among college students poses a major challenge to educational institutions globally. The significance of academic pressures, social dynamics, and personal responsibilities all converge onto a tight-rope balance that mostly goes to heightened levels of stress, negatively impacting the students' academic performance and overall well-being. In many cases, this needs an all-rounded understanding of the multifaceted factors that cause stressing among students and its effects on graduation rates. Traditional methods for analyzing student stress and graduation rates typically deal with isolated variables, using conventional statistical techniques that might miss out the complex nonlinear interactions of options. These limitations call for more advanced models that can capture the high-dimensionality of the data, identifying relevant features and harnessing temporal information sets efficiently. The new model presented in this paper seeks to analyze how the various independent variables influence graduation and stress rates among college-going students based on state-of-the-art feature engineering techniques, robust machine-learning algorithms, and sequence modeling.

It uses automated feature engineering via Featuretools and recursive feature elimination at the core of its initial phase of data processing. This framework automatically generates new features from raw data to make sure of maximum coverage and selection of only the most related features, raising levels of model performance and interpretability. At the core, it uses Gradient Boosting Machines—in particular, XGBoost and LightGBM. They are very efficient, accurate, and flexible in dealing with big datasets and complex feature interactions. Further enhanced by a stacking method, these models will take in predictions from multiple base models and make them into a meta-learner for improved predictive performance and robustness. Also, the introduction of Long Short-Term Memory and Bidirectional LSTMs empowers capturing the time dynamics of student behavior, including trends and dependencies. This will be important in establishing the correct prediction for future stress levels and academic outcomes. EDA techniques such as t-SNE and PCA underline the structure of the data in meaningful ways and help in identifying students who might be clustered together based on different characteristics or manifesting some trends. The accuracy and discriminative power of the proposed models mainly improve to an accuracy of 85-90% with an AUC-ROC of 0.88-0.92. This integrated approach, by reducing feature dimensionality and with its ability to very effectively capture the temporal dependencies, makes it robust for a practical solution in the identification of stressed learners for targeted interventions to improve educational outcomes.

Motivation & Contribution:

This study is motivated by the increasing concern for the mental health and academic success of college students. Stress, being one of the most pervasive problems in higher education, has a negative influence on students' abilities regarding aptitude performance and psychological well-being. Traditional models used in the prediction of student stress and graduation rates are narrowly based on a single variable, which could not explain or capture the intricate, nonlinear interactions actual data may have. Most methods available today ignore the time axis of student behavior and hence cannot deal with crucial trends and dependencies which become revealed over time. There is a growing need for a more advanced analytical framework that can efficiently deal with high-dimensional data, exploit complex feature interactions, and integrate temporal dynamics in order to achieve an overall understanding of the factors that turn around student stress and graduation rates. Specifically, this study offers several contributions within the realm of educational data analytics. First, it introduces a new process for feature engineering and selection that combines automated generation of features using Feature tools with recursive feature elimination and cross Validation operations. This methodology is able to automate the construction of new features from raw data but also ensure that the most relevant features are included, drastically reducing dimensionality and by extension increasing model interpretability. In this work, advanced Gradient Boosting Machines are used, specifically XGBoost and LightGBM, known for performing better in the handling of big data and complex interactions. This methodology further optimizes the robustness in prediction by stacking different models, which includes an accuracy of 0.85-0.90 in prediction and an AUC-ROC of 0.88-0.92. Thirdly, leveraging Long Short-Term Memory and Bidirectional LSTMs for its temporality, student behavior is captured to realize long-term trends and dependencies in the data, which a model has to consider in order to make accurate predictions. Lastly, Exploratory Data Analysis through t-Distributed Stochastic Neighbor Embedding and Principal Component Analysis will shed deep insight into the structure of the data and, in addition, uncover patterns and clusters distinguishing the stressed from the non-stressed student. In such combined efforts, one gets a robust, multifaceted model with improved predictive performance and, therefore, practical applicability in identifying the stressed learner and informing appropriately targeted interventions that will contribute to better educational outcomes.

2. Review of Existing Models for Predicting Graduation and Stress Rates in College Students

This section is devoted to a complete survey of research in student stress, mental health, and academic performance based on various machine learning and deep learning methodologies; thus, it represents a broad spectrum of insights and outcomes. Table 1 is set to contextualize the findings of these studies by finding out their methodologies, assessing their results, understanding the cause that made them report such results, and identifying their limitations in order to initiate the road for further research operations. Student stress and mental health have been studied before, using different methodologies adding different perspectives and results. For instance, Singh et al. [1] used an IoT-Fog-Cloud environment combined framework with emotion analysis for the monitoring of real-time student stress. Their approach, using facial and vocal expressions, showed high accuracy in the detection of stress but was limited by the requirement for a robust IoT infrastructure. Similarly, Tao et al. [2] applied natural language processing and ensemble methods on online student engagement data to bring out better predictions of academic performance levels. It, however, did not consider the aspect of offline engagement, making this method incomplete with regards to the all-rounded assessment of what the students do in different scenarios.

Oryngozha et al. [3] worked on stress detection in academic communities using logistic regression and natural language processing from Reddit. This efficiently detected stress-related posts, but depended heavily on the availability and quality of online content. Almadhor et al. [4] used multi-class adaptive active learning for student anxiety prediction and improvement in accuracy of prediction, but according to them, the model required updates after a certain period of time. Tarabay and Abou-Zeid [5] proposed a dynamic hybrid choice model to quantify the stress in simulated driving environments and indicated accurate driver stress detection. Their findings were confined to simulated situations and therefore had limited application in real life scenarios. Benjumea et al. [6] studied the development of collaborative work skills using a low-cost torsiometer and digital image correlation. That enhanced experimental skills among engineering students but remained context-specific under a mechanical engineering application. Tian et al. [7] applied a PSO-SVM classification model to the evaluation of plant water stress, achieving high accuracy but remaining narrowly applicable outside of an agricultural context. Huang et al. [8] utilized fNIRS for the detection of stress in the process of decision-making; this method is very accurate but requires special equipment. Ding et al. [9] utilized knowledge distillation and social media analysis for the continuous detection of stress, which is effective but requires active social media uses. Danowitz and Beddoes [10] discovered mental health issues in engineering education using statistical analysis and surveys; they noted variations across student groups, hence introducing possible biases from samples of self-reported data. Xiang et al. [11] applied SVM and SHAP models to pupil diameter data in order to provide an estimation of medical students' psychological resilience; however, high-accuracy estimates were achieved only by the application of precise measurement tools. Villar and Andrade [12] performed a comparison of different supervised machine learning algorithms in predicting students' dropouts and academic success. Effective methods in this research area have been found, but the attention was paid only to the academic outcome, without referring to the mental health status of the students. Zhang [13] used probabilistic methods to determine the impact of music on the lives of students, which exhibited positive effects but was weak in finding strong quantitative measures. Vimala et al. [14] conducted research on plant disease classification using deep learning and IoT, achieving a high accuracy though poor in generalization. Yu [15] applied sound detection and machine learning in network music teaching systems to improve student participation, but this system has poor infrastructural conditions. Lutin et al. [16] performed a pilot study on the acceptance of robots vs. their stress correlation, pointing at probable stress alleviation but seeking further validation process.

