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Emily Barnes
Capitol Technology University

James Hutson
Lindenwood University, jhutson@lindenwood.edu

Karriem Perry
Capitol Technology University

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Optimizing Adult Learner Success: Applying Random Forest Classifier in Higher Education Predictive Analytics

[1,]Emily Barnes, EdD, PhD, [2,]James Hutson, PhD , [3,]Karriem Perry, PhD
[1,]*Capitol Technology University AI Center of Excellence (AICE)*
https://orcid.org/0000-0001-9401-0186
[2,]*Lindenwood University*
https://orcid.org/0000-0002-0578-6052
[3,]*Capitol Technology University*
https://orcid.org/0000-0002-9992-6027

ABSTRACT: This study examines the application of the Random Forest Classifier (RF) model in predicting academic success among adult learners in higher education. It focuses on evaluating the model's effectiveness using key statistical measures like accuracy, precision, recall, and F1 score across a comprehensive dataset from 2013–14 to 2021–22, which includes variables such as age, ethnicity, gender, Pell Grant eligibility, and academic performance metrics. The research highlights the RF model's capability to handle large datasets with varying data types and demonstrates its superiority over traditional regression models in predictive accuracy. Through an iterative process, the study refines the RF model to better predict educational outcomes and explores the significant predictors of academic success among adult learners. Age, attendance, and financial aid availability (Pell Grant eligibility) emerge as critical factors influencing graduation rates. The study emphasizes the need for educational institutions to leverage machine learning to develop more personalized, data-driven strategies that address the unique needs of adult learners. It proposes future research directions to further explore the impacts of socio-demographic factors on student success and to expand the application of machine learning in educational policy and practice. This research contributes to the broader discourse on enhancing adult education through advanced analytical techniques and offers insights into optimizing educational strategies to support a diverse student population.

KEYWORDS: *Machine Learning, Adult Education, Predictive Analytics, Random Forest Classifier, Educational Outcomes*

I. INTRODUCTION

Machine learning (ML) has emerged as a transformative force in educational research, particularly through its application in analyzing and evaluating student performance data. According to Baashar et al. (2022) and Mandinach and Schildkamp (2020), the efficacy of machine learning models in accurately forecasting student performance, highlighting the broad potential of ML technologies in education. Further research by Oyedeji et al. (2020) and Ghasemaghaei (2019) emphasize the importance of early performance predictions, which are crucial for timely interventions in educational systems. Additionally, investigations into technical education by Berriri et al. (2021) and Chen et al. (2020) explore how different algorithms can be effectively selected and implemented to enhance teaching and learning processes. ML can be used in higher education to create personalized learning experiences through adaptive learning systems, as demonstrated by Roberts et al. (2016), who revealed how ML could adjust educational content to suit the individual needs of students. Likewise, Marzuqi et al. (2021) applied decision tree graphical methods and the CHAID algorithm to categorize and forecast various educational outcomes with a high accuracy rate. Lee et al. (2020) concentrated on dropout prediction in online courses, finding key predictors like technological self-efficacy and previous online learning experiences using ensemble methods and neural networks. These varied uses of ML not only improve the ability to examine complex educational data but also support the creation of data-driven strategies that enhance educational programs and inform policy making.

The National Student Clearinghouse Research Center (NSCRC, 2023) found that fewer young people are going to college compared to previous years, because of low birth rates, less interest in higher education, and less high school graduates. To cope with this change, colleges are targeting adult learners, who make up over 44 million “stop out” students with some college but no credential (NSCRC, 2024). Factors like job market demands and lifelong learning goals drive this trend (Albreiki et al., 2021; Rueda & Swift, 2023). Colleges are also offering more flexible ways of learning, such as online courses, part-time programs, and recognition of prior learning, to suit the different needs of adult students (Rueda & Swift, 2023). These efforts show how higher education needs to adjust and cater to a diverse and changing student population.The conventional models and approaches, while proficient in general student data analysis, often overlook the specific nuances and variables pertinent to adult education. Adult learners present distinct characteristics and requirements, such as balancing education with work and family commitments, which may not be adequately captured by traditional predictive models. This oversight can lead to a lack of tailored interventions and support mechanisms, potentially hindering the academic success and retention of this demographic (Ashaari et al., 2020; Feng, 2021).

As the landscape of higher education shifts focus to attracting the growing number of SCNC population, a group with vastly different educational needs and challenges than traditional students, there is an opportunity to utilize ML applications to dissect and address the distinct challenges and backgrounds associated with adult learner. The institutions that can effectively leveraging these technologies, also have the opportunity understand and support the unique challenges faced by this growing population (Rueda & Swift, 2023). Therefore, this study aims to employ advanced machine learning techniques, specifically utilizing the RF classifier model, to accurately predict and enhance the academic trajectories of adult learners and explore the effectiveness and accuracy of this model in understanding the factors that most influence adult learner success in higher education, specifically graduation rates.

Random Forest Classifier : The Random Forest Classifier (RF) is a classification and regressive ensemble learning model that constructs decision trees trained on different segments of the same training set (Raschka & Mirjalili, 2022). This powerful tool analyzes complex data sets and for high performance metrics in terms of accuracy, precision, and recall across several studies (Hamoud et al., 2018; Moscoso-Zea et al., 2019; Xu et al., 2019; Ivanov, 2020). Its adequacy in handling giant datasets, relatively low computational demands, and superior predictive accuracy renders it an optimal instrument for educational data analysis (Taye, 2023). This ML model's effectiveness surpasses traditional regression techniques in the field of institutional research and provided deeper insights and more reliable forecasts (Xu et al., 2019).

