# Skill Progress Prediction Using Machine Learning Algorithms

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**Abstract.** It is crucial to a school that they predict the performance of their students and be able to shift their teaching strategies accordingly. With the ability to foresee academic outcomes, you will know which students will possibly require more help. Incorporating these techniques helps improve the learning process and outcomes. Provided that there is sufficient information regarding the student's past academic records and appropriate education measures, performance prediction will ensure the necessary intervention is provided to facilitate course completion in a timely manner. Student performance prediction and AT-RISK student identification can and should be done through the application of machine learning techniques. Timely intervention can thus improve the educational outcomes for those students. Identifying the right features to include in machine learning models is crucial. Possible features which are academic performance measures, personal characteristics, psychological attributes, and prior education.

**Keywords:** Student Performance Prediction, Machine Learning, At-Risk Students, Educational Intervention, Academic Analytics.

## 1 Introduction

To locate students in danger of failing, a predictive model focusing on student performance has been created in the area of educational data mining, which has received significant attention over the years. This can be categorized as a complex problem due to there being multifactorial dependencies involving the characteristics of the students such as GPA, grades, demographics, psychological profile, culture, academic performance, and educational background. Predictively, a student\\'s performance can be forecasted based on their GPA and is arguably the most significant indicator available. A student's GPA regionally indicates the value of their prospective professional and educational opportunities. Moreover, a student's academic capabilities can be inferred from their GPA. Attributes concerning adult family members, age, sex, and disability status also form a significant part of the demographic data. This study proposes two new variables that use descriptive factors of internet and social network usage and their relationship to performance. On the contrary, a variety of machine learning and data mining techniques have been engaged to predict students' outcomes, including: Artificial Neural Network (ANN), K-Nearest Neighbor (KNN), Support Vector Machine (SVM), Linear Regression, Logistic Regression, and Decision.

### 1.1 Classification Model

The approaches for machine learning (ML) are broadly divided into supervised and unsupervised learning. In unsupervised ML, unstructured data is processed, while in supervised

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ML, structured datasets that have input variables which relate to output variables are processed. Supervised ML problems are divided into regression and classification tasks. Regression is where the model predicts continuous numerical values. For example, estimating a student's final grade. In contrast, ML classification predicts a category of a class based on input data. The category can be dichotomous "pass" and "fail" or multi-class "excellent", "good", "satisfactory", "poor", and "failure." Classification in ML attempts to evaluate data that is based on predefined categories or classes. Building an ML classifier is done by first importing the required ML libraries and then loading the dataset. The dataset then undergoes preprocessing and cleaning to identify and deal with null values, duplicates, and invalid entries, as well as encode non-numeric and categorical data attributes.

The dataset for this research was gathered from the Archaeology and Sociology departments at Al-Muthanna University during the 2015 and 2016 academic years. It includes two main sources of data: survey responses from students and their academic grade records. In total, the dataset features information on 161 students, with 76 males and 85 females. There are twenty attributes organized into five categories: personal and lifestyle factors, study habits, family-related aspects, satisfaction with the educational environment, and students' grades. You can find the attributes used to create the dataset. Each student is classified as either Weak or Good based on their final grade in the computer science course. The paper elaborates on supervised ML methods used for classification tasks, where the model predicts categories (e.g., pass/fail or various performance levels) (Livieris et al., 2012).

**1.2 Machine Learning Model**

Solutions in machine learning (ML) are typically grouped into unsupervised learning or supervised learning. Unsupervised learning employs unorganized or unstructured data, while supervised learning uses structured data sets, where some input variables are connected with some output variables. Supervised ML tasks are further separated into regression and classification problems.

Regression focuses on continuous or discrete numerical outcomes, such as predicting how many students would score above the minimum requirement on a final examination. Classification, on the other hand, provides an indicator of a category. The output of a classified student can be a dichotomy (i.e., pass or fail) or an indicator of their performance within ordered categories (e.g., outstanding, very good, satisfactory, poor, and fail). In supervised classification ML, the input variables are labelled data, which are associated with a particular output value. That is, the ML model uses labelled data to learn the patterns in input and output to predict the outcomes of a similar prediction task.

