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A WEB-BASED STUDENTS' ATTENDANCE PREDICTION SYSTEM USING MACHINE LEARNING

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ABSTRACT

This study details the creation of a web-based system designed to predict student attendance using machine learning. The main goal is to provide educational institutions with accurate attendance predictions to help address potential issues early. The system used past two years attendance from the school of electrical systems engineering at the Federal University of Technology, Akure, Nigeria. The dataset comprises of records of students' lectures attendance of four departments for two academic sessions. These records show students response to classes for the five working days of the week. The preprocessed data was used to train and evaluate three machine learning models; Linear Regression, ARIMA, and XGBoost. The research was implemented on Python independent development environment for data processing and model development. Flask was employed as the web framework, and HTML/CSS for the front-end design. Visual Studio Code (VS Code) was the chosen environment for writing and debugging the code. After testing the models, Linear Regression showed the best results due to its ability to model the data with a linear relationship. The web platform allows users to input data and receive attendance predictions, providing a useful tool for educators and administrators. Overall, this study highlights how machine learning can be applied to education management, offering a scalable solution for predicting attendance, which can support better planning and student engagement.

Keywords: Attendance, Prediction, Machine Learning, Web Framework, Python, Visual Studio

INTRODUCTION

Attendance plays a pivotal role in educational, as it reflects student engagement and participation. Regular attendance is often linked to better academic performance and positive learning outcomes. Traditional methods like roll calls and sign-in sheets, however, have limitations in terms of efficiency and accuracy (Tuge et al., 2022). With advancements in technology, automated systems using biometrics, RFID, QR codes, and mobile applications have been developed to offer more accurate and real-time attendance monitoring (Abir, 2024). Given its importance, educational institutions around the world prioritize tracking student attendance as a measure of engagement, performance, and overall success. Consequently, there is growing interest in using machine learning to create automated systems that can predict attendance.

Integrating machine learning into attendance tracking presents significant opportunities for educational institutions. These algorithms can analyze past attendance data to predict future patterns, helping to identify students at risk of poor attendance early and enabling tailored interventions (Nordin and Fauzi, 2020). Such systems can streamline the monitoring process and provide educators, advisors, and counsellors with valuable insights to better understand and manage student attendance. Predictive models also assist in optimizing resource allocation and offer essential data for policy-making and strategic decisions regarding attendance management (Bhattacharya et al., 2018).

However, challenges remain in incorporating machine learning into attendance systems. The accuracy of predictive models depends heavily on the quality and completeness of the training data, making data integrity crucial (Bhattacharya et al., 2018). Additionally, privacy concerns about the collection and use of student data require strong data governance measures (Lim et al., 2009). Addressing these challenges requires specialized skills, alongside efforts to ensure that users are comfortable with and willing to adopt the new systems (Ershov et al., 2021). To overcome these hurdles, there is a growing demand for a web-based attendance prediction system. Such a system would provide an easy-to-use platform for managing and analyzing attendance data while utilizing machine learning to predict students' future engagements.

Most existing attendance systems do not offer predictive capabilities, which restricts early intervention based on historical data and related factors (Tuge et al., 2022). To fill this gap, this research aims to develop a machine-learning model that can generate accurate insights from student attendance data, allowing academic institutions to address attendance issues proactively and make informed decisions that improve overall student outcomes. By collecting, cleansing, and preprocessing attendance data from four semesters, the study ensures that the data used is consistent, accurate, and appropriate for machine learning algorithms. The ultimate goal is to developed a user-friendly web-based interface that integrates the developed attendance model, making it accessible for School of Electrical Systems Engineering (SESE) Heads of Department. This tool will support their ongoing efforts to enhance student attendance and engagement.

A web-based student attendance prediction system using machine learning presents a transformative solution for educational institutions, addressing inefficiencies and inaccuracies in traditional attendance tracking methods (Sanchez-Condori and Andrade-Arenas, 2022). A key advancement of this system is its ability to provide real-time insights into attendance patterns, enabling educators and administrators to promptly identify and address attendance issues (Lawpoolsri et al., 2014). This proactive approach allows schools to support students at risk of poor attendance early, preventing adverse effects on their academic performance (Delgado, 2020). By leveraging machine learning algorithms, the system can predict future attendance trends, helping identify students who are likely to struggle with attendance and enabling targeted interventions (Ayop et al., 2018). Early intervention can lead to improved student retention and greater academic success (Qureshi, 2020).

