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Integrating Random Forest with Neutrosophic Logic for Predicting Student Academic Performance and Assessing Prediction Confidence

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Abstract: This study proposes a hybrid approach to predict students' final academic performance in a mathematics course by integrating Random Forest, a supervised machine learning model, with neutrosophic logic to assess prediction reliability. The objective is to improve educational forecasting by not only predicting grades but also quantifying the confidence of each prediction through neutrosophic components—truth (T), indeterminacy (I), and falsity (F). The model was trained on a dataset of demographic, academic, and social attributes from Portuguese schools, achieving robust performance (MAE = 1.54, R^2 = 0.61). Key contributions include: (1) a framework for transparent AI-assisted decision-making in education, (2) actionable insights for identifying at-risk students, and (3) a novel application of neutrosophic logic to interpret prediction uncertainties. The results demonstrate the potential of combining machine learning with neutrosophic analysis to improve academic interventions.

Keywords: Random Forest, neutrosophic logic, academic performance prediction, educational data mining, prediction confidence, supervised learning

1. Introduction

Education is crucial for long-term economic success [1]. Knowing in advance the performance of students to the final evaluation can improve the situation because in this way teachers can take actionable insights, especially useful in educational settings where the identification of at-risk students is crucial [2]. To achieve it, we may use information and communication technologies to improve things, just as in other situations [3–7].

This work has considered a public dataset on the secondary school academic performance of two Portuguese institutions that is available [8]. In it, two datasets on performance in two different subjects are provided: Mathematics and Portuguese Language. Student grades and other demographic, socioeconomic, and educational data were among the properties of the information, which was obtained from school surveys and reports [9]. In [1], regression and binary / five-level classification tasks were used to model them. Three input selections (e.g., with and without prior grades) and four classification tree models were also examined.

In this work, we will present the training and evaluation of a Random Forest model with the integration of neutrosophic logic for obtaining a hybrid model that not only predicts student outcomes but also interprets the confidence of those predictions. This framework improves transparency in AI-assisted decision-making and supports better academic interventions. With the code available in [10], this work can serve as a basis for future studies on the joint application of

Random Forest and Neutrosophic logic not only to predict outcomes (as in [11– 14]) but also to interpret the confidence of those predictions.

2. Materials and Methods

This study aims to predict the final grades of students using a supervised machine learning model and interpret the reliability of the prediction using neutrosophic logic. The dataset includes demographic, academic, and social variables. Figure 1 describes the steps that we follow to achieve our goal. We describe each one of them in this section.

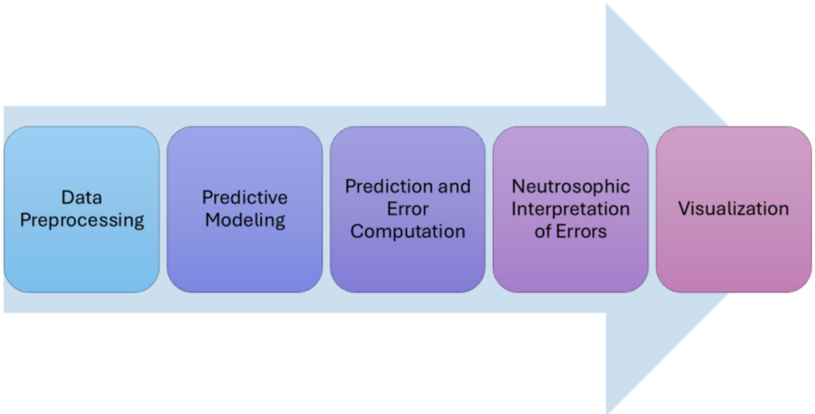

Figure 1. Proposed framework that integrates predictive modeling and neutrosophic logic to assess the confidence of the predictions.

2.1 Data Preprocessing

The dataset considered in this work was loaded from the "student-mat.csv" file containing mathematic student records extracted from [8]. Although the repository includes the academic records of students enrolled in two secondary education courses (Portuguese language and mathematics), only the mathematics results are considered in this work. They were gathered from two Portuguese schools. The data offers comprehensive details on demographics, family history, academic achievement, extracurricular activities, and educational support for students.

