**Student Performance Prediction Using Artificial Intelligence**

**Abstract**

A student's education is crucial, whether it is for humanities advancement or for them to live a productive life. With the advancement of artificial intelligence, predicting students' performance can easily be achieved. Machine Learning (ML) is used in developing Predictive Analytics, Classification, Spam detection, Identifying Patterns, Image Recognition, Autonomous Systems. Predictive Analytics are going to be used for the students’ performance with the help of 16 chosen Regression Models. XGB Regressor, Random Forest Regressor, Gradient Boosting Regressor, Extra Trees Regressor, KNeighbors Regressor, Linear Regression, Lasso, LBGM Regressor, Ridge, Support Vector Regression, ElasticNet, Decision Tree Regressor, Huber Regressor, BayseianRidge, MLP Regressor, and Neural Network Regressor were all used to predict the students' scores based on multiple influencing factors such as hours studied, teacher quality, parental involvement, etc. A dataset of 6607 students were collected from, Kaggle was processed, trained and evaluated. Model evaluation like Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R Squared were used to evaluate their performances. Results showed that Support Vector Regression (SVR) generally performed better than other models with an R Squared value of 0.71 and Neural Network Regressor (NNR) came in close second with an R Squared value of 0.705 while decision tree regressor has the worst result with an R Squared value of 0.15. With these findings, students’ performance prediction generally should use SVR and NNR, since these models are created to handle complex datasets such as the students’ performance.

1. **Introduction**

Education has been a driving force in advancing humanities into the current state in every aspect imaginable. Institutions and government have been finding methods to constantly improve the quality of education and student performance, but it has been a tough challenge so far due to external factors that influence the student performance, which are often overlooked or hard to identify.

Although this problem has existed for a while, fortunately, Artificial Intelligence is an exciting field that has emerged and significantly improved over the past few years. Artificial Intelligence researchers have developed advanced algorithms and models, providing powerful tools for developers to leverage. It has been implemented in various sectors such as healthcare, finance, retail, manufacture, agriculture and even transportation. For instance, in healthcare, Artificial Intelligence is used to predict the likelihood of diseases based on symptoms, medical history, or genetic data and in finance, it is being used to identify unusual transaction patterns that may indicate fraudulent activity, in which these usages were proven to be effective. One of the key subfields of artificial intelligence is machine learning which focuses on training computers to learn and make decisions based on provided algorithms and datasets. Large datasets and computer resources are crucial in training and developing Artificial Intelligence to perform specific tasks effectively.

As a result, there have been numerous studies and proposals to implement the Artificial Intelligence in predicting student performance due to its ability to handle large data and find complex patterns to identify which factor contributes positively and negatively to the student performance. This enables institutions to help students be more successful.

This research paper aims to highlight the usage of regression techniques, which is one of the key concepts in machine learning, to predict student's exam score based on various predictor variables and determine the best model. Moreover, evaluation metrics such as **Mean Absolute Error (MAE)**, **Mean Squared Error (MSE)**, **Root Mean Squared Error (RMSE)**, and **R-squared (R²)** will also be shown. The 16 regression techniques include XGB Regression, Random Forest Regression, Gradient Boosting Regression, Extra Trees Regression. KNeighbors Regression, Linear Regression, Lasso, LGBM Regressor, Ridge, Support Vector Regression (SVR), ElasticNet, Decision Tree Regression, Huber Regression, Bayesian Ridge, Multi-layer Perceptron (MLP) Regression and Neural Network Regression (NNR). Each test was implemented using a dataset from Kaggle, which contains over 6000 rows, pre-trained models from scikit-learn and other Python libraries such as pandas, numpy and tensorflow.

1. **Literature Review**

In this section we are going to review published papers published from 2008 to 2024.

Huang, S., & Fang, N (2010) [1], Multiple criteria have been employed to evaluate and validate the developed predictive models, including R-square, shrinkage, the average prediction accuracy, and the percentage of good predictions.