The advantages of the RF Classifier extends beyond its technical capabilities. Its ensemble approach, aggregating the outcomes of numerous decision trees to improve the model's overall accuracy and reduce the risk of overfitting, has been important in its success in educational settings. By leveraging this methodology, can capture a more nuanced understanding of the factors influencing adult learners' educational trajectories, thereby facilitating the development of targeted interventions and support mechanisms (Ivanov, 2020; Taye, 2023). Moreover, the adaptability of the RF Classifier to various data types and its inherent feature selection capabilities have allowed researchers to identify and prioritize the most significant predictors of graduation rates among adult learners. This aspect is particularly beneficial in educational research, where the determinants of student success are multifaceted and intertwined. This body of research emphasizes machine learning's capacity to enhance data-driven decision-making and support the development of inclusive and flexible educational models that cater to adult learners (Ryan & Deci, 2000; Ivanov, 2020; Salihoun, 2020; Rueda & Swift, 2023).

II. LITERATURE REVIEW

Utilizing Random Forests to Forecast Performance of Adult Learners : Studies have examined the application of RFs in forecasting the success rates of adult learners in higher education settings. Akmeshe et al. (2021) and Olukoya (2023) observed that ensemble algorithms were effective in predicting student performance, with Hasan et al. (2020) reporting an accuracy of 88.3 percent. Nirmala et al. (2022) conducted a comparative analysis of boosting machines in determining the completion status of undergraduate studies, concluding that XGBoost, coupled with MissForest imputation, surpassed the performance of RF. Xu et al. (2019) implemented an enhanced RF algorithm for assessing student performance in physical education, attaining an accuracy rate of 88.55 percent. Beaulac and Rosenthal (2019) utilized a RF classifier to forecast student performance based on motivation levels, and Berriri et al. (2021) applied Random Forest for multi-class assessments and predicting academic outcomes. Bantjes et al. (2020) discovered that Random Forests were 82 percent accurate in identifying student dropout rates at a South African university.Contemporary research discussed the significance of machine-learning methodologies in the realm of educational research. Hilbert et al. (2021) and Kannan (2023) both spotlighted the capabilities of random forest models in forecasting student performance and dropout probabilities, with Hilbert et al. (2021) advocated for a fundamental shift in the approach to model evaluation. Korkmaz and Correia (2019) and Son et al. (2021) offered comprehensive reviews of the deployment of ML within educational science research, with Korkmaz and Correia (2019) pinpointed emerging trends such as automation and the assessment of cognitive processes. Meanwhile, Albreiki et al. (2021) and Alturki and Alturki

(2021) concentrated on the application of random forests and ML models in educational data mining, particularly for predicting student outcomes and identifying students at risk. Gaftandzhieva et al. (2022) continued the exploration of these ML techniques within online learning platforms and decision-support systems, particularly for predicting students' academic grades. Triayudi and Fitri (2021) emphasized the vital importance of feature selection and balancing classes in the construction of models for student performance. Son et al. (2021) illustrated how these methodologies can extract meaningful insights from educational datasets. Hilbert et al. (2021) discussed the broad potential and the accompanying challenges of employing ML in the educational sector, touching on aspects like automated assessments and customized feedback. Additionally, Rufai et al. (2021) and Jaiswal et al. (2020) investigated the use of RF and other ML models for forecasting student dropouts and academic performance in higher education settings.

Retention Rates and Socio-Economical Factors : Machine learning has been recognized as a method of predicting patterns of student enrollment, performance, and retention with repeated accuracy. Marcinkowski et al. (2020) noted student retention as a common concern for educational institutions as a stream of annual revenue. Their targeted investigation into which factors influence student retention reinforced the utility of ML models to effectively forecast enrollment and performance metrics (Marcinkowski et al., 2020).

Building on model performance, Cardona et al. (2020) and Palacios et al. (2021) demonstrated the ability of ML models to accurately predict student retention. Their research identifies key predictive factors such as secondary educational scores and community poverty indexes, offering valuable insights into the socio-economic dimensions that necessitate a role in student retention. By pinpointing these factors, their work suggests that ML models can be used to construct pathways for early intervention and strategies to support students more effectively. Job and Pandey (2020) contributed to this discourse by showcasing the high accuracy of RF models in predicting student performance. Their work emphasized the use of ML to provide actionable intelligence for educational institutions and more effective student support mechanisms.

Advancing the analysis, Arqawi et al. (2022) and Pagano et al. (2022) explored the efficacy of ML-based recommendation systems specifically designed to enhance student retention. Their work confirms the utility of machine learning in predicting retention with notable F1 scores but also demonstrates how ML can be leveraged to create personalized interventions (Arqawi et al., 2022). This report on ML-based recommendation systems shows how development in-house ML is used in higher education, evolving from prediction to actively shaping educational policies and practices that support student success.These studies showcased the transformative potential of ML, with emphasis on random forest classifiers, in addressing the challenge of student retention. They highlighted the importance of a holistic approach to educational research and policymaking, empowering educational institutions to craft and execute targeted, efficient, and effective educational initiatives (Arqawi et al., 2022; Pagano et al., 2022). This compilation of work represents the ongoing effort to improve adult student retention and success in higher education.

The Role of Feature Importance in Higher Education : The integration of machine learning in higher education transcends traditional frameworks, playing a crucial role in the analysis of student performance data and forecasting educational outcomes. Various machine learning algorithms, including Random Forests, have proven effective in forecasting student achievement, retention, and graduation probabilities. In educational research, understanding feature importance is essential for pinpointing the key determinants that influence student learning outcomes (Zeineddine et al., 2021).

