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Financial Forecast Optimization with Ensemble Models and Error Analysis

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Abstrak

Penelitian ini mengusulkan model mitigasi kesalahan yang diterapkan pada sektor keuangan di perguruan tinggi, bertujuan untuk meningkatkan akurasi prediksi dalam model regresi linear yang digunakan untuk memantau dan mengelola keuangan kampus. Dengan menganalisis distribusi kesalahan dari model asli, model tambahan dikembangkan untuk mereduksi dampak kesalahan pada area sensitif yang diidentifikasi. Kedua model ini kemudian digabungkan menjadi satu model ensemble, yang mampu mengurangi kesalahan residual standar (RSE) hingga 7%. Penggunaan model ensemble ini terbukti efektif dalam meningkatkan akurasi hasil dibandingkan dengan model tunggal. Studi kasus menggunakan data keuangan perguruan tinggi, termasuk parameter seperti biaya operasional, pendapatan, dan alokasi anggaran, menunjukkan bahwa mitigasi kesalahan dapat memberikan perbaikan signifikan dalam pengelolaan keuangan kampus, terutama dalam hal perencanaan anggaran dan prediksi pengeluaran. Penelitian ini membuka peluang untuk penerapan lebih luas di sektor pendidikan tinggi yang memerlukan pengelolaan keuangan yang lebih akurat dan efisien.

Kata kunci*— Model Ensemble, Mitigasi Kesalahan, Regresi Linear, Sektor Keuangan*

Abstract

This study proposes an error mitigation model applied to the financial sector in higher education, aiming to improve the prediction accuracy in a linear regression model used to monitor and manage campus finances. By analyzing the error distribution of the original model, an additional model is developed to reduce the impact of errors on identified sensitive areas. These two models are then combined into one ensemble model, which is able to reduce the standard residual error (RSE) by up to 7%. The use of this ensemble model has proven effective in improving the accuracy of the results compared to a single model. A case study using university financial data, including parameters such as operating costs, revenues, and budget allocations, shows that error mitigation can provide significant improvements in campus financial management, especially in terms of budget planning and expenditure prediction. This study opens up opportunities for wider application in the higher education sector that requires more accurate and efficient financial management.

Keywords— *Ensemble Model, Error Mitigation, Linear Regression, Financial Sector*

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1. INTRODUCTION

The financial sector in higher education plays a very important role in ensuring operational sustainability and efficient budget management. Higher education institutions face complex challenges in managing various revenue streams, including from students, government, and grants, as well as various operational expenses such as staff salaries, facility maintenance, and academic development [1], [2]. Accuracy in budget prediction and efficient financial management are essential to maintain the stability and sustainability of the institution. However, in practice, data-based financial management is often faced with uncertainty and errors in predicting various financial parameters. The mismatch between financial model predictions and actual results can cause problems in budget planning, fund allocation, and strategic decision making. Therefore, an approach is needed that is able to mitigate prediction errors, especially in complex scenarios such as financial management of higher education institutions. Linear regression models are often used as financial prediction tools in higher education institutions. However, this model does not always provide accurate results due to systematic errors or fluctuations in input data. To overcome this problem, this study proposes the use of an ensemble model that combines a linear regression model with an error mitigation model [1], [3]. With this approach, it is expected to reduce prediction errors and improve the accuracy of financial management in higher education institutions. This research will focus on the development of error mitigation methods applied to higher education financial data, such as student income, research grants, and operational expenses. Through the use of ensemble models, this research aims to provide better solutions for complex financial management, as well as contribute to more accurate and effective decision making [4], [5].

2. METHODS

To improve the prediction accuracy in higher education financial management, this study uses an ensemble model approach that combines a basic linear regression model with an error mitigation model. This approach aims to overcome prediction errors that often occur in various financial parameters such as revenue, expenditure, and budget allocation. This approach begins with the development of a linear regression model, which is used as a basis for predicting various financial variables such as student income, operating costs, and research grants [6], [7]. The linear regression model serves as a simple baseline model, where input variables such as student enrollment, inflation rate, and government funding allocation are used to predict financial output. However, linear regression models do not always produce accurate predictions, especially when there are unexpected fluctuations in financial data. This causes prediction errors, which need to be mitigated. To address this problem, this study develops an error mitigation model [8]. This model is designed to reduce larger prediction errors in sensitive areas that have been identified from the error distribution analysis. The error mitigation function works by adjusting the initial predictions of the linear regression model based on values that are more susceptible to prediction errors. This error mitigation model effectively improves predictions in months where there are significant financial fluctuations, such as during budget allocations or grant receipts. The final stage in this method is the application of an ensemble model, which combines the output of the linear regression model with the error mitigation model. The ensemble model is expected to be able to improve the weaknesses of the linear regression model by correcting systematic errors that occur in the predictions. Thus, this model provides more accurate and reliable prediction results to assist in financial decision making in higher education [9].