The following preprocessing steps were applied:

- Categorical variables were converted to factors (e.g., sex, school).
- The target variable G3 (final grade) was converted to numeric to support regression modeling.
- The dataset was split into 80% training and 20% testing using stratified sampling.

2.2. Predictive Modeling with Random Forest

G3 (grade in the third quarter) was considered the attribute to predict in [1]. They selected that because G3 (given during the third period) reflects the final year grade and G1 and G2 refer to the grades for the first and second academic periods, respectively, there is a high correlation between the three. Without G2 and G1, predicting G3 is more challenging. For this reason, we considered G3 as the attribute to be predicted.

A Random Forest regression model was trained using the training data, where G3 was predicted based on all other variables. Random Forest was chosen for its robustness, ability to handle nonlinearities, and resistance to overfitting [15]. This model was trained to predict the target variable G3 based on all other available features. The model was built with 100 trees and was evaluated on the test data.

2.3. Prediction and Error Computation

The absolute prediction errors were calculated for each test instance:

$$Absolute\ Error = |Predicted - Actual| \tag{1}$$

These absolute errors serve as the basis for evaluating prediction confidence.

In addition, to assess the performance of the Random Forest regression model, three commonly used evaluation metrics were computed: Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and the Coefficient of Determination (R^2). These metrics provide a comprehensive understanding of the model's accuracy, consistency, and explanatory power.

2.3.1. Mean Absolute Error (MAE)

The MAE measures the average magnitude of errors between the predicted and actual values, regardless of direction. It is calculated as follows:

$$MAE = \left(\frac{1}{n}\right)\sum_{i=1}^{n} |\, y_i - \hat{y}_i| \tag{2}$$

where $\hat{y}_i$ is the predicted value, y_i is the actual value, and n is the number of observations. This metric is intuitive and reflects the average prediction error in the same unit as the target variable. MAE is especially useful when all prediction errors are to be treated equally.

2.3.2 Root Mean Squared Error (RMSE)

The RMSE quantifies the average magnitude of the prediction errors, giving more weight to larger errors by squaring them:

$$RMSE = \sqrt{\left(\frac{1}{n}\right)\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{3}$$

Due to its sensitivity to outliers, RMSE is particularly valuable when large prediction deviations carry significant consequences, such as incorrectly predicting student failure or excellence.

2.3.3. Coefficient of Determination (R^2)

The R^2 score, also known as the coefficient of determination, indicates the proportion of variance in the target variable explained by the model:

$$R^2 = 1 - \frac{\left(\sum_{i=1}^{n}(y_i - \hat{y}_i)^2\right)}{\left(\sum_{i=1}^{n}(y_i - \bar{y})^2\right)} \tag{4}$$

A value closer to 1 indicates a strong model fit. In the educational context, a high R^2 means that the model successfully captures patterns affecting student performance.

2.3.4. Summary of Metrics

Table 1. Summary of Evaluation Metrics

Metric	Purpose	Strength
MAE	Average absolute error	Simple and interpretable
RMSE	Penalizes large errors	Sensitive to outliers and highlights high-risk predictions
R^2	Variance explained by the model	Measures overall model fit

These three metrics offer complementary perspectives on model performance, making them well-suited for evaluating predictive models in academic contexts.

2.4 Neutrosophic Interpretation of Errors

Neutrosophy deals with truth (T), indeterminacy (I), and falsity (F). We'll integrate it by:

- Classifying predictions as confident, uncertain, or incorrect based on residuals.
- Assigning neutrosophic values based on prediction error margins.

To assess the reliability of each prediction, neutrosophic values were assigned according to the error magnitude. In this work, T, I, and F imply the following:

- T (Truth): how likely the prediction is correct,
- I (Indeterminacy): the level of uncertainty
- F (Falsity): how likely the prediction is wrong.

The values for T, I, and F were manually defined using the following thresholds:

Table 2. Neutrosophic Logic Rules

Error Range	Truth (T)	Indeterminacy (I)	Falsity (F)	Interpretation
≤ 1	0.9	0.1	0.0	Very confident prediction
$1 < error \leq 3$	0.5	0.4	0.1	Moderate uncertainty
> 3	0.2	0.3	0.5	Poor/unreliable

2.5. Visualization

To show errors in predicted values, a scatter plot that compares the final actual and predicted grades (G3) of the students is considered. To improve this scater plot, we can add the indeterminacy (I) range of values to each predicted value, creating a scatter plot where the size or color of the points represents the indeterminacy level. This will visually communicate the confidence of each prediction alongside the actual vs. predicted values. In addition, another scatter plot is considered to show how T, I, and F vary with the absolute prediction error. This allows an interpretation of prediction reliability across different student cases.

