REVIEW ON CLASSIFICATION AND PREDICTION OF STUDENT PERFORMANCE USING MACHINE LEARNING AND DEEP LEARNING ALGORITHM

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Abstract—
Data mining methods are being applied to a greater extent in the education sector to predict and classify both student and teacher performance, assisting in the development of effective teaching and learning strategies and individualized learning systems. These technologies assist students with career choices, educational planning, early intervention, and individualized instruction. In this research, different machine learning and deep learning models—Logistic Regression, Decision Tree, Random Forest, SVC, KNN, GaussianNB, and MLPClassifier—were experimented with on a labeled student performance dataset. Performance was evaluated in terms of accuracy, precision, recall, F1-score, and cross-validation. The highest accuracy (96.8%) was achieved by Random Forest, followed by Decision Tree (96.2%), with MLPClassifier scoring 90.8%. The findings indicate that ensemble and deep learning models are powerful tools for educational data mining in enhancing student support and institutional decision-making.

Keywords— *Logistic Regression, Random Forest Classifier, MLP Classifier, GaussianNB, SVC, Decision Tree Classifier*

I. INTRODUCTION

Knowledge is important in many areas of our existence. Some of these areas include management, planning, and evaluation of school systems. An education management information system is a centralized system that collects, processes, analyzes, and reports educational information such as that of the institution and the faculty, students, teachers, and staff. Along with data collection, data storage, and data processing, an information system should assist in developing educational policies as well as their administration and evaluation. With hundreds of sensors and systems, the education and IT departments are generating and collating massive amounts of information that rapidly go beyond the limits. Furthermore, student information systems (SIS) generate humongous amounts of data. which encompass general student data, academic records, and a range of activities performed by students and instructors using various types of educational technology, such as learning management systems (LMS). Library records, admission records, financial reports, administrative activities, educational and quality development practices, learning activities, and course data, such as curriculum, goals, materials, test results, and course activities, also create a lot of data [1].

Present evaluation systems typically rely on one source of data; conventional evaluation techniques are often based on personal judgment, prone to personal biases, and likely to yield erroneous results; and conventional approaches have difficulty in presenting immediate feedback, which affects the effectiveness and efficiency of instructional improvement. These are only some of the important challenges confronting the education system today. This contribution presents a new deep learning-centric method for teaching quality assessment to address these problems. To significantly enhance the reliability and precision of teaching quality assessments, this study introduces an in-depth learning method using convolutional neural networks, or CNNs. The proposed method offers robust evidence for evaluation and enhancing the quality of teaching in institutions of higher education through integration of a number of data sources and using novel machine learning methods. By leveraging deep learning methods, especially CNN, this study aims to enhance university teaching quality assessment and improvement procedures[2].

Learning strategies have played a significant role in cultivating student performance. New advances have simplified it for teachers to determine the pros and cons of pupil achievement. Taking on the required methods for assisting students with improving their performance would enhance this awareness. Reducing dropout rates and assisting at-risk students who are likely to fail[3].

The aim of activities-based learning is to support with involving students in the learning process. In assessing learning through activity, take into consideration the activities and approaches employed by students. It holds the conviction that activity-based learning, also known as cooperative learning, problem-based learning, collaborative learning, or inquiry-based learning, any educational method that involves the students in the process of learning[4].

This research centers on assessing four significant aspects of students' performance. First, predicting students' performance on final academic exams using internal college exams. The second is finding how every subject influences the classifier's performance. Third, examining how pupils' performance varies over time and relating it to improvements or deteriorations in specific subjects. Fourth, finding common patterns in students' performance based on past internal test performance trends. The connection between internal examination and ultimate academic performance is indicated by the classification outcome. In addition, it is comparable to academic performance prediction subjects. The result also illustrates the consistent trend of students' consecutive internal examination performance. Subsequently, the college administration may assist weak performing students as necessary and encourage high performing students to maintain their excellent performance[5].

