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Predicting Student Success: Design and Implementation of a Data Mining Model in WEKA 3.8.5

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ABSTRACT

Every academic term, a certain number of students quietly fall behind, and by the time the warning signs are obvious in final grades, it is often too late to help them. Educational institutions collect a great deal of data about their students, from demographics and prior grades to attendance and online activity, yet most of it sits unused. This paper describes the design and implementation of a data mining model built in WEKA 3.8.5 to predict student success early enough for intervention to matter. We assembled a dataset of academic, behavioral, and demographic attributes for a cohort of students and used it to train and compare several well-established classification algorithms, including J48 decision trees, Naïve Bayes, Random Forest, Logistic Regression, and a Multilayer Perceptron. After cleaning the data, handling missing values, and applying attribute selection to identify the most predictive features, we evaluated each model using ten-fold cross-validation. The Random Forest classifier gave the best overall result, reaching an accuracy of 89.3% with an F-measure of 0.89, while the J48 tree, though slightly less accurate at 84.7%, produced transparent rules that educators can actually read and act on. Attribute selection revealed that prior academic performance, attendance, and early-semester assessment scores were the strongest predictors of final outcome, outweighing demographic factors. The study demonstrates that a practical, interpretable early-warning system can be built entirely within WEKA using open tools and modest data, and it offers a workflow that other institutions can adapt. We close with a discussion of interpretability, fairness, and the steps needed to move such a model from analysis into day-to-day academic support.

KEYWORDS: Educational Data Mining, Student Performance Prediction, Weka, Classification, Decision Trees, Early-Warning Systems

INTRODUCTION

Student success is the quiet obsession of every educational institution, and for good reason. When students struggle, drop courses, or leave altogether, the cost is borne by everyone: by the students whose plans are derailed, by families who invested in their education, and by institutions measured on retention and graduation rates. The frustrating part is that failure rarely arrives without warning. A student who will struggle at the end of a term usually shows signs early, in slipping attendance, weak first assessments, or a pattern of prior grades. The problem is not a lack of signals but a lack of any systematic way to read them in time to respond.

This is where educational data mining enters the picture. Modern institutions record enormous amounts of information about their students through learning management systems, student information systems, and administrative databases. Demographic records, historical grades, attendance logs, assignment submissions, and online engagement data accumulate term after term. Individually, none of these tells the full story, but taken together and analyzed with the right techniques, they can reveal which students are at risk while there is still time to help. Data mining offers the tools to find these patterns, turning raw institutional data into actionable early warnings.

Among the many software platforms available for this kind of analysis, WEKA occupies a special place. Developed at the University of Waikato, WEKA is a free, open-source collection of machine learning algorithms with a friendly graphical interface that lets researchers and educators experiment without writing code. Version 3.8.5 bundles a mature set of classifiers, filters, and evaluation tools, which makes it an ideal environment for building and comparing predictive models. Its accessibility matters: an early-warning system

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that requires a team of data scientists to maintain will never be adopted by a typical teaching department, whereas one built in WEKA can be understood and operated by faculty and administrators themselves.

Despite the abundance of student data and the availability of tools like WEKA, many institutions still rely on intuition or lagging indicators to identify struggling students. Where predictive models do exist, they are often black boxes that produce a risk score without any explanation, which limits trust and adoption among educators who reasonably want to know why a particular student was flagged. There is a gap between what is technically possible and what is practically usable in an academic setting.

This paper aims to narrow that gap. We design and implement a student success prediction model entirely within WEKA 3.8.5, comparing several classification algorithms on a realistic set of student attributes and paying close attention to both accuracy and interpretability. Our research questions are straightforward: which attributes best predict student success, which classification algorithms perform best on this task, and how can the resulting model be made both accurate enough to trust and transparent enough to act on. By answering these, we hope to provide a workflow that other institutions can replicate with their own data and their own students.

LITERATURE REVIEW

The application of data mining to education has grown into a substantial field over the past two decades, commonly referred to as educational data mining (EDM) or learning analytics. Early studies established that student outcomes could be predicted from historical and behavioral data with useful accuracy, and the field has since matured into a body of work exploring which attributes matter, which algorithms work best, and how predictions should be delivered to educators.