3. Results

3.1. Random Forest Classic Evaluation

When training the Random Forest model, we get the following results, summarized in Table 3.

Table 3. Summary of Metric Results

Metric	Result	Meaning
MAE	1.544304	Average absolute difference between prediction and reality.
RMSE	3.023118	Penalizes larger errors more than MAE.
R^2	0.6122818	How much of the variance in G3 is explained by the model (closer to 1 is better).

Figure 2 presents a scatter plot that compares the final actual and predicted grades (G3) of the students, with the red dashed line representing perfect predictions (Predicted = Actual). The model demonstrates strong performance, as most data points cluster closely around this line, indicating low prediction errors. Points above the line represent over-predictions (where the model overestimates grades), while points below indicate under-predictions.

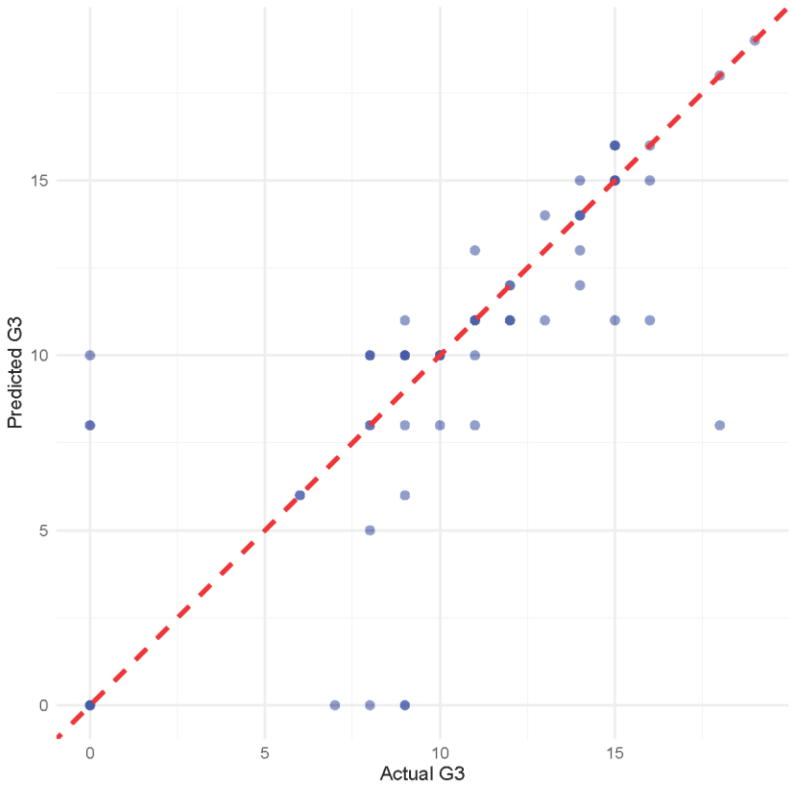

Figure 2. Actual vs Predicted G3 Values.

In Figure 2, the tight distribution of points near the line suggests that the Random Forest model effectively captures the underlying patterns in student performance data, particularly for grades within typical ranges. However, a few outliers deviate significantly from the line, reflecting instances where the model struggles to predict accurately. These discrepancies may arise from unique student circumstances or unaccounted variables in the dataset. The overall alignment of most points with the ideal line underscores the model's reliability for most cases, while the outliers highlight areas where additional data or feature engineering could improve accuracy. This visualization provides educators with a clear and intuitive understanding of the model's strengths and limitations in predicting academic outcomes.

3.2. Neutrosophic Evaluation

The scatter plot of Figure 3 visualizes the relationship between the actual final grades (G3) of students and the grades predicted by the Random Forest model, with the added dimension of indeterminacy (I) represented by the size and color of the points. The dashed red line indicates perfect predictions (where predicted equals actual) and points closer to this line reflect higher accuracy. The size and color of each point correspond to the model's uncertainty: larger, orange points indicate higher indeterminacy (less confidence in the prediction), while smaller, blue points indicate lower indeterminacy (greater confidence). This dual representation allows educators to quickly identify not only the accuracy of predictions but also their reliability, highlighting cases where the model is uncertain—such as outliers or edge cases—that may require further investigation or additional data.