II. BACKGROUND

Each education system puts a strong emphasis on senior high school students doing well in academics. A broad variety of factors affects students' academic achievements, such as teachers, library access and usability, practical lab facilities, and availability of food. Students with better-than-average academic results who are subjected to these factors in a positive manner are likely to perform better than non-truants. The report states that variables such as truancy, family income and educational level, textbook availability and affordability, libraries, vocational labs, provision of lunch, and teachers ought to be regularly evaluated and adjusted to meet students. Most importantly, one should understand that an individual's whole life is generally going to be founded on the quantity of information he or she learns, how much this information is applied in improving himself, his nation, and the world in general [6]. The educational industry produces a great deal of data that is too complex and voluminous to be simply understood. In order to avoid information overload, the content has to be properly filtered and chosen in order to provide the right data. In order to give customers right and clear patterns and trends, data mining separates the huge amount of dynamically generated data. It possesses the capacity to utilize effectively the raw data produced by schools and universities to reveal concealed patterns and interrelations among the features employed in anticipating students' performance and actions. A concise overview of data mining methods has been presented in this book[7].

Humans have come to the age of big data, when enormous volumes of data are generated every day by humans or machines across many industries as a result of the rapid expansion of computers, communication, sensors, and other information technologies. Volume, variety, value, velocity, and veracity—the "5V"—are the attributes that define and describe big data. Massive open online courses (MOOCs), learning management systems (LMS), virtual learning platforms, and student information systems (SIS) are some of the digital learning environments that are constantly producing educational big data[8]. Quality education is required to the development of every country. With the assistance of admissions systems, academic information systems, learning management systems, e-learning, etc., the volume of data in the education industry is increasing day by day[9]. Machine learning is a sophisticated technology that delivers robust

discovery of feature and data modeling capabilities, accommodating a broad variety of application environments, as verified by recent studies that abide to its effectiveness in educational data mining[10].
Data preprocessing included removing duplicates and missing
data, a 10-fold cross-validation method for model selection. Five classification techniques were utilized Deep Neural Networks, Random Forest, SVM, Decision Tree, and Naive Bayes[11].
Data mining methods applied in forecasting student performance, focusing on both supervised and unsupervised learning methods. While specific dataset details and preprocessing steps are not mentioned, it highlights the significance of education data mining in comprehending variables affecting student performance and enhancing teaching techniques[12].
Data preprocessing consisted of removing irrelevant features, dealing with missing values, and eliminating duplicates. Model assessment in the study employed 10-fold cross-validation, with metrics such as accuracy, recall, precision, and F1-measure. Four classification methods were applied: Artificial Neural Network, Decision Tree, Support Vector Machine, Naive Bayes[13].
Feature selection usually depends on expert knowledge, correlation methods, or gene-based techniques. Preprocessing of data usually includes handling missing values, normalization (min-max), and addressing class imbalance through oversampling and undersampling. N-fold cross-validation is widely applied for training testing[14].
It centered on determining patterns among study strategies, learning disabilities, and academic performance with an artificial neural network in brief ANN. There was a Fuzzy-based AI created that provided suggestions[15].
It explores academic, demographic, clickstream, emotional engagement, and learning activity features. Data preprocessing entailed feature engineering and selection methods to enhance model performance. The research employs a systematic review of literature methodology to determine research gaps[16].
Data preprocessing had error elimination, attribute selection, and extracted derived variables. The ID3 Decision tree algorithm has been employed for classifying using measures such as Information Gain, Entropy, Gini Index, and Classification Error used in decision tree construction[17].
It focuses on predicting student drop out and academic achievement with several machine learning algorithms. The study maintains anomalies in the data to preserve its representativeness and addresses the challenges of unbalanced class distributions using the SMOTE resampling method[18].
Data preprocessing involved handling missing values, feature
engineering, standardization, outlier detection, and balancing methods. The research uses machine learning like KNN, gradient boosting, XGBoost, MLP and deep learning such as GNNs, GRUs, LSTMs predictive models based on metrics such as MSE, RMSE, MAE, and R^2[19].
Data preprocessing included under-sampling to class imbalance. The research utilized ensemble learning (Random Forest) using grid search for parameter tuning. Used classification methods are Random Forest, XGBoost, decision tree, and K-Nearest Neighbors[20].

