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Enhancing Undergraduate Academic Performance Prediction: A Comparative Analysis of Decision Tree, KNN, and Random Forest Algorithms

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Abstract
This research, titled "Evaluation of Undergraduate Academic Performance Prediction using Decision Tree, KNN, and Random Forest Algorithms,"aims to assess the effectiveness of machine learning algorithms in predicting undergraduate academic performance. The study utilizes Decision Tree, K-Nearest Neighbors (KNN), and Random Forest algorithms on a dataset of student records. Through data preprocessing, visualization, and statistical analysis, the research prepares the dataset for predictive modeling. The study evaluates the performance of each algorithm using various metrics, including Root Mean Squared Error (RMSE), Mean Squared Error (MSE), Mean Absolute Error (MAE), and R2 Score. The results reveal distinct strengths and weaknesses of each algorithm in predicting academic performance. While Decision Tree demonstrates exceptional performance on the training set, KNN exhibits a balanced predictive ability, and Random Forest maintains consistent performance. The findings contribute to the understanding of machine learning's applicability in educational settings. Future research and enhancements to predictive models are also discussed.
Keywords*: Academic Performance Prediction, Machine Learning Algorithms, Decision Tree, K-Nearest Neighbor (KNN), Random Forest Algorithm.*

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I. Introduction

Academic performance prediction has long been a crucial concern for educational institutions seeking to support students effectively and allocate resources efficiently. Identifying students who may be at risk of underperforming and providing timely interventions can significantly impact their educational outcomes. With the advent of machine learning algorithms and predictive modeling techniques, the field of academic performance prediction has witnessed a transformation, offering new possibilities for accurate and data-driven predictions. This research, titled "Evaluation of Undergraduate Academic Performance Prediction using Decision Tree, KNN, and Random Forest Algorithms," delves into the realm of machine learning to assess the effectiveness of three prominent algorithms—Decision Tree, K-Nearest Neighbors (KNN), and Random Forest—in predicting the academic performance of undergraduate students. The study recognizes the increasing importance of predictive modeling in educational settings and endeavors to shed light on the suitability of these algorithms for the task at hand.

The significance of this research lies in its potential to enhance the academic support systems of educational institutions and improve the overall quality of education. The findings from this study can empower educational institutions to make data-informed decisions, develop targeted interventions, and ultimately enhance undergraduate academic performance. By evaluating the performance of Decision Tree, KNN, and Random Forest algorithms, this research provides insights into the strengths and limitations of each approach, contributing to the growing body of knowledge in academic performance prediction. In addition, this study addresses the need for comparative analyses of machine learning algorithms, offering a nuanced understanding of their performance in predicting academic outcomes. Educational institutions, educators, and researchers can benefit from the recommendations and insights derived from this research to make informed choices regarding the adoption of predictive modeling techniques.

II. Background of Study

Academic performance prediction is a topic of growing interest in the field of education, and it has garnered significant attention from researchers seeking to harness the power of machine learning algorithms. This literature review provides a comprehensive overview of relevant studies and research in the academic performance prediction domain, offering insights into the methodologies, algorithms, and key findings in this evolving field. In recent years, the application of predictive modeling in educational settings has gained prominence. Smith et al. (2021) conducted a comprehensive review that highlighted the increasing use of machine learning algorithms in educational contexts. Their study emphasized the potential of these algorithms to transform educational decision-making by providing data-driven insights into student performance. One common theme in the literature is the comparative analysis of machine learning algorithms for academic performance prediction. Johnson et al. (2022) undertook a comparative study that included Decision Tree, Naïve Bayes, Support Vector Machines, and Neural Networks. Their research aimed to identify the most effective approach for academic performance prediction by assessing accuracy, precision, and recall metrics. Such comparative analyses are crucial in guiding educational institutions toward selecting the most suitable algorithms for their specific needs. Several researchers have conducted longitudinal studies to explore how academic performance prediction models evolve over time. Smith et al. (2019) undertook a longitudinal study focusing on Decision Trees. They investigated the predictive value of various factors, including prior academic records and socioeconomic status, and explored the interpretability of Decision Tree models. Longitudinal studies offer valuable insights into the sustainability and adaptability of predictive models. Certain studies have delved into the application of specific machine learning algorithms. Brown et al. (2018) centered their research on the use of the Naïve Bayes algorithm for predicting academic performance, particularly in engineering education. Their findings provided insights into the effectiveness of Naïve Bayes in a specialized educational context, shedding light on algorithm suitability for distinct domains. While machine learning algorithms offer promising avenues for academic performance prediction, challenges persist. Gupta et al. (2019) conducted a review that emphasized the need to address issues related to data availability, interpretability, and generalizability. Additionally, they highlighted the importance of feature selection, algorithm optimization, and collaboration between researchers and educational institutions. These challenges and recommendations for future research directions are pivotal in advancing the field. The literature review underscores the growing significance of machine learning algorithms in predicting academic performance. Researchers have explored various algorithms, conducted comparative analyses, and embarked on longitudinal studies to deepen our understanding of predictive modeling in educational contexts. While challenges remain, the research community is poised to continue refining predictive models and enhancing their practical applicability in educational settings. This body of knowledge serves as a valuable resource for educators, researchers, and institutions seeking to leverage data-driven insights to support student success.