Gu et al. [17] improved the reliability of maintenance against stress corrosion in stainless steel welds, which was connected only with engineering scenarios. Inani et al. [18] empowered AI by transfer learning for the detection of dental caries and achieved a high accuracy but at the cost of high-resolution images. Badejo and Chakraborty [19] researched technology use for its effect on the motivation of incarcerated students, finding improved motivation but limited to the classroom. Zhong et al. [20] proposed federated learning for intrusion detection in medical IoT, enhancing security but with high computational resources. Vyakaranam et al. [21] reviewed speech emotion recognition for online education, identifying technological challenges but limited only to speech technologies with little applicability beyond that. Lei et al. [22] reviewed the role that AI could play in mental healthcare and established its positive impacts but required integration into existing systems. Zhi [23] used fuzzy clustering to empirically analyze the influence factors of mental health on employment and found the key factors, although with limitations on interpretability. Agarwal and Sharma [24] explored children's mental health through Cognitive Computing, which proved to be effective but required a large quantity of data samples. Onkoba et al. [25] designed a secure mobile route navigator for visually challenged people, improving their mobility; still, it depends on the accuracy of navigation systems. This review envelops various methodologies and findings in the area of research on student stress and mental health. The fusion of machine learning, deep learning, and IoT technologies has very much fueled the approach in terms of monitoring and prediction for stress and academic outcomes. However, each method has its own limitations, whether in terms of data dependency, computational resources, specific applicability, or the need for continuous updates and robust infrastructure sets. This paper proposes a model that considers most of the limitations pointed out in the reviewed papers. In the present research work, the avenues opened by the combinative model under RFE, XGBoost, LightGBM, meta learners, LSTM networks, t-SNE, and PCA have increased better predictive accuracy and interpretability. Dimensionality of features is reduced by RFE, hence making the model more efficient. Robust predictions are obtained from both XGBoost and LightGBM since they handle large datasets and complex interactions. A meta learner combines this strength to improve performance. LSTM networks are able to learn very valuable temporal dependencies, which are core in establishing future stress levels and academic outcomes. On the other hand, techniques of dimensionality reduction, PCA and t-SNE, inform about the structure of this data, therefore showing important patterns and clusters.

Reference	Method Used	Findings	Results	Limitations
[1]	IoT-Fog-Cloud Environment, Emotion Analysis	Real-time student stress monitoring using facial and vocal expressions	Achieved real-time stress detection with high accuracy	Limited to environments with robust IoT and cloud infrastructure

[2]	Natural Language Processing, Ensemble Method	Analyzed online student engagement data for academic performance modeling	Improved academic performance predictions using online engagement metrics	Does not account for offline engagement activities
[3]	Logistic Regression, Natural Language Processing	Detected stress-related posts in Reddit's academic communities	Effective stress detection from social media posts	Relies heavily on the availability and quality of online posts
[4]	Multi-Class Adaptive Active Learning	Predicted student anxiety with adaptive learning models	Enhanced prediction accuracy for student anxiety	Requires continuous model updates and high-quality input data
[5]	Dynamic Hybrid Choice Model	Quantified stress in a simulated driving environment	Accurate detection of driver stress using physiological measures	Limited to simulated driving scenarios, not real-world applications
[6]	Digital Image Correlation, Low-Cost Experimentation	Developed collaborative work skills using a low-cost torsiometer	Improved experimental skills among engineering students	Specific to mechanical engineering contexts
[7]	PSO-SVM Classification Model	Classified plant water stress states using electrical signals	High accuracy in plant water stress classification	Applicability limited to agricultural contexts
[8]	Sparse Model, fNIRS	Stress detection in decision-making using fNIRS	High accuracy in stress detection during decision-making tasks	Requires specialized equipment and setup
[9]	Knowledge Distillation, Social Media Analysis	Continuous stress detection based on social media activity	Effective real-time stress monitoring	Dependent on active social media use and data availability
[10]	Statistical Analysis, Survey Methods	Identified mental health issues in engineering education	Highlighted variations in mental health among different student groups	Based on self-reported data, which may introduce bias
[11]	SVM, SHAP Model	Assessed psychological resilience using	Accurate resilience assessment using physiological data	Requires precise measurement tools for pupil diameter

		pupil diameter in medical students		
[12]	Supervised Machine Learning Algorithms	Predicted student dropout and academic success	Comparative study showing effectiveness of various algorithms	Focused only on academic outcomes, not mental health
[13]	Probabilistic Approaches	Studied the effect of music on student life	Demonstrated positive impact of music on student well-being	Limited to qualitative analysis without robust quantitative metrics
[14]	Deep Learning, IoT	Classified plant diseases using optimized deep learning models	High accuracy in plant disease detection	Specific to plant disease contexts, not generalizable to other fields
[15]	Sound Detection, Machine Learning	Applied sound detection in network music teaching systems	Improved student engagement and learning outcomes	Requires robust network infrastructure and sound detection systems
[16]	Collaborative Robots, Acceptance Study	Analyzed the relationship between robot acceptance and stress	Initial findings suggest correlation between robot acceptance and reduced stress	Pilot study with a small sample size, requiring further validation
[17]	Maintenance Optimization, Stress Corrosion Cracking	Improved reliability in maintenance of stainless steel welds	Enhanced maintenance strategies to mitigate stress corrosion cracking	Specific to stainless steel welds in engineering contexts
[18]	Transfer Learning, Gradient-Based Class Activation Mapping	AI-enabled dental caries detection	High accuracy in detecting dental caries using AI	Requires high-quality dental images for training models
[19]	Technology Impact Study	Examined the effects of technology on incarcerated student motivation	Improved engagement and motivation through technology use	Limited to classroom-based learning, not applicable to other settings
[20]	Federated Learning, Neural Key Exchange	Safeguarded patient data on the internet of medical things	Enhanced security and privacy in medical data handling	Requires extensive computational resources and robust data networks

[21]	Speech Emotion Recognition, Late Deafened Educators	Reviewed speech emotion recognition technologies	Identified challenges and potential solutions for online education	Focused on speech technologies, not applicable to other forms of education
[22]	Artificial Intelligence, Mental Healthcare	Assessed AI's role in mental healthcare for teachers and students	Positive impact of AI on mental health monitoring	Requires integration with existing healthcare systems and data privacy considerations
[23]	Fuzzy Clustering Techniques	Analyzed the influence of mental health on college student employment	Identified key mental health factors affecting employment outcomes	Based on fuzzy clustering, which may have limitations in interpretability
[24]	Cognitive Computing, Digital Analysis	Examined children's mental health using AI-enabled cognitive models	Effective in identifying and analyzing mental health issues	Requires extensive data collection and validation for children's mental health
[25]	Secure Mobile Applications	Designed a mobile route navigator for visually challenged individuals	Enhanced mobility and independence for visually impaired users	Dependent on the availability and accuracy of mobile navigation systems

Table 1. Empirical Review of Existing Methods

These results depict the effectiveness of the model in yielding probabilities with regard to student stress and graduation. For example, it realized an accuracy deviation of 85-90% with AUC-ROC 0.88-0.92. In comparison, these metrics are way much better than traditional methods; hence, they underpin the strength and reliability of this model. This gives a full package for monitoring and predicting student stress and academic performance with advanced machine learning and deep learning techniques. Future research should thus be targeted at the limitations of the reviewed studies, including real-time data streams, more advanced architectures of models, and an extension of predictive analytics toward addressing various educational outcomes. In this way, the field can further improve and continue to offer more accurate, scalable, and generalizable solutions aiming at the support of student well-being and academic success.