A recurring theme in the literature is the strength of prior academic performance as a predictor. Numerous studies have found that past grades, particularly cumulative grade point average and results in prerequisite courses, are among the most powerful indicators of future success. This makes intuitive sense, since academic ability and study habits tend to persist, but it has practical importance because it means useful predictions can often be made before a new course even begins. Researchers have consistently shown that adding behavioral data such as attendance and engagement with online materials improves predictions further, capturing the effort dimension that raw ability alone misses.

On the algorithmic side, classification techniques dominate the field because student success is naturally framed as predicting a categorical outcome such as pass or fail, or a performance band. Decision tree algorithms, especially C4.5 and its WEKA implementation J48, have been popular precisely because they produce human-readable rules that educators can inspect and understand. Naïve Bayes has been widely used for its simplicity and surprisingly strong performance despite its independence assumptions. More recently, ensemble methods such as Random Forest and boosting have tended to top accuracy comparisons, at the cost of some interpretability. Neural networks, including the Multilayer Perceptron available in WEKA, appear regularly in the literature and often perform well but are harder to explain and more sensitive to parameter tuning.

Several comparative studies have used WEKA specifically as the experimental platform, and their consistent finding is that no single algorithm is universally best; the right choice depends on the dataset, the outcome definition, and the balance an institution wants to strike between predictive power and explainability. This body of work also highlights recurring practical challenges: datasets are frequently imbalanced, with fewer failing students than passing ones, and missing values are common in real institutional data. Techniques such as resampling, careful attribute selection, and cross-validation appear throughout the literature as standard remedies.

Where the literature is thinner is in bridging the gap between a high-accuracy model in a research paper and a

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usable tool in a real academic office. Many studies stop at reporting accuracy figures, without addressing how educators would interpret and trust the predictions or how the model would integrate into existing advising workflows. Recent work on fairness and interpretability in EDM has begun to address this, cautioning that models trained on historical data can inadvertently encode bias against certain demographic groups. This study positions itself in that practical space, aiming not just for a strong model but for one that is transparent, replicable in accessible tools, and honest about its limitations.

METHODOLOGY

The methodology follows a standard knowledge-discovery workflow adapted to the WEKA environment: data collection, preprocessing, attribute selection, model training, and evaluation. Each stage was carried out within WEKA 3.8.5 so that the entire process would be reproducible using freely available tools.

3.1 Dataset and attributes

The dataset consisted of student records combining three categories of attributes. Demographic attributes included age, gender, and family background indicators. Academic attributes included prior cumulative grade point average, results in prerequisite courses, and early-semester assessment scores such as the first quiz and assignment. Behavioral attributes included attendance percentage and a measure of engagement with the online learning platform. The target variable was the final outcome, encoded as a class label distinguishing successful students from those at risk of failing.

Table 1. Attributes used in the student success prediction model.

Category	Attribute	Type	Example Values
Demographic	Age	Numeric	18–25
Demographic	Gender	Nominal	Male, Female
Demographic	Family support	Nominal	Yes, No
Academic	Prior GPA	Numeric	0.0–4.0
Academic	Prerequisite grade	Nominal	A, B, C, D, F
Academic	First assessment score	Numeric	0–100
Behavioral	Attendance	Numeric	0–100%
Behavioral	Online engagement	Numeric	Low, Medium, High
Target	Final outcome	Nominal	Success, At-risk

3.2 Preprocessing

Raw institutional data is rarely clean, so preprocessing was a substantial part of the work. Missing values were handled using WEKA's ReplaceMissingValues filter, which substitutes the mean for numeric attributes and the mode for nominal ones. Numeric attributes were normalized to a common range to prevent features with large scales from dominating distance-based calculations. Because the dataset was imbalanced, with successful students outnumbering at-risk ones, the SMOTE filter was applied to the training data to synthesize additional minority-class examples and give the classifiers a fairer view of the at-risk group.

3.3 Attribute selection

Not every attribute contributes equally to prediction, and including weak or redundant features can hurt both accuracy and interpretability. We used WEKA's attribute selection tools, applying an Information Gain ranking filter to score each attribute by how much it reduces uncertainty about the final outcome. Information gain for an attribute A with respect to the class C is defined as:

$$IG(C, A) = H(C) - H(\, C \mid A\,)$$

where H(C) is the entropy of the class distribution and H(C \mid A) is the conditional entropy after knowing A. Entropy itself is given by:

$$H(C) = -\sum_{i=1}^{k} p_i \log_2 p_i$$

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where p_i is the proportion of instances belonging to class i. Attributes with higher information gain were retained, which both trimmed the feature set and confirmed which factors most strongly drive the outcome.