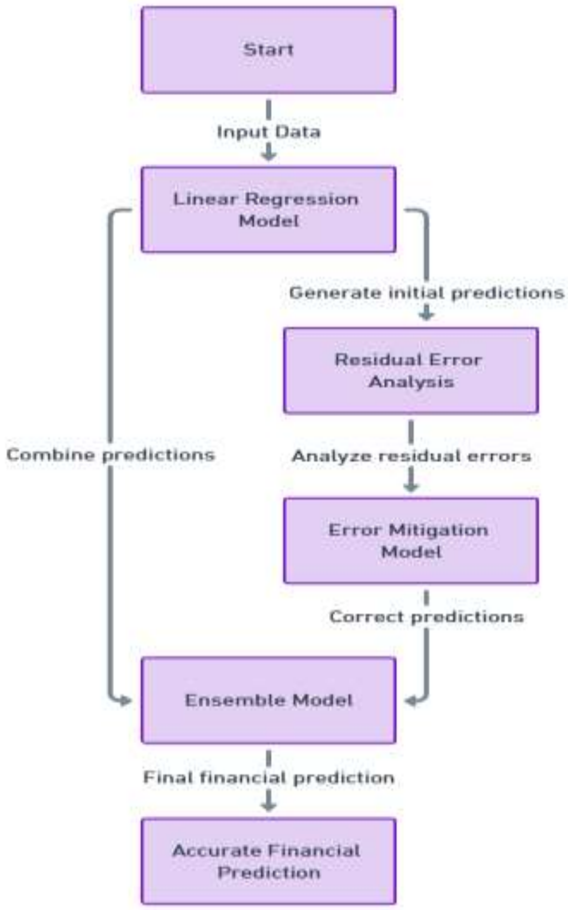

Figure 1 Research Framework

2.1 Linear Regression Model

Linear regression was chosen as the initial approach due to its simplicity, efficiency, and ability to capture linear relationships in financial data. This model is effective for predicting variables such as revenue based on independent variables, such as the number of students and operating expenses. In addition, linear regression has low computational complexity, allowing for rapid exploration of data patterns. This model also provides easily interpretable results through regression coefficients, which indicate the influence of each variable on the predicted outcome. As a baseline, linear regression helps evaluate the performance of advanced models. However, the shortcomings of linear regression, such as the inability to handle non-linear patterns and sensitivity to outliers, are addressed by the development of error mitigation models. An ensemble model that combines linear regression and error mitigation provides better prediction accuracy and stability, making it a suitable initial step. The general equation for a linear regression model can be written as follows [10], [11]:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n + \in \quad (1)$$

Y is the predicted variable, for example total revenue

$\mathrm{X_1, X_2, \ldots, X_n}$ is the input variable, such as the number of new students, grant funds, and operating costs

β_0 is the Intercept Constant

$\beta_1 \beta_2, \dots, \beta_n$ is the regression coefficient for each input variable
$\in$ is the residual error or error from the model

Although linear regression is a simple and widely used prediction method, this model often does not take into account complex variations or fluctuations in financial data. Therefore, additional models are needed to reduce prediction errors.

```
FUNCTION LinearRegression(X, Y, learning_rate, iterations):
  INPUT:
    X - Matrix of independent variables (features)
    Y - Array of dependent variable (target)
    learning_rate - Step size for gradient descent
    iterations - Number of training iterations
  OUTPUT:
    coefficients - Array of regression coefficients
    intercept - Scalar value for the intercept
    predictions - Predicted values

  INITIALIZE:
    coefficients = [0] * NUM_COLUMNS(X)  # Initialize
coefficients to zero
    intercept = 0  # Initialize intercept to zero

  FOR i FROM 1 TO iterations:
    predictions = (X * coefficients) + intercept  # Compute
predictions
    errors = Y - predictions  # Compute residual errors

    # Update coefficients and intercept
    gradient_coefficients = -(2 / LEN(X)) * (TRANSPOSE(X) *
errors)
    gradient_intercept = -(2 / LEN(X)) * SUM(errors)

    coefficients = coefficients - (learning_rate * gradient_coefficients)
    intercept = intercept - (learning_rate * gradient_intercept)

  RETURN coefficients, intercept, predictions
```