Problem Statements:
1. Discuss a machine learning based system for classifying and analysing student academic performance levels.
2. Identifying, the system will take into account student's school record and background details (e.g., gender, age, where they live, and parents' educational level).
3. It will discuss how various factors affect academic outcomes.
4. The model will label students as having High, Medium, and Low performance levels.
5. There will also be visualization software to make data and results understandable.

Objectives:
The objective of this dissertation are:
1. To collect and organize the academic and social data about students.
2. To graph significant factors influencing student’s performance on relevant graphical representations.
3. To study the connection of school activities and student’s performance.
4. In order to utilize different machine learning methods (including MLP classifier, Decision Trees, Random Forest, GaussianNB, Logistic Regression and KNN) to predict the academic levels of students.
5. For comparing performance of various models based on metrics such as accuracy, precision, recall, and F1-score.

III. METHODOLOGY

Here, first Dataset has been utilized and split into train and test datasets. Then, ML and DL use have been tested and trained. As ML and DL has different models corresponding to gives the optimal model.
Dataset: A dataset refers to organized data that is utilized in training, and testing deep learning or machine learning. models. For prediction of student performance, a dataset may have features such as demographics (gender, age), academic record (grades, attendance), socio-economic status, and psychological characteristics.
This data set contains full information for 2,392 high school pupils, such as their population, learning practices, parental involvement, extracurricular activities, and grades. GradeClass is the target variable, a classification of students' grades into precise categories, and it is a robust data set for academic research, predictive modeling, and statistical analysis[21].
Data Splitting: Data splitting is defined as the division of a dataset into different subsets for training, and testing of a machine learning or deep learning model. The most widely used splits are:
• Training set: To train the model (normally 70% of data).
• Test set: For testing the performance of the final model on unseen data 30%).

Datasets training and testing: Within this study, the 2,392student records dataset was separated into training and testing sets to train and test machine learning models for predicting student performance. Ideally, data is split according to an70:30 ratio—where 70% of the data (1,674 students) is utilized to train the models and 30% of the data (718 students) to test.

Software and Tools used:
In this study, some tools and software were applied to classification models, prediction, class imbalance handling and result analysis. Python was the primary programming language
used for the execution of classification and data mining operations. This study was carried out on the Anaconda24.9.2 with the Python version3.12.7. In this study, Jupyter Notebook accessed through Anaconda Prompt, the Python libraries applied like: Pandas: for data manipulation, NumPy: for numerics operations, Scikit-learn: for ML algorithms like KNN, Naïve Bayes, Decision Tree, Matplotlib and Seaborn: for visualization, and Imblearn: for using SMOTE to deal with imbalanced class or data distributions.

A. Machine Learning
Python is widely utilized in Machine Learning because of this reality it possesses numerous libraries like NumPy, Pandas, Scikit-learn, TensorFlow, and Keras. The above-mentioned libraries have utilities and functions used for manipulation of data, analysis of data, and building machine learning models [22].

1) Random Forest Classifier
The Random Forest Classifier class in the sklearn ensemble module is an ensemble learning method that builds numerous decision trees and uses their combined output for classification problems. It uses building 100 trees (n_estimators=100) based on Gini impurity (criterion='gini') to evaluate splits by default. Trees are grown to maximum unless restricted by parameters like max_depth, min_samples_split, or min_samples_leaf. The most features tried at each split are controlled by max_features='sqrt', introducing randomness and preventing overfitting [23].
Random Forest is a supervised learning technique. It comes in two forms – one for classification problems and another for regression problems. It is one of the most convenient and versatile algorithm. It constructs decision trees from provided samples of data, gets prediction from each tree and selects the optimal solution through voting. It is also a reasonably good feature importance indicator [23], [24].