Saa, A. A. & Ajman University of Science and Technology (2016) [2], interesting results were drawn from the classification models, as well as interesting patterns in the Naïve Bayes model was found.

Kim, B., Vizitei, E., & Ganapathi, V (2018) [3], have recast the student performance prediction problem as a sequential event prediction problem and propose a new deep learning-based algorithm, termed GritNet, which builds upon the bidirectional long short-term memory.

Xu, J., Han, Y., Marcu, D., & Van Der Schaar, M. (2017) [4], have developed a novel algorithm that enables progressive prediction of students’ performance by adapting ensemble learning techniques and utilizing education-specific domain knowledge.

Acharya, A., & Sinha, D. (2014) [5], In this paper a set of attributes are first defined for a group of students majoring in Computer Science in some undergraduate colleges in Kolkata. It was found that the best results were obtained with the decision tree class of algorithms.

Rincón Flores, Elvira G. & Lopez, Eunice & Mena, Juanjo & Lopez, Omar. (2020) [6]. In this study, artificial intelligence (AI) algorithms like K-Nearest Neighbor and Random Forest were used.

Abu-Naser, Samy & Zaqout, Ihab & Abu Ghosh, Mahmoud & Atallah, Rasha & Alajrami, Eman. (2015) [7], In this paper an Artificial Neural Network (ANN) model, for predicting the performance. Test data evaluation shows that the ANN model is able to correctly predict the performance of more than 80% of prospective students.

AI APPROACH TO PREDICT STUDENT PERFORMANCE (CASE STUDY: BATTUTA UNIVERSITY). (2024) [8], At Battua University many models were used to predict student's scores. As for results Random Forest has the highest accuracy of 80-90%.

Haron, Nor & Mahmood, Ramlan & Md Amin, Noornajwa & Ahmad, Airuddin & Jantan, Siti Robaya. (2024) [9], the prediction models used in this research are RepTree, k-NN and Naïve Bayes. The finding states that RepTree had the highest accuracy compared to k-NN and Naïve Bayes techniques.

Chen, Z., Zhang, J., Jiang, X., Hu, Z., Han, X., Xu, M., V, S., & Vivekananda, G. (2020) [10], in this paper, Hybridized Deep Neural Network (HDNN) is used to predict student performance in Education 4.0.

Chavez, H., Chavez-Arias, B., Contreras-Rosas, S., Alvarez-Rodríguez, J. M., & Raymundo, C. (2023) [11], In this research, an artificial neural network model was proposed to predict students’ scores, which obtained an accuracy of 93.81%.

Farhood, H., Joudah, I., Beheshti, A., & Muller, S. (2024) [12], the research provides a comprehensive comparison to evaluate and improve ten different machine learning and deep learning models.

Maulana, A., Idroes, G. M., Kemala, P., Maulydia, N. B., Sasmita, N. R., Tallei, T. E., Sofyan, H., & Rusyana, A. (2023) [13], the research employs a comparative analysis of six ML algorithms Results indicate that the Random Forest algorithm outperforms others.

Deo, R. C., Yaseen, Z. M., Al-Ansari, N., Nguyen-Huy, T., Langlands, T. a. M., & Galligan, L. (2020) [14], A computationally efficient articficial intelligence (AI) model called Extreme Learning Machines (ELM) is adopted to analyze student's performances.

Lykourentzou, I., Giannoukos, I., Mpardis, G., Nikolopoulos, V., & Loumos, V. (2008b) [15], The proposed method uses multiple feed-forward neural networks to dynamically predict students’ score. The results were compared against those of linear regression and the neural network approach was found to be more effective in all prediction stages.

Ahajjam, T., Moutaib, M., Aissa, H., Azrour, M., Farhaoui, Y., & Fattah, M. (2022) [16], this article is to predict Moroccan students’ performance in the region of Guelmim Oued Noun using an intelligent system based on neural networks.