The classifier is created by importing the relevant ML packages, loading the dataset, and performing data cleaning, which is one aspect of pre-processing prior to training the ML model. The data cleaning includes missing data handling, duplicate rows, correcting invalid inputs, and encoding categorical types of data which are considered non-numerical data types. It emphasizes data cleaning, encoding, and partitioning into training and testing sets to build an accurate predictive model (Guleria et al., 2015; Li et al., 2013).

After preprocessing, feature engineering is executed in order to investigate the relationships between the features. This stage identifies the key or significant features, which can positively influence the model's accuracy by removing the less important ones. Once reduced, the dataset is then partitioned into training and testing sets. There will be a set used to fit the model, while the testing set can evaluate the model's accuracy through cross-validation.

Different ML classification algorithms are applied in this study: Random Forest, Support Vector Machine (SVM), Stochastic Gradient Descent (SGD), Decision Tree, Adaptive Boosting (AdaBoost), Logistic Regression, and Deep Learning. Deep learning based on neural networks train models by passing a dataset through numerous layers. A deep learning model typically has an input layer (where the data comes in), then many hidden layers (to extract meaningful features), and an output layer. For the current analysis, a Convolutional Neural Network (CNN) model with 4 hidden layers was used to successfully accomplish the purpose of the study.

Gray, McGuinness and Owende (2014) learned classification models to anticipate tertiary education student progression. They assessed decision trees and logistic regression based on student demographic and academic data. In conclusion, the article showed machine learning strategies can be used to reliably predict at-risk students leading to improved academic outcomes through timely interventions.

### 1.3 Data Preprocessing

To ensure the best performing model possible, the dataset was rigorously pre-processed before being used for training. As most of the data was not numeric, extensive pre-processing was required. The pre-processing was divided into three key stages. The first step involved cleaning the data to detect and remove any missing or noisy values that could potentially dilute the overall quality of the dataset. Data categorization was then carried out, converting categorical data into numeric formats.

The document describes how non-numeric data was converted into numeric formats for better compatibility with ML algorithms (Buniyamin et al., 2016). More specifically, label encoding was applied to make sure data was consistent and offered usability, translating categories such as "distinction", "pass", "withdrawn", and "fail" to numeric values. This conversion is immensely valuable given typical machine learning algorithms are happier and perform better with numerical inputs. Ordinal data, which has a definitive order among the categories, maintained rankings as the labels have numeric equivalents.

An example of this is the "entrance result" where the categories used were assigned ordinal numbers to allow distinctions as to their order, ordinal ranking being retained. On the other hand, the nominal data does not have a standardized order. The region, disability, and final_ result features for example, were represented by encoding presence or absence as there is no ranking associated with them. Lastly, there was a data reduction step, to condense and organize the dataset to make it easier to explore and process. The dataset contained sparse matrices, most of which were sparse, and contained little application going forward.

Features that significantly influence model performance are identified and refined through preprocessing (Livieris et al., 2012). The model used data prepared from an online educational platform to extract features and categorize student academic performance into three categories: bad, average and good. The results showed that Support Vector Machine (SVM) was more accurate than logistic regression, obtaining an accuracy of 79%. The authors evaluated the system's effectiveness by measuring confusion matrix metrics (accuracy, recall, precision and F1-score). A second study applied Naïve Bayes, Random Forest and Ensemble learning classifiers to predict student academic performance using a dataset containing 887 records with 19 attributes from first year students.

Random Forest had the best results of the three models with an accuracy of 93%. The study also measured its model performance using recall, precision and F1-score metrics based on confusion matrix. Although the research in machine learning (ML) in education is still new, there are concerns related to prediction accuracy, overfitting, underfitting, and deployment of the model. The proposed method is to compare ML models to deep learning models, as deep learning models usually have more accuracy because they facilitate the progressive extraction of features. The ML algorithms were applied to the dataset to examine which features were most important to student academic performance. Using these features various ML.