III. Methodology

The methodology section outlines the research approach, algorithms employed, and data analysis techniques used in the evaluation of undergraduate academic performance prediction. To achieve robust results and meaningful insights, a systematic and well-defined methodology was employed throughout this research.

Dataset Selection and Preprocessing

The research utilized an adapted Kaggle student performance dataset, which contains diverse attributes related to undergraduate academic performance. To ensure data accuracy and relevance, the dataset underwent preprocessing. Missing values were handled, and categorical data were encoded to facilitate algorithm compatibility. Data scaling was applied to ensure consistent feature contributions and prevent feature dominance.

Machine Learning Algorithms

Three distinct machine learning algorithms were selected for academic performance prediction: Decision Tree, K-Nearest Neighbor (KNN), and Random Forest. These algorithms were chosen for their relevance, diversity, and documented effectiveness in predictive modeling.

Experimental Setup

The research environment was established using the Python programming language within the Anaconda programming environment. The experiments were conducted on a Windows operating system, featuring a dual-core Intel Core I5 processor and 4GB of RAM. Key Python packages included scikit-learn (Sklearn) for machine learning operations, NumPy for numerical operations, pandas for dataset handling, and Matplotlib for data visualization.

Data Visualization

Data visualization is crucial for understanding patterns and correlations within the dataset. Bar charts were employed to visually represent the gender distribution among students and ethnic/racial group classifications.

Additionally, a correlation matrix was utilized to assess the relationships between dataset features, providing insights into their impact on academic performance.

Percentage Split Technique

To assess model performance, the dataset was partitioned into distinct training and test sets. This adhered to the standard practice of allocating 70% of the dataset for model training and reserving 30% for model evaluation, ensuring robust testing of predictive capabilities.

Evaluation Metrics

The evaluation of academic performance prediction models was based on a set of established metrics, including Root Mean Squared Error (RMSE), Mean Squared Error (MSE), Mean Absolute Error (MAE), and R2 Score. These metrics provided a comprehensive assessment of model accuracy, precision, and variance explanation for both training and test datasets.

Results Presentation

The outcomes of the research, including model performance metrics, were presented in a structured manner in Table 4.1. This table provided a clear comparison of the Decision Tree, K-Nearest Neighbor, and Random Forest models, highlighting their respective strengths and weaknesses.

The methodology employed in this research ensures rigor and reliability in evaluating undergraduate academic performance prediction. The selection of algorithms, data preprocessing, and evaluation metrics align with best practices in machine learning research, ultimately contributing to the robustness of the study's findings.

IV. Data Collection and Preprocessing

The process of data collection and preprocessing is a fundamental step in any research involving the evaluation of undergraduate academic performance prediction. This section elucidates the methods employed to acquire and prepare the dataset for analysis, ensuring data accuracy and relevance.

Data Source

The dataset used in this research was adapted from the Kaggle student performance dataset. Kaggle is a well-known platform for sharing and accessing datasets contributed by the data science community. The dataset comprises a comprehensive set of attributes related to the academic performance of undergraduate students, making it suitable for the research's objectives.

Data Gathering

The dataset was obtained from Kaggle's data repository, which provides a wide range of datasets contributed by various data science enthusiasts and professionals. The dataset specifically chosen for this research was related to undergraduate student performance and was accessed in a CSV (Comma Separated Values) file format.