Various studies have analyzed the role of feature importance in educational modeling. Zaffar et al. (2020) and Jalota and Agrawal (2021) both emphasized the significance of feature selection algorithms, fast correlation-based filter (FCBF) and correlation-based feature selection (CFS) in refining the precision score in predicting student performance. Hessen et al. (2022) compared different feature selection algorithms and introduced attention-based neural networks for feature importance assessment. Alturki and Alturki (2021) and Lebrun and Wuillemin (2021) examined feature selection metrics and proposed a novel interpretation of feature importance. Furthermore, Aguilar et al. (2020) assessed various techniques for extracting features from digital educational resources. Jointly, these studies highlighted the vital role of feature importance in increasing both the accuracy and the interpretability of educational models and underline its importance in the creation of effective educational models. The literature presents a compelling role for machine learning in enhancing educational outcomes for adult learners. The diversity in application of machine learning, from predictive analytics to the creation of adaptive learning systems, discusses the potential to meet the challenges faced by adult learners in higher education. The review identifies key areas where machine learning has been applied, such as student performance prediction and dropout risk assessment, illustrating how these applications contribute to more engaging and effective learning environments (Feng, 2021; Teng et al., 2022). This synthesis points to a continued need for research to refine these models, enhance their accuracy, and expand their applicability, allowing institutions to fully leverage the benefits offered by machine learning technologies.

II. METHODS

In this study, a quantitative evaluation of the Random Forest Classification model, was conducted to assess the effectiveness in predicting degree completion rates among adult learners. Utilizing key statistical measures such as accuracy, precision, recall, and F1 score, the analysis aimed to provide the most reliable forecasts of academic success. The dataset encompassed variables including age, ethnicity, gender, Pell Grant eligibility, and academic performance metrics, spanning the academic period from 2013–14 to 2021–22. This comprehensive dataset allowed for a robust analysis of various factors impacting academic outcomes among adult learners.

Data Collection and Preprocessing : The initial stages of the study involved meticulous data collection and preprocessing, which are crucial for maintaining the integrity and confidentiality of the data. Data was collected securely from a student management system, anonymized, and stored in a cloud-based system with stringent security measures to prevent unauthorized access. The preprocessing phase involved rigorous data cleaning to correct inaccuracies, integration of data from various sources, and transformation techniques such as normalization and encoding. These steps were essential for preparing the data for machine learning algorithms, ensuring that the data was accurate, cohesive, and suitable for detailed analysis.

The preprocessing efforts also included the validation and transformation of data to ensure uniformity and reliability for analysis. Issues such as missing values were addressed by removing records, refining the dataset to 9,999 records with enhanced reliability. The feature selection process was driven by a deep understanding of how various demographic, socioeconomic, and academic factors influence educational pathways. Features such as student type, generation, gender, age, ethnicity, and Pell Grant eligibility were considered for their potential impact on educational trajectories. This meticulous approach to feature selection and data preparation aimed to optimize the predictive accuracy of the models and provide meaningful insights that could inform educational strategies and support systems for adult learners.

Model and Evaluation : The model building and evaluation procedures for this study involved a structured approach, beginning with the segmentation of the dataset into training and testing subsets. An 80/20 split ratio was employed, assigning 7,999 entries to the training subset and 2,000 entries to the testing subset. This division is a widely recognized strategy within machine learning (ML) and data science communities, as it ensures a balanced allocation for model training and validation. The training subset is used to calibrate the model's parameters and allows the model to learn from a comprehensive array of data points and scenarios, which is critical for understanding the underlying patterns within the data. Conversely, the testing subset is used to evaluate the model's performance on new, unseen data, assessing its ability to generalize and maintain accuracy across different scenarios.

The development of the predictive models, specifically focusing on Random Forest Classifier, followed a detailed and recursive methodology. The initial parameter settings for this were selected based on a combination of industry best practices and empirical research findings. the initial parameters were chosen to prevent overfitting. The initial parameter selection for each model was a deliberate process guided by established ML theories, empirical evidence from the literature, and insights gained from our dataset's preliminary analysis. This approach ensured that the model was well-suited to uncover meaningful patterns and relationships within the educational data, setting a strong foundation for the subsequent iterative optimization process. Further, this method aimed to optimize the models' predictive accuracy and generalization capabilities, ensuring that it performed consistently well across various data samples. This iterative refinement and evaluation phase is essential for fine-tuning the model to achieve the highest level of accuracy and reliability in predicting outcomes.

Feature Selection Rationale : The rationale behind selecting specific features for forecasting student graduation outcomes is deeply rooted in the recognition of how various student characteristics can impact educational trajectories. This approach aligns with established research methodologies in educational data mining and predictive modeling, aiming to enhance the predictive accuracy and relevance of the model for stakeholders involved in educational planning and support.

The feature selection process for forecasting student graduation outcomes leverages an in-depth understanding of how various demographic, socioeconomic, and academic factors influence students' educational pathways. In the sophisticated landscape of educational data analysis, the feature set composed of 'Type of Student', 'Generation', 'Gender', 'Age', 'Ethnicity', 'Pell Grant Eligibility', 'Attendance', 'Entry GPA', and 'Graduated' serves as a multidimensional framework for understanding and predicting student outcomes. 'Type of Student' is split into 'Traditional' and 'Non-traditional' categories, setting the stage for a comparative analysis between these two distinct demographics. The 'Generation' attribute delineates students as either first-generation college-goers or not, a factor that is indicative of the educational legacy within their families and carries implications for the unique challenges they may encounter, such as navigation through higher education and financial burdens (Davari et al., 2022; Baffa et al., 2023).