### 1.4 Teaching

Agricultural meteorologists commonly gain their foundational education by supplementing conventional research in meteorology, physics, or environmental science with guides in plant, soil, or animal science, forestry, or horticulture. Only a few universities within the US and Europe provide committed undergraduate or graduate tiers in agricultural meteorology. Instead, most agricultural meteorology education is included into broader agricultural applications like agronomy. In comparison, India has adopted a greater structured technique to teaching agricultural meteorologists at the college stage, reflecting the country's emphasis on this specialised subject. As climate exchange and common weather-associated failures more and more threaten worldwide agricultural manufacturing, the scope of agricultural meteorology has multiplied. The World Meteorological Organization (WMO) has emphasised the significance of socioeconomic elements like irrigation, garage, agroforestry, floods, droughts, erosion, desertification, frost, wind safety, managed increase environments, and sustainable farming practices, specifically in growing international locations. The sensible demands of agricultural meteorology have led to the development of specialized training packages designed to enhance the skills, information, and practices of experts in this discipline. The WMO offers in-service training through nearby meteorological schooling centers, focusing on topics such as primary agricultural meteorology, facts control, agricultural meteorology modeling, and hydrometeorology. These quick, venture-oriented publications intention to enhance and standardize agricultural meteorology practices, especially in regions like commentary strategies and facts management, making sure that specialists are higher prepared to fulfill the challenges in them.

As meteorology advances swiftly, there is a growing need for ongoing training and schooling possibilities in agricultural meteorology. The developing hobby in global observation networks, which reveal a broader variety of environmental variables, has intensified this want. The Internet offers a valuable platform for presenting standardized, authoritative instructional and education materials to a much broader target market within the global agricultural meteorology community, making lifelong studying greater on hand and supporting professionals live modern-day with the today's trends in the field. As meteorology advances unexpectedly, there is an increasing need for ongoing education and training possibilities in agricultural meteorology. The growing hobby in international statement networks, which monitor a broader variety of environmental variables, has intensified this need. The Internet offers a precious platform for offering standardized, authoritative instructional and education materials to a wider audience inside the international agricultural meteorology network, making lifelong gaining knowledge of extra on hand and helping professionals live modern-day with the cutting-edge developments inside the area.

## 2 Proposed Work and Method

Educational Data Mining (EDM) makes use of advanced data analytics techniques and machine learning (ML) methods to improve learning. EDM implements data mining (DM) techniques that allow for insights and patterns which improve student success and assist educational institutions in making decisions through analysis of raw academic data.

Data mining techniques leverage machine learning models such as neural networks, support vector machines (SVM), and decision trees to process and analyze data to develop interactive learning tools that leverage predictive analytics and student performance improvements. The increased availability of data, combined with cheaper storage solutions and increased computing power, have primed machine learning methods to continue to develop from simple pattern recognition methods to today's sophisticated Deep Learning (DL) models. For instance, the University of Cordoba implemented a grammar-guided genetic programming algorithm, G3PMI to predict course completion from course data, achieving 74.29% accuracy. For another example, the Vishwakarma Engineering Research Journal created a machine learning site that predicts student performance based on attendance and grades in a subject. Another study produced by Somaiya College Mumbai, was able to successfully implement a model to predict student performance with 70.48%, but particularly interesting was that accuracy increased with sample size.

Moreover, Talwar et al. used artificial neural networks (ANNs) to evaluate success on student exams, obtaining a high degree of accuracy of 85%. Similarly, Kotsiantis et al. pointed out the Naïve Bayes algorithm's effectiveness, maintaining an accuracy level of 73% in predicting student performance. Moreover, Eindhoven University of Technology used the J48 classifier to accurately predict dropout rates for students. Similarly, at three universities in India, researchers studied multiple algorithms on student datasets, where they found performance prediction accuracy was highest with the ADT decision tree architecture.

University of Minho in Portugal similarly evaluated decision trees, random forests, and SVM to predict success in students' mathematics and language courses using ML. More recently, researchers also applied supervised ML models, including K-nearest neighbors (KNN), logistic regression, and linear regression, in predicting student performance. One of the studies applied 6 ML models across multiple tertiary institutions, where ANN predictably led the other methods in accuracy. Another research effort added in artificial intelligence (AI) complementary to the early intervention process to support teachers to identify students struggling across classes with personalized strategies that were effective at improving failure rates and student outcomes overall. Despite these trends, EDM models today share similar limitations to earlier, such as accuracy and determining new features. Even when ANNs exhibit high accuracy, they remained underutilized for EDM methods.

### 2.1 Data Analysis

Introduction to Skill-Based Prediction, an application of ML algorithms for skill-based prediction entails examining data of individual or groups to explore their skill level, knowledge/competency, or possible future performance. As illustrated above, this use case is widely employed in educational contexts, recruiting talent, training, and workforce management. ML algorithms can spot trends in historical data to better predict skill gaps, identify personalized learning paths, or provide evidence for hiring decisions.