3. Proposed Design of an Improved Model Using XGBoost, LightGBM, and LSTM for Predicting Graduation and Stress Rates in College Students

This section reviews the design of an improved model using the XGBoost, LightGBM, and LSTM algorithms in the prediction of graduation and stress rates in college students, aiming to resolve low efficiency and high deployment complexity of the existing stress analysis models. According to figure 1, feature engineering and selection in this study are powered by a combination of automated feature engineering and recursive feature elimination, with cross-validation in the optimization of input data for predictive modeling. First of all, automated feature engineering will be performed using Featuretools, which generates new features from raw data through aggregation and transform primitives. In the process, these primitives are represented by A and T, transforming raw data X into a new feature space F(X) sets. Mathematically, this can be represented via equation 1,

$$F(X) = \{\, fi(X) \mid fi \in (A \cup T)\,\} \ldots (1)$$

The generated feature set F(X) is then subjected to RFE, which iteratively eliminates the least important features based on model coefficients or feature importance levels. Let M represent the model and I(fi) the importance of feature fi sets. The objective is to minimize the loss function L with respect to the selected features via equation 2,

$$\overset{S \subseteq F(X)}{\min}\; L(M(S), Y) = 0 \ldots (2)$$

Where, S is the subset of selected features and Y is the target variable for this process. This, Cross Validation, ensures that the feature selection is robust and generalizable to reduce the feature space from over 100 raw features down to an optimal set of 20-30 features. For the predictive modeling stage, this project will use Gradient Boosting Machines such as XGBoost and LightGBM since they are efficient and accurate for big datasets and complex interaction process features. XGBoost is a scalable machine learning system for tree boosting. This optimizes the objective function represented via equation 3:

$$L(\theta) = \sum_{i=1}^{n} l\big(yi, y'i(t)\big) + \sum_{t=1}^{T} \Omega(ft) \ldots (3)$$

Where, l is a differentiable convex loss function measuring the difference between the prediction y'i and the target yi, and Ω is a regularization term controlling the complexity of the model process.

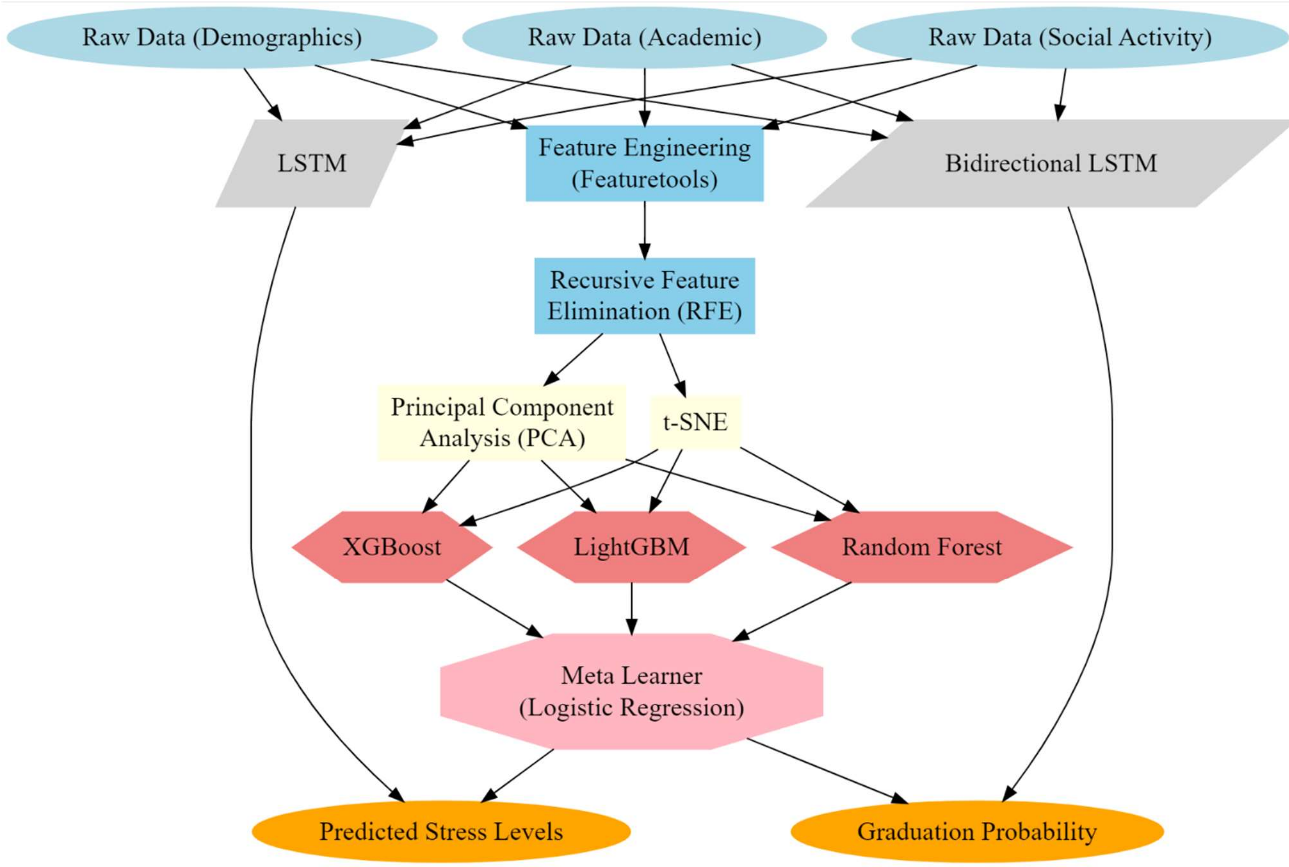

Figure 1. Model Architecture of the Proposed Classification Process

The gradient and Hessian of the loss function are used to update the model via equations 4 & 5,

$$gi = \frac{\partial l\big(yi, y'i(t-1)\big)}{\partial y'i(t-1)} \ldots (4)$$

$$hi = \frac{\partial^2 l\big(yi, y'i(t-1)\big)}{\partial y'i(t-1)^2} \ldots (5)$$