'Gender' acknowledges the diverse identities of students and the societal, cultural, and institutional forces that shape educational trajectories. This feature, which encompasses categories 'Male', 'Female', and 'No Gender', allows for the identification of gender-based patterns in graduation rates, thereby informing gender-responsive educational policies (Baffa et al., 2023). 'Age' is segmented into five bins to reflect the varying life stages and associated responsibilities that can influence a student's academic engagement and success, with older students often balancing education with other commitments (Huynh-Cam et al., 2021). 'Ethnicity', represented by five categories, brings to light the socio-cultural dynamics and systemic inequities that influence educational experiences, thereby guiding efforts to promote equity in higher education. Pell Grant eligibility, serving as a marker of socioeconomic status, is necessary for modeling the impact of financial background on academic achievement, offering insights for financial aid strategies (Davari et al., 2022).

The mode of attendance, distinguished between 'Part-time' and 'Full-time', captures the student's engagement level and time constraints, which are vital for understanding how these factors affect academic outcomes. Entry GPA, binned to represent ranges of academic preparedness, acts as a predictor of a student's success trajectory in higher education. These variables enhance the predictive power of models to accurately gauge and address the multifarious factors contributing to student graduation, which is the focal outcome of this analysis (Mustapha, 2023).By weaving together these attributes into a composite picture, the analysis aims to unearth the intricate tapestry of influences that culminate in the pivotal academic milestone of graduation. This approach identifies the precursors of dropout but also underpins the development of targeted interventions to bolster graduation rates. The selection of specific features in Table 1 is guided by a body of research that highlights the importance of each variable in impacting student success and graduation rates.

Table 1

Summary of All Features

No.	Feature	Description	Dummy Variables
1	TYPE	Type of student	1 = Traditional 2 = Non-traditional
2	GENERATION	Generation	1 = Biological parent has completed a college degree 2 = First generation student; Biological parent has not completed a college degree
3	GENDER	Gender	1 = Male 2 = Female 3 = No gender
4	AGE	Age	Data Binned 1 = under age 24 2 = 24–32 3 = 33–48 4 = 49–57 5 = 58+
5	ETHNICITY	Ethnicity	1 = Black/African American 2 = White/Caucasian 3 = Indigenous 4 = Asian/Pacific Islander 5 = Multiple races
6	PELL	Pell Eligible	1 = Pell eligible 2 = Not eligible

No.	Feature	Description	Dummy Variables
7	ATTENDANCE	Attendance	1 = Part-time attendance 2 = Full-time attendance
8	ENTRY GPA	Entry GPA	Data Binned 1 = 3.2–4.0 2 = 2.5–3.1 3 = 2.0–2.4 4 = 1.5–1.9
9	GRADUATED	Graduated	1 = Graduated 2 = Dropout

Note. Table 1 serves as a catalog of features utilized in the analysis, complete with a description and categorical encoding for the purpose of machine learning.

Random Forest Classifier and Model Compatibility : The exploration of ML models relative to their suitability for specific data characteristics is a critical endeavor in educational data science. This analysis draws upon seminal works, including those by Raschka and Mirjalili (2022), Cardona et al. (2020), Saidani (2022), and Salihoun (2020), to evaluate the distinct strengths and limitations of the RF model, especially in processing datasets with a blend of categorical and continuous variables. Random Forest Classifier, recognized for its versatility, excels in managing a wide range of data types. Its robustness to overfitting and ability to maintain model generalizability across various datasets are particularly noteworthy. Moreover, the RF classifier offers insights into which data features most significantly impact predictions through feature importance scores, providing a clear measure of each attribute's contribution to the model's predictive accuracy.The selection of the Random Forest Classifier model hinges on the dataset's unique features and the interplay between them. The RF Classifier brings specific advantages to the table when analyzing data that includes both categorical and continuous variables. The final choice of model should consider the research goals and the dataset's intricacies to ensure the selected approach meets the analytical requirements of the study.

Model Building and Evaluation Procedures : A detailed and recursive methodology was meticulously implemented for the development of the models, specifically focusing on Random Forest Classifier. This approach was designed to encompass the initial construction, subsequent refinement, and thorough evaluation of the model. The initial settings for the model parameters were carefully chosen based on a blend of industry best practices and insights gleaned from empirical research findings. The development of the Random Forest model followed a structured and iterative process. This methodology encompassed not only the initial construction of the models but also their ongoing refinement and rigorous evaluation. The aim was to fine-tune the models in a manner that would yield the most accurate predictions possible.

Initial Parameter Selection Rationale : The foundational parameters for the RF classifier model were carefully chosen to align with both the theoretical framework and practical observations noted in the literature. In the case of the RF classifier, Breiman's (2001) recommended the use of a substantial number of trees to improve accuracy, while also being mindful of the computational load this entails. The initial parameter selection was guided by a balance between computational resources and the quality of the model's output. The number of trees, or 'Estimators', and the 'Max_Depth' of the trees were chosen to optimize this balance. Table 2 illustrates the parameters chosen for three iterations of the RF model and their respective accuracy scores. Adhering to this guidance, the models RF1, RF2, and RF3 were set with varying numbers of estimators: 100, 200, and 50, respectively, to explore the balance between computational efficiency and model performance.

Table 2

Random Forest Model Parameters

Model	Max_Depth	Estimators
RF1	3	100
RF2	5	200
RF3	10	50

Note. Table 2 provides an overview of the parameter configurations and the resulting accuracy for three iterations of the RF Classifier model: RF1, RF2, and RF3.

Findings : The model was subjected to three rounds of iteration, with performance assessed using an array of metrics such as mean accuracy, standard deviation, cross-validation score, precision, recall, and F1 score. These outcomes shed light on the efficacy, dependability, and appropriateness in forecasting student performance within educational datasets. Through repeated cycles of training and evaluation, the model was refined and examined to address the central research questions: determining the effectiveness and accuracy of the model for predicting degree completion and exploring how which factors influence academic success among adult learners.