Data Collection and Preprocessing Before executing ML algorithms, it is important to consider the acquisition, assembly, and preprocessing of the relevant data for analysis. The data can include: - Contextual information regarding the people involved (e.g., demographic factors such as age, education level, and experience). - Skill assessments (e.g., the result of a test, a practical exam, and certifications). - Behavioral data (e.g., engagement, consistency, or amount of time spent undertaking the learning tasks). -

Performance metrics (e.g., accuracy, speed, or quality of completion of learning task). The following steps demonstrate how to preprocess this data for analysis. - Data cleaning- remove any missing or inconsistent values. - Feature Selection- identify the relevant features to events of skill performance. - Normalization/Standardization- scale the numerical features to ensure consistency. - Encoding Categorical Variables- categorical data should be converted to numerical data (using either one-hot encoding or label encoding).- Splitting the Data- divide metadata into training and testing (e.g., 80:20 split || 70:30 split).

Several ML Algorithms Used for Skill-Based Prediction There are several ML algorithms that are regularly used to predict skill levels:

a) Decision Trees (DT) How it works: The DT model builds a structure like a tree, and using the features in your data, is used to make decisions. Use case: To predict the level of skill through analyzing the scores on a test and the learning patterns of the test-taker. Advantages: Easy to interpret; can analyze both numeric and categorical data. Limitation: Can have issues of overfitting with larger datasets.

b) Random Forest (RF) How it works: RF will use many decision trees to arrive at an accurate answer; the idea of RF is to use ensemble learning to gain a better answer. Use case: For a skill-based employee assessment, using multiple skills as metrics. Advantages: Less overfitting; more accurate assessments. Limitation: Computationally expensive with larger data sets.

c) Support Vector Machines (SVM) How it works: SVM will create a hyperplane that can separate groups of the data points into different classes. Use case: To predict the technical skill levels or the analytical skills of individuals based on assessment scores. Advantages: These are a great technique in high-dimensional spaces. Limitation: Sensitive to noise with larger datasets.

d) K-Nearest Neighbors (KNN) How it works: KNN will classify data points based on how close they are the closest neighbors. Use case: Prediction of levels of proficiency in programming languages or technical skills. Advantages: Easy to implement; works well with smaller datasets.

These are various ML classifiers mentioned in the study, with the paper noting the strengths and weaknesses of each method (Guleria et al., 2015; Livieris et al., 2012). A Convolutional Neural Network (CNN) model with multiple layers was used for higher accuracy in predicting performance (Li et al., 2013).Limitation: Will be inefficient and impractical with larger datasets.

e) Artificial Neural Networks (ANN) Performance Evaluation Metrics: The following are common metrics that can be used to assess effectiveness of ML Models:

- Accuracy: Indicates the percentage of correct predictions. Precision: Indicates how many of the positive predictions were correct.
- Recall: Indicates the percentage of actual positives that were predicted correctly. F1 Score - This is the harmonic mean of precision and recall, providing a balance of the two metrics.
- Confusion Matrix: Facilitates visualization of a model's performance by providing true positives, true negatives, false positives and false negatives.
- RMSE (Root Mean Square Error): Assess the difference between predicted values and actual values in a regression task.

Real World Applications of Skill Based Prediction Education: Predicting future skill level based on students' learning patterns and making appropriate course recommendations. Recruiting: Identifying job candidates who may possess the greatest potential match of skills, based on resume and assessment data to predict job candidate skills. Employee Training: Use of workforce performance data to identify skill gaps and recommend learning experiences. Health Care: Predicting and modeling practical skill retention of health care professionals based on the effectiveness of a specific training strategy. E-Learning Platforms: Making course or skill track recommendations to a learner based on the user interaction history and progress throughout a specific course or skill track. Challenges and Future Trends Data Imbalance: Skill datasets have often included imbalance classes which can lead to biased predictions. Feature Selection: Determining which features are appropriate is vital in the use of skill-based prediction.

Artificial Neural Networks (ANNs) are a type of machine-learning model that is inspired by the neural structure of the human brain. ANNs consist of input and output units that are connected by weighted links. They learn by modifying the weights of the links, thus allowing them to predict the target label for a given data input. The Backpropagation Algorithm is the most commonly used method to train ANNs because it reduces the weights by propagating the error backward through the network and converging the prediction.