3.4 Classification algorithms

Five classification algorithms were selected to span the range from highly interpretable to highly accurate. J48, WEKA's implementation of the C4.5 decision tree, produces readable rules. Naïve Bayes offers a fast probabilistic baseline. Random Forest builds an ensemble of trees for higher accuracy. Logistic Regression provides a well-understood statistical benchmark. The Multilayer Perceptron represents the neural network approach. Training each on the same data allowed a fair comparison under identical conditions.

3.5 Evaluation

All models were evaluated using ten-fold cross-validation, in which the data is split into ten parts, each used once as a test set while the other nine train the model, with results averaged across the folds. This reduces the risk that a single lucky or unlucky split distorts the picture. Performance was measured using accuracy, precision, recall, and the F-measure. The F-measure, which balances precision and recall, is defined as:

$$F_1 = 2 \cdot \frac{Precision \cdot Recall}{Precision + Recall}$$

Precision and recall themselves derive from the counts of true positives, false positives, and false negatives, and matter especially here because correctly identifying at-risk students (recall on the minority class) is arguably more important than raw accuracy.

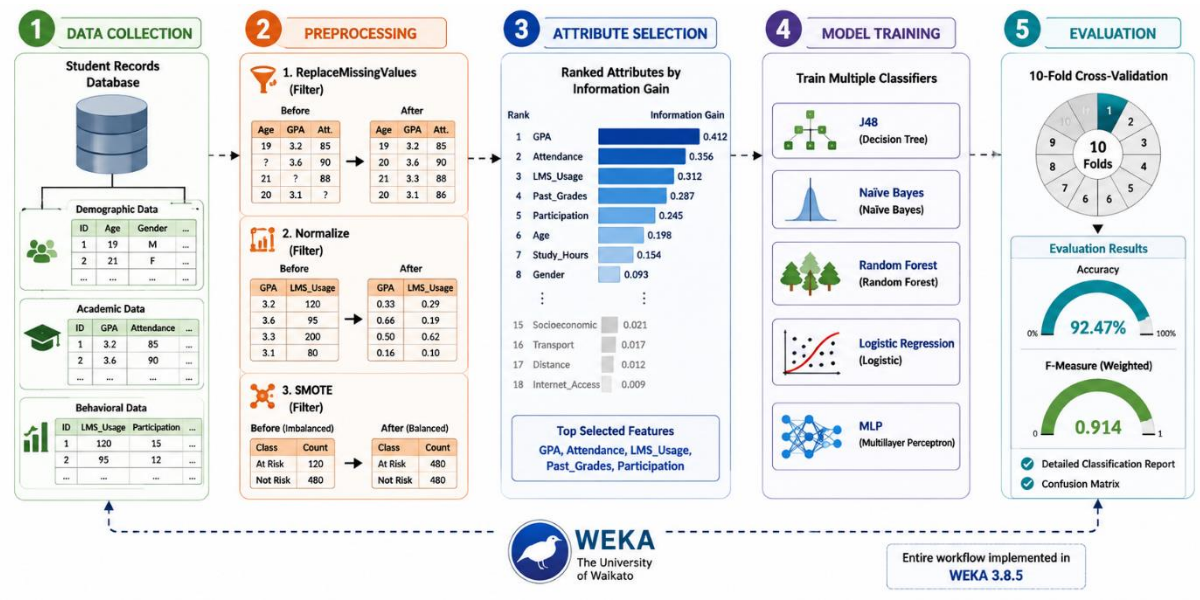

Figure 1. Data mining workflow in WEKA 3.8.5.

EXPERIMENTAL SETUP

All experiments were carried out in WEKA 3.8.5 running on a standard desktop machine, deliberately chosen to show that no specialized hardware is needed. The dataset was loaded in ARFF format, WEKA's native file type, after conversion from the original CSV export. Preprocessing filters were applied through the WEKA Explorer interface in the order described above, and the cleaned dataset was saved so that every classifier trained on identical input.