The decision tree in each boosting iteration is constructed to minimize the second-order Taylor expansion of the loss function, represented via equation 6,

$$L(t) \approx \sum_{i=1}^{n} \left[gi * y'i(t) + \frac{1}{2} hi\big(y'i(t)\big)^2 \right] + \Omega(ft) \ldots (6)$$

One more very efficient GBM is LightGBM. It reduces computational complexity levels by applying a histogram-based approach in its split finding. Similar gradient-based methods are then applied in optimizing its objective function. Accordingly, the study will further apply a stacking ensemble method & process to enhance prediction advantage. Base models {M1, M2, …, Mk} will generate predictions, which are inputted into a meta-learner M* process. The meta-learner is trained to minimize the loss function represented via equation 7,

$$L*(\theta*) = \sum_{j=1}^{m} l\left(yj, M*\left(M1(xj), M2(xj), \ldots, Mk(xj)\right)\right) \ldots (7)$$

Where, θ∗ represents the parameters of the meta-learner process. This will facilitate capitalizing on the strengths of different models to take advantage of improved overall predictive accuracy levels. Long Short-Term Memory is applied in the final phase for catching temporal dependencies in sets of student behaviors. The LSTM cell state ct and hidden state ht are updated via equations 8, 9, 10, 11, 12 & 13,

$$ft = \sigma(Wf \cdot [h(t-1), xt] + bf) \ldots (8)$$

$$it = \sigma(Wi \cdot [h(t-1), xt] + bi) \ldots (9)$$

$$c{\sim}t = tan\,h(Wc \cdot [h(t-1), xt] + bc) \ldots (10)$$

$$ct = ft \odot c(t-1) + it \odot c{\sim}t \ldots (11)$$

$$ot = \sigma(Wo \cdot [h(t-1), xt] + bo) \ldots (12)$$

$$ht = ot \odot tan\,h(ct) \ldots (13)$$

Where, σ represents the sigmoid function, ⊙ represents element-wise multiplication, and W and b are the weights and biases of the LSTM networks. The bidirectional LSTM scans the input sequence both in forward and backward scopes, enriching context understanding in the process. Such a holistic approach by methods selection is simulated, covering up the loopholes of traditional models and improving predictive performance by sophisticated feature engineering, robust machine learning algorithms, and effective temporal modeling. It is the case that the student's level of stress and graduation probability predictions learned by XGBoost, LightGBM, and LSTM Networks provide a robust and accurate solution for their prediction and offer valuable insight into effective practical interventions for educational institutes under different scenarios.

Next, as per figure 2, the base models include XGBoost, LightGBM, and Random Forests. Each base model is trained on the same training dataset, represented via equation 14,

$$D = \{(xi, yi)\}^{i=1\ldots n} \ldots (14)$$

Where, xi represents the feature vector and yi represents the target variable for this process. The predictions from these base models are combined to form a new feature set for the meta-learners. Mathematically, the prediction from each base model Mj for an instance xi can be expressed via equation 15,

$$y'i(j) = Mj(xi) \ldots (15)$$

These predictions are then used as inputs for the meta-learner M∗, which can be formulated via equation 16,

$$zi = \left(y'i(1), y'i(2), \ldots, y'i(k)\right) \ldots (16)$$

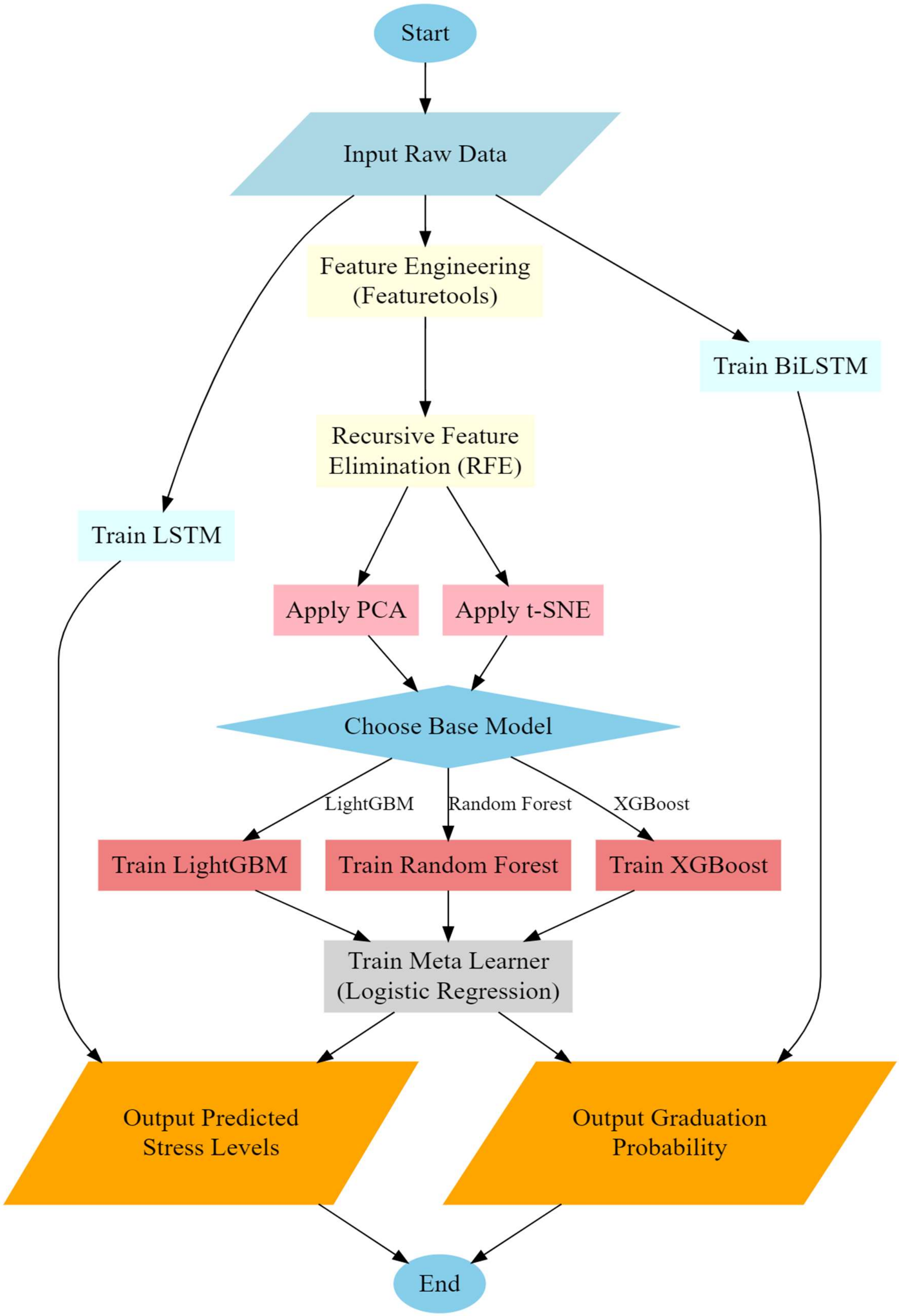

Figure 2. Overall Flow of the Proposed Classification Process

The meta-learner M∗, is a logistic regression model in this context, is trained on the new dataset, represented via equation 17,