Yangsheng, Z. (2020) [17], this article combines artificial intelligence teaching system to build an artificial intelligence sports teaching evaluation model based on neural network.

Jiao, P., Ouyang, F., Zhang, Q., & Alavi, A. H. (2022) [18], this study develops an artificial intelligence-enabled prediction model for student academic performance based on students’ learning process and summative data.

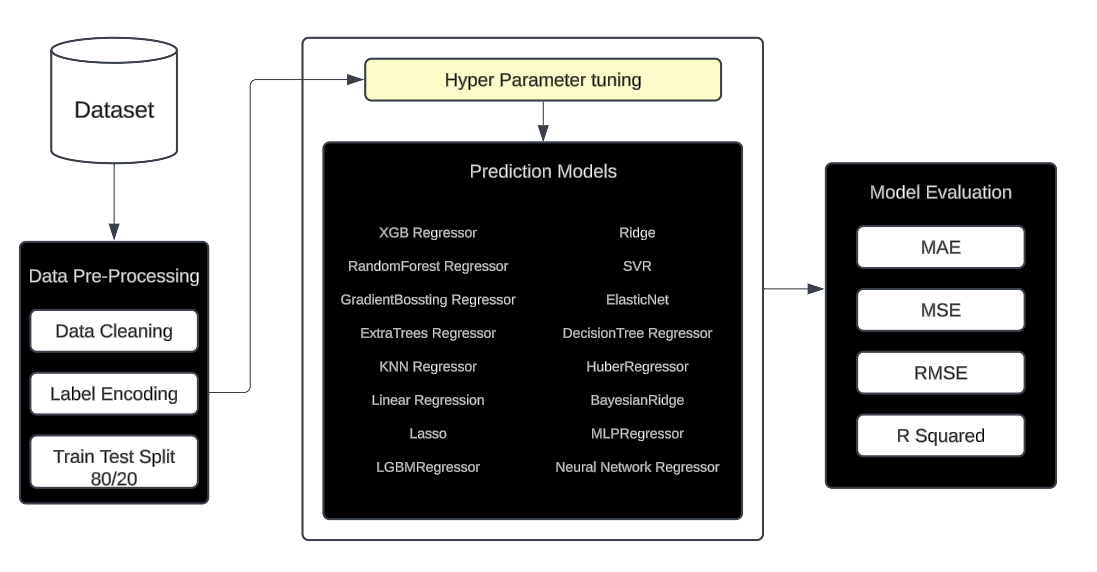
Lau, E. T., Sun, L., & Yang, Q. (2019) [19], This paper presents an approach with both conventional statistical analysis and neural network modelling/prediction of students’ performance. Results show that neural network regressors had an accuracy of 84.8%.

Sekeroglu, B., Dimililer, K., & Tuncal, K. (2019c) [20], In this paper, totally 4 different algorithms are used for two kinds of problems, prediction and classification.

Hamoud, A. K., Hashim, A. S., & Awadh, W. A. (2018) [21], Three built classifiers (J48, Random Tree and REPTree) were used in this model with the questionnaires filled in by students. The J48 algorithm was considered the best algorithm based on its performance.

1. **Methodology**

The proposed model in this research paper has four components which are data preprocessing, hyperparameter tuning, prediction models, and model evaluation.

`

3.1 Data Collection

First, this dataset was collected from Nguyen, Lai and a public site known as Kaggle [39]. Kaggle is an online community for data scientists and machine learners while also providing public datasets. This dataset provides a comprehensive overview of various factors affecting student performance in exams.

3.2 Data Preprocessing

The dataset had information on 6607 students and 16 factors or columns, It includes information on hours studied, attendance, parental involvement, access to resource, extracurricular-activities, sleep hours, previous scores, motivation level, internet access, tutoring sessions, family income, teacher quality, school type, peer influence, physical activity, learning disabilities, parental education level distance from home, gender, and exam score.

