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A Data-Driven Classification of Student Productivity Based on Academic Performance, Lifestyle Patterns, and Digital Habits

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Abstract

Student productivity is influenced by various factors, including academic habits, lifestyle characteristics, and digital distraction behaviors. The increasing use of digital technologies, such as smartphones, social media, and online gaming, has created new challenges for maintaining student focus and academic performance. Therefore, understanding and predicting student productivity levels is important for supporting effective educational management and student success. This study aims to classify student productivity levels using machine learning techniques based on academic, behavioral, and digital distraction variables. The study utilized the Student Productivity & Digital Distraction Dataset obtained from Kaggle, consisting of 20,000 student records. The productivity score was transformed into five productivity categories, namely very low, low, medium, high, and very high productivity. Four machine learning algorithms, including Decision Tree (DT), and K-Nearest Neighbors (KNN), Gradient Boosting (GB), and Random Forest (RF) were evaluated using accuracy, precision, recall, F1-score, and confusion matrix analysis. The results showed that RF achieved the best performance with an accuracy of 81.15%, precision of 81.35%, recall of 81.15%, and F1-score of 81.23%, outperforming GB, DT, and KNN. The findings indicate that ensemble learning methods are more effective in modeling the complex relationships among academic habits, lifestyle factors, digital distraction, and student productivity. Furthermore, the study demonstrates the potential of machine learning as a decision-support tool for educational management, enabling the identification of students with different productivity levels and supporting data-driven interventions to improve academic outcomes.

1. Introduction

Student productivity is an important factor in determining academic success and educational achievement [1–3]. Productive students are generally characterized by effective study habits, good time management, consistent attendance, and the ability to maintain focus during learning activities [2–4]. In recent years, the rapid development of digital technology has significantly transformed the educational environment, providing students with easier access to information, communication, and learning resources [5]. Although technology offers many educational benefits, its increasing use has also introduced new challenges related to digital distraction and reduced academic focus [5, 6]. Recent studies have shown that excessive engagement with digital platforms, including social media, smartphones, and online gaming, can negatively affect students' concentration, learning behavior, and academic performance [6–9].

Digital distraction has become one of the major concerns in modern education [5, 6]. The widespread use of smartphones, social media platforms, online entertainment, and digital gaming has increased students' exposure to non-academic activities during study time [10]. Previous studies have reported that excessive social media usage and digital multitasking may reduce learning concentration, disrupt time management, and negatively influence academic productivity [11]. Furthermore, students often experience difficulties balancing educational responsibilities with digital engagement, leading to decreased focus and reduced academic effectiveness [11]. The growing prevalence of digital distraction highlights the need for educational institutions to better understand the factors that influence student productivity and to develop strategies that support effective learning behaviors.

To address these challenges, machine learning has emerged as a powerful analytical approach for identifying patterns and predicting outcomes from educational data [12, 13]. Machine learning techniques have been widely applied in educational data mining to analyze student performance, learning behavior, and academic achievement [14, 15]. Unlike traditional statistical approaches, machine learning algorithms can model complex and nonlinear relationships among multiple variables [16], enabling more accurate predictions and deeper insights into student-related factors. Recent studies have demonstrated the potential of machine learning methods in analyzing the relationship between digital distraction and academic performance, suggesting that predictive models can support data-driven educational decision-making.

Despite the growing body of research on digital distraction and academic performance, several research gaps remain. Many previous studies have primarily focused on examining the direct impact of social media usage or digital technology on academic outcomes through conventional statistical methods. In addition, existing studies often utilize relatively small datasets and focus on limited behavioral variables, making it difficult to capture the broader interactions among academic habits, lifestyle factors, digital distraction, and productivity. Furthermore, comparative investigations involving multiple machine learning algorithms for student productivity classification remain limited, particularly within the context of educational management and student support systems.

Therefore, this study aims to classify student productivity levels using machine learning techniques based on academic habits, lifestyle characteristics, and digital distraction variables. Specifically, this research compares the performance of Decision Tree (DT), K-Nearest Neighbors (KNN), Gradient Boosting (GB), and Random Forests (RF) algorithms in predicting student productivity categories. The findings are expected to provide insights into the factors associated with student productivity and demonstrate the potential of machine learning as a decision-support tool for educational management and student performance improvement.