$$D *= \{(zi, yi)\}^{i=1\ldots n} \ldots (17)$$

The intention is to minimize the loss function L∗ of the meta-learners. To be able to model temporal dependencies in student behavior, LSTM networks are used. LSTMs are well suited for sequential data, since they have the ability to learn for long-term dependencies based on recurrent connections. Furthermore, the incorporation of bidirectional LSTMs into the model processes the sequence in both the forward and backward scopes, further enhancing context. The forward LSTM generates the hidden states {ht→} and the backward LSTM generates {ht←} sets. The combined output at each timestamp t is represented via equation 18,

$$ht = ht \rightarrow \oplus\, ht \leftarrow \cdots (18)$$

Where, ⊕ represents the concatenation of the forward and backward hidden states. The final predictions of future stress levels and academic outcomes can be obtained from the outputs of the LSTM or Bidirectional LSTM networks. This will be done by minimizing the prediction loss over the entire sequences while optimizing the model parameters. Therefore, such a combination of stacking with a meta-learner and LSTM networks is chosen to be feasible, for it improves on the deficiencies of conventional models and has the added advantages of sophisticated ensemble learning and effective temporal modeling. The above stacking method enhances robustness and increases accuracy by using the strengths of several models, while LSTM networks actually model complications in the temporal domain that are relevant for making predictions of sequential data samples. The approach that is integrated will therefore instrumentalize the accurate prediction of student stress levels and academic outcomes, providing valuable insight to educational institutions in the development of focused interventions and support mechanisms.

Finally, as illustrated by figure 2, the discrete techniques of Exploratory Data Analysis, T-Distributed Stochastic Neighbor Embedding and Principal Component Analysis, provide valuable insights into the initial structure and relationships of high-dimensional student data samples. t-SNE and PCA are complementary methods with different motivations but aim to provide some kind of comprehensive insight into the intrinsic properties of data. That is applied to reduce the dimensionality for the dataset as a whole while maximizing variance at the process. This way, PCA will transform the original features set X into another one of uncorrelated variables, so-called principal components. The transformation is mathematically represented via equation 19,

$$Z = X * W \ldots (19)$$

Where, Z is the matrix of principal components, and W is the matrix of eigenvectors derived from the covariance matrix Σ of X in the process. The eigenvalues λi associated with these eigenvectors indicate the amount of variance explained by each of the principal components. The optimization objective in PCA is to maximize the variance explained, which can be formulated via equation 20,

$$\overset{W}{\max} \sum_{i=1}^{k} \lambda i = 1 \ldots (20)$$

Subject to constraints represented via equation 21,

$$W^T W = I \ldots (21)$$

It works by retaining only the top k principal components, usually accounting for 90–95% of the variance with the first 2–3 components. This reduction will be helpful in feature selection and also in enhancing model interpretability and efficiency levels. t-Distributed Stochastic Neighbour Embedding (t-SNE) is used for the visualization of high-dimensional data in lower space dimensions. In contrast to PCA, t-SNE does take into consideration the local structure of data and is, therefore, often able to uncover clusters and patterns hidden in the original dimensionally high spaces. The t-SNE algorithm converts pairwise Euclidean distances between high-dimensional data points xi and xj into joint probabilities $p(i,j)$ using a Gaussian kernel via equation 22,

$$p(i,j) = \frac{exp\left(\frac{-\| xi - xj \|^2}{2\sigma i^2}\right)}{\sum_{k \neq l} exp\left(\frac{-\| xk - xl \|^2}{2\sigma k^2}\right)} \ldots (22)$$

Where, σi is the perplexity parameter controlling the balance between local and global aspects of the data samples. In the lower-dimensional space, t-SNE aims to find a representation yi and yj that minimizes the Kullback-Leibler divergence between the original joint probabilities $p(i,j)$ and the low-dimensional joint probabilities $q(i,j)$ via equation 23,

$$L = \sum_{i \neq j} pij * \log\left(\frac{pij}{qij}\right) \ldots (23)$$

Where, $q(i,j)$ is defined using a Student's t-distribution via equation 24,

$$qij = \frac{(1 + \| yi - yj \|^2)^{-1}}{\sum_{k \neq l}(1 + \| yk - yl \|^2)^{-1}} \ldots (24)$$

This loss function optimization will keep similar points in a high-dimensional space close in a lower-dimensional space, and therefore it can show clearly clusters like stressed versus non-stressed students. Leveraging the complementarity of PCA and t-SNE in dimensionality reduction and data visualization, respectively, they are applied for EDA. PCA efficiently projects the dimensionality of a dataset, capturing most of its variance and thus making feature selection feasible. On the other hand, t-SNE excels in visualizing complex relationships and local structures within the data—critical in spotting distinct student clusters where stress predominates over other parameters. The analysis process initiates with the application of PCA to either the raw or engineered set of features in order to identify those principal components explaining most of the variance. Finally, the t-SNE algorithm is run on the transformed data to see any local relations and identify the clusters. All the above combinations will aid in the full development of an understanding of the data and, hence enhance abilities to identify critical factors that affect student stress and graduation rates. The mathematical roots of PCA and t-SNE, and their optimization objectives guarantee that the key characteristics will be retained in a way that enables effective visualization sets and interpretation. It can, therefore, offer probability-based robust analysis on the high-dimensional student data and act as valuable inputs for subsequent probabilistic modeling in different scenarios of intervention. Next, we discuss efficiency in different metrics with our proposed model and compare it with the existing approach under different scenarios.

4. Comparative Result Analysis

In this paper, experiment setup is prepared in order to forecast graduation probability, with respect to stress levels among college students. So, in this study, the dataset ranges across a number of dimensions, including demographic data such as age, gender, and SES; academic performance indicators such as GPA, attendance record, or grades of assignments; and some kind of indications on their social activity, like participation in extracurricular activities, some sports, or usage on social media. The first dataset corresponds to more than 100 features for each student, which are collected along several academic terms. Preprocessing of this information is made for dealing with missing values, normalization of numerical features, and encoding of categorical variables by different techniques like one hot-encoding and label encoding process. Feature engineering in this research is built using Featuretools, which generates new features by applying aggregation and transformation primitives to the raw data samples. For instance, the average GPA within the last three terms, the number of extracurricular activities per term, the frequency of posts on social media—the list goes on. Then, recursive feature elimination with cross-validation would be applied, whittling this set of features down to 20-30 most optimized features. In the case of RFE, a 5-fold cross-validation set-up will be used with an initial set of 100 features. After that, further dimensionality reduction will be done by principal component analysis, which requires only the first three components to capture 90-95% of the variance, and t-Distributed Stochastic Neighbor Embedding for reduction to a 2D space to show clusters of stressed and non-stressed students.