Since the dataset contains noisy data and numerous null values. The researcher has prep-processed the data by first deleting any rows with null data and deleting any rows with abnormal and noisy data. After eliminating every incompetent data, the dataset now has 6378 rows. Then for the dataset to be able to work in the model training, the researcher applied label encoding to every categorical column. Finally, a train test split of 80/20 was applied to the dataset.

3.3 Hyperparameter Tuning

In this study hyper parameter tuning was used on models such as Neural Network Regressor, KNeighbors Regressor, MLP Regressor, Ridge, ElasticNet, Extra Trees Regressor, and Random Forest Regressor. By optimizing hyperparameter, the model evaluation of (MAE, MSE, RMSE and R Squared) has improved significantly.

3.4 Prediction Models

Sixteen prediction models were used to predict the student's score. They are XGB Regressor, Random Forest Regressor, Gradient Boosting Regressor, Extra Trees Regressor, KNeighbors Regressor, Linear Regression, Lasso, LBGM Regressor, Ridge, Support Vector Regression, ElasticNet, Decision Tree Regressor, Huber Regressor, BayseianRidge, MLP Regressor, and Neural Network Regressor.

XGB Regressor: XGBoost dominates structured or tabular datasets on classification and regression predictive modeling problems. The evidence is that it is the go-to algorithm for competition winners on the Kaggle competitive data science platform [22].

Random Forest Regressor: A Random Forest regression model combines multiple decision trees to create a single model. Each tree in the forest builds from a different subset of the data and makes its own independent prediction [23].

Gradient Boosting Regressor: Gradient boosting is one of the variants of ensemble methods where you create multiple weak models and combine them to get better performance [24].

Extra Trees Regressor: The extra trees algorithm, like the random forest algorithm, creates many decision trees, but the sampling for each tree is random, without replacement. The most important and unique characteristic of extra trees is the random selection of a splitting value for a feature [25].

KNeighbors Regressor: The KNN algorithm can be used for both classification and regression. It predicts new data points based on their similarity to points in the training set [26].

Linear Regression: Linear regression is an algorithm that provides a linear relationship between an independent variable and a dependent variable to predict the outcome of future events [27].

Lasso: Lasso stands for Least Absolute Shrinkage and Selection Operator. It is frequently used in machine learning to handle high dimensional data as it facilitates automatic feature selection with its application [28].

LGBM Regressor: LGBM Regressor is a machine learning algorithm based on the Light Gradient Boosting Machine (LightGBM) framework [29].

Ridge: Ridge regression is a model-tuning method that is used to analyze any data that suffers from multicollinearity. This method performs L2 regularization [30].

Support Vector Regression: SVR uses an ε-insensitive loss function which penalizes predictions farther than ε from the desired output. Different loss functions can be used, such as linear or quadratic. The value of ε determines the width of the tube [31].

ElasticNet: ElasticNet linear regression uses the penalties from both the lasso and ridge techniques to regularize regression models. The technique combines both the lasso and ridge regression methods by learning from their shortcomings to improve the regularization of statistical models [32].

Decision Tree Regressor: Decision tree builds regression or classification models in the form of a tree structure. It breaks down a dataset into smaller and smaller subsets while at the same time an associated decision tree is incrementally developed [33].

Huber Regressor: Huber regression (Huber 1964) is a regression technique that is robust to outliers. The idea is to use a different loss function rather than the traditional least-squares [34].

Bayesian Ridge: Bayesian ridge regression is a statistical method that applies Bayesian statistics to ridge regression, which is used to analyze data with multiple variables. It helps in determining the most probable values of the regression coefficients, which describe the relationship between each predictor and the response variable while accounting for past knowledge or assumptions [35].

MLP Regressor: MLPRegressor implements a Multi-Layer Perceptron algorithm for training and testing data sets using backpropagation and stochastic gradient descent methods [36].