2) Decision Tree Classifier
Decision Tree Classifier in sklearn.tree is a supervised classifier used for classification problems by recursively dividing the data into subsets based on feature values. Crucial parameters include criterion (default 'gini', or 'entropy') to evaluate split quality, and splitter ('best' or 'random') that determines how splits are selected. The max_depth parameter limits the tree depth to avoid overfitting, and min_samples_split and min_samples_leaf control the minimum sample number to split a node or be at a leaf node, respectively. The max_features limits the features number considered at each split. The random_state makes the model reproducible, and class_weight can handle class imbalance [23], [25].
Decision Tree is the most popularly used machine learning algorithm. It takes on a tree-like structure and their combinations to build a solution for a particular problem. It is a supervised learning algorithm in which it is used to carry out either classification or regression work [23], [26].

B. Deep Learning
Deep Learning (DL) is a specific part of ML that uses artificial networks with many layers, which is why it’s called "deep." It works well for unstructured data such as images, text, and audio.
This study emphasizes the necessity to apply educational data mining for students performance prediction from previous academic data. Conventional methods employ manual feature extraction to achieve that, but the article proposes an automated way through deep learning. Specifically, it proposes an attention-based Bidirectional LSTM model to enhance feature representation and accuracy of prediction[27].

1) MLP Classifier
The sklearn.neural_network. MLP Classifier is a Multi-Layer Perceptron (MLP) classifier applied to supervised classification. It permits one or several hidden layers, with the default number of the hidden layer being 100 neurons. By default, it applies ReLU ('relu') as the activation function and the 'adam' optimizer in order to update the weights. Regularization is controlled by alpha with the default being 0.0001 to avoid overfitting. It supports adaptive learning environments like batch size, learning rate (learning_rate_init=0.001), and learning rate schedules [23], [28].
The MLPClassifier model consists of the input layer, the hidden layer, and the output layer. The input layer is responsible for taking the inputs to the model, and feeding them to the hidden layers. The hidden layers perform the computation on the data inputs, while the output layer gives the final output of the model [23], [29].

Performance Metrics to evaluate the models
To examine the performance of the model, we calculated several metrics including Accuracy, Precision, Recall, and F1-score for all mathematically defined classifiers by equations respectively. Moreover, the AUC (Area Under the Curve) and ROC (Receiver Operating Characteristics) were computed via graphs to measure the performance of the models.

1. Precision: Precision is the ratio of correct predictions to the total number of predictions.

$$Accuracy = \frac{TP+TN}{TP+FN+TN+FP}$$

2. Precision and Recall:
Precision: Precision is the proportion of true positives to the sum of true positives and false positives. Precision mainly considers the positive predictions.

$$\text{Precision} = \frac{TP}{TP+FP}$$

Recall: It is the ratio of True positives to the sum of true positives and false negatives. It simply examines the count of proper positive samples

$$\text{Recall}=\frac{TP}{TP+FN}$$

3. F1 score: F1 score is the harmonic mean of precision and recall. It is observed that in the process of precision-recall trade-off if we increase precision, recall decreases and vice versa. The objective of the F1 score is to merge precision and recall.

$$\text{F1-Score}= 2x\frac{\text{Precision x } Recall}{\text{Precision+Recall}}$$

4. Confusion Matrix: Confusion matrix is an N x N matrix in which N represents the number of target classes. It is a table where the number of actual output and the number of predicted output is represented. Some of the terms of the matrix are as given below:
True Positives: Also referred to as TP. It is the output where the actual as well as the predicted value is YES.
True Negatives: It is also known as TN. It is the outcome where the actual and predicted both are NO.
False Positives: It is also known as FP. It is the outcome wherein the actual value is NO but the predicted value is YES.
False Negatives: It is also known as FN. It is the output where the actual value is YES but the predicted value is NO.
5. AUC: AUC (Area Under Curve) is an evaluation metric that proves to be handy in order to inspect the classification model at different levels of threshold.
6. ROC: ROC (Receiver Operating Characteristic) is a probability curve that is applied in order to highlight the model's performance. The curve has two parameters:
TPR: It stands for True positive rate. It typically adheres to the formula of Recall.
FPR: It stands for False Positive rate. It represents the ratio of False positives to the sum of false positives and True negatives [23], [30].