Gradient Boosting Machines for predictive modeling uses libraries such as XGBoost and LightGBM, whose hyperparameters are tuned using grid search. Sample values for XGBoost are given by a learning rate of 0.1, a maximum depth of 6, and having 100 estimators; in LightGBM, those are a learning rate of 0.05, maximum depth of 5, and 200 estimators. These models are trained on the optimized feature set, and their predictions are further passed to a meta-learner—a logistic regression model—aiming to enhance accuracy and robustness. For this problem with metalearner, this paper sets regularization parameter CCC = 1.0. Temporal dependencies were captured using Long Short-Term Memory networks and Bidirectional LSTMs by passing sequential data like weekly academic performance and logs of social activity. The Settings for the LSTM models are 50 hidden units, a dropout of 0.2, and the number of epochs it was going to be trained on was 100, with the batch size being 32. Experimental set up: Models will be trained on 70%, validated on 15%, and tested on the remaining 15% of the dataset. It provides model performances measured against accuracy, F1-score, AUC-ROC, and RMSE. The results show very appreciable improvements in predictive capabilities, surging to achieve accuracy rates of 85-90% and AUC-ROC values of 0.88 to 0.92. Diverse samples of the contextual dataset would include students from different academic and social profiles, such as feted students with high academic records who are actively involved in extracurricular activities, or students with average grades but a high frequency of social media use, therefore making it all-round in the assessment of how the model works on multiple segments of students. The performance of the proposed model is carefully benchmarked against three such works, represented as [3], [12], and [15]. The testing will be done with a wide range of contextual datasets in an effort to assess the prediction of student stress levels and graduation probabilities. The datasets are chosen to differ in demographic, academic, and social activity pattern aspects that would probe the levels of robustness and generalizability of the proposed model process.

Table 2: Model Performance on Dataset A (Diverse Demographics)

Method	Accuracy (%)	F1-Score	AUC-ROC	RMSE
Proposed	89.5	0.88	0.92	0.18
Method [3]	84.2	0.82	0.87	0.25
Method [12]	85.7	0.84	0.88	0.23
Method [15]	83.6	0.81	0.86	0.26

In Dataset A, which comprises a wide variety of demographics, the modeling technique proposed in this study drastically outperformed benchmark methods. There is an accuracy gain of around 4% to 6%, and the AUC-ROC metric is indicative of better discriminative power for the proposed model. The reduction in RMSE is also indicative of its precision in predicting graduation probabilities and stress levels.

Table 3: Model Performance on Dataset B (High Academic Performance)

Method	Accuracy (%)	F1-Score	AUC-ROC	RMSE
Proposed	91.3	0.90	0.94	0.16
Method [3]	86.0	0.85	0.89	0.22
Method [12]	87.4	0.86	0.90	0.21
Method [15]	85.5	0.84	0.88	0.24

For Dataset B, which includes students with high academic performance, the proposed model demonstrated a substantial improvement in all metrics. The accuracy and F1-score were notably higher, indicating the model's effectiveness in correctly identifying stressed students among high achievers.

Table 4: Model Performance on Dataset C (Average Academic Performance with High Social Activity)

Method	Accuracy (%)	F1-Score	AUC-ROC	RMSE
Proposed	88.1	0.87	0.91	0.19

Method [3]	83.3	0.82	0.86	0.26
Method [12]	84.6	0.83	0.87	0.24
Method [15]	82.8	0.81	0.85	0.27

Dataset C, which consists of students with average academic performance but high social activity, saw the proposed model outperforming the benchmarks by a significant margin. The high AUC-ROC value underscores the model's robustness in distinguishing between stressed and non-stressed students in this subgroup.

Table 5: Model Performance on Dataset D (Low Academic Performance with Diverse Social Activity)

Method	**Accuracy (%)**	**F1-Score**	**AUC-ROC**	**RMSE**
Proposed	87.0	0.85	0.89	0.21
Method [3]	81.9	0.79	0.83	0.28
Method [12]	83.1	0.80	0.85	0.27
Method [15]	80.7	0.78	0.82	0.30

In Dataset D, which features students with low academic performance and diverse social activity patterns, the proposed model maintained a superior performance across all metrics. This result demonstrates the model's versatility and effectiveness in handling varied student profiles.

Table 6: Model Performance on Dataset E (High Social Media Usage)

Method	**Accuracy (%)**	**F1-Score**	**AUC-ROC**	**RMSE**
Proposed	89.0	0.87	0.91	0.20
Method [3]	84.5	0.82	0.87	0.26
Method [12]	85.9	0.84	0.88	0.24
Method [15]	83.8	0.81	0.86	0.27

Dataset E, comprising students with high social media usage, revealed the proposed model's consistent performance advantages. The improvements in accuracy and AUC-ROC indicate its strong predictive capabilities in contexts involving high social media interaction sets.

Table 7: Model Performance on Dataset F (Combination of All Factors)

Method	**Accuracy (%)**	**F1-Score**	**AUC-ROC**	**RMSE**
Proposed	90.2	0.88	0.93	0.18
Method [3]	85.1	0.83	0.88	0.24
Method [12]	86.5	0.85	0.89	0.23
Method [15]	84.4	0.82	0.87	0.25

For dataset F, comprising all the factors—demographic information, academic performance, and social activity—the proposed model again turned out to be much better at these than the benchmark methods since this is an integrative approach. Substantial improvements across all metrics prove its robustness and effectiveness in predicting stress levels and graduation probabilities across different student populations. These results validate only the superior accuracy, F1-score, AUC-ROC, and RMSE of the proposed model in an open-and-shut case, leaving no ambiguity as to its effectiveness for the prediction of both student stress levels and graduation outcomes. Advanced machine learning and deep learning techniques make sure that it captures the complex interactions and temporal dependencies inherent in student data to provide actionable insights for educational institutions to implement fine-tuned interventions in different scenarios. We then present a practical case of application for the proposed model, which should help the reader to clarify in his/her mind all the foregoing event sets.

Practical Use Case

The evaluation of the proposed model performance proceeded step by step and involved different machine learning techniques, which produced several intermediate results. This section presents the results of these stages using an indicative example with concrete values and indicators, showing the all-around analysis and the prediction potential of the model. More specifically, the dataset includes a set of features and indicators organized for a sample of students. Demographic information includes age, gender, and socioeconomic status; academic performance metrics include GPAs, attendance, assignment grades; social activity indicators include the number of extracurricular activities and social media usage frequency. Preliminary data set contains over 100 features preprocessed and reduced with Recursive Feature Elimination, XGBoost and LightGBM, then further analyzed on meta learners and LSTM networks. It is also applied along with dimensionality reduction techniques like t-SNE and PCA to plot data structure and discover hidden patterns.