Neural Network Regressor: Neural network regression is a supervised learning method, and therefore requires a tagged dataset, which includes a label column. Because a regression model predicts a numerical value, the label column must be a numerical data type [37].

3.5 Model Evaluation

In this paper, Mean Absolute Error, Mean Squared Error, Root Mean Squared Error and R-Squared were used to determine the model's performance and accuracy.

MAE (Mean Absolute Error): Mean Absolute Error is the mean size of the mistakes in collected predictions [38].

Mean Squared Error and Root Mean Squared Error: The Mean Absolute Error is the squared mean of the difference between the actual values and predictable values and RMSE is the standard deviation of the errors which occur when a prediction is made on a dataset [38].

R-Squared: It is also known as the coefficient of determination. This metric gives an indication of how good a model fits a given dataset. It indicates how close the regression line (i.e the predicted values plotted) is to the actual data values. The R squared value lies between 0 and 1 where 0 indicates that this model doesn't fit the given data and 1 indicates that the model fits perfectly to the dataset provided [38].

1. **Results**

The goal of this research is to find the best model in predicting students’ exam scores, which are influenced by several factors, through testing different models. There were 16 models being evaluated to test the accuracy and reliability of each model through the performance metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R-Squared (R²). These metrics are used to measure the difference between the predicted values and the actual target values, but each has its own uniqueness. MAE is used to simply show the difference without taking outliers into accountability, which is what MSE does. On the other hand, RMSE does not take outliers as seriously as MSE, which makes the data more interpretable than MSE. R² represents the percentage of variation in the dependent variable that can be explained by the independent variables, which is the most important metric to analyze the performance of each model. A bar graph with text

Description automatically generated Figure 1: R-Squared Values

Figure 1 shows that Support Vector Regression (SVR) is the best performing model with the R-Squared value of 0.713, followed closely by Neural Network Regression (NNR) and Gradient Boosting with the value of 0.706 and 0.704 respectively. On the other hand, Decision Tree is the worst performing model by far with the R-Squared value of only 0.157.

|  |  |
| --- | --- |
| A graph of blue bars with white text  Description automatically generated |  |
| Figure 2: Mean Absolute Error Values | Figure 3: Mean Square Error Values |
| A graph of blue bars with white text  Description automatically generated | |
| Figure 4: Root Mean Square Error Values | |

In figure 2, SVR had the lowest MAE value with 0.65 after NNR and Gradient Boosting with 0.78 and 0.83 respectively. However, in figure 3, SVR ranked 4th best with MSE value of 4.49 behind NNR, Gradient Boosting and Light Gradient Boosting Machine (LGBM) with the value of 4.35, 4.37 and 4.35 respectively. Similarly, figure 4 reveals the exact same ranking with NNR (2.09) coming in top, followed by Gradient Boosting (2.09), LGBM (2.11) and SVR (2.12). The worst performing model by far is Decision Tree which had the MAE value of 1.82, MSE value of 13.2 and RSME value of 3.63.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Name | MAE | MSE | RMSE | R-Squared |
| SVR | 0.648607135 | 4.49066428 | 2.119118751 | 0.713122633 |
| NNR | 0.778841548 | 4.352644054 | 2.086299129 | 0.705659807 |
| Gradient Boosting | 0.825082107 | 4.378055711 | 2.092380393 | 0.703941364 |
| LGBM | 0.832908051 | 4.452431283 | 2.110078502 | 0.698911841 |
| Multiple Linear | 1.028672176 | 4.911577296 | 2.216207864 | 0.667862866 |
| HUBER | 1.038180524 | 5.214879335 | 2.28361103 | 0.666857561 |
| Ridge | 1.047696441 | 5.268201105 | 2.295256218 | 0.663451203 |
| BAYESIAN Ridge | 1.048264532 | 5.270671645 | 2.295794339 | 0.663293378 |
| Extra Trees | 1.072868339 | 5.008615831 | 2.237993707 | 0.661300799 |
| ElasticNet | 1.102284077 | 5.444006542 | 2.333239495 | 0.652220214 |
| Lasso | 1.129498093 | 5.172633482 | 2.274342429 | 0.650209381 |
| XGB | 0.999735231 | 5.269425203 | 2.295522861 | 0.643664005 |
| Random Forest | 1.30830721 | 5.928338558 | 2.434817972 | 0.5991061 |
| KNN | 1.528683386 | 7.085485893 | 2.661857602 | 0.520855962 |
| MLP | 1.848931375 | 9.290415841 | 3.048018347 | 0.406499826 |
| Decision Tree | 1.819749216 | 13.19592476 | 3.632619546 | 0.157003973 |