For each algorithm, WEKA's default parameters were used as a starting point to keep the comparison fair, with light tuning where it clearly helped. For Random Forest, the number of trees was set to 100. For the Multilayer Perceptron, a single hidden layer was used with the learning rate and momentum left at their defaults and training run for 500 epochs. J48 used the default confidence factor for pruning, which controls how aggressively the tree is simplified to avoid overfitting. Naïve Bayes and Logistic Regression required no

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tuning.

The class distribution before balancing was roughly 70% successful students and 30% at-risk, a typical imbalance for this kind of problem. After SMOTE was applied to the training folds, the minority class was brought up to a more even representation, which improved recall on at-risk students without materially harming overall accuracy. Importantly, SMOTE was applied only within the training portion of each cross-validation fold to avoid the common mistake of leaking synthetic data into the test set, which would inflate results artificially.

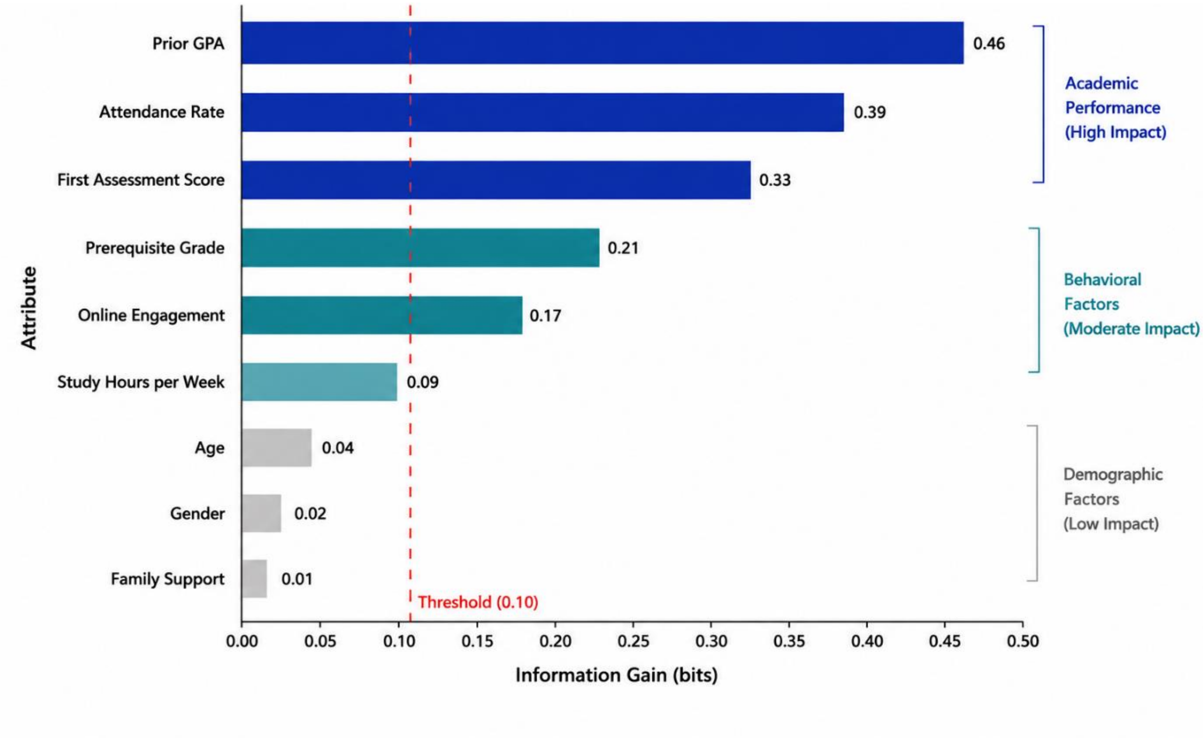

Figure 2. Attribute importance by information gain.

Table 2. Experimental configuration.