The main contribution of this study is the development and evaluation of machine learning models for classifying student productivity levels based on academic habits, lifestyle factors, and digital distraction behaviors. Unlike previous studies that primarily focused on the relationship between individual factors and academic performance, this research integrates multiple behavioral and academic variables within a comprehensive predictive framework. In addition, this study provides a comparative analysis of DT, KNN, GB, and RF algorithms to identify the most effective approach for student productivity classification. The findings contribute to the educational management literature by demonstrating how predictive analytics can be utilized to support early identification of students with different productivity levels and facilitate data-driven interventions to enhance learning outcomes.

2. Materials and Methods

This study employed a machine learning approach to classify student productivity levels based on academic habits, lifestyle characteristics, and digital distraction factors. The research process consisted of several stages, including dataset collection, data preprocessing, model development, and performance evaluation. The overall workflow of the study is illustrated in Figure 1.

2.1. Dataset

This study utilized the Student Productivity & Digital Distraction Dataset obtained from Kaggle, published by Mansehaj Preet in 2026 and contains 20,000 student records [17]. It provides comprehensive information

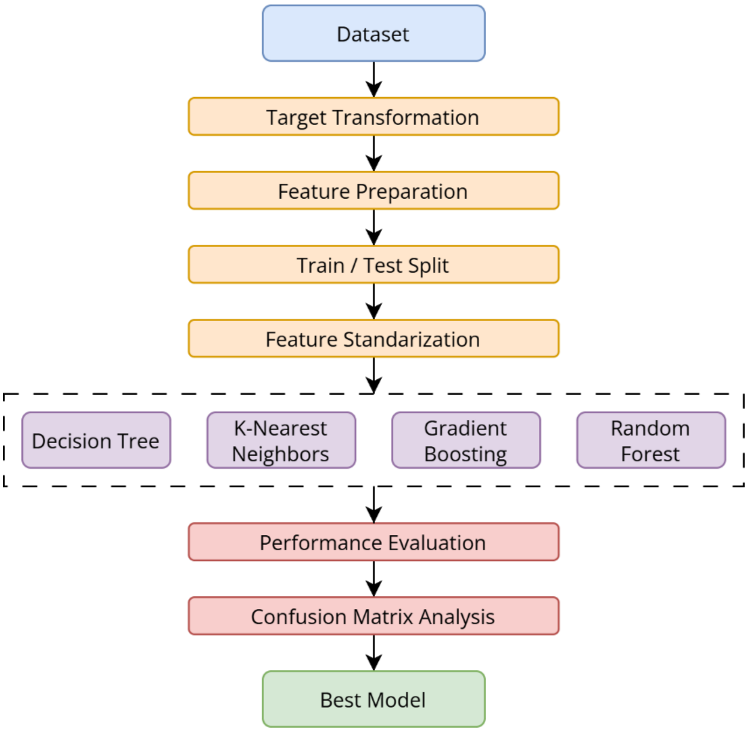

Figure 1. Workflow of this study.

Table 1. Variables in the student productivity & digital distraction dataset.

No.	Variable	Explanation
1	study_hours_per_day	Average daily study time (hours)
2	sleep_hours	Average daily sleep duration (hours)
3	phone_usage_hours	Average daily phone usage (hours)
4	social_media_hours	Time spent on social media per day (hours)
5	gaming_hours	Daily gaming duration (hours)
6	stress_level	Student stress level measured on a scale of 1–10
7	focus_score	Student focus score ranging from 0–100
8	attendance_percentage	Percentage of class attendance (%)
9	final_grade	Student academic performance grade
10	productivity_score	Overall productivity score (0–100), used as the target variable

regarding students' academic habits, lifestyle factors, digital distraction behaviors, and productivity levels.

Each record in the dataset represents an individual student, while each variable describes a specific characteristic that may influence student productivity. The dataset includes measures related to study habits, sleep patterns, technology usage, stress levels, academic engagement, and academic performance. The target variable is the productivity score, which represents the overall productivity level of a student on a scale ranging from 0 to 100. The variables used in this study are summarized in Table 1.

2.2. Data Preprocessing

Before model development, several preprocessing steps were applied to prepare the dataset for classification analysis. The original target variable, productivity_score, which was recorded as a continuous numerical value ranging from 0 to 100, was transformed into a categorical variable named productivity_class using a quantile-based classification approach. The productivity scores were divided into five groups with approximately equal numbers of students in each group. Class 1 represents very low productivity, class 2 represents low productivity, class 3 represents medium productivity, class 4 represents high productivity, and class 5 represents very high productivity. This transformation converted the prediction task from a regression problem into a multiclass classification problem.