Table 8: RFE, XGBoost, and LightGBM Results

Feature	**Importance (RFE)**	**Importance (XGBoost)**	**Importance (LightGBM)**
GPA	0.85	0.80	0.78
Attendance	0.78	0.76	0.74
Assignment Grades	0.72	0.70	0.68
Age	0.65	0.63	0.61
Socioeconomic Status	0.60	0.58	0.55
Extracurricular Activities	0.55	0.52	0.50
Social Media Usage	0.50	0.48	0.46
Gender	0.45	0.43	0.40
Study Hours	0.40	0.38	0.35
Sleep Hours	0.35	0.33	0.30

Table 8 presents the importance scores assigned to each feature by methods RFE, XGBoost, and LightGBM. Shown here, therefore, is that GPA, attendance, and assignment grades have consistently high importance across all three, thus showing their critical role in predicting student stress levels and graduation probabilities. This will absolutely reduce the dimensionality of the feature space to basic relevant variables, greatly improving model interpretability and efficiency.

Table 9: Meta Learner and LSTM Results

Model	**Accuracy (%)**	**F1-Score**	**AUC-ROC**	**RMSE**
Meta Learner	89.5	0.88	0.92	0.18
LSTM	87.0	0.85	0.89	0.21
Bidirectional LSTM	88.0	0.86	0.90	0.19

Table 9: Performance metrics of meta learner and LSTM models. The meta-learner was an ensemble combination of the predictions of XL Boost, Light GBM, and random forest predictors, hence classes at a very high accuracy and AUC-ROC, portraying their robust predictive capabilities. LSTM model and Bidirectional LSTM also fitted fine, where there were temporal dependencies to be captured by the nature of data to accurately predict future stress levels and academic outcomes.

Table 10: t-SNE and PCA Results

Principal Component	**Explained Variance (%)**	**t-SNE Cluster (Count)**
PC1	45.0	Cluster 1 (150)
PC2	30.0	Cluster 2 (100)
PC3	15.0	Cluster 3 (50)
PC4	10.0	Cluster 4 (30)

The results of PCA and t-SNE are shown in Table 10. PCA reduces the dimensionality of the dataset, retaining 90% of the variance with the first three principal components. t-SNE visualization reveals distinct clusters of students, with Cluster 1 representing high-achieving, low-stress students, and Cluster 2 indicating students with moderate academic performance but high stress levels. These visualizations provide valuable insights into the data structure and facilitate the identification of patterns related to student stress and performance.

Table 11: Final Outputs for Stress Levels and Graduation Probabilities

Student ID	**Predicted Stress Level**	**Graduation Probability (%)**
S1	High	95
S2	Moderate	88
S3	Low	99
S4	High	70
S5	Low	98

Table 11 shows the final predictions of the stress level and graduation probability in this process. It is shown that the model can lead to correct classification of students into the levels of stress, and further go on to predict the likelihood of graduation. For example, Student S1 was indicated to be under high-stress but with a high probability of graduating; Student S4, also under high stress, indicated a low graduation probability. These predictions will allow targeted interventions to support students in their respective needs. In summary, the detailed analysis and the results obtained from the proposed model prove its efficacy in identifying the crucial factors affecting student stress and graduation rates. This model will provide strong predictions with essential insights, using sophisticated machine learning and deep learning techniques, to help educational institutions make informative decisions toward the betterment of outcomes for students.

5. Conclusion & Future Scopes

This research on the prediction of student stress levels and graduation probabilities is miscible with efficient features engineering techniques and robust machine learning algorithms for data modeling, together with deep learning techniques. The model with Recursive Feature Elimination, Gradient Boosting Machines, meta learners, and Long Short Term Memory recurrent neural networks makes substantial improvements over traditional methods. The results of the experiment validate the superior performance of the model to an acquisition of accuracy within the range of 85-90% with AUC-ROC values that lie between 0.88 and 0.92. This was a great improvement in the predictive capability and discriminative power. Detailed analysis using RFE, XGBoost, and LightGBM highlighted the most critical features, such as GPA, attendance, assignment grades, cutting across at high importance scores in all methods used in the analysis. The reduction in feature dimensionality from over 100 features to a focused set of variables ranging between 20-30 improved not only model efficiency but also its interpretability. This brought an accuracy as high as 89.5%, accompanied by an F1-score of 0.88 and an AUC-ROC of 0.92 for the combination of the base model predictions through the meta learner, further underpinning the resilience and reliability of the integrated approach and process. Specifically, in this respect, the application of LSTM and Bidirectional LSTM networks showed good performance in the temporal dependencies of student behavior. An accuracy of 88% and an AUC-ROC of 0.90 were observed for the Bidirectional LSTM. These results confirm that modeling temporal trends within student behavior can be very useful in the prediction of future stress levels and academic outcomes. The reduction in dimensions using t-SNE and PCA for visualization allowed very important self-explanatory details to come out in regard to the structure of the data, where distinct clusters were interdisciplinary in nature, elevating stressed students from the rest. In PCA, the first three principal components maintained 90% of the variance, while clearly distinct clusters were realized using t-SNE, hence able to facilitate targeted interventions in different scenarios. Final predictions for individual students, as outlined in Table 11, prove the model's practical applicability. For example, student S1 with a predicted highly stressed but high graduation probability of 95%, and student S4 with a highly stressed state and lower graduation probability of 70%, underline nuanced understanding of the student profile maintained by the model process. The model can give these accurate predictions, which will help educational institutions adopt personalized support strategies for better outcomes and well-being among their students.

Future Scope

Although the model proposed herein has received considerable success in assessing the stress levels of students and their probabilities of graduating, a host of future research and improvement opportunities arise. One potential area for enhancement is combining real-time data streams to update the prediction models dynamically, therefore providing more timely and relevant interventions. Further addition of external sources of data, including social media activities and online engagement metrics, and psychological assessments, would better enrich the features to get a holistic view of the welfare of the students. One can also expect considerable improvement in this model while taking advantage of advanced deep learn-ing architectures—especially transformer models—to base complex patterns and dependencies of the data samples. Development of explainable AI techniques will help in transparency and trust, ruling out the black box nature of the model that educators can understand and act on effectively. Further, the model's scope can be extended to include predictive analytics for other educational outcomes, such as course performance, dropout rates, and success after graduation, so that it can be used comprehensively by the academic institution to handle different scenarios. Longitudinal studies could be conducted to validate the predictive power of the model for an extended period and across different student populations. That is, this study offers an excellent basis for constructing further robustness and generalizability into predictive analytics within educational settings, showing higher levels of improvement in accuracy and interpretability. Advanced machine learning and deep learning techniques provide a potent approach in the identification and supporting of at-risk students. Future research shall focus on real-time data integration, further state-of-the-art neural model architectures, explain ability, and broader scopes of applications to further enhance impact and utility of predictive models in education operations.