Review of Related Works

Alboaneen et al. (2022) utilized Educational Data Mining (EDM) to identify patterns in educational datasets with machine learning (ML) algorithms. They developed a web-based system that predicted academic performance and identified at-risk students by applying algorithms like Support Vector Machine (SVM), Random Forest (RF), K-nearest neighbours (KNN), Artificial Neural Networks (ANN) and Logistic Regression (LR) to data from 168 female Computer Science students at IAU. The model achieved a Mean Absolute Percentage Error (MAPE) of 6.34%, with midterm exam scores being particularly influential. However, the study's focus on a single gender and department limited its broader applicability.

Tharsha et al. (2021) developed a Smart application that used data mining techniques to manage students online, especially during the pandemic. This user-friendly tool incorporated Machine Learning, Deep Learning, and Artificial Intelligence to solve common educational challenges. Feedback indicated that it improved learning effectiveness, although there were potential challenges with users adapting to the new technology.

Afan et al. (2023) created a system for tracking student assessments and predicting grades through educational data mining. The system analyzed class attendance and study hours to predict performance and helped lecturers monitor academic progress. It was built with PHP for the backend, MySQL for the database, and HTML/CSS/JavaScript for the frontend. However, it relied on students' self-reported study hours which could not be trusted.

Kishor et al. (2021) focused on predicting student performance by analyzing various study environment factors. They used linear regression, decision trees, Naïve Bayes, and KNN algorithms with data on students' backgrounds. The model effectively predicted success rates, but the data was based only on the students' study environment without a consideration for students' interests and weekly activities that influences their school lives.

Kakarla et al. (2020) introduced a Convolutional Neural Networks (CNN) architecture for face recognition in attendance systems, demonstrating 99% accuracy and facilitating the creation of a web-based "Smart Attendance Management System (SAMS)" but the system has no capability for predicting the future attendance of students.

This study focuses on predicting students' future attendance, an area that has received less attention compared to academic performance or dropout rates. By integrating various machine learning techniques within a web-based framework, the system ensures accessibility and practicality. Unlike other studies that primarily target academic outcomes, this study specifically addresses attendance, which is crucial for student engagement and overall success. By providing a predictive tool for attendance, the system enables early interventions, helping educational institutions address potential issues before they negatively impact academic results. This proactive approach, combined with the web-based nature of the system, ensures it is effective and easy to incorporate into existing educational settings, offering a comprehensive solution for enhancing student success.

MATERIALS AND METHODS

The stages for the Web-Based Students' attendance prediction system using machine learning are divided into four namely; data collection, data preprocessing, model development and Model Evaluation. Figure 1 shows the framework of the developed students' attendance prediction system.

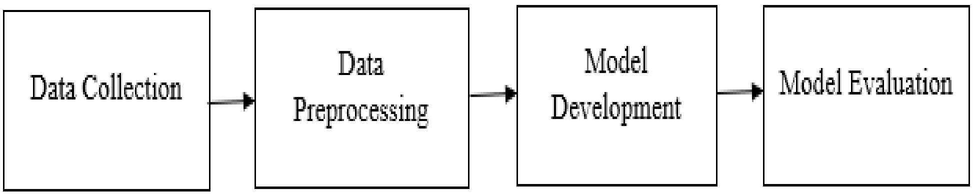


Figure 1: Framework of the Developed Students' Attendance Prediction System

System Design

The research adopts a quantitative approach, leveraging ARIMA (Auto Regressive Integrated Moving Average) with exogenous variables for predictive modelling and subsequent deployment of a web-based system. To implement and deploy the predictive model, the research integrates it into a web-based application, designed with a simple yet effective frontend built using HTML and CSS, while the backend powered by Flask, a lightweight Python web framework, manages the communication between the frontend and the ARIMA model, processing requests and delivering real-time predictions. Communication between the predictive model and the web-based application is facilitated via the backend. The system architecture for the student attendance prediction system is designed to ensure seamless integration of various components, providing a robust, scalable, and efficient solution. The architecture includes a frontend, a backend, and a machine learning model, each playing a crucial role in the overall functionality of the system. Figure 2 shows the complete system architecture of the whole system.