After the productivity classes were generated, the original productivity_score variable was removed to prevent data leakage during model training [18]. The id variable was also excluded because it only serves as a unique identifier and does not provide predictive information. The categorical variable gender was then converted into a numerical format using Label Encoding so that it could be processed by machine learning algorithms.

The dataset was subsequently divided into training and testing subsets using an 80:20 ratio [19]. The training subset was used to build the classification models, while the testing subset was reserved for evaluating model performance. Finally, numerical features were standardized using StandardScaler [20]. The scaler was fitted only on the training data and then applied to both the training and testing data to ensure consistent scaling while avoiding information leakage from the test set.

2.3 Machine Learning Models

This study employed four supervised machine learning algorithms to classify student productivity levels: DT, KNN, GB, and RF. These algorithms were selected because they represent different classification approaches and have been widely applied in educational data mining and predictive analytics [21, 22]. All models were implemented using the scikit-learn library with their default hyperparameter settings [23]. For reproducibility, a random state of 42 was specified for algorithms that support random initialization.

The DT algorithm constructs a hierarchical tree structure by recursively splitting the data according to feature values that maximize class separation [24]. The resulting model is easy to interpret because the classification process can be represented as a set of decision rules. In this study, the DT model was used as a baseline classifier for predicting student productivity classes.

The KNN algorithm classifies a new observation based on the classes of its nearest neighbors in the feature space [25]. The predicted class is determined by the majority class among the selected neighboring instances. Because KNN relies on distance calculations, feature standardization was performed during preprocessing to ensure that all variables contributed equally to the classification process.

The GB algorithm is an ensemble learning method that builds multiple weak learners, typically DTs, in a sequential manner [26]. Each new tree is trained to correct the errors made by the previous trees, allowing the model to gradually improve its predictive performance. GB is effective in capturing complex patterns in data and is commonly used for classification tasks because of its ability to produce strong predictive models.

The RF algorithm is an ensemble learning method that combines multiple DTs to improve predictive performance and reduce overfitting [27]. Each tree is trained using a randomly selected subset of the training data and features, and the final prediction is determined through majority voting among all trees. RF is known for its robustness, ability to handle complex relationships among variables, and strong classification performance across a wide range of datasets. The performance of the four classification models was evaluated using the testing dataset to determine their effectiveness in predicting student productivity levels.

2.4 Performance Evaluation

The performance of the classification models was evaluated using several commonly used classification metrics, including accuracy, precision, recall, and F1-score. These metrics provide complementary perspectives on model performance and enable a comprehensive assessment of the ability of each algorithm to classify student productivity levels correctly [28].

Accuracy measures the proportion of correctly classified instances relative to the total number of instances in the testing dataset. Precision evaluates the proportion of correctly predicted instances within a particular class among all instances predicted as that class. Recall measures the proportion of correctly identified instances within a class relative to the total number of actual instances belonging to that class. The F1-score combines precision and recall into a single metric by calculating their harmonic mean, providing a balanced measure of classification performance, particularly when class distributions are uneven.

In addition to these quantitative metrics, a confusion matrix was used to analyze the classification results in greater detail. The confusion matrix presents the number of correct and incorrect predictions for each productivity class, allowing the identification of specific classes that are frequently misclassified. This analysis provides additional insight into the strengths and weaknesses of each classification model and supports a more comprehensive evaluation of their predictive performance.

3. Results and Discussion

The performance of the four machine learning models was evaluated using the testing dataset. Accuracy, precision, recall, and F1-score were used as evaluation metrics to assess the classification performance of each model. The weighted average values were used for precision, recall, and F1-score because they account for the number of instances in each class and provide a more representative measure of overall model performance.

Table 2. Performance comparison of machine learning models.

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Decision Tree	65.55	65.72	65.55	65.63
K-Nearest Neighbors	51.98	53.11	51.98	52.23
Gradient Boosting	79.05	79.29	79.05	79.03
Random Forest	81.15	81.35	81.15	81.23

As shown in Table 2, the RF model achieved the highest performance among all evaluated algorithms, obtaining an accuracy of 81.15%, a precision of 81.35%, a recall of 81.15%, and an F1-score of 81.23%. These results indicate that RF was the most effective model for classifying student productivity levels based on academic habits, lifestyle factors, and digital distraction variables. The strong performance of RF can be attributed to its ensemble learning mechanism, which combines the predictions of multiple DTs and reduces the risk of overfitting.
GB achieved the second-best performance with an accuracy of 79.05% and an F1-score of 79.03%. Although its performance was slightly lower than that of RF, the results demonstrate that boosting-based ensemble methods are also highly effective for modeling the complex relationships between student behaviors and productivity outcomes.