ANNs can be a good choice because they are robust with noisy datasets and able to classify unseen patterns. ANNs are useful in instances where little is known a priori about the association between input features and output labels. ANNs are widely used in various real-world applications, including image and handwriting recognition, speech, laboratory medicine, and pathology

ANNs can be classified based on their architecture and function. The most common type is the fully connected multilayer feedforward network, which generally consists of: Input layer: accepts raw data, with each neuron in the input layer representing a single feature.

Hidden layers: conduct intermediate computation of activations. These hidden layers can have non-linear activation functions. Output layer: outputs a final prediction (e.g., skill proficiency, probability of mastering a skill). Within this research study, a three-layered fully connected feedforward ANN was built to predict skill proficiency where the network contained: Input layer: represented a total of 20 neurons as input features such as previous performance views, training time, and test scores. First hidden layer: contained 6 neurons using ReLU activation function to learn the intermediate representations level of performance that mapped to the input features. Second hidden layer: contained 3 neurons, with a ReLU activation function, which generated supportive refinements in understanding the developed patterns from the previous neurons' activations.

Output layer: contains a single output neuron responsible for the skill proficiency prediction. The connections between each layer are one directional from input to output, with no cyclical connectivity. The necessary backpropagation of the prediction to proficiency. The Backpropagation Algorithm is an essential component for improving the accuracy of the forward pass networks. The learning algorithm consisted of: Forward pass: Where data input is passed through the developed forward feed network to generate a prediction Error prediction computation: calculation of the exact error in relation to the prediction and model output.

### 2.2 Decision trees

Decision Tree (DT) is a supervised machine learning model that employs a flowchart-like structure for both classification and prediction of data. DT is composed of nodes, branches, and leaves. The root node is at the top of the tree, as it represents the first attribute employed to split the dataset. Internal nodes represent a decision or test regarding an attribute, which indicates how the dataset was split. The branches represent the results of those tests, leading to either additional decision nodes or terminal points. The leaf nodes carry the final prediction labels, which represent the final outcomes or classifications of skills. Decision trees may be binary (two branches per node) or multi-way (more than two branches) depending on the characteristics of the dataset and decision criteria. Working Mechanism in Skill Prediction In predicting skills, DT models are favored in practice due to the predictive power and the use of easy-to-understand data and model. The model looks at several factors, such as test scores, training hours, prior performance, or course participation, and divides the data into groups with akin skill levels. For example, predicting whether a student will master a certain skill: the root node may identify training hours spent for a course.

Various decision tree algorithms are utilized in the context of skill assessment, including: ID3 (Iterative Dichotomiser 3): Based on information gain, ID3 produces smaller trees that are simpler to interpret, making it very well-suited to forecasting skills on small datasets. CART (Classification and Regression Trees): Based on the Gini Index, CART supports classification and regression and is therefore very useful for predicting continuous skill scores such as student performance. C4.5: C4.5 is simply an enhancement of ID3 based on gain ratio, and can produce superior predictions, particularly for assessments that contain more than 2 classes.

### 2.3 Random Forest

Random Forest: Random forest combines detection trees to improve accuracy and reduce overfitting, making it very beneficial for modeling complex skill assessments that enable predictions. Potential Uses in Skill-Based Prediction Decision trees are commonly used in education (higher education), human resource management (pre-hiring assessments), and workforce management, including: Educational Performance Prediction: Decision trees can be used to predict educational performance by forecasting student skills based on their grades, attendance, and records of participation. Some schools and universities develop alert systems powered by decision trees to identify at-risk students, who can then receive intermediary supports. Corporate Skill Evaluation: Corporate HR departments use decision trees to generate employee skill proficiencies based on collected training data, task completion, compliance, and performance reviews to inform decisions about promotion and training needs. Online Learning Courses: Online and e-learning systems utilize decision trees to recommend courses for users. The recommendations reflect the types of skills the user is missing. Certain social factors, like health status, time with friends, and family quality, were found to be more impactful than demographic factors in determining academic success (Alharbi et al., 2016). The study extends its focus to skill prediction, exploring how ML can predict future performance in educational and workforce settings (Arsad et al., 2013).