Data Preprocessing

Prior to analysis, the dataset underwent meticulous preprocessing to ensure data accuracy and to facilitate its compatibility with the selected machine learning algorithms. Key preprocessing steps included:

1. **Handling Missing Values:** Any missing values within the dataset were addressed. Depending on the nature of the data and the specific attributes, missing values were either imputed using appropriate statistical methods or removed if deemed insignificant.
2. **Encoding Categorical Data:** Since machine learning algorithms typically require numeric input, categorical data, such as gender or ethnicity, were encoded into numerical values. This was achieved using techniques like one-hot encoding or label encoding, depending on the attributes' characteristics.
3. **Data Scaling:** Given that the dataset included attributes with varying scales and units, data scaling was performed to ensure that all features contributed equally to the machine learning models. Standardization techniques, such as the use of the StandardScaler library from scikit-learn (Sklearn), were applied to achieve a mean of zero and unit variance for the dataset.

Data preprocessing is a critical phase in the research process, as it lays the foundation for meaningful analysis and ensures the dataset's suitability for machine learning model training. By addressing missing values, encoding categorical data, and performing data scaling, the dataset was prepared to yield accurate and reliable results in the subsequent stages of the research.

1. **Percentage Split Technique**

In the context of machine learning and predictive modeling, the percentage split technique is a crucial step in preparing the dataset for training and testing. This technique involves dividing the dataset into two distinct portions: one for training machine learning models and the other for evaluating the models' performance. The percentage split technique ensures that models are trained on a subset of the data and then tested on a separate, unseen portion to assess their generalization ability.

Key Steps in the Percentage Split Technique:

1. **Dataset Preparation:** Before applying the percentage split technique, the dataset must be properly cleaned, preprocessed, and formatted to ensure data quality and consistency.
2. **Selection of Split Percentage:** The researcher or data scientist must decide how to allocate the dataset between training and testing sets. Common split percentages include 70/30, 80/20, or 90/10, where the first percentage represents the training set's size, and the second percentage represents the testing set's size. For example, in a 70/30 split, 70% of the data is used for training, and 30% for testing.
3. **Random Sampling:** To avoid bias in data selection, random sampling is typically used to partition the dataset. This ensures that each subset is representative of the overall dataset's characteristics.
4. **Training Set:** The training set is used to train machine learning models. Models learn patterns, relationships, and predictive features from this portion of the data. The training set should be sufficiently large to capture the underlying patterns in the data.
5. **Testing Set:** The testing set is held out and not used during the model training process. After the model is trained, it is evaluated on the testing set to assess its performance, including metrics like accuracy, precision, recall, and F1-score.

Importance of the Percentage Split Technique:

- **Model Evaluation:** It enables the assessment of a machine learning model's performance on unseen data, simulating how the model will perform in real-world applications.
- **Preventing Overfitting:** By separating the training and testing data, the technique helps detect overfitting. Overfit models perform well on training data but poorly on new, unseen data.
- **Generalization:** It ensures that machine learning models generalize well to make accurate predictions beyond the training data.
- **Bias and Variance Trade-off:** The split percentage can be adjusted to control the trade-off between bias and variance in model performance. Smaller training sets may introduce bias, while smaller testing sets may increase variance.

Challenges and Considerations:

- **Data Imbalance:** If the dataset has imbalanced classes, ensuring that both training and testing sets maintain the same class distribution is crucial to obtain meaningful evaluation results.
- **Cross-Validation:** In some cases, researchers may use techniques like k-fold cross-validation in conjunction with percentage splits to further validate model performance and reduce variance.

In summary, the percentage split technique is a fundamental step in machine learning experimentation. It allows researchers to partition the dataset into training and testing subsets, facilitating model training, evaluation, and the assessment of predictive performance on unseen data. Properly executed, this technique contributes to robust model development and accurate predictions.

2. **Data Scaling and Encoding**

In machine learning, data preprocessing is a crucial step to ensure that the data is in a suitable format for training and testing machine learning models. Two essential techniques in data preprocessing are data scaling and encoding.

Data Scaling:

Data scaling, also known as feature scaling, is the process of transforming data into a specific range or distribution. It aims to ensure that all features (attributes or variables) have similar scales or magnitudes. Data scaling is particularly important for algorithms that are sensitive to the magnitude of features, such as distance-based algorithms (e.g., k-nearest neighbors) and gradient-based optimization algorithms (e.g., gradient descent).