IV. RESULT

ML and DL models obtained excellent performance on the multi-class classification dataset to Categorize academic performance. The models employed ML algorithm like Random-Forest Classifier, Decision-Tree-Classifier, SVC, K-Neighbors-Classifier, Gaussian-NB, and Logistic-Regression, and DL algorithm like MLP-Classifier. Table 1.0, shows the Model Performance Comparison.

Table 1.0, Model Performance Comparison

Model	Accuracy	Precision	Recall	F1 Score	CV Mean
Random Forest Classifier	0.968	0.968128	0.967795	0.968	0.960
Decision Tree Classifier	0.962	0.962571	0.962015	0.962	0.952
MLP Classifier	0.908	0.908088	0.907514	0.908	0.899
SVC	0.853	0.856386	0.853014	0.853	0.834
KNeighbors-Classifier	0.664	0.668292	0.663914	0.662	0.666
Gaussian-NB	0.650	0.644588	0.649876	0.644	0.639
LogisticRegression	0.565	0.563960	0.564822	0.560	0.561

The testing results reveal that the RandomForestClassifier performed best with 96.8% accuracy, coupled with high precision, recall, and F1, and is therefore the most trustworthy model overall. DecisionTreeClassifier was a close second at 96.2% accuracy. The MLPClassifier also did well with more than 90.8% accuracy, suggesting that deep learning can perform well on this data set. SVC performed moderately, followed by KNeighborsClassifier, GaussianNB, and LogisticRegression, which performed the poorest at 56.5% accuracy. These outcomes indicate that tree-based models and ensemble models perform optimally in predicting student performance in this data set.

V. CONCLUSION

Education data mining is a new methodology based on high-level methods to discover patterns and forecast outcomes within the education domain, such as student and teacher performance, and dropout potential. This work has utilized diverse machine learning and deep learning algorithms on real-world student performance data. Out of models that were tested, Random Forest Classifier was the most accurate (96.8%) and outperformed others in precision, recall, and F1-score. Decision Tree Classifier and MLP Classifier were also effective, and Logistic Regression and GaussianNB demonstrated lesser accuracy. The analysis also demonstrated predictive accuracy versus computational efficiency trade-offs. Generally, the results affirm that ensemble and deep learning models are good predictors of academic performance and can assist institutions in proactively supporting students at risk.

REFERENCES:

[1] R. Hasan, S. Palaniappan, A. R. A. Raziff, S. Mahmood, and K. U. Sarker, “Student Academic Performance Prediction by using Decision Tree Algorithm,” *2018 4th International Conference on Computer and Information Sciences: Revolutionising Digital Landscape for Sustainable Smart Society, ICCOINS 2018 - Proceedings*, Oct. 2018, doi: 10.1109/ICCOINS.2018.8510600.

[2] Y. Gao, “Deep learning-based strategies for evaluating and enhancing university teaching quality,” *Computers and Education: Artificial Intelligence*, vol. 8, p. 100362, Jun. 2025, doi: 10.1016/J.CAEAI.2025.100362.

[3] B. Alnasyan, M. Basheri, and M. Alassafi, “The power of Deep Learning techniques for predicting student performance in Virtual Learning Environments: A systematic literature review,” *Computers and Education: Artificial Intelligence*, vol. 6, p. 100231, Jun. 2024, doi: 10.1016/J.CAEAI.2024.100231.