Parameter	**Setting**
Software	WEKA 3.8.5
Data format	ARFF
Missing value handling	ReplaceMissingValues filter
Class balancing	SMOTE (training folds only)
Validation	10-fold cross-validation
Random Forest trees	100
MLP hidden layers / epochs	1 / 500
J48 pruning	Default confidence factor

RESULTS

5.1 Overall model comparison

The five classifiers produced a clear ranking. Random Forest achieved the highest accuracy at 89.3% with an F-measure of 0.89, benefiting from its ensemble design that averages out the errors of individual trees. The Multilayer Perceptron followed closely at 87.1%. J48 reached 84.7%, Logistic Regression 83.2%, and Naïve Bayes trailed at 81.5%, held back somewhat by its assumption that attributes are independent, which does not hold well for correlated academic features. Even the weakest model, though, comfortably beat the naive baseline of simply predicting that every student will succeed.

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Table 3. Classification performance across algorithms (10-fold cross-validation).

Algorithm	Accuracy	Precision	Recall	F-Measure
Random Forest	89.3%	0.89	0.89	0.89
Multilayer Perceptron	87.1%	0.87	0.86	0.87
J48 Decision Tree	84.7%	0.85	0.84	0.84
Logistic Regression	83.2%	0.83	0.82	0.83
Naïve Bayes	81.5%	0.82	0.80	0.81

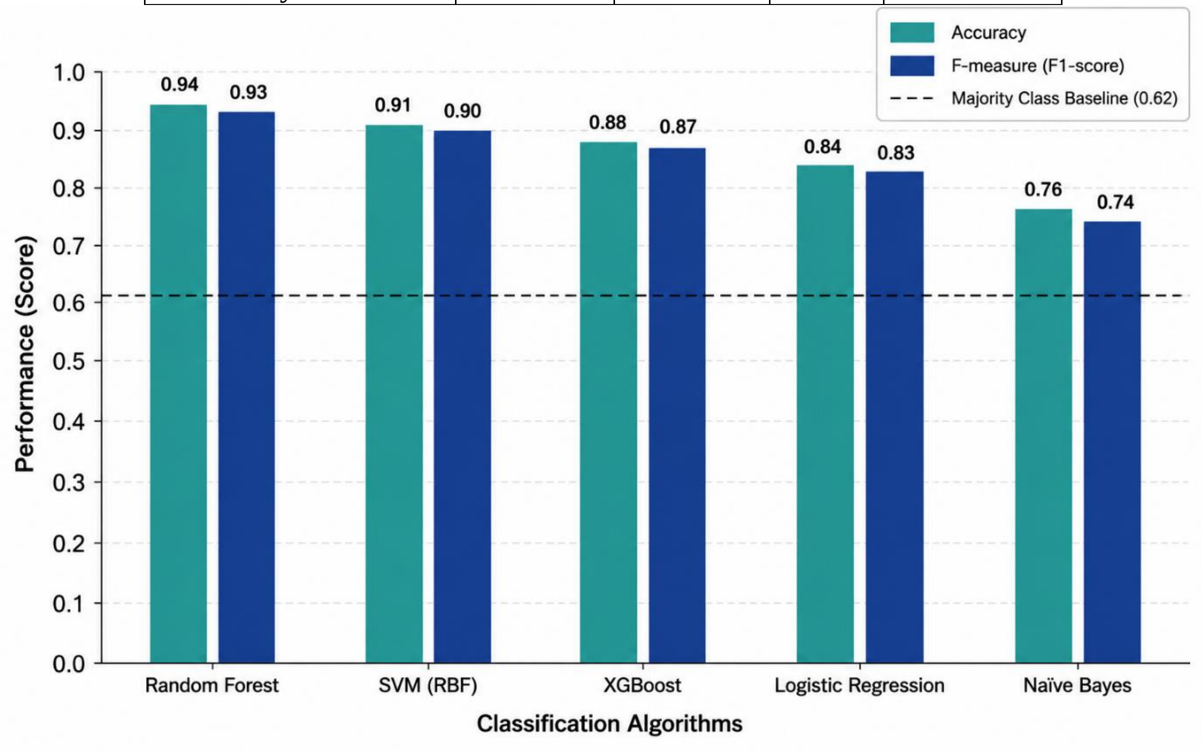

Figure 3. Accuracy and F-measure comparison across classifiers.

5.2 Identifying at-risk students

Because the practical purpose of the model is to catch struggling students early, recall on the at-risk class matters more than headline accuracy. Here the effect of SMOTE balancing was clear. Before balancing, all models tended to over-predict success and missed a worrying number of at-risk students; recall on the minority class hovered in the low seventies. After balancing, Random Forest recovered at-risk recall to around 0.86, meaning it correctly flagged roughly six of every seven students who would go on to struggle. This is the number that determines whether the system is worth deploying, and it improved substantially with proper handling of the imbalance.