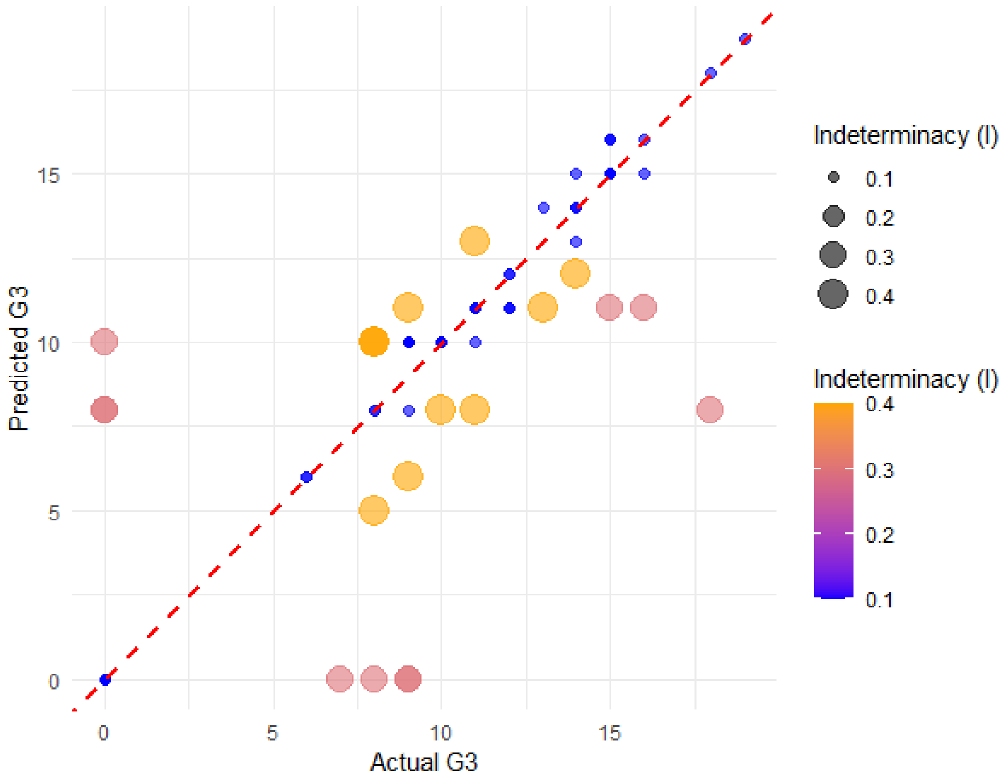

Figure 3. Actual vs Predicted G3 Values with Indeterminacy

The analysis of the plot reveals that the Random Forest model performs well for most students, as evidenced by the clustering of smaller, bluer points near the ideal line. However, larger, orange points—indicating higher uncertainty—tend to appear where predictions deviate significantly from actual grades, particularly at the extremes of the grading scale. This suggests that the model struggles with predicting very high or very low grades, possibly due to fewer data points in these ranges or unaccounted variables influencing performance. The integration of indeterminacy values provides actionable insights: educators can prioritize interventions for students with high-uncertainty predictions, while confidently relying on the model's accurate forecasts for most cases. This approach bridges the gap between raw predictions and practical decision-making, enhancing the model's utility in real-world educational settings.

In addition, the Neutrosophic evaluation added a new layer of interpretation by assigning confidence levels to each prediction. When we apply it to residuals, we get Figure 4. It demonstrates the integration of neutrosophic logic to assess the reliability of the Random Forest model's predictions. The visualization maps each prediction according to its associated truth (T), indeterminacy (I), and falsity (F) values, derived from absolute prediction errors. Predictions with minimal errors (≤ 1) exhibit high truth values (T ≈ 0.9), indicating strong confidence in their accuracy.