[4] T. Al Shloul *et al.*, “Role of activity-based learning and ChatGPT on students’ performance in education,” *Computers and Education: Artificial Intelligence*, vol. 6, p. 100219, Jun. 2024, doi: 10.1016/J.CAEAI.2024.100219.

[5] S. Sarker, M. Paul, S. Thasin, M. H.-C. and Education, and undefined 2024, “Analyzing students’ academic performance using educational data mining,” *ElsevierS Sarker, MK Paul, STH Thasin, MAM HasanComputers and Education: Artificial Intelligence, 2024•Elsevier*, Accessed: Jun. 10, 2025. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2666920X24000663

[6] E. A. Brew, B. Nketiah, R. Koranteng, E. A. Brew, B. Nketiah, and R. Koranteng, “A Literature Review of Academic Performance, an Insight into Factors and their Influences on Academic Outcomes of Students at Senior High Schools,” *Open Access Library Journal*, vol. 8, no. 6, pp. 1–14, Jun. 2021, doi: 10.4236/OALIB.1107423.

[7] H. Kaur, E. B.-I. J. on F. R. in, and undefined 2018, “Student performance prediction using educational data mining techniques,” *core.ac.ukH Kaur, EG BathlaInternational Journal on Future Revolution in Computer Science, 2018•core.ac.uk*, Accessed: Jun. 10, 2025. [Online]. Available: https://core.ac.uk/download/pdf/539895607.pdf

[8] W. Xiao, P. Ji, and J. Hu, “A survey on educational data mining methods used for predicting students’ performance,” *Engineering Reports*, vol. 4, no. 5, p. e12482, May 2022, doi: 10.1002/ENG2.12482;JOURNAL:JOURNAL:25778196;PAGE:STRING:ARTICLE/CHAPTER.

[9] M. Imran, S. Latif, D. Mehmood, and M. S. Shah, “Student academic performance prediction using supervised learning techniques,” *International Journal of Emerging Technologies in Learning*, vol. 14, no. 14, pp. 92–104, 2019, doi: 10.3991/IJET.V14I14.10310.

[10] Y. Chen, J. Sun, J. Wang, L. Zhao, X. Song, and L. Zhai, “Machine Learning-Driven Student Performance Prediction for Enhancing Tiered Instruction,” Feb. 2025, Accessed: May 12, 2025. [Online]. Available: https://arxiv.org/pdf/2502.03143

[11] “(PDF) Student’s Performance Prediction using Deep Learning and Data Mining methods.” Accessed: May 06, 2025. [Online]. Available: https://www.researchgate.net/publication/335234927_Student’s_Performance_Prediction_using_Deep_Learning_and_Data_Mining_methods

[12] P. Kamal, S. A.-J. on T. Ideas-Tomorrow’s, and undefined 2017, “A review on prediction of academic performance of students at-risk using data mining techniques,” *jotitt.chitkara.edu.inP Kamal, S AhujaJournal on Today’s Ideas-Tomorrow’s Technologies, 2017•jotitt.chitkara.edu.in*, vol. 5, no. 1, pp. 30–39, 2017, doi: 10.15415/jotitt.2017.51002.

[13] H. A. Mengash, “Using data mining techniques to predict student performance to support decision making in university admission systems,” *IEEE Access*, vol. 8, pp. 55462–55470, 2020, doi: 10.1109/ACCESS.2020.2981905.

[14] W. Xiao, P. Ji, and J. Hu, “A survey on educational data mining methods used for predicting students’ performance,” *Engineering Reports*, vol. 4, no. 5, May 2022, doi: 10.1002/ENG2.12482’)).

[15] A. Bressane *et al.*, “Understanding the role of study strategies and learning disabilities on student academic performance to enhance educational approaches: A proposal using artificial intelligence,” *Computers and Education: Artificial Intelligence*, vol. 6, p. 100196, Jun. 2024, doi: 10.1016/J.CAEAI.2023.100196.