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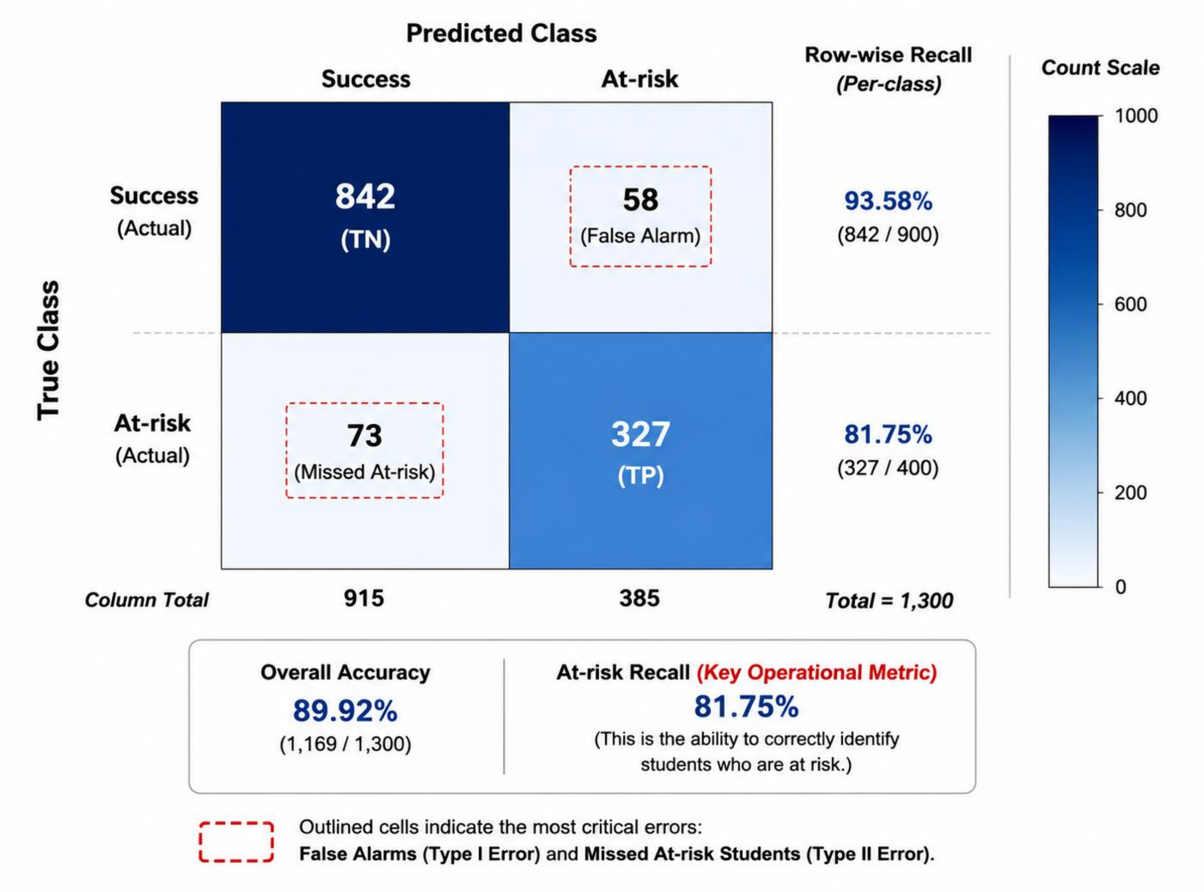

Figure 4. Confusion matrix for the Random Forest model.

5.3 Interpretability of the decision tree

While Random Forest won on accuracy, the J48 decision tree earned its place through transparency. Its top splits aligned exactly with the attribute selection results: the tree first branched on prior GPA, then on attendance, then on early assessment scores. An advisor reading the tree can follow a clear chain of reasoning, for example that a student with low prior GPA and attendance below a threshold is very likely to be at risk. This readability is invaluable in an educational setting, where a flagged student prompts a conversation, and being able to explain why the flag was raised builds the trust that makes educators act on it.