The DT model produced moderate performance, achieving an accuracy of 65.55% and an F1-score of 65.63%. While the model is easy to interpret and provides clear decision rules, its predictive capability was substantially lower than that of the ensemble methods. This finding suggests that a single DT may not be sufficient to capture the complex interactions among the variables influencing student productivity.

The KNN model exhibited the lowest performance, with an accuracy of 51.98% and an F1-score of 52.23%. The relatively poor performance of KNN may be attributed to the overlapping characteristics among productivity classes, particularly in the low, medium, and high productivity categories. Because KNN relies on distance-based classification, students with similar academic habits, lifestyle patterns, and digital distraction behaviors may be assigned to neighboring but different productivity classes. This overlap can make it difficult for KNN to clearly separate class boundaries, leading to a higher rate of misclassification compared with ensemble-based models.

The confusion matrices presented in Figure 2 provide a more detailed evaluation of the classification performance of the four machine learning models. In all confusion matrices, the rows represent the true productivity classes and the columns represent the predicted classes in the following order: very low, low, medium, high, and very high.

For the DT model, the correctly classified instances along the diagonal were 639, 454, 421, 473, and 635 for the very low, low, medium, high, and very high productivity classes, respectively. Misclassifications mainly occurred between adjacent classes, such as very low being predicted as low (147), low being predicted as medium (193), medium being predicted as low (184) or high (174), high being predicted as medium (175) or very high (144), and very high being predicted as high (152). These results indicate that DT achieved moderate classification performance, but it had difficulty distinguishing neighboring productivity levels.

For the KNN model, the diagonal values were 605, 365, 299, 322, and 488. This model produced the lowest number of correct predictions among the evaluated algorithms. The confusion matrix shows substantial misclassification among neighboring classes, particularly low predicted as very low (224) or medium (176), medium predicted as low (273) or high (151), high predicted as medium (259) or very high (114), and very high predicted as high (233). These results suggest that KNN had difficulty separating students with similar academic habits, lifestyle patterns, and digital distraction behaviors, especially in the middle productivity categories.

For the GB model, the diagonal values were 712, 615, 491, 643, and 701. Compared with DT and KNN, GB produced a higher number of correct classifications across all productivity classes. Most errors were still concentrated between adjacent categories, such as very low predicted as low (88), low predicted as medium (115), medium predicted as low (161) or high (148), high predicted as medium (94) or very high (63), and very high predicted as high (98). These results indicate that GB was effective in capturing the underlying relationships among the predictor variables, although some overlap remained among neighboring productivity levels.

For the RF model, the diagonal values were 722, 615, 567, 636, and 706, representing the highest overall number of correct classifications. Misclassifications were mostly limited to adjacent classes, including very low predicted as low (78), low predicted as very low (63) or medium