Figure 5: Evaluation Metrics in Descending Order of R-Squared Values

Figure 5 shows the best performing models in descending order of R-Squared value. Overall, the best performing models are the type of models that allow parameter tuning (e.g., kernel selection in SVR, layer adjustments in NNR, learning rates in Gradient Boosting) to optimize performance for specific datasets, while also minimize errors, which result in better accuracy.

1. **Conclusion**

This research tested 16 machine learning regression models to predict students’ final exam scores, which are influenced by different factors such as parental involvement, teacher quality, study hours, and more, to determine which model performed the best based on evaluation metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R-Squared (R²).

The results show that Support Vector Regression is the best performing model with the highest accuracy and lowest errors, followed by Neural Network Regression and Gradient Boosting with close scores. Their consistently high performance is due to their allowance of parameter tuning to be optimized for certain datasets and minimize errors. The results also show that Decision Tree is the worst performing model in every evaluation metrics ranking.

As shown above, Artificial Intelligence has a high potential in assisting the educational field to be improved tremendously. By leveraging advanced machine learning techniques with larger and diverse datasets, it could provide new perspectives to educators to make their decision-making better in helping students improve their learning.

**References**

[1] Huang, S., & Fang, N. (2010, June 20). Regression models for predicting student academic performance in an Engineering Dynamics course. [https://strategy.asee.org/](https://strategy.asee.org/regression-models-for-predicting-student-academic-performance-in-an-engineering-dynamics-course) regression-models-for-predicting-student-academic-performance-in-an-engineering- dynamics-course

[2] Saa, A. A. & Ajman University of Science and Technology. (2016). (IJACSA) International Journal of Advanced Computer Science and Applications. IJACSA, Vol. 7(No. 5), 212–213. <https://www.ijacsa.thesai.org>

[3] Kim, B., Vizitei, E., & Ganapathi, V. (2018). GriTNet: Student Performance Prediction with Deep Learning. arXiv.org. <https://arxiv.org/abs/1804.07405>

[4] Xu, J., Han, Y., Marcu, D., & Van Der Schaar, M. (2017). Progressive prediction of student performance in college programs. Proceedings of the AAAI Conference on Artificial Intelligence, 31(1). <https://doi.org/10.1609/aaai.v31i1.10713>

[5] Acharya, A., & Sinha, D. (2014). Early Prediction of Students Performance using

Machine Learning Techniques. *International Journal of Computer Applications*, *107*(1), 37–38.

[6] Rincón Flores, Elvira G. & Lopez, Eunice & Mena, Juanjo & Lopez, Omar. (2020). Predicting academic performance with Artificial Intelligence (AI), a new tool for teachers and students. 1049-1054. 10.1109/EDUCON45650.2020.9125141.

[7] Abu-Naser, Samy & Zaqout, Ihab & Abu Ghosh, Mahmoud & Atallah, Rasha & Alajrami, Eman. (2015). Predicting Student Performance Using Artificial Neural Network: in the Faculty of Engineering and Information Technology. International Journal of Hybrid Information Technology. 8. 221-228. 10.14257/ijhit.2015.8.2.20.