## 3 Implementation

The plot_ importance () function from the Scikit-learn library is useful for visualizing which features impact students' final grade the most. The function produces a ranked plot showing the importance score for each feature in the prediction model. It gives an idea of which features have the largest and smallest impact. There are also several social factors that influence student performance that are meaningful: Current health status, Spending time with friends, Free time availability after school, and Quality of family connections. These factors are clearly critical for students' academic performance and reveal the impact of personal well-being and social context for students' learning achievement in school. Conversely, demographic and background factors had a less impactful role: Mother and father's jobs, Parents' living situation, Location of residence, and the rationale for attending the school. While these features served as components in the model, the lower importance scores showed that these features had a much weaker correlation with final grades. It reflects that behavior, socialization and personal well-being are more impactful in student academic success than background factors. Fig 1 Shows the Proposed System Model Architecture and Demographic, Academic, and Preference Data of BCA Students for Career and Degree Analysis Shown in Fig 2.

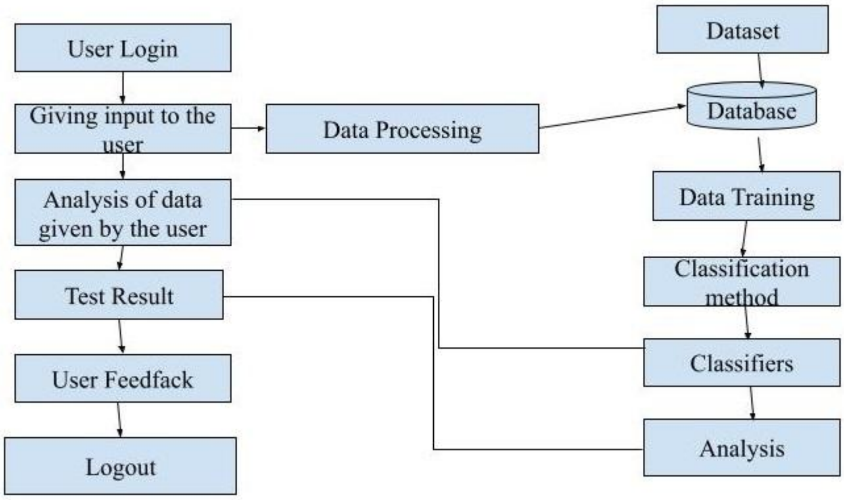


**Fig.1.** Proposed System Model Architecture.

## 4 Results

| Certification Course | Gender | Department | Height(CM) | Weight(Kg) | $10^{th}$ Mark | $12^{th}$ Mark | Hobbies | Daily Study Time | Prefer to study | Salary Expectation | Do you like your degree? | Willingness to pursue a career based on their degree? | Social media and videos |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **No** | Male | BCA | 120 | 78 | 400 | 432 | Cricket | 0-20 mins | Morning | 40000 | Yes | 52% | 1.30 – 2 hours |
| **No** | Female | MBA | 138 | 56 | 435 | 440 | Cinema | 50-60 mins | Evening | 60000 | Yes | 70% | More than 2 hours |
| **No** | Female | B.E | 125 | 80 | 420 | 410 | Reading Books | 1-2 hour | Anytime | 12000 | Yes | 80% | 1 hour |
| **Yes** | Male | BCA | 140 | 65 | 457 | 450 | Youtube Videos | 1-2 hour | Morning | 45000 | No | 100% | 1.30 -2 hours |
| **No** | Male | BA | 170 | 64 | 400 | 420 | Football | 30-60 mins | Anytime | 35000 | No | 50% | 1.30 – 2 hours |

**Fig. 2.** Demographic, Academic, and Preference Data of BCA Students for Career and Degree Analysis.

The findings underscore the ability of machine learning techniques to accurately predict performance based on skill. Recognition of the superior accuracy achieved by the ANN model indicates that it is particularly suited for more intricate, non-linear relationships in student performance data, thus making it a dependable tool for predicting students' academic performance. Additionally, factors chosen by the Decision Tree in feature selection bear importance regarding skills. It will benefit the student if the student is SATISFYING with learning environment IN particular, it improves all their extracurricular activities and the activities needed for the Student's carrier. The ANN model showed superior performance in predicting student outcomes, suggesting its robustness for handling non-linear relationships in student data (Buniyamin et al., 2016).

They played an essential role in the experience to data processing, model planning and evaluation; with the intervals that contribute towards meaningful experiences. We sincerely hope that this systematic research project provides enhanced quality of academic programs to provide educators the actionable opportunity to implement data-informed techniques to aid students in wholesome learning, and ultimately better outcomes.

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