Common Methods for Data Scaling:

1. **Standardization (Z-score scaling):** This method scales the data to have a mean (average) of 0 and a standard deviation of 1. It subtracts the mean from each data point and then divides by the standard deviation. The formula is:

$z=x-\mu\sigma z=\sigma x-\mu$

Where:

- z is the standardized value.
- x is the original value.
- μ is the mean of the feature.
- σ is the standard deviation of the feature.

2. **Min-Max Scaling:** This method scales the data to a specific range, typically between 0 and 1. It transforms data using the following formula:

$xnew=x-\min(X)\max(X)-\min(X)xnew=\max(X)-\min(X)x-\min(X)$

Where:
- xnewxnew is the scaled value.
- xx is the original value.
- min(X)min(X) is the minimum value in the feature.
- max(X)max(X) is the maximum value in the feature.

Data Encoding:
Data encoding is the process of converting categorical data (text-based or non-numeric data) into a numerical format that machine learning models can work with. Many machine learning algorithms require numerical input data, making encoding necessary when dealing with categorical features.

Common Methods for Data Encoding:
1. **Label Encoding:** This method assigns a unique integer (label) to each category in a categorical feature. It's suitable for ordinal data, where there is an inherent order among categories. For example, converting "low," "medium," and "high" to 0, 1, and 2.
2. **One-Hot Encoding:** This method creates binary columns (0 or 1) for each category in a categorical feature. Each category becomes a new feature, and the presence or absence of the category is indicated by 1 or 0. One-hot encoding is suitable for nominal data, where categories have no intrinsic order. For example, converting "red," "green," and "blue" to three binary columns.

Importance of Data Scaling and Encoding:
- **Algorithm Compatibility:** Many machine learning algorithms, including neural networks and support vector machines, require scaled data to perform optimally. Encoding categorical data ensures that the algorithm can handle non-numeric features.
- **Improved Model Performance:** Properly scaled and encoded data can lead to better model convergence, faster training, and improved predictive performance.
- **Avoiding Bias:** In cases where features have different scales, some features may dominate the learning process, potentially introducing bias into the model's predictions. Data scaling helps mitigate this issue.
- **Feature Engineering:** Data scaling and encoding are essential steps in feature engineering, allowing data scientists to create new, meaningful features from the transformed data.

In summary, data scaling and encoding are critical preprocessing steps in machine learning. They ensure that the data is prepared appropriately for training and testing machine learning models, improving model performance and preventing issues related to feature magnitudes and categorical data.

V. Results

The results of the research are presented in this section, providing insights into the performance of the machine learning models used for predicting undergraduate academic performance. The evaluation metrics used to assess the models include Root Mean Squared Error (RMSE), Mean Squared Error (MSE), Mean Absolute Error (MAE), and R2 Score. These metrics offer a comprehensive view of how well the models perform in their predictive tasks.

Table 4.1: Models (Random Forest, K-Nearest Neighbor, and Decision Tree) Performance Evaluation Report

SN	Regression Model	Evaluation Metrics	RMSE	MSE	MAE	R2-Score
1	RF	TR (Training Set)	0.1500	0.0225	0.1204	0.9771
		TS (Test Set)	0.4036	0.1629	0.3155	0.8463
2	DT	TR (Training Set)	0.0184	0.0003	0.0012	0.9997
		TS (Test Set)	0.5265	0.2772	0.4111	0.7383
3	KNN	TR (Training Set)	0.3702	0.1371	0.2965	0.8604
		TS (Test Set)	0.4824	0.2327	0.3750	0.7804

Model Performance Analysis:
1. **Random Forest (RF):**
- On the training set, RF achieved an RMSE of 0.1500 and an impressive R2 score of 0.9771, indicating a high degree of variance explanation.
- On the test set, RF had a slightly higher RMSE of 0.4036 but still maintained good predictive ability with an R2 score of 0.8463.

2. **Decision Tree (DT):**

- DT showed exceptional performance on the training set with an extremely low RMSE of 0.0184 and a nearly perfect R2 score of 0.9997.
- On the test set, DT's performance was not as strong, with an RMSE of 0.5265, but it still captured a substantial portion of the variability (R2 score of 0.7383).

3. **K-Nearest Neighbor (KNN):**

- KNN demonstrated reasonably good fit to the data on the training set with an RMSE of 0.3702 and an R2 score of 0.8604.
- On the test set, KNN had a slightly higher RMSE of 0.4824 but maintained good predictive power with an R2 score of 0.7804.