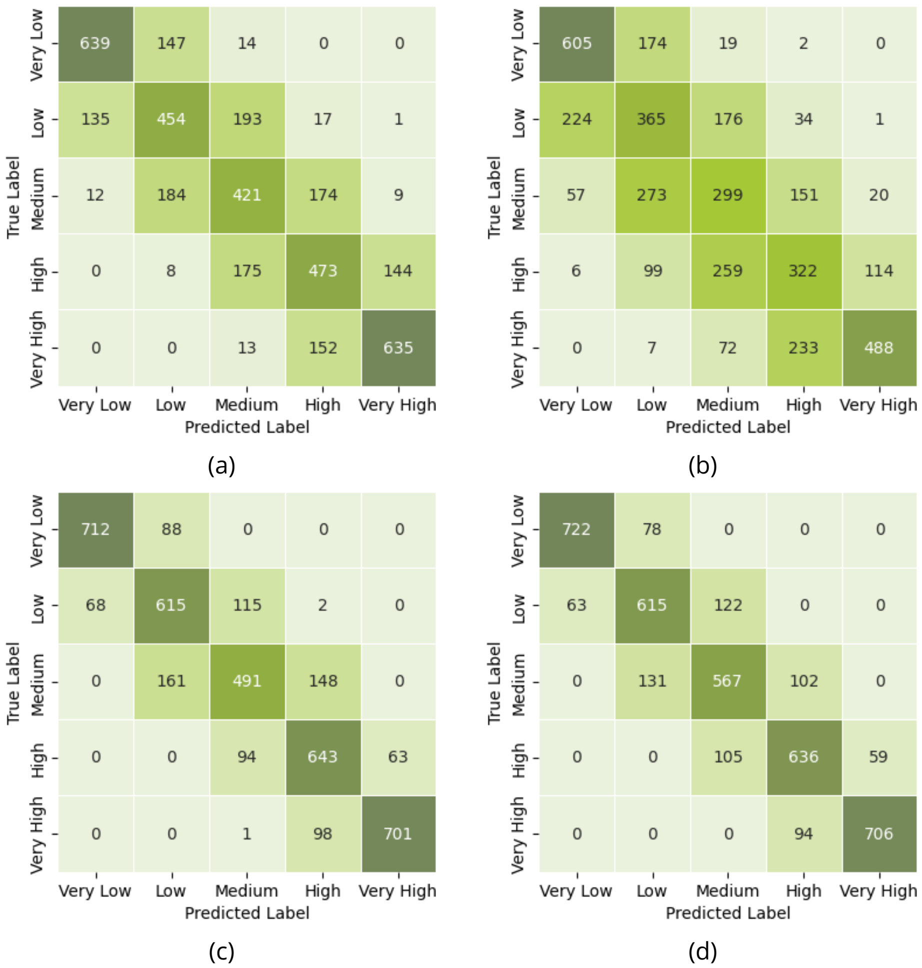

Figure 2. Confusion matrices of the evaluated machine learning models for student productivity classification: (a) Decision Tree, (b) K-Nearest Neighbors, (c) Gradient Boosting, and (d) Random Forest.

(122), medium predicted as low (131) or high (102), high predicted as medium (105) or very high (59), and very high predicted as high (94). These results confirm that RF achieved the strongest classification capability among the four models. The high number of correct predictions in the very low and very high classes also suggests that RF was particularly effective in distinguishing students with clearly different productivity characteristics.

The results obtained from both the performance metrics and confusion matrix analysis consistently indicate that RF outperformed the other machine learning models in classifying student productivity levels. Although GB produced comparable results, its overall performance remained slightly lower. In contrast, DT and KNN exhibited substantially lower predictive capability, particularly in distinguishing students belonging to the middle productivity classes. These findings suggest that the relationships between academic habits, lifestyle factors, digital distraction, and student productivity are complex and nonlinear in nature. Consequently, ensemble learning methods, particularly RF, are better suited to capture these relationships and provide more accurate predictions of student productivity levels. Therefore, RF can be considered the most effective model for student productivity classification in this study.

Because RF achieved the highest classification performance among the evaluated models, further analysis was conducted to examine the importance of each predictor variable. As shown in Figure 3, study_hours_per_day was the most influential feature in the RF model, indicating that daily study duration had the strongest contribution to student productivity classification. This was followed by focus_score, phone_usage_hours, and sleep_hours, suggesting that both academic behavior and personal habits play important roles in determining productivity levels. Attendance_percentage and stress_level also showed noticeable contributions, although their importance was lower than the top-ranked variables. In contrast, variables such as age and gender had the smallest importance values, indicating a relatively limited contribution to the model. Overall, the feature importance results suggest that student productivity is primarily influenced by a combination of study habits,

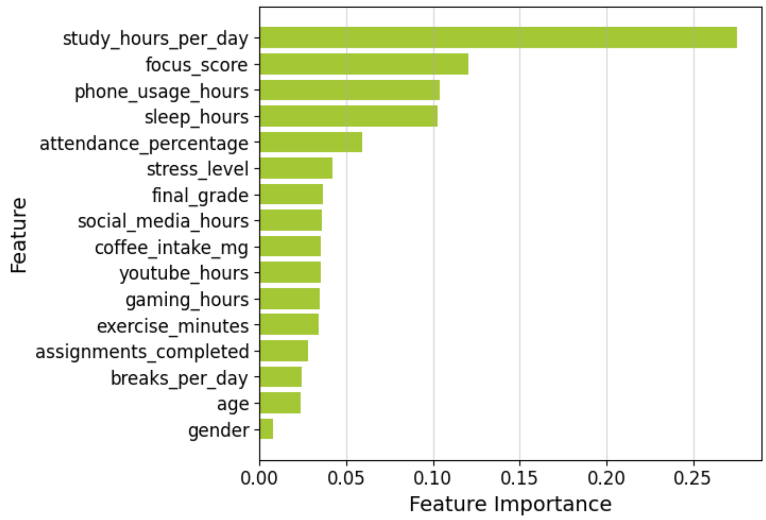

Figure 3. Feature importance of the Random Forest model for student productivity classification.

concentration, digital device usage, and lifestyle-related factors.