Table 2 illustrates the results for the RF classifier, which shown notable performance across its three iterations (RF1, RF2, and RF3). In Table 3, the mean accuracy for all iterations stood at 74.9 percent, with standard deviations ranging from 11.6 percent to 15.3 percent, indicating a moderate variation in the model's performance.

Table 3

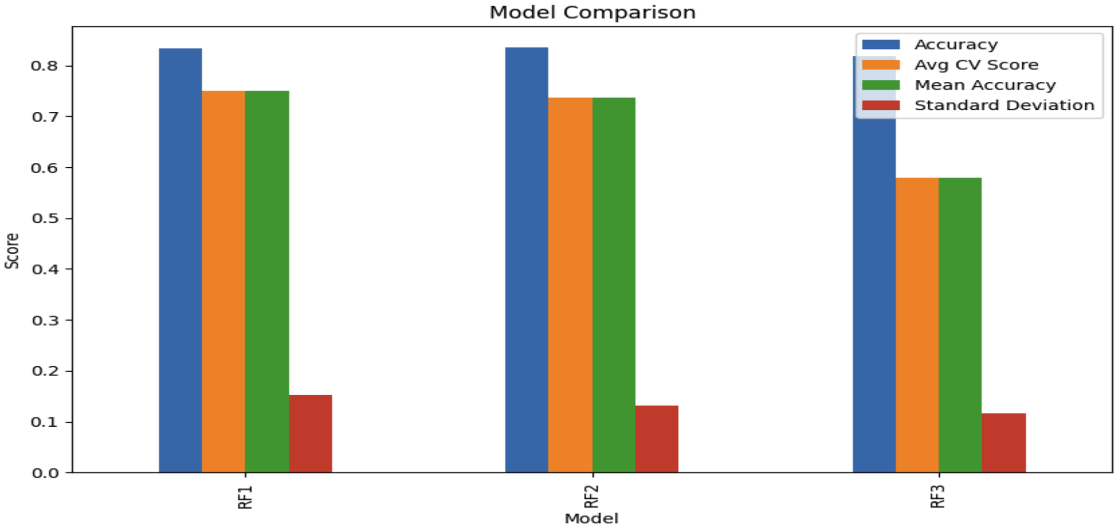
Random Forest Performance Metrics

Model	Accuracy	Avg CV Score	Mean Accuracy	Standard Deviation
RF1	0.8335	0.74918	0.74918	0.15
RF2	0.8350	0.73708	0.73708	0.13
RF3	0.8185	0.57968	0.57968	0.11

Note. Number of records in training set = 7999, Number of records in testing set = 2000.
RF2 exhibits the highest accuracy at 83.5 percent, indicating its strong predictive performance.

In Figure 1, the RF models, in particular RF3, demonstrated a high degree of consistency, as evidenced by its cross-validation score and mean accuracy both aligning at 57 percent. Conversely, RF2, despite having the highest accuracy score, features a notable precision rate of 84.1 percent in Table 4. This high percentage reflects efficiency in accurately predicting positive instances. The standard deviation values for each model (0.15 for RF1, 0.13 for RF2, and 0.11 for RF3) offer insights into the variability of each model's performance across different data subsets, which highlight the importance of model consistency and reliability in the prediction of student outcomes.

Figure 1
Random Forest Models – Accuracy Results



Note. Figure 1 provides a comparative visualization of the performance metrics for three RF Classifier models (RF1, RF2, and RF3) across accuracy, average CV score, mean accuracy, and standard deviation. The scaling of the y-axis from 0.0 to 0.8 compares the models' performance, illustrating their individual strengths and potential areas for enhancement.

The number of records in training set = 7999, Number of records in testing set = 2000.

Table 4

Random Forest Model Effectiveness and Reliability Scores

Model	Accuracy	Precision	Recall	F1-Score
RF1	0.8335	0.824251	0.941634	0.879041
RF2	0.8350	0.840828	0.916732	0.877141
RF3	0.8185	0.823282	0.913619	0.866101

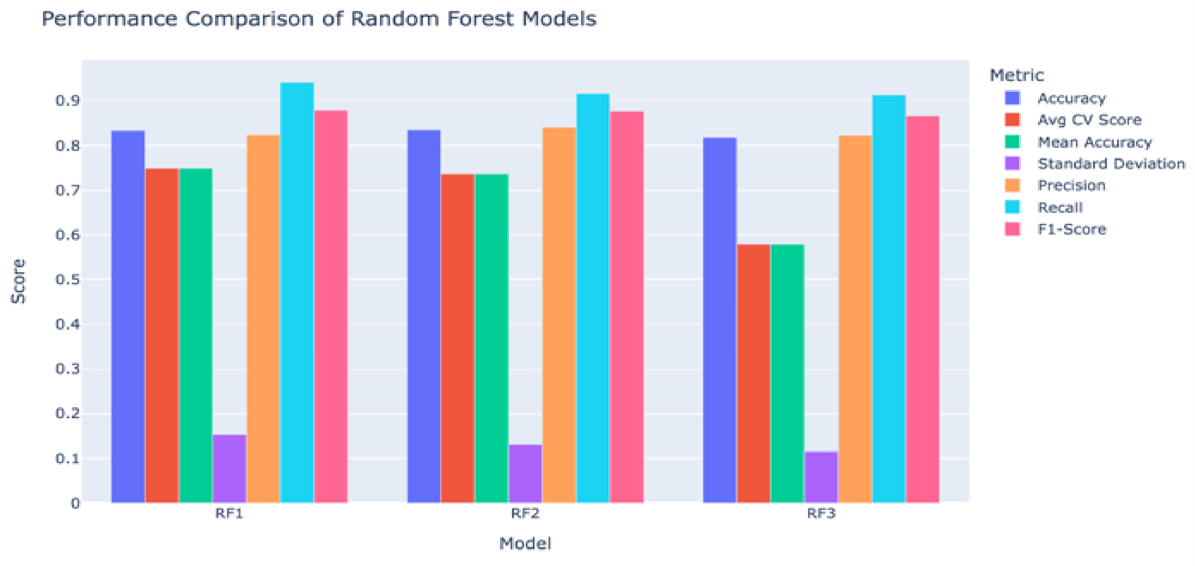
Note. Table 4 presents a detailed comparative analysis of the effectiveness and reliability of three RF Classifier models—RF1, RF2, and RF3—through the lens of four critical performance metrics: accuracy, precision, recall, and F1-score. Number of records in training set = 7999, Number of records in testing set = 2000.