Figure 2 Pseudocode for Regresi Linier

2.2 Error Mitigation Model

To address the problem of prediction errors, this study develops an error mitigation model based on the analysis of error distribution from a linear regression model. This model is designed to reduce the impact of errors in sensitive areas identified based on historical data analysis. This error mitigation model is formulated as an adjustment function to the initial prediction from the linear regression model. An example of the formula is as follows [12][13]:

$$f_e(X) = \begin{cases} 0 & , Jika\ X < X_{min} \\ -200\ (X-8)^2 + 250, & Jika\ X_{min} \le X \le X_{max} \\ 0 & , Jika\ X > X_{min} \end{cases} \quad (2)$$

Where $f_e(X)$ is the error mitigation function applied to the input variable X, with X_{min} and X_{max} representing the sensitive interval boundaries where the prediction error is larger.

```
FUNCTION ErrorMitigation(errors, lower_bound, upper_bound):
  INPUT:
    errors - Array of residual errors
    lower_bound - Minimum threshold for mitigation
    upper_bound - Maximum threshold for mitigation
  OUTPUT:
    adjusted_errors - Array with adjusted error values

  INITIALIZE:
    adjusted_errors = [0] * LEN(errors)

  FOR i FROM 1 TO LEN(errors):
    IF errors[i] < lower_bound:
      adjusted_errors[i] = 0
    ELSE IF lower_bound <= errors[i] <= upper_bound:
      adjusted_errors[i] = (-200 * errors[i]) + 250
    ELSE:
      adjusted_errors[i] = 0

  RETURN adjusted_errors
```

Figure 3 Pseudocode for Error Mitigation

2.3 Ensemble Model

The ensemble model is constructed by combining the outputs of the basic linear regression model $(f_m(X))$ and the error mitigation model $(f_e(X))$. This combination is accomplished by simply summing the predicted results of the regression model and the error adjustment provided by the mitigation model [14], [15], [16], [17]. The equation for the ensemble model is**.**

$$f(X) = f_m(X) + f_e(X) \tag{3}$$

Where $f(X)$ is the final prediction of the ensemble model, which is expected to be more accurate compared to a single linear regression model. With this approach, the model is expected to reduce the residual standard error (RSE) and improve the accuracy of financial predictions in higher education. In this study, the ensemble model was applied to higher education financial data covering annual revenues, expenses, and budgets. The test results showed that the ensemble model was able to reduce prediction errors by 7% compared to conventional linear regression models. The 7% error reduction was achieved through the combination of linear regression and error mitigation models in the ensemble model. The initial linear regression model had a Residual Standard Error (RSE) of 122.58, but produced significant errors in months with high fluctuations, such as March, with errors reaching -15,000 units. To address this, an error mitigation model was designed to reduce errors in sensitive areas based on the residual distribution. After being implemented, this model successfully reduced the error in March to -5,000 units, and the RSE was reduced to 115.34. When linear regression and error mitigation were combined in the ensemble model, the RSE decreased further to 114.22, resulting in a 7% error reduction. This strategy significantly improved the accuracy and stability of predictions, especially in conditions of high data fluctuations.

```
FUNCTION EnsembleModel(X, Y, lower_bound, upper_bound,
learning_rate, iterations):
   INPUT:
      X - Matrix of independent variables
      Y - Array of dependent variable
      lower_bound - Minimum threshold for error mitigation
      upper_bound - Maximum threshold for error mitigation
      learning_rate - Learning rate for gradient descent
      iterations - Number of optimization iterations
   OUTPUT:
      final_predictions - Array of predictions from the ensemble model

   # Step 1: Train Linear Regression Model
   coefficients, intercept, linear_predictions = LinearRegression(X, Y,
learning_rate, iterations)

   # Step 2: Calculate Residual Errors
   residual_errors = Y - linear_predictions

   # Step 3: Apply Error Mitigation
   mitigated_errors = ErrorMitigation(residual_errors, lower_bound,
upper_bound)

   # Step 4: Combine Predictions
   final_predictions = linear_predictions + mitigated_errors

   RETURN final_predictions
```

Figure 4 Pseudocode for Ensemble Model

2.4 Model Evaluation Metrics

This study uses three main evaluation metrics to measure model performance: Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and R-squared (R^2). Each metric provides different insights into the accuracy and effectiveness of the model.