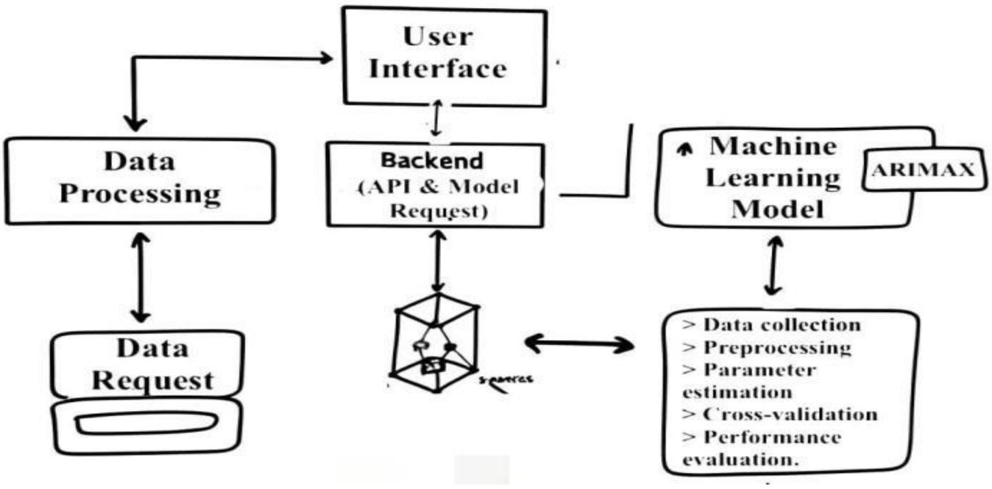


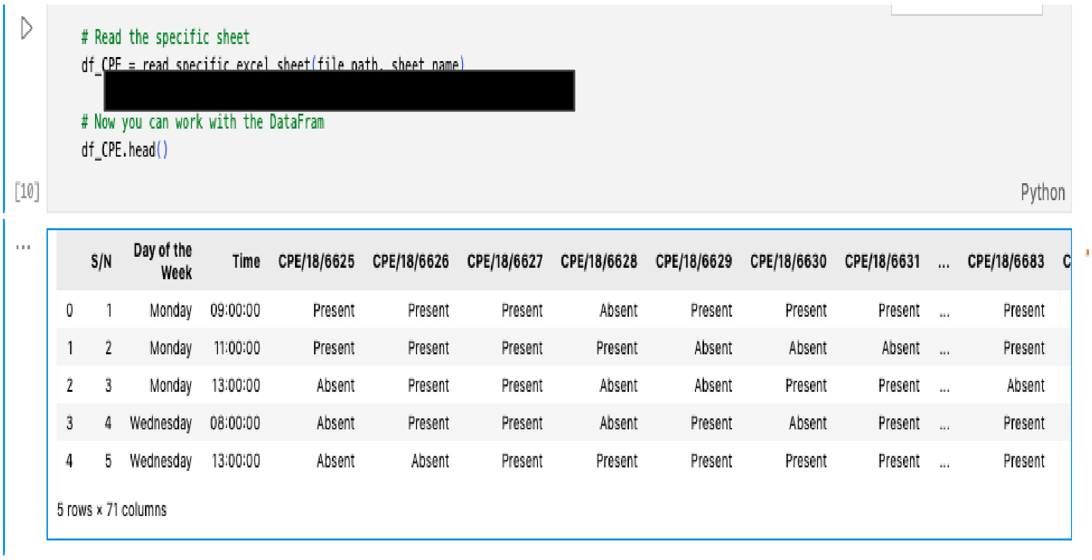
Figure 2: System Architecture

Ethical Considerations

The development of this web-based student attendance prediction system involves several important ethical considerations. The system's collection and analysis of attendance data raise privacy concerns, necessitating strong protections against unauthorized access and use (Hussain et al., 2019). Addressing bias in machine learning is essential to ensure fairness, as predicting low attendance could stigmatize students and harm their performance. Informed consent from students is crucial, ensuring they understand the system's purpose and how their data will be collected and used. The system should be used solely to improve attendance and academic performance, with clear guidelines to prevent misuse. While technology can enhance education, it is important to ensure that the system does not negatively impact students' physical and mental health. By adhering to these ethical guidelines and principles, the attendance prediction system can be utilized effectively to improve attendance rates and academic performance while respecting students' privacy, dignity, and rights.