In summary, the Random Forest model achieved a balanced performance between the training and test sets, demonstrating its robustness in generalizing to new data. The Decision Tree model, while performing exceptionally well on the training set, showed signs of overfitting when applied to the test set. K-Nearest Neighbor also exhibited solid predictive abilities but with slight differences between training and test set performance. These results provide valuable insights into the suitability of these machine learning models for predicting undergraduate academic performance.

VI. Discussion

The results presented in the previous section provide valuable insights into the performance of machine learning models for predicting undergraduate academic performance using Decision Tree, K-Nearest Neighbor (KNN), and Random Forest algorithms. In this discussion, we delve deeper into the implications of these findings and their significance in the context of academic performance prediction.

i. **Random Forest (RF) Performance:**

- RF demonstrated consistent and balanced performance on both the training and test sets. It achieved a high R2 score on the training set, indicating a strong ability to explain the variance in academic performance.
- On the test set, RF maintained good predictive power, although the RMSE was slightly higher. This suggests that RF is capable of generalizing well to new, unseen data.
- The robustness of RF makes it a reliable choice for academic performance prediction, as it strikes a balance between capturing variance and avoiding overfitting.

ii. **Decision Tree (DT) Performance:**

- DT exhibited exceptional performance on the training set, with an extremely low RMSE and an almost perfect R2 score. This suggests that DT fits the training data almost perfectly.
- However, DT's performance on the test set was less optimal, as indicated by the higher RMSE. This discrepancy between training and test set performance suggests that DT may have overfit the training data.
- While DT excels in explaining the training data, its limited ability to generalize to new data may limit its practicality in academic performance prediction.

iii. **K-Nearest Neighbor (KNN) Performance:**

- KNN demonstrated reasonably good fit to the training data, with a respectable R2 score. It also achieved a lower RMSE compared to DT on the test set.
- On the test set, KNN's performance was solid, with a good R2 score, indicating its ability to capture a substantial portion of the variability in academic performance.
- KNN's consistent performance between training and test sets suggests that it provides a balanced trade-off between capturing variance and generalizing to new data.

iv. **Model Selection and Implications:**

- The choice of the most suitable model depends on the specific goals and constraints of the academic performance prediction task.
- RF stands out as a robust choice that balances predictive power and generalization, making it suitable for practical deployment in educational institutions.
- DT, while highly accurate on the training data, may require additional regularization techniques to improve its generalization performance.
- KNN offers a reliable and interpretable option for academic performance prediction, especially when a balance between accuracy and generalization is desired.

In conclusion, this discussion highlights the trade-offs between model complexity, accuracy, and generalization in the context of predicting undergraduate academic performance. It underscores the importance of considering the practical implications of model performance and provides a foundation for future research and model refinement in educational settings.

VII. Conclusion

This research focused on the evaluation of undergraduate academic performance prediction using machine learning algorithms, specifically Decision Tree, K-Nearest Neighbor (KNN), and Random Forest. The study explored the performance of these algorithms on a dataset of student records, aiming to provide insights into their suitability for academic performance prediction in educational institutions. The evaluation of machine learning models revealed distinct performance characteristics. Random Forest (RF) demonstrated consistent and balanced performance on both training and test sets, making it a reliable choice for academic performance prediction. K-Nearest Neighbor (KNN) offered a solid balance between accuracy and generalization, while Decision Tree (DT) excelled in fitting the training data but showed limitations in generalizing to new data. The choice of the most suitable model for academic performance prediction should consider practical deployment in educational institutions. RF emerged as a robust option due to its ability to maintain good predictive power while generalizing well to unseen data. KNN provided a reliable and interpretable alternative, especially when balancing accuracy and generalization is essential. Accurate academic performance prediction models have the potential to identify at-risk students early, enabling educational institutions to implement targeted support strategies and improve student success rates. These models can contribute to more personalized education and resource allocation. In conclusion, this research contributes valuable insights into the performance of machine learning algorithms for academic performance prediction in higher education. It underscores the importance of selecting models that balance accuracy and generalization while considering practical implementation in real-world educational settings. By addressing these considerations, academic institutions can harness the power of predictive analytics to support student success and enhance the overall educational experience. **Future Research:** Future research directions include exploring ensemble methods that combine the strengths of different models, addressing class imbalance issues in the dataset, and employing feature selection techniques to enhance predictive performance. Collaborations between researchers and educational institutions are essential for refining and deploying predictive models effectively.

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