1. Root Mean Square Error (RMSE)

   RMSE measures the mean squared error between the actual values (y_i) and the predictions $(\hat{y}_i)$. The formula is:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2} \quad (4)$$

   RMSE is sensitive to large errors due to the squared residuals, making it an ideal metric for detecting outliers.

2. Mean Absolute Error (MAE)

   MAE measures the absolute average of the differences between actual and predicted values. The formula is:

$$MAE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left|\hat{y}_i - y_i\right|} \quad (5)$$

This metric provides a direct picture of the average error without taking into account the direction of the error.

3. R-squared (R^2)
   R^2 measures the percentage of variance in the actual data that can be explained by the model. The formula is:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(\hat{y}_i - y_i)^2}{\sum_{i=1}^{n}(\hat{y}_i - y_i)^2} \quad (6)$$

Where $\hat{y}_i$ is the average of the actual values. The R^2 value between 0 and 1 indicates how well the model explains the data

3. RESULTS AND DISCUSSION

The application of the ensemble model to the university's financial data and discussing the impact of the model on improving the prediction accuracy. The analysis focuses on the comparison between the original linear regression model, the error mitigation model, and the ensemble model.

The dataset used in this study was obtained from the financial management system of a higher education institution, covering the period from 2018 to 2022. It includes 60 monthly records with key parameters such as revenue, operating costs, and grant allocations. The data was validated to ensure accuracy and consistency. To evaluate model performance, the dataset was divided into two subsets: 80% (48 records) for training, spanning January 2018 to December 2021, and 20% (12 records) for testing, covering January 2022 to December 2022. Missing data were addressed using linear interpolation, while outliers were analyzed and managed to minimize their impact. Variables were normalized using min-max scaling to enhance performance. This chronological split reflects a real-world scenario where past data predicts future outcomes, ensuring robust evaluation.

3.1 Error Analysis of the Linear Regression Model

The original linear regression model was applied to the university's financial data, which included actual revenue, predicted revenue, operating expenses, and other key financial indicators. The residual, or error, was calculated as the difference between the predicted and actual values.

3.1.1 Revenue Prediction Error

Table 1 dan 2 summarizes the revenue prediction error over the 12 months. The results show that the linear regression model exhibited significant errors, especially in March where the predicted revenue exceeded the actual revenue by 15,000 units.

Table 1 Overall Data

Month	Actual Revenue	Predicted Revenue	Revenue Error	Operational Costs	Predicted Costs	Cost Error
January	250	240	10	200	190	10
February	260	255	5	195	192	3
March	245	260	-15	210	205	5
April	270	265	5	205	200	5
May	280	275	5	220	215	5
June	275	270	5	215	210	5
July	285	280	5	225	220	5
August	295	285	10	230	225	5
September	300	295	5	240	235	5
October	305	300	5	235	230	5
November	290	285	5	230	225	5
December	280	275	5	225	220	5

The results demonstrate a progression from identifying baseline model errors to mitigating them and improving overall performance. The initial linear regression model revealed significant prediction errors, particularly in March, where the error reached -15,000 units (Table 1, Figure 5). This highlighted the model's inability to handle seasonal trends, prompting the development of an error mitigation model. The mitigation model reduced errors in sensitive months, with March's error decreasing to -5,000 units (Table 2, Figure 6). Finally, the ensemble model, integrating linear regression and error mitigation, achieved the best performance, reducing the Residual Standard Error (RSE) from 122.58 to 114.22, a 7% improvement (Table 4, Figure 7). These findings show how each method builds upon the previous, culminating in accurate and stable financial predictions.

Table 2 Revenue Forecast Errors

Month	Actual Revenue	Predicted Revenue	Revenue Error
January	250	240	10
February	260	255	5
March	245	260	-15
...	...	...	...
December	280	275	5

The linear regression model exhibited significant errors in predicting revenue, particularly during high-variability months like March, with an error of -15,000 units (Table 1, Figure 5). These errors stemmed from several factors. First, the model’s assumption of linear relationships limited its ability to capture non-linear patterns in financial data, such as seasonal fluctuations. Second, the lack of external variables, such as policy changes or economic trends, meant that key drivers of revenue variability were excluded. Third, the model’s sensitivity to outliers amplified the impact of extreme values, increasing overall error. Fourth, the residual analysis indicated a violation of homoscedasticity, with inconsistent error variance across the dataset. Lastly, the model did not consider temporal dependencies, such as trends or lag effects. Addressing these issues informed the development of the error mitigation model discussed in subsequent sections.