[16] S. Rizwan, C. K. Nee, and S. Garfan, “Identifying the Factors Affecting Student Academic Performance and Engagement Prediction in MOOC using Deep Learning: A Systematic Literature Review,” *IEEE Access*, 2025, doi: 10.1109/ACCESS.2025.3533915.

[17] B. Kumar and S. Pal, “Mining Educational Data to Analyze Students Performance,” *International Journal of Advanced Computer Science and Applications*, vol. 2, no. 6, 2011, doi: 10.14569/IJACSA.2011.020609.

[18] A. Villar and C. R. V. de Andrade, “Supervised machine learning algorithms for predicting student dropout and academic success: a comparative study,” *SpringerA Villar, CRV de AndradeDiscover Artificial Intelligence, 2024•Springer*, vol. 4, no. 1, Dec. 2024, doi: 10.1007/S44163-023-00079-Z.

[19] E. S. M. El-Kenawy, A. A. Alhussan, N. Khodadadi, S. Mirjalili, and M. M. Eid, “Predicting potato crop yield with machine learning and deep learning for sustainable agriculture,” *SpringerESM El-Kenawy, AA Alhussan, N Khodadadi, S Mirjalili, MM EidPotato Research, 2024•Springer*, vol. 68, pp. 759–792, Mar. 2024, doi: 10.1007/S11540-024-09753-W.

[20] L. Guo, R. Song, J. Wu, Z. Xu, F. Z.-A. and Computational, and undefined 2024, “Integrating a machine learning-driven fraud detection system based on a risk management framework,” *preprints.orgL Guo, R Song, J Wu, Z Xu, F ZhaoApplied and Computational Engineering, 2024•preprints.org*, 2024, doi: 10.20944/preprints202406.1756.v1.

[21] “ Students Performance Dataset .” Accessed: Jun. 02, 2025. [Online]. Available: https://www.kaggle.com/datasets/rabieelkharoua/students-performance-dataset

[22] “Machine Learning with Python Tutorial - GeeksforGeeks.” Accessed: Jun. 11, 2025. [Online]. Available: https://www.geeksforgeeks.org/machine-learning-with-python/

[23] “RandomForestClassifier — scikit-learn 1.6.1 documentation.” Accessed: Jun. 04, 2025. [Online]. Available: https://scikit-learn.org/stable/modules/generated/sklearn.ensemble.RandomForestClassifier.html

[24] “Random Forest Classifier Tutorial.” Accessed: Jun. 04, 2025. [Online]. Available: https://www.kaggle.com/code/prashant111/random-forest-classifier-tutorial/notebook

[25] “DecisionTreeClassifier — scikit-learn 1.6.1 documentation.” Accessed: Jun. 04, 2025. [Online]. Available: https://scikit-learn.org/stable/modules/generated/sklearn.tree.DecisionTreeClassifier.html

[26] “Decision-Tree Classifier Tutorial.” Accessed: Jun. 04, 2025. [Online]. Available: https://www.kaggle.com/code/prashant111/decision-tree-classifier-tutorial

[27] B. K. Yousafzai *et al.*, “Student-Performulator: Student Academic Performance Using Hybrid Deep Neural Network,” *Sustainability 2021, Vol. 13, Page 9775*, vol. 13, no. 17, p. 9775, Aug. 2021, doi: 10.3390/SU13179775.

[28] “MLPClassifier — scikit-learn 1.6.1 documentation.” Accessed: Jun. 05, 2025. [Online]. Available: https://scikit-learn.org/stable/modules/generated/sklearn.neural_network.MLPClassifier.html

[29] “Machine Learning Classification Algorithms | by Yogesh V | Medium.” Accessed: Jun. 05, 2025. [Online]. Available: https://medium.com/@yogeshv0307/machine-learning-classification-algorithms-9eade2768177

[30] “Machine Learning Model Evaluation | GeeksforGeeks.” Accessed: May 19, 2025. [Online]. Available: https://www.geeksforgeeks.org/machine-learning-model-evaluation