[8] AI APPROACH TO PREDICT STUDENT PERFORMANCE (CASE STUDY: BATTUTA UNIVERSITY). (2024). In Journal of Science and Social Research: Vol. VII–VII (Issue 4, pp. 1800–1807) [Journal-article]. <http://jurnal.goretanpena.com/index.php/JSSR>

[9] Haron, Nor & Mahmood, Ramlan & Md Amin, Noornajwa & Ahmad, Airuddin & Jantan, Siti Robaya. (2024). An Artificial Intelligence Approach to Monitor and Predict Student Academic Performance. Journal of Advanced Research in Applied Sciences and Engineering Technology. 44. 105-119. 10.37934/araset.44.1.105119.

[10] Chen, Z., Zhang, J., Jiang, X., Hu, Z., Han, X., Xu, M., V, S., & Vivekananda, G. (2020). Education 4.0 using artificial intelligence for students performance analysis. INTELIGENCIA ARTIFICIAL, 23(66). <https://doi.org/10.4114/intartif.vol23iss66pp124-137>

[11] Chavez, H., Chavez-Arias, B., Contreras-Rosas, S., Alvarez-Rodríguez, J. M., & Raymundo, C. (2023). Artificial neural network model to predict student performance using nonpersonal information. Frontiers in Education, 8. <https://doi.org/10.3389/feduc.2023.1106679>

[12] Farhood, H., Joudah, I., Beheshti, A., & Muller, S. (2024). Evaluating and enhancing artificial intelligence models for predicting student learning outcomes. Informatics, 11(3), 46. <https://doi.org/10.3390/informatics11030046>

[13] Maulana, A., Idroes, G. M., Kemala, P., Maulydia, N. B., Sasmita, N. R., Tallei, T. E., Sofyan, H., & Rusyana, A. (2023). Leveraging Artificial intelligence to predict Student performance: A Comparative Machine Learning approach. Journal of Educational Management and Learning, 1(2), 64–70. <https://doi.org/10.60084/jeml.v1i2.132>

[14] Deo, R. C., Yaseen, Z. M., Al-Ansari, N., Nguyen-Huy, T., Langlands, T. a. M., & Galligan, L. (2020). Modern Artificial Intelligence model Development for Undergraduate Student Performance Prediction: An investigation on Engineering Mathematics courses. IEEE Access, 8, 136697–136724. <https://doi.org/10.1109/access.2020.3010938>

[15] Lykourentzou, I., Giannoukos, I., Mpardis, G., Nikolopoulos, V., & Loumos, V. (2008b). Early and dynamic student achievement prediction in e‐learning courses using neural networks. Journal of the American Society for Information Science and Technology, 60(2), 372–380. <https://doi.org/10.1002/asi.20970>

[16] Ahajjam, T., Moutaib, M., Aissa, H., Azrour, M., Farhaoui, Y., & Fattah, M. (2022). Predicting students’ final performance using artificial neural networks. Big Data Mining and Analytics, 5(4), 294–301. <https://doi.org/10.26599/bdma.2021.9020030>

[17] Yangsheng, Z. (2020). An AI based design of student performance prediction and evaluation system in college physical education. Journal of Intelligent & Fuzzy Systems, 40(2), 3271–3279. <https://doi.org/10.3233/jifs-189367>

[18] Jiao, P., Ouyang, F., Zhang, Q., & Alavi, A. H. (2022). Artificial intelligence-enabled prediction model of student academic performance in online engineering education. Artificial Intelligence Review, 55(8), 6321–6344. <https://doi.org/10.1007/s10462-022-10155-y>

[19] Lau, E. T., Sun, L., & Yang, Q. (2019). Modelling, prediction and classification of student academic performance using artificial neural networks. SN Applied Sciences, 1(9). <https://doi.org/10.1007/s42452-019-0884-7>