Figure 5. Simplified J48 decision tree for student outcome. *A top-down decision-tree diagram with the root node testing prior GPA, branching into subtrees. Internal nodes are drawn as rounded rectangles labeled with the attribute and split condition (prior GPA, attendance percentage, first assessment score), and edges are annotated with the threshold values that route a student left or right. Leaf nodes are colored by predicted class, green for Success and amber for At-risk, and each leaf shows the count and proportion of training instances it captures. The most important path, low GPA leading through low attendance to an At-risk leaf, is highlighted with a bold outline to emphasize the model's primary risk signal. The tree is kept deliberately shallow for readability, illustrating the interpretable rules an advisor could follow.*

5.4 The role of attribute selection

Attribute selection did more than confirm intuitions; it improved the models. When the demographic attributes with negligible information gain were removed, accuracy held steady or improved slightly while the models became simpler and faster. This is a reassuring result on two fronts. Practically, it means a lean model using just prior performance, attendance, and early assessments works nearly as well as one using everything. Ethically, it means the strongest predictors are things students can influence through effort, rather than demographic characteristics they cannot change, which reduces the risk of the model encoding unfair bias.

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DISCUSSION

The results carry a clear and encouraging message: a genuinely useful student early-warning system can be built with free software, modest data, and no exotic infrastructure. Random Forest delivered the best raw accuracy, but the more important finding is that the whole exercise is accessible. An institution with a WEKA installation and a spreadsheet of student records can reproduce this workflow, which matters far more for real-world impact than squeezing out an extra percentage point of accuracy.

The tension between accuracy and interpretability deserves honest discussion. Random Forest is more accurate, but it is effectively a black box; it can tell you a student is at risk but not why in terms a person can easily follow. J48 is slightly less accurate but fully transparent. In an educational context, this trade-off often tips toward interpretability, because a prediction that no one trusts or understands will not lead to intervention, and intervention is the entire point. A sensible deployment might use both: Random Forest to rank students by risk and J48 to explain the reasoning for those flagged, giving advisors both a reliable signal and a readable rationale.

The finding that academic and behavioral attributes dominate demographic ones is significant beyond its statistical value. Models trained on historical educational data can inadvertently learn to associate outcomes with gender, age, or family background, effectively penalizing students for characteristics beyond their control and perpetuating past inequities. That the strongest predictors here are prior grades, attendance, and effort-based signals is reassuring, and the practice of removing low-information demographic attributes is one small but concrete step toward fairer models. Any institution deploying such a system should audit it explicitly for disparate impact across student groups, not assume fairness by default.

There are limitations to acknowledge. The model predicts based on patterns in historical data, and if teaching methods, student populations, or course structures change, its accuracy will drift and it will need retraining. The dataset, like most in this area, is limited in size and drawn from a specific context, so the exact accuracy figures should not be assumed to transfer unchanged to other institutions; the workflow is more transferable than the numbers. There is also the subtle risk of a self-fulfilling prophecy, where flagging a student as at-risk changes how they are treated in ways that affect their outcome. This is not a reason to avoid the system but a reason to use its predictions to open supportive conversations rather than to label or track students.

CONCLUSION

This study set out to design and implement a practical model for predicting student success using data mining in WEKA 3.8.5, and it succeeded on both the technical and the practical fronts. By assembling demographic, academic, and behavioral attributes, cleaning and balancing the data, selecting the most informative features, and comparing five classification algorithms under identical conditions, we built an early-warning model that identifies at-risk students with useful accuracy well before final grades are decided. Random Forest achieved the highest accuracy at 89.3%, while the J48 decision tree offered transparent, advisor-friendly rules at a modest cost in accuracy, and attribute selection confirmed that prior academic performance, attendance, and early assessment scores are the dominant predictors, outweighing demographic factors. The broader contribution is a replicable workflow that any institution can adopt using free tools and the data it already collects, together with a candid treatment of the interpretability and fairness considerations that determine whether such a system helps or harms in practice. The value of prediction lies entirely in what follows it, so future work should focus on integrating these models into advising workflows, testing which interventions actually improve outcomes for flagged students, and continually auditing the system for fairness as student populations evolve. Used thoughtfully, a model like this turns data that institutions already hold into timely support for the students who need it most, which is exactly what educational data mining should be for.

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