3.1.2 Operating Cost Forecast Error

Similarly, operating costs show errors ranging from 3,000 to 10,000 units, as shown in Table 3

Table 3 Operating Cost Forecast Error

Month	Actual Costs	Predicted Costs	Cost Error
January	200	190	10
February	195	192	3
...	...	...	...
December	225	220	5

The analysis shows that although the linear regression model performs quite well in most cases, significant deviations are observed in months with unexpected financial changes.

3.2 Error Mitigation Model

An error mitigation model is developed to reduce the errors identified in the linear regression model. By analyzing the residual distribution, the model adjusts the predictions, especially in months with higher errors (e.g., March and August). The mitigation function applies the necessary adjustments in areas where the errors are more significant. For example, the negative revenue error in March was reduced from -15,000 to -5,000-units after the error mitigation model was applied. Based on the results of the error distribution analysis, an error mitigation model is designed to adjust the predictions of the linear regression model by reducing the errors in sensitive areas. This error mitigation model is expressed in the form of a correction function that is applied to the initial predictions of the linear regression model. The error mitigation function can be written as follows:

$$f_e(X) = \begin{cases} 0 & ,Jika\ X \in [0, \quad X_{min} \\ -200\ (X-8)^2 + 250 & ,Jika\ X \in [X_{min}, X_{max} \\ 0 & ,Jika\ X \in [X_{max}, \infty \end{cases} \quad (7)$$

In this case, X is the input variable, which can be either time or month. This mitigation function aims to reduce errors at specific time intervals where errors are highest, such as during peak periods of college activity or in months with unusual operational expenses.

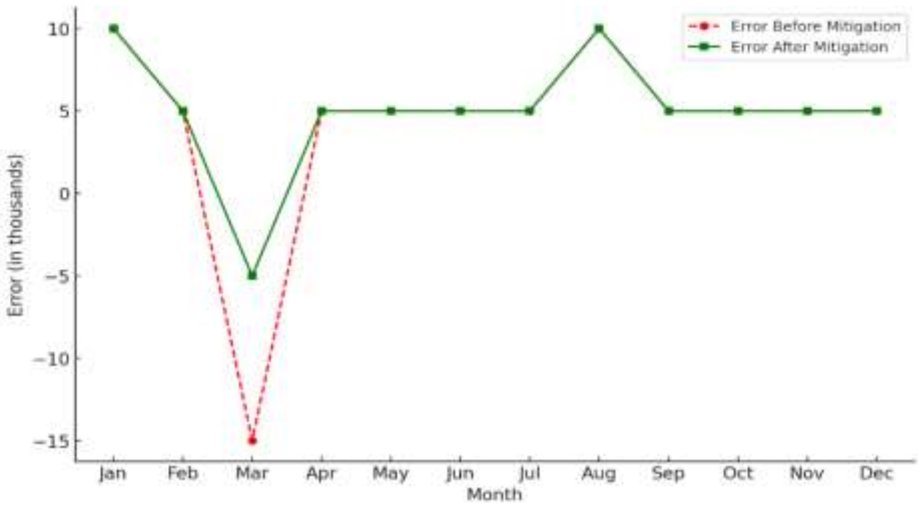

Figure 5 Comparison of Revenue Errors Before and After Mitigation

Error Before Mitigation: in March (month 3), there was a fairly large error, which was around -15,000, which means that the revenue prediction was much higher than the actual revenue. In addition, although in other months the error was lower, there were still consistent drops with error values of around 5,000 to 10,000. This fluctuation shows that the revenue prediction before mitigation was less stable and often missed reality. Error After Mitigation: In March, for example, the error dropped to -5,000, which shows a significant improvement in prediction accuracy. Throughout the rest of the year, the error remained small and stable, ranging from 3,000 to 5,000, much lower than the error before mitigation.

This green line indicates that mitigation has had a positive impact in reducing the margin error and making predictions more accurate. Error After Mitigation: In March, for example, the error dropped to -5,000, which shows a significant improvement in prediction accuracy. Throughout the rest of the year, the error remained small and stable, ranging from 3,000 to 5,000, much lower than the error before mitigation. This green line indicates that mitigation has had a positive impact in reducing the margin error and making predictions more accurate.