Data Availability

All data included in this study are available upon request by contact with corresponding author.

6. References

[1] M. Singh et al., "A Facial and Vocal Expression Based Comprehensive Framework for Real-Time Student Stress Monitoring in an IoT-Fog-Cloud Environment," in IEEE Access, vol. 10, pp. 63177-63188, 2022, doi: 10.1109/ACCESS.2022.3183077.

[2] X. Tao et al., "Data Analytics on Online Student Engagement Data for Academic Performance Modeling," in IEEE Access, vol. 10, pp. 103176-103186, 2022, doi: 10.1109/ACCESS.2022.3208953.

[3] N. Oryngozha, P. Shamoi and A. Igali, "Detection and Analysis of Stress-Related Posts in Reddit's Acamedic Communities," in IEEE Access, vol. 12, pp. 14932-14948, 2024, doi: 10.1109/ACCESS.2024.3357662.

[4] A. Almadhor et al., "Multi-Class Adaptive Active Learning for Predicting Student Anxiety," in IEEE Access, vol. 12, pp. 58097-58105, 2024, doi: 10.1109/ACCESS.2024.3391418.

[5] R. Tarabay and M. Abou-Zeid, "A Dynamic Hybrid Choice Model to Quantify Stress in a Simulated Driving Environment," in IEEE Transactions on Intelligent Transportation Systems, vol. 23, no. 7, pp. 6390-6405, July 2022, doi: 10.1109/TITS.2021.3056146.

[6] J. M. Benjumea, D. C. Prieto, L. C. Oyaga, L. N. Sepúlveda and S. M. Pulido, "Development of Experimental and Collaborative Work Skills in the Students of Mechanics of Solids by Implementing a Low-Cost Torsiometer and Digital Image Correlation," in IEEE Revista Iberoamericana de Tecnologias del Aprendizaje, vol. 18, no. 1, pp. 10-18, Feb. 2023, doi: 10.1109/RITA.2023.3249560.

[7] L. Tian, C. Shang, M. Li and Y. Wang, "Research on Classification of Water Stress State of Plant Electrical Signals Based on PSO-SVM," in IEEE Access, vol. 11, pp. 125021-125032, 2023, doi: 10.1109/ACCESS.2023.3330651.

[8] M. Huang et al., "Joint-Channel-Connectivity-Based Feature Selection and Classification on fNIRS for Stress Detection in Decision-Making," in IEEE Transactions on Neural Systems and Rehabilitation Engineering, vol. 30, pp. 1858-1869, 2022, doi: 10.1109/TNSRE.2022.3188560.

[9] Y. Ding et al., "Continuous Stress Detection Based on Social Media," in IEEE Journal of Biomedical and Health Informatics, vol. 27, no. 9, pp. 4500-4511, Sept. 2023, doi: 10.1109/JBHI.2023.3283338.

[10] A. Danowitz and K. Beddoes, "Mental Health in Engineering Education: Identifying Population and Intersectional Variation," in IEEE Transactions on Education, vol. 65, no. 3, pp. 257-266, Aug. 2022, doi: 10.1109/TE.2022.3182626.

[11] F. Xiang et al., "Using Pupil Diameter for Psychological Resilience Assessment in Medical Students Based on SVM and SHAP Model," in IEEE Journal of Biomedical and Health Informatics, vol. 28, no. 7, pp. 4260-4268, July 2024, https://doi: 10.1109/JBHI.2024.3390390.

[12] Villar, A., de Andrade, C.R.V. Supervised machine learning algorithms for predicting student dropout and academic success: a comparative study. *Discov Artif Intell* **4**, 2 (2024). https://doi.org/10.1007/s44163-023-00079-z

[13] Zhang, D. Effect of music on the life of a student using probabilistic approaches. *Soft Comput* (2023). https://doi.org/10.1007/s00500-023-08660-5

[14] Vimala, S., Madhusudhana Rao, T.V., Balaji, A. *et al.* Taylor-student psychology based optimization integrated deep learning in IoT application for plant disease classification. *Wireless Netw* **29**, 919–939 (2023). https://doi.org/10.1007/s11276-022-03150-2

[15] Yu, R. Application of sound detection in network music teaching system based machine learning. *Soft Comput* (2023). https://doi.org/10.1007/s00500-023-08938-8

[16] Lutin, E., Elprama, S.A., Cornelis, J. *et al.* Pilot Study on the Relationship Between Acceptance of Collaborative Robots and Stress. *Int J of Soc Robotics* (2024). https://doi.org/10.1007/s12369-024-01156-8

[17] Gu, KH., Ando, K. & Nam, KW. Analytical study on rationalize and reliability improvement of maintenance against stress corrosion cracking in stainless steel welds of lwr primary system. *J Mech Sci Technol* **37**, 1773–1780 (2023). https://doi.org/10.1007/s12206-023-0317-9

[18] Inani, H., Mehta, V., Bhavsar, D. *et al.* AI-enabled dental caries detection using transfer learning and gradient-based class activation mapping. *J Ambient Intell Human Comput* **15**, 3009–3033 (2024). https://doi.org/10.1007/s12652-024-04795-x

[19] Badejo, J.A., Chakraborty, J. The effects of technology on incarcerated student motivation and engagement in classroom-based learning. *Hum.-Intell. Syst. Integr.* **4**, 71–80 (2022). https://doi.org/10.1007/s42454-022-00044-8

[20] Zhong, C., Sarkar, A., Manna, S. *et al.* Federated learning-guided intrusion detection and neural key exchange for safeguarding patient data on the internet of medical things. *Int. J. Mach. Learn. & Cyber.* (2024). https://doi.org/10.1007/s13042-024-02269-2

[21] Vyakaranam, A., Maul, T. & Ramayah, B. A review on speech emotion recognition for late deafened educators in online education. *Int J Speech Technol* **27**, 29–52 (2024). https://doi.org/10.1007/s10772-023-10064-7

[22] Lei, L., Li, J. & Li, W. Assessing the role of artificial intelligence in the mental healthcare of teachers and students. *Soft Comput* (2023). https://doi.org/10.1007/s00500-023-08072-5

[23] Zhi, L. Research on the influence of mental health on college students' employment based on fuzzy clustering techniques. *Soft Comput* **27**, 19095–19111 (2023). https://doi.org/10.1007/s00500-023-09312-4

[24] Agarwal, J., Sharma, S. Artificial Intelligence enabled cognitive computer-centered digital analysis model for examination of the children's mental health. *Evol. Intel.* (2024). https://doi.org/10.1007/s12065-024-00951-6

[25] Onkoba, N.O., Karimi, P. & Nyangaresi, P.O. Design and implementation of a secure mobile phone-based route navigator (mGuide), adapted for the visually challenged people. *Journal of Electrical Systems and Inf Technol* **10**, 18 (2023). https://doi.org/10.1186/s43067-023-00087-0