Data Collection and Analysis

Data is collected from daily attendance logs of students in the School of Electrical Systems Engineering over four semesters, ensuring a comprehensive dataset for predictive modelling. Throughout the data collection process, ethical considerations and data privacy regulations were strictly followed to protect student information. Figure 3 shows a sample of the Dataset used for this study.



```
# Read the specific sheet
df_CPE = read_specific_excel_sheet(file_path, sheet_name)
[redacted]

# Now you can work with the DataFram
df_CPE.head()
```

[10] Python

	S/N	Day of the Week	Time	CPE/18/6625	CPE/18/6626	CPE/18/6627	CPE/18/6628	CPE/18/6629	CPE/18/6630	CPE/18/6631	...	CPE/18/6683	C
0	1	Monday	09:00:00	Present	Present	Present	Absent	Present	Present	Present	...	Present	
1	2	Monday	11:00:00	Present	Present	Present	Present	Absent	Absent	Absent	...	Present	
2	3	Monday	13:00:00	Absent	Present	Present	Absent	Absent	Present	Present	...	Absent	
3	4	Wednesday	08:00:00	Absent	Present	Present	Absent	Present	Absent	Present	...	Present	
4	5	Wednesday	13:00:00	Absent	Absent	Present	Present	Present	Present	Present	...	Present	

5 rows × 71 columns

Figure 3: Sample of the Raw Dataset

Data Preprocessing

Effective data preprocessing is essential for achieving accurate predictive modelling. The following steps are involved in data preprocessing:

i. ***Data Cleaning***: This is done to remove duplicate entries to avoid skewing the analysis, addressing missing values through imputation (filling in missing values with estimated ones) or deletion (removing records with missing data) and to correct inconsistencies in the data to ensure accuracy and reliability.
ii. ***Feature Selection:*** This is used to identify relevant features that significantly influence attendance, including demographic data (e.g., age, gender), academic performance (e.g., grades), and historical attendance patterns.
iii. ***Normalisation/Feature Scaling***: Normalisation is used to scale numerical features to a standard range to ensure

uniformity and enhance the model's performance. This step helps prevent any single feature from disproportionately influencing the model's predictions.

Model Development
The model development is an iterative loop between training and evaluation, where the model is continuously improved based on performance metrics until it reaches satisfactory accuracy and reliability. Once the model is deemed effective, it can be deployed to make real-time predictions using new input data.

Machine Learning Model
The core of the prediction system is the ARIMA model with exogenous variables (ARIMAX) for predicting student attendance. ARIMA (Auto Regressive Integrated Moving Average) is a powerful time series forecasting method that captures temporal dependencies in the data. By including exogenous variables (ARIMAX), the model can incorporate additional factors that may influence attendance. The model formula is given by:

$$y_t = \propto + \sum_{i=1}^{p} \emptyset_i y_{t-i} + \sum_{i=1}^{q} \theta_i \epsilon_{t-i} + \epsilon_t + \beta X_t \quad (1)$$

Where y_t is the attendance at time t, $\propto$ is the intercept, $\emptyset_i$ are the autoregressive coefficients, θ_i are the moving average coefficients, ϵ_t is the whole noise error term, X_t are the exogenous variables (e.g. academic performance). The ARIMA model works by combining autoregression (AR), differencing (I for Integrated), and moving average (MA) components. The inclusion of exogenous variables (X) enhances the model by incorporating external factors that might affect attendance, thus improving prediction accuracy.
The development process of the ARIMA model includes several key steps. First, data collection involves gathering historical attendance data along with relevant exogenous variables, ensuring the data is clean and suitable for modelling. Next, the model training phase focuses on training the ARIMA model using historical data, estimating model parameters through maximum likelihood estimation. After training, model validation is conducted using cross-validation techniques to ensure the model generalizes well to new, unseen data. Evaluation metrics such as Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) are used to assess the model's performance. Finally, once validated, the model generates predictions for future attendance based on input data, which are then integrated into the backend system for further processing and visualization. Figure 4 shows block diagram for the model training phase.

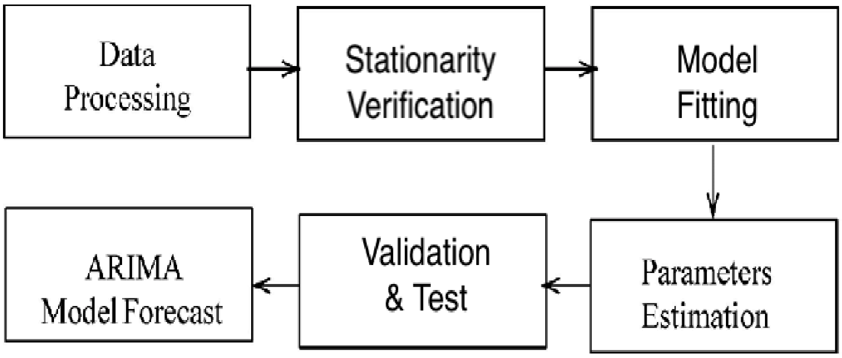


Figure 4: Model Training Block Diagram

Model Evaluation and Validation
Evaluating the performance of the model is critical for ensuