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Integration of ARIMA Models and Machine Learning for Academic Data Forecasting: A Case Study in Applied Mathematics

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ABSTRACT

This study explores the use of ARIMA models and machine learning algorithms, specifically Random Forest and Multiple Linear Regression, to predict student academic performance. A mixed-method approach analyzed academic grades data from the past three years, with ARIMA identifying time series trends and machine learning models predicting academic outcomes based on various variables. Results show ARIMA effectively maps academic trends, while Random Forest excels in handling complex relationships, with an RMSE of 1.12 and an MAE of 0.94. These findings highlight the potential of combining statistical models and machine learning in developing adaptive learning strategies and data-driven decision-making. This approach offers a robust framework for improving educational outcomes and can guide future research in predictive analytics for educational systems.

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1. INTRODUCTION

Applied mathematics plays an important role in modern education, especially in connecting theoretical concepts with practical applications in various fields. However, many students do not yet know its application and often face challenges in understanding and applying applied mathematics concepts effectively. Difficulties occur due to various internal and external factors such as the use of teaching approaches that still emphasize too much on memorizing formulas and procedures without providing a deep understanding of the real applications of these concepts [1].

Several studies have identified challenges in applied mathematics learning. Developed an intervention in mathematics learning and education to help students who are struggling and at risk of having difficulty understanding mathematics, showing that a tailored approach can improve students' understanding. In addition, an approach to mathematics learning that still emphasizes exploration and understanding rather than performance has been shown to improve students' motivation and learning outcomes.

One of the main problems in traditional teacher practice is the reliance on subjective judgment and personal experience in teaching and predicting student academic performance, which is often not supported by historical or objective data analysis. This approach is prone to bias, is less adaptive to the complexity of the modern education system, and has the potential to cause delays in intervention for students with learning difficulties. In this context, the integration of ARIMA models and Machine Learning algorithms becomes very relevant as a solution based on Applied Mathematics. ARIMA can identify long-term trends in academic score data, while algorithms such as Random Forest are able to capture the complex relationships between variables that influence student performance. The combination of these two methods allows for more accurate, adaptive, and evidence-based decision-making, so that teachers can design more targeted interventions and support more responsive learning strategies. Thus, a shift from the traditional approach to data-driven education systems becomes essential to improve teaching effectiveness and the overall quality of learning outcomes.

In this context, several previous studies have explored the application of applied mathematics in education. For example, research by [2] , shows that the use of mathematical models in educational data analysis can improve the effectiveness of learning strategies. [3] Revealed that the application of statistical and probabilistic models in evaluating student academic performance can provide better insight into the factors that influence learning outcomes. [4] Showed that the application of mathematical analysis techniques in education can facilitate the prediction of student performance and design more appropriate interventions.

These studies point to the importance of academic data forecasting as a tool to improve the quality of education. Academic data forecasting allows educators to identify trends and patterns in student performance, thereby designing more effective interventions. In this regard, the use of mathematical models such as ARIMA (Autoregressive Integrated Moving Average) and machine learning techniques have proven effective in analyzing time series data to forecast trends in various fields, including education [5]. Several studies have shown that ARIMA models are effective in analyzing time series data, including in the educational context. For example, [6] developed a hybrid model of ARIMA and artificial neural networks for forecasting time series data, which showed improved prediction accuracy. [7] used ARIMA to predict student exam results based on historical data, while [8] discussed the application of ARIMA to predict academic performance at the university level.

On the other hand, machine learning techniques such as regression, decision trees, and artificial neural networks have been applied to predict academic performance with promising results. [9] showed that decision trees and artificial neural networks can be used to predict academic performance with higher accuracy compared to traditional methods. [10] discussed the application of machine learning techniques to predict student graduation based on previous demographic and academic data, while [11] explored the use of machine learning algorithms to predict student exam results with satisfactory results.

Although the application of ARIMA and Machine Learning offers solutions and challenges in the implementation of existing technology. One of them is the lack of understanding and technical skills among educators in using mathematical techniques and technology to analyze academic data. Therefore, solutions that can be taken include developing training for educators to master the application of applied mathematics in educational contexts and providing easier-to-use tools to analyze academic data. In addition, it is important to integrate ARIMA and machine learning into the educational curriculum to improve students' skills in data-based problem solving [12].

This study aims to explore the application of applied mathematics through ARIMA models and machine learning techniques in academic data forecasting. Specifically, this study will analyze the effectiveness of both approaches in predicting students' academic performance, and evaluate how the integration of ARIMA and machine learning can improve prediction accuracy. The results of this study are expected to contribute to the development of more effective and data-driven learning strategies, as well as provide guidance for educators in implementing data analysis technology in educational contexts.

2. RESEARCH METHOD

This research method uses a mixed method with a qualitative and quantitative approach to explore the application of Applied Mathematics through ARIMA and Machine Learning in academic data forecasting. This study aims to gain an in-depth understanding of the application of mathematical concepts in academic data analysis that can provide new insights for the development of prediction-based learning strategies. The type of qualitative research used is an exploratory study with an inductive approach, which allows researchers to explore naturally occurring and complex phenomena without significant intervention. The quantitative approach used in this study is a type of quasi-experimental research. The aim is to compare the performance of traditional statistical forecasting models (ARIMA) with machine learning models in predicting student academic data. The research method used in this study is explained in the following figure.

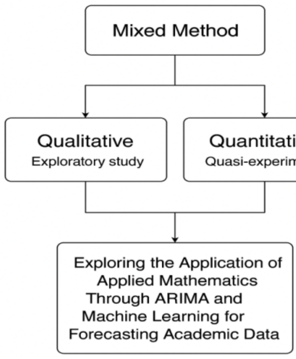

Figure 1. Mixed-Methods Research Design for Academic Data Forecasting Using ARIMA and Machine Learning

The research instruments used in this study include in-depth interviews, observations, and document analysis related to academic data. Interviews were conducted with relevant parties such as educators, data experts, and academic information system managers to understand the challenges and opportunities in implementing ARIMA and Machine Learning in the context of academic forecasting. Observations were used to identify patterns in existing academic data, as well as to understand how the data can be analyzed using mathematical models. Document analysis was conducted by examining related literature on the use of Applied Mathematics and the application of statistical methods and machine learning in education. In this study, the relationship between qualitative and quantitative data is clearly seen in how findings from interviews, observations, and documentation are used to enrich and validate the results of the predictive analysis. For example, interview results show that many students have difficulty understanding the application of mathematics in real life because the teaching method is too expository and lacks contextualization. This is confirmed by classroom observation data that notes low interest in learning in conventional approaches, as well as literature support that exploratory and technology-based methods are more effective [13]. These qualitative findings are then linked to quantitative results, where the ARIMA model successfully maps the downward trend in mathematics scores over several semesters (for example, the prediction of odd scores in 2022 is 75.1 with an actual score of 74.5).

Furthermore, quantitative data from the Random Forest algorithm shows that factors such as attendance, class participation, and assignment grades contribute significantly to academic outcomes, with a low RMSE of 1.12 and MAE of 0.94. This supports qualitative findings from interviews that students' non-cognitive behaviors significantly affect academic outcomes. Thus, qualitative data provides context to quantitative numbers, while quantitative data empirically proves the patterns found qualitatively. This integration shows that the use of ARIMA and Machine Learning models is not only accurate in predicting grades, but also contextual when supported by a deep understanding of the social and pedagogical background of the data. Data collection was conducted through three main methods: semi-structured interviews, direct observation of data available in academic systems, and review of relevant literature. In interviews, data was collected by recording conversations and making transcripts for further analysis. Observations were conducted to analyze how academic data is collected, processed, and used in the forecasting process. Document analysis was conducted by examining various scientific publications and reports related to the application of ARIMA and Machine Learning in education.

For data analysis, this study uses thematic analysis techniques that aim to identify patterns and themes that emerge from interviews, observations, and documents reviewed. The analysis process begins with coding raw data, followed by categorizing emerging themes based on research questions. The findings obtained will be analyzed qualitatively to describe how ARIMA and Machine Learning can be applied in academic data forecasting and the challenges faced by educators and academic system managers. This technique allows researchers to draw conclusions based on a deep understanding of the phenomena that occur in the context of education that continues to evolve.

3. RESULT AND ANALYSIS

Data collection in this study was conducted through three main methods, namely in-depth interviews, classroom observations, and analysis of student academic grade documentation for the past three years. In-depth interviews were conducted to obtain subjective perspectives from lecturers and students regarding the learning process and factors that influence academic achievement. Classroom observations aim to observe the dynamics of learning interactions directly, while academic grade documentation is analyzed to obtain objective and measurable historical data as a basis for forecasting.

Table 1. Summary of Data Collection Methods

No.	Method	Participant/Object	Goal	Execution time
1	In-depth Interview	Lecturers and students	Exploring perceptions	February - March 2024

			of applied mathematics	
2	Class Observation	Learning activities	Assessing teaching approaches	March - April 2024
3	Documentation of Values	3-year academic grades	Building a predictive dataset	January - March 2024

Based on table 1 above, it summarizes the methods and details of data collection in the study. Interviews were conducted to understand students' challenges in linking mathematics to real life [14]. Classroom observations noted that the expository approach was less interesting, while the exploratory method with technology was more acceptable [13]. Documentation of academic grades became the basis of the dataset for ARIMA and Machine Learning analysis.

Academic grade data is analyzed using the Autoregressive Integrated Moving Average (ARIMA) model to identify and understand time series patterns contained in the data. This approach allows the detection of long-term trends, seasonal fluctuations, and stationarity characteristics of the data, which are then used as a basis for forecasting academic grades in the next period."

Table 2. Results of Predicting Average Mathematical Values Using ARIMA (1,1,1)

Semester	Actual Value	Prediction Value	Difference	RMSE
Odd 2022	74.5	75.1	0.6	
Even 2022	73.8	74.0	0.2	
Odd 2023	76.1	75.6	-0.5	
Even 2023	75.0	75.4	0.4	0.44

Based on table 2 above, it shows the accuracy of the ARIMA (1,1,1) model in predicting mathematics scores. The prediction shows a small difference between the actual and predicted values, with an RMSE of 0.44. This supports the findings that ARIMA is effective for forecasting time series data in an academic context.

Next, the data was analyzed using a Machine Learning approach to evaluate the influence of various complex factors on students' final grades. This approach allows modeling of non-linear relationships between input variables, such as attendance, class participation, and assignment grades, with academic outcomes. Using algorithms such as Random Forest and Multiple Linear Regression, this analysis is able to identify patterns and contributions of each variable to the prediction of final grades more accurately and comprehensively than conventional statistical approaches."

Table 3. Results of Final Value Prediction Using Multiple Linear Regression and Random Forest

Model	RMSE	MAE	Main Input Factors
Regresi Linier	2.31	1.87	Attendance, assignment grades, class participation
Random Forest	1.12	0.94	All factors + non-linear interactions

Based on table 3 above, it shows that the Random Forest model produces lower prediction errors (RMSE and MAE) than linear regression, indicating its superiority in capturing non-linear relationships and complex variables. It also indicates that Random Forest provides more accurate and reliable predictions for student academic performance, with fewer large errors and a closer average prediction to the actual values. This is in accordance with the results [15], which state that Machine Learning techniques have advantages in the context of data-based education. Comparison between models is conducted to evaluate the level of optimality of each approach in predicting student academic performance. ARIMA models are assessed based on their ability to capture linear and seasonal time series patterns, while Machine Learning models, such as Linear Regression and Random Forest, are analyzed in terms of prediction accuracy for complex multivariate variables. Evaluation is conducted by measuring performance indicators such as Root Mean Square Error (RMSE) and Mean Absolute Error (MAE), which show that Machine Learning models, especially Random Forest, have advantages in modeling non-linear relationships and producing more accurate predictions. The results of this comparison provide a comprehensive picture of the effectiveness of each model in the context of historical data-based academic data forecasting.

Table 4. Comparison of ARIMA and Machine Learning Models in Forecasting Academic

Aspect	ARIMA (1,1,1)	Regresi Linier	Random Forest
Prediction Accuracy	Pretty good	Good	Very good
Non-linear Ability	Low	Low	High

Data Requirements	Minimum	Medium	High
Interpretability	High	High	Medium

Based on table 4 above, it compares the effectiveness of the three models in terms of accuracy and complexity. ARIMA excels for simple, linear, time-based forecasting when there are clear, predictable trends, linear regression is effective for linear relationships between predictors and outcomes, though it struggles with non-linearity. While Random Forest excels in situations with complex, non-linear relationships and large amounts of data with multiple interacting variables, offering the best prediction accuracy in these cases. This is in line with the findings [16], that the Machine Learning approach is very suitable for multidimensional data-based predictions.

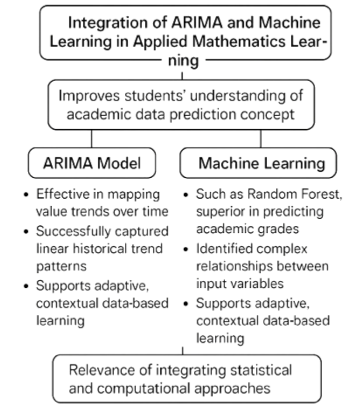

Figure 2. Integration of ARIMA and Machine Learning in Applied Mathematics Learning

The results of the study show that the integration of ARIMA and Machine Learning methods in applied mathematics learning can be an innovative solution in improving students' understanding of the concept of academic data prediction. The ARIMA model is effective in mapping value trends over time, while Machine Learning such as Random Forest has proven to be superior in predicting academic grades based on various input variables. Both approaches support adaptive and contextual data-based learning, in line with the idea of the importance of technology in mathematics education [17].

Based on the results of the research conducted, the results of this study indicate that the application of Applied Mathematics through the ARIMA model and Machine Learning algorithms is able to provide an accurate and applicable approach in predicting student academic performance. The implementation of the ARIMA model successfully captured the linear historical trend pattern in student grade data, while the Machine Learning model, especially Random Forest, was able to identify complex relationships between input variables that affect academic outcomes. These findings strengthen the relevance of the integration of two statistical and computational approaches in educational data processing.

The RMSE (1.12) and MAE (0.94) values obtained from the Random Forest model in this study indicate that the prediction of students' academic grades only deviates by about one point from the actual grade, which in the context of a 0–100 assessment scale is a very small error rate and can be categorized as accurate. In comparison, the linear regression model produces a larger error (RMSE 2.31 and MAE 1.87), confirming the superiority of Random Forest in capturing complex non-linear relationships. This explanation is important because without an interpretive context, these figures are difficult to interpret practically. Therefore, the addition of a discussion regarding a reasonable error threshold in predicting academic grades will strengthen the reader's understanding that a model with RMSE <2.0 is already suitable for use in data-based decision making in the education system.

The application of ARIMA (1,1,1) in this study successfully accommodates short-term trends that indicate a decline in academic performance, which is in line with the study [18] which used ARIMA to analyze the dynamics of students' mathematics scores and found a similar downward trend. Meanwhile, the applied Random Forest algorithm produced high prediction accuracy, confirming the findings of [19] which stated that decision tree-based approaches tend to excel in handling multivariate predictions in the field of education.

ARIMA and Random Forest offer valuable insights into predicting student academic performance based on historical data and complex interactions. In real-world educational settings, these insights translate to a better understanding of student performance trajectories. ARIMA's capability to capture linear trends can guide educators in recognizing when students are likely to be struggling based on past performance (e.g., a consistent decline in grades), while Random Forest helps identify which non-cognitive factors (e.g., attendance, participation) are most influential in shaping academic outcomes.

Furthermore, the relationship between variables such as attendance, participation, and assignment grades that were successfully mapped by the machine learning algorithm strengthens the results of the study [20], which shows that the integration of non-cognitive data can improve the predictivity of the academic evaluation system. This study also enriches scientific contributions by combining the predictive capabilities of classical statistics (ARIMA) and artificial intelligence (Machine Learning), a hybrid approach introduced in the study [21] and is considered promising for the context of time-based educational data. Furthermore, this study offers novelty in terms of integrating quantitative and computational methods based on machine learning for Applied Mathematics courses, especially in higher education environments in Indonesia. Unlike previous studies that tend to use economic or health data as the basis for ARIMA predictions and machine learning [22], this study applies it contextually in the local education system, thus opening up opportunities for similar models to be widely adopted in academic management systems. These findings not only prove the effectiveness of the forecasting model, but also show the urgency of reformulating the Applied Mathematics learning approach to align with the needs of technology and data. In line with the findings [23], which emphasize the importance of data literacy and the use of AI in the education system, this integration provides a new direction for educational institutions to transform digitally and be responsive to data.

The implications of this study include the potential application of predictive models in data-based academic systems to detect early academic risks, as well as strengthening adaptive learning systems based on analytical data. With insights gained from machine learning models, educators can analyze how different variables affect learning outcomes and adjust instructional materials accordingly. Suggestions for further research include developing a web-based predictive dashboard system that integrates ARIMA and machine learning results in real-time, and expanding input variables by adding psychosocial data and online learning activities to improve the accuracy and context of predictions. The combination of machine learning and statistical models suggests that educators should incorporate technology-based solutions into the classroom to enhance data collection and analysis. For example, learning management systems (LMS) could be used to track students' attendance, participation, and grades more effectively, allowing teachers to identify patterns and intervene promptly when needed. For an updated ARIMA model that could potentially improve the forecasting accuracy and reflect the more complex data patterns discussed, suggested ARIMA Model: ARIMA (2,1,2)

ARIMA (2,1,2) would offer the following improvements:

- AR (2): The autoregressive part can now account for the influence of the previous two periods of data, allowing the model to capture longer-term dependencies and more subtle patterns in the time series.
- I (1): This keeps the integration of data to achieve stationarity, as was used in the previous ARIMA model.
- MA (2): The moving average term accounts for the error terms from the previous two periods, capturing the noise and random fluctuations better than a simpler model like ARIMA (1,1,1).nThis model is better suited to handle seasonal variations or multiple cyclic patterns that may be present in academic performance trends (e.g., fluctuations due to semester-based schedules or external factors impacting student performance).

Expected Improvements:

- Better trend forecasting: With the additional AR and MA terms, the ARIMA (2,1,2) model would likely capture a broader range of trends, including more complex cyclical patterns in academic performance over time.
- Higher prediction accuracy: By including an additional autoregressive and moving average term, the model can better account for delayed influences and external shocks (such as interruptions in the academic year) on student performance.

4. CONCLUSION

Based on the results of qualitative data analysis obtained through interviews, observations, and documentation studies, it can be concluded that the use of Applied Mathematics in the form of ARIMA models and Machine Learning algorithms has significant potential in increasing the accuracy of academic data forecasting. Although most educational institutions already have fairly complete academic data, its use is still limited to administrative and reporting functions, not yet directed at in-depth predictive analysis. This research shows the value of predictive analytics in education, using ARIMA models and Machine Learning algorithms to forecast student performance. By identifying at-risk students early, educators can implement targeted interventions and personalized learning, helping improve student success. To apply these findings, educational institutions should adopt predictive analytics tools, train educators to use data effectively, and create early warning systems for struggling students. Incorporating adaptive learning technologies and promoting collaboration between educators and data analysts will also improve teaching strategies. For future work, improving the accuracy of the prediction model can be done by adding more varied input parameters, such as psychosocial data, learning motivation, or student activities on online learning platforms. In addition, other algorithms such as XGBoost, Support Vector Regression (SVR), or Long Short-Term Memory (LSTM) can be explored to accommodate more complex and dynamic data patterns, especially in the context of long-term prediction. Future research, also recommend to include factors like socioeconomic status, psychological aspects, and cultural influences in predictive models. These will provide a fuller picture of student performance and help create more inclusive and equitable interventions. Additionally, using long-term data and insights from online learning will enhance prediction accuracy.

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