The findings of this study demonstrate that student productivity can be effectively predicted using information related to academic habits, lifestyle factors, and digital distraction behaviors. Among the evaluated machine learning models, RF achieved the highest classification performance, indicating that ensemble-based approaches are particularly suitable for capturing the complex relationships between student characteristics and productivity outcomes. The superior performance of RF suggests that student productivity is not determined by a single factor but rather by the interaction of multiple variables, including study time, sleep duration, phone usage, social media engagement, gaming behavior, stress level, focus score, attendance, and academic achievement.

The results also highlight the important role of digital distraction in student productivity. Variables such as phone usage, social media activity, and gaming time are closely associated with students' ability to maintain focus and achieve productive academic behaviors. Excessive engagement with digital activities may reduce the time and attention available for learning tasks, thereby affecting overall productivity. Conversely, students who demonstrate balanced technology use and stronger academic habits are more likely to achieve higher productivity levels.

Another notable finding is that the extreme productivity categories, namely very low and very high productivity, were classified more accurately than the middle categories. This pattern suggests that students at the ends of the productivity spectrum exhibit more distinctive behavioral characteristics, making them easier to identify. In contrast, students with low, medium, or high productivity levels may share similar habits and behaviors, resulting in greater overlap between these categories. From an educational management perspective, this finding indicates that students with moderate productivity levels may require more individualized monitoring and support because their characteristics are less clearly differentiated.

The study further demonstrates the potential of machine learning as a decision-support tool in educational settings. By identifying patterns associated with student productivity, educational institutions can develop data-driven strategies to support student success. For example, early identification of students with low productivity levels may enable educators and administrators to implement targeted interventions, such as academic counseling, time management training, stress management programs, or initiatives aimed at reducing excessive digital distraction.

Several limitations should be considered when interpreting the findings of this study. First, the dataset used in this research was obtained from a publicly available source and may not fully represent the characteristics of students from different educational institutions, regions, or cultural backgrounds. Second, the analysis relied on a limited set of variables related to academic habits, lifestyle, and digital distraction, while other potentially influential factors such as socioeconomic status, learning environment, motivation, and psychological well-being were not included. Third, the productivity classes were generated through categorization of productivity scores, which may reduce some of the detailed information contained in the original continuous variable. Finally, the study evaluated only four machine learning algorithms, and therefore the results may not reflect the performance of other advanced approaches.

Future research may extend this work by incorporating additional variables that capture broader aspects of student behavior and educational experiences. The inclusion of demographic, psychological, and institutional factors may improve the predictive capability of machine learning models. Future studies may also evaluate more advanced machine learning and deep learning techniques, such as Extreme Gradient Boosting (XGBoost), LightGBM, Artificial Neural Networks, or hybrid ensemble methods, to determine whether higher classification performance can be achieved. Additionally, validating the developed models using datasets collected from different educational contexts would improve the generalizability and practical applicability of the findings. Future work may also focus on developing real-time student productivity monitoring systems that can support educational managers and instructors in providing early interventions for students at risk of low productivity.

4. Conclusions

This study investigated the use of machine learning techniques to classify student productivity levels based on academic habits, lifestyle factors, and digital distraction behaviors. The results demonstrated that ensemble learning methods outperformed conventional classification approaches, with RF achieving the best performance, obtaining an accuracy of 81.15%, a precision of 81.35%, a recall of 81.15%, and an F1-score of 81.23%. The findings indicate that student productivity is influenced by complex interactions among study habits, sleep patterns, technology usage, stress levels, focus, attendance, and academic performance. Furthermore, the study highlights the potential of machine learning as a decision-support tool for educational management by enabling the early identification of students with different productivity levels. Such predictive insights can assist educators and institutions in designing targeted interventions to improve student learning outcomes and overall academic success.

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