[20] Sekeroglu, B., Dimililer, K., & Tuncal, K. (2019c). Student performance prediction and classification using machine learning algorithms. Student Performance Prediction and Classification Using Machine Learning Algorithms. <https://doi.org/10.1145/3318396.3318419>

[21] Hamoud, A. K., Hashim, A. S., & Awadh, W. A. (2018). Predicting student performance in higher education institutions using decision tree analysis. International Journal of Interactive Multimedia and Artificial Intelligence, 5(2), 26. <https://doi.org/10.9781/ijimai.2018.02.004>

[22] Brownlee, J. (2019, August 2). *XGBoost for regression*. Machine Learning Mastery. <https://machinelearningmastery.com/xgboost-for-regression/>

[23] AnalytixLabs. (n.d.). *Random forest regression*. AnalytixLabs. <https://www.analytixlabs.co.in/blog/random-forest-regression/>

[24] Patel, P. (2019, December 16). *All you need to know about gradient boosting algorithm – Part 1 (Regression)*. Towards Data Science. <https://towardsdatascience.com/all-you-need-to-know-about-gradient-boosting-algorithm-part-1-regression-2520a34a502>

[25] Esri. (n.d.). *How extra tree classification and regression works*. ArcGIS Pro. <https://pro.arcgis.com/en/pro-app/latest/tool-reference/geoai/how-extra-tree-classification-and-regression-works.htm>

[26] Sharma, A. (2018, August 17). *Introduction to k-nearest neighbor: Simplified regression and implementation in Python*. Analytics Vidhya. <https://www.analyticsvidhya.com/blog/2018/08/k-nearest-neighbor-introduction-regression-python/>

[27] Spiceworks. (n.d.). *What is linear regression?* Spiceworks. <https://www.spiceworks.com/tech/artificial-intelligence/articles/what-is-linear-regression/>

[28] IBM. (n.d.). *Lasso regression*. IBM. <https://www.ibm.com/topics/lasso-regression/>

[29] Microsoft. (n.d.). *LightGBM documentation*. LightGBM. <https://lightgbm.readthedocs.io/en/stable/>

[30] Great Learning Team. (n.d.). *What is ridge regression?* Great Learning. <https://www.mygreatlearning.com/blog/what-is-ridge-regression/>

[31] ScienceDirect. (n.d.). *Support vector regression*. ScienceDirect. <https://www.sciencedirect.com/topics/computer-science/support-vector-regression>

[32] Corporate Finance Institute. (n.d.). *Elastic net*. Corporate Finance Institute. <https://corporatefinanceinstitute.com/resources/data-science/elastic-net/>

[33] Sayad, S. (n.d.). *Decision tree regression*. Saed Sayad. <https://saedsayad.com/decision_tree_reg.htm>

[34] CVXR. (n.d.). *Huber regression*. CVXR. <https://cvxr.rbind.io/cvxr_examples/cvxr_huber-regression/>

[35] Ikigai Labs. (n.d.). *Bayesian ridge regression*. Ikigai Labs. <https://www.ikigailabs.io/glossary/bayesian-ridge-regression/>

[36] Agrawal, M. (n.d.). *Sklearn neural network regression example using MLPRegressor*. VitalFlux. <https://vitalflux.com/sklearn-neural-network-regression-example-mlpregressor/>

[37] Microsoft. (n.d.). *Neural network regression*. Microsoft Learn. <https://learn.microsoft.com/en-us/azure/machine-learning/component-reference/neural-network-regression?view=azureml-api-2>

[38] Studytonight. (n.d.). *What is mean squared error, mean absolute error, root mean squared error, and R-squared?* Studytonight. <https://www.studytonight.com/post/what-is-mean-squared-error-mean-absolute-error-root-mean-squared-error-and-r-squared>

[39] Nguyen, Lai. "Student Performance Factors Dataset." Kaggle, <https://www.kaggle.com/datasets/lainguyn123/student-performance-factors>.