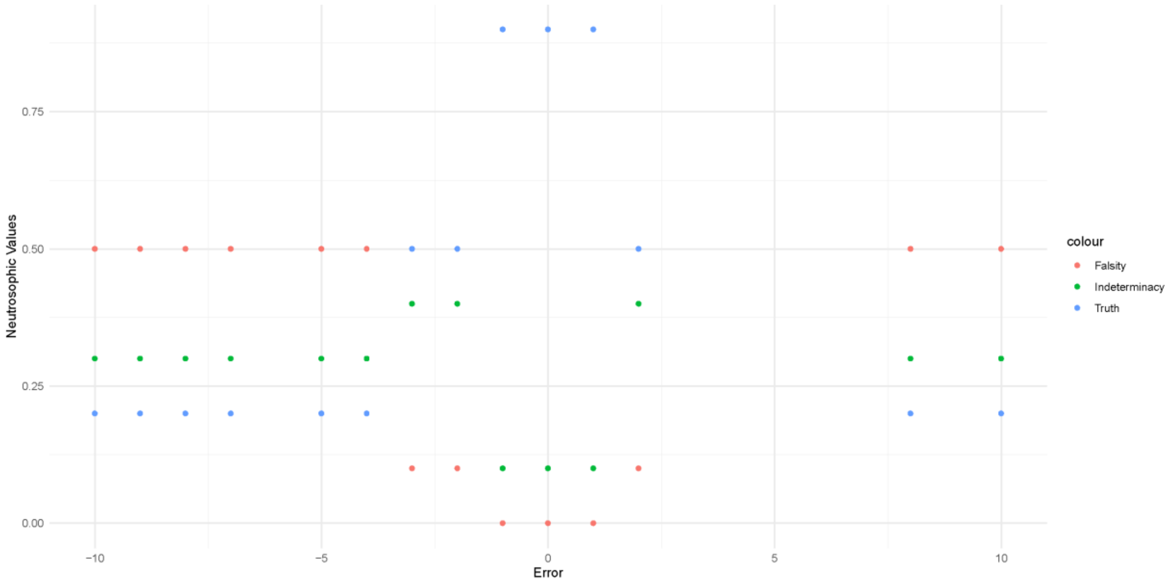

Figure 4. Neutrosophic Interpretation of Prediction Error.

For predictions with moderate errors (1 < error ≤ 3), the figure reveals increased indeterminacy (I ≈ 0.4) and reduced truth (T ≈ 0.5), reflecting uncertainty in the model's output. Such scenarios suggest the need for additional contextual data to improve prediction reliability. Predictions with large errors (> 3) are characterized by high falsity (F ≈ 0.5) and low truth (T ≈ 0.2), flagging them as unreliable. These instances help identify model limitations, prompting further investigation into factors affecting prediction accuracy [16].

Overall, the results of this section have been obtained when executing the code available in [10]. Figures 2 and 3 validate the model's overall accuracy but identifies outliers for improvement. Figure 4 adds interpretability by quantifying confidence, providing actionable insights, especially useful in educational settings where the identification of at-risk students is crucial.

4. Conclusion

This study successfully demonstrates the effectiveness of combining Random Forest regression with neutrosophic logic to predict and interpret student academic performance. The Random Forest model achieved strong predictive accuracy, as evidenced by the clustering of points around the ideal line in Figure 2 and the evaluation metrics (MAE = 1.54, R^2 =0.61). The integration of neutrosophic logic (Figures 3 and 4) further enhanced the model's utility by quantifying prediction confidence through truth (T), indeterminacy (I), and falsity (F) values. This hybrid approach not only provides actionable predictions but also transparently communicates their reliability, enabling educators to prioritize interventions for at-risk students while acknowledging uncertainties. The framework represents a significant advancement in educational forecasting, bridging the gap between machine learning outputs and practical decision-making.

Despite its strengths, the study has limitations. The model's performance may be constrained by the dataset's scope, which excludes contextual factors like individual learning styles or unmeasured socio-economic variables. Additionally, the manual assignment of neutrosophic thresholds (Table 3) introduces subjectivity, suggesting a need for automated or data-driven methods to define these rules. Future work could explore dynamic threshold adaptation, integration of additional data sources (e.g., behavioral or real-time performance metrics), and validation across diverse educational contexts. Expanding the model to other disciplines or longitudinal studies could further generalize its applicability. Addressing these limitations would strengthen the framework's robustness and scalability, paving the way for more nuanced and universally applicable educational tools.

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Conflicts of Interest: The authors declare no conflict of interest.

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