These metrics offer a comprehensive overview of each iteration's capability to predict student outcomes accurately and reliably within a dataset. RF1 showcases a commendable accuracy of 83.35 percent, which is slightly surpassed by RF2 with an accuracy of 83.5 percent. RF3, while displaying a robust performance, has a marginally lower accuracy of 81.85 percent. This slight variance in accuracy among the models indicates their close competitiveness in terms of overall predictive performance. Precision, a metric that evaluates the model's ability to identify only the relevant instances correctly, is highest in RF2 at 84.08 percent, suggesting that it is the most reliable model for minimizing false positives. RF1 and RF3 exhibit similar precision levels, 82.42 percent and 82.32 percent points to their effectiveness in predicting accurate outcomes but with a slightly higher chance of including false positives than RF2.

The recall metric, which assesses the model's ability to capture all relevant instances, is exceptionally high in RF1 at 94.16 percent, indicating its superior capability of identifying true positive outcomes. RF2 and RF3 show a slightly lower recall, 91.67 percent and 91.36 percent, revealing that each is somewhat less effective than RF1 at capturing all positive cases. The F1-score, which balances precision and recall, is highest for RF1 at 87.90 percent, demonstrating its strong ability to maintain an equilibrium between accurately predicting positive instances and minimizing false negatives. RF2 and RF3 follow closely with F1-scores of 87.71 percent and 86.61 percent. Figure 2 captures these comparative visualizations of all performance metrics for three RF Classifier models (RF1, RF2, and RF3). These metrics include accuracy, average CV score, mean accuracy, standard deviation, precision, recall, and F1-Score.

Figure 2

Random Forest – All Metrics



Note. The number of records in training set = 7999, Number of records in testing set = 2000. The scaling of the y-axis from 0.0 to 0.8 compares the models' performance, illustrating their individual strengths and potential areas for enhancement.

These findings show the differences in model performance, with RF2 leading in accuracy and precision, RF1 excelling in recall and achieving the highest F1-score, and RF3 showing strong overall performance but trailing slightly behind the other two models in all metrics. These findings highlight the importance of considering multiple metrics to evaluate the effectiveness and reliability of ML models, as each model exhibits unique strengths that might make it more suitable for specific applications or contexts.

Analysis : The Random Forest Classifier, comprising RF1, RF2, and RF3, underwent a meticulous evaluation to determine their generalization capabilities on a test dataset. Table 5 lists the model parameters, such as Max_Depth and Estimators, which were deliberately varied to identify the configuration that yielded optimal performance. The analysis, detailed in Table 5, indicated that RF2, which was configured with a Max_Depth of 5 and 200 Estimators, reached the highest accuracy of 83.5 percent. This suggests that a more intricate model structure is adept at discerning subtle patterns within the data, thereby enhancing predictive accuracy.

Table 5
Random Forest Parameters and Accuracy

Model	Max_Depth	Estimators	Accuracy
RF1	3	100	0.8335
RF2	5	200	0.8350
RF3	10	50	0.8185

Note. Number of records in training set = 7999, Number of records in testing set = 2000.

Table 5's exposition of model parameters lays the foundation for understanding the complexity and capability of each Random Forest iteration. RF1, with a Max_Depth of 3 and 100 Estimators, demonstrated considerable effectiveness with an F1 score of 87.9 percent as reflected in Table 4. This performance highlights the fact that even less complex models can yield high generalizability, potentially reducing the risk of overfitting and ensuring robust performance on unseen data. RF2's configuration represents a balanced approach, offering a deeper insight into the data without overly complicating the model. The increase in both Max_Depth and the number of Estimators, as compared to RF1, correlates with the improved accuracy, substantiating the hypothesis that a moderate increase in model complexity can enhance performance. RF3, with the most profound Max_Depth of 10 and the least number of Estimators at 50, did not achieve the same level of accuracy as RF2. This could imply that there is a threshold beyond which increasing the depth without enough estimators may not contribute positively to model performance, possibly due to overfitting or not capturing enough generalizable patterns in the training data.

Table 6
Random Forest Feature Importance

Model	Age	Attendance	Pell	Entry GPA	Ethnicity	Generation
RF1	0.40	0.33	0.15	0.01	.01	.01
RF2	0.46	0.29	0.08	0.02	.01	.01
RF3	0.50	0.22	0.07	0.04	.03	.01

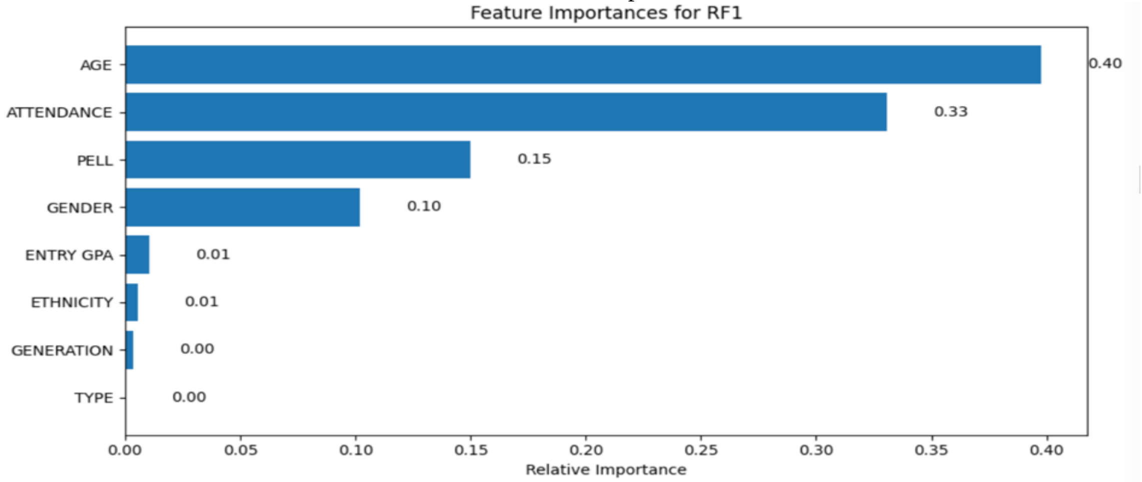
Note. Table 12 provides a quantitative analysis of the feature importance as assessed by three different RF models: RF1, RF2, and RF3.

Across all three RF iterations, Age was consistently attributed the highest feature importance, with its impact rising from 40 percent in RF1 to 50 percent in RF3. This progression accentuates the centrality of Age as a variable, potentially indicating that older students have different success rates or challenges compared to their younger counterparts. Attendance was the second most influential feature in RF1 but saw a decrease in its relative importance across RF2 and RF3. This persistent yet diminishing importance could reflect the nuanced interplay between regular attendance and other factors that contribute to a student's likelihood of graduating.

The Pell Grant feature, indicative of receiving financial aid, also showed notable importance, particularly in RF1. Although its relative influence decreased across the models, it remained a significant predictor, highlighting financial aid's role in a student's educational trajectory. Other attributes such as Entry GPA,

Ethnicity, and Generation held less sway in the models, suggesting that while they do contribute to the prediction of graduation outcomes, their impact is overshadowed by factors such as Age and Attendance.
In Table 6, the exploration of feature importance across the three iterations provided a substantive understanding of the variables that significantly influence graduation outcomes. In Figure 3, the first iteration, RF1, Age developed as the primary predictor, with a feature importance of 40 percent. This suggests that the likelihood of graduation is strongly associated with the student's age, potentially reflecting the impact of maturity and life phase on educational attainment. Also seen in Figure 3, Attendance was identified as the second most influential feature, with a 33 percent contribution, underscoring the critical role of consistent engagement in academic success. Pell Grant eligibility was also a notable factor, accounting for 15 percent of the predictive power, highlighting the significance of financial support in the journey towards graduation.

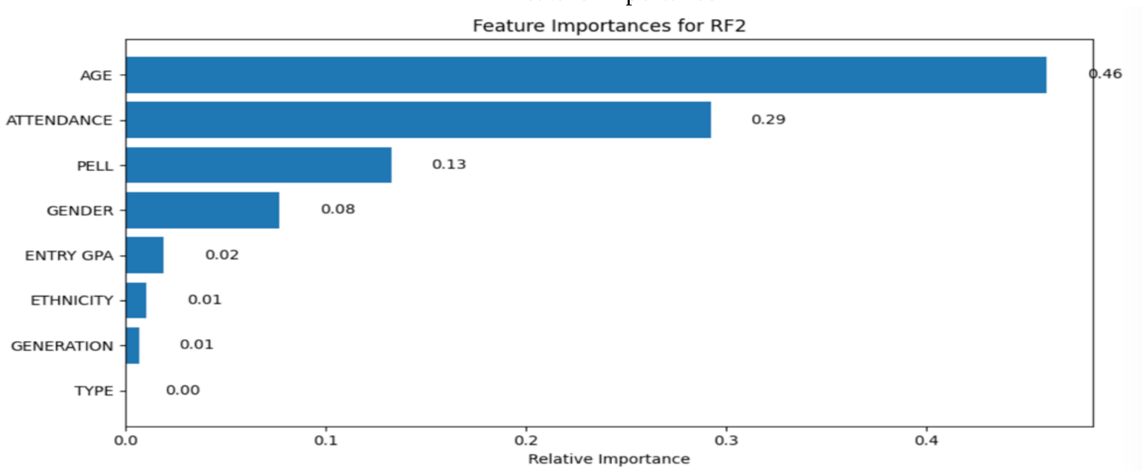
Figure 3
RF1 Feature Importance



Note. Figure 3 identifies the three most important predictors in relation to graduation outcomes resulting from RF1 model iteration.

In Figure 4, the second iteration, RF2, reaffirmed the predominance of Age as a predictor, increasing its feature importance to 46 percent. This increment might be attributed to the model's enhanced complexity, which allowed for a deeper understanding of how age interacts with other variables in the context of graduation. Attendance, while still a significant predictor, saw a slight decrease in its relative importance, contributing 29 percent. Pell Grant eligibility continued to be a pertinent factor, though its influence slightly decreased to 13 percent, indicating that while essential, the model began capturing additional nuances that affect graduation outcomes.

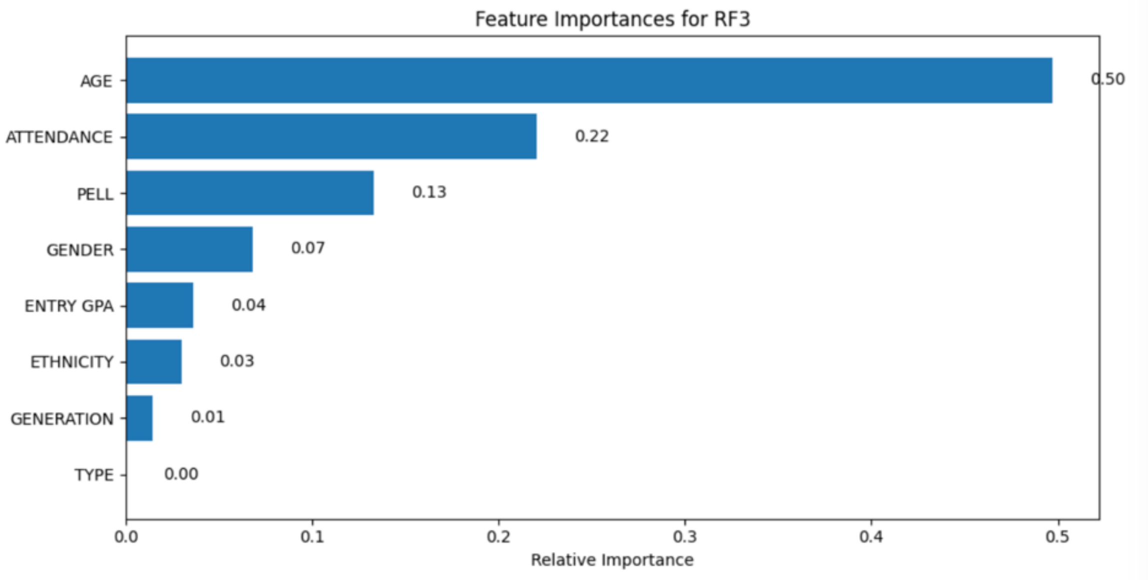
Figure 4
RF2 Feature Importance



Note. Figure 4 identifies the three most important predictors in relation to graduation outcomes resulting from RF2 model iteration.

In Figure 5, the final iteration, RF3, shows the trend of Age as a dominant predictor continued, with its feature importance peaking at 50 percent. This substantial weightage indicates a consistent recognition across models of the age factor as a critical determinant of graduation likelihood. Attendance, with a feature importance of 22 percent, remained an essential predictor, albeit with reduced influence compared to the previous iterations. Pell Grant eligibility maintained a steady significance with a 13 percent contribution, reiterating the consistent role of socioeconomic status in educational achievement.

Figure 5
RF3 Feature Importance



Note. Figure 5 identifies the three most important predictors in relation to graduation outcomes resulting from RF3 model iteration.

These results show the factors that influenced graduation outcomes. The consistency of age as a leading indicator across all iterations highlights a clear pattern, suggesting that initiatives aimed at supporting students should be cognizant of the different needs and challenges associated with their age groups. The importance of attendance across models signals the value of engaging students actively in their educational journey (Mustapha, 2023). Pell Grant eligibility's persistent presence as a key factor emphasizes the need for financial aid and support mechanisms to assist students from diverse socioeconomic backgrounds in completing their educations. These insights are invaluable for shaping targeted strategies that can enhance student retention and graduation rates.

III. CONCLUSIONS

The RF classifier showed a robust balance between accuracy and generalizability and revealed varying degrees of accuracy, influenced by their respective configurations of Max_Depth and Estimators. RF2, with its medium complexity (Max_Depth of 5 and 200 Estimators), achieves the highest accuracy (83.5%), suggesting an optimal balance between model depth and the number of trees for capturing generalizable patterns without overfitting. The feature importance analysis across RF models consistently highlights Age and Attendance as significant predictors of academic success, with Age gaining prominence in more complex models (RF3). This trend shows the critical role of demographic and engagement factors in influencing educational outcomes, with financial aid (Pell) also recognized as a key determinant. The comparative analysis of the RF iterations revealed insightful findings into the complexity of forecasting academic success among adult learners. A critical observation was the nuanced balance required between model complexity and predictive accuracy. Iterations that are too complex risk overfitting and thus losing their generalizability, while overly simplicity may not capture the intricate patterns essential for accurate predictions. Across the board, Age, Attendance, and Pell Grant eligibility stand out as universal predictors of academic success, highlighting the significance of these factors in the predictive model focused on education. Similar to the findings in Suhaimi et al. (2019), Roy et al. (2017), and Anuradha et al. (2017), Age, among other factors, was highlighted as one of the most significant factors in predicting student graduation.

Recommendations for Future Research : There are many research possibilities for examining how adult student success is related to age, attendance, and Pell Grant eligibility. A qualitative study could investigate how different adult age groups are affected by their learning experiences, study habits, and cultural backgrounds by interviewing adults who have come back to higher education. Also, using new data to repeat previous studies that highlighted GPA as an important measure of success could show if GPA is still a valid indicator. Further research could explore how GPA affects the first and subsequent college attempts of adult learners, and how its influence may differ as students come back to school after significant life experiences. Expanding this research to include factors such as socioeconomic status, employment, and family responsibilities would provide a holistic view of the student experience using both quantitative and qualitative methods.

Additionally, examining faculty and policymaker views on machine learning and data-driven decision-making could show how these tools shape institutional policies, especially when data contradicts traditional views. This could inform resource distribution and institutional changes. There's also potential to investigate how higher education institutions handle technological developments and the implementation of machine learning, focusing on data gathering and operational capacities.These research directions emphasize the need for a subtle, evidence-based approach in making educational choices that could improve the inclusivity, flexibility, and supportiveness of higher education for adult learners. The findings could have a major impact on policy development, improve institutional practices, and enrich services for adult students.

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