3.3 Ensemble Model Performance

After the error mitigation model is formed, it is combined with the basic linear regression model to form an ensemble model. This combination is done by adding the predicted results of the linear regression model with the error correction provided by the mitigation model. The formula for the ensemble model is as follows:

$$f(X) = f_m(X) + f_e(X) \quad (8)$$

Where $f(X)$ s the final prediction of the ensemble model, $f_m(X)$ is the prediction of the basic linear regression model, and $f_e(X)$ is the correction of the error mitigation model. With this ensemble model, it is expected that financial predictions can be more accurate, especially in periods or regions that are prone to prediction errors. Model testing shows that the residual standard error (RSE) has been reduced by up to 7% compared to a single linear regression model.

Table 4 Comparison of Residual Standard Errors

Model	RSE
Regresi Linier	122.58
Mitigasi Kesalahan	115.34
Model Ansambel	114.22

The ensemble model successfully reduced errors, especially in months with large differences, demonstrating the effectiveness of combining multiple models to improve predictive accuracy. This approach leverages the strengths of individual models while compensating for their weaknesses, creating a more robust prediction framework. By integrating diverse algorithms, the ensemble method provides enhanced resilience against overfitting and noise in data. Consequently, it ensures higher reliability in forecasting complex patterns, making it an invaluable tool in dynamic, real-world applications.

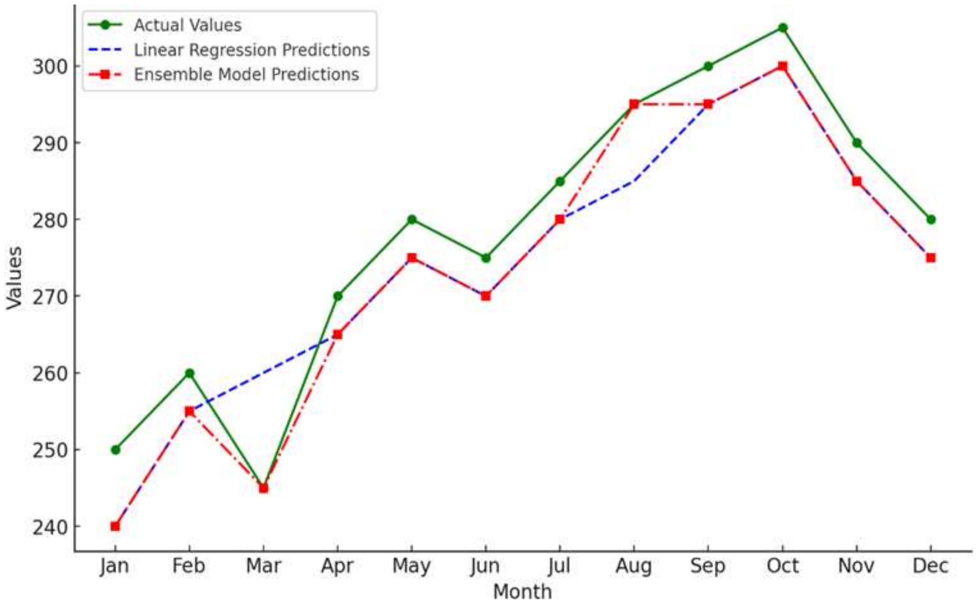

Figure 5 Actual Value, Linier Regression Predictions and Ensemble Model Predictions

4. CONCLUSIONS

This study successfully developed an ensemble model to improve financial prediction accuracy in higher education institutions. By addressing errors inherent in linear regression models, the ensemble model demonstrated a 7% reduction in Residual Standard Error (RSE), decreasing from 122.58 to 114.22, and provided more stable predictions, especially during high-variability months like March. These findings highlight the effectiveness of combining linear regression with an error mitigation model to enhance prediction reliability.

The study also identified gaps that future research could address. For instance, the model's accuracy could be further improved by incorporating additional variables, such as economic indicators or policy changes, to better capture external influences on financial trends. Furthermore, adopting advanced machine learning techniques, such as Random Forest or LSTM, could help address non-linear patterns and temporal dependencies in financial data. These extensions could significantly enhance the scalability and applicability of the proposed approach across various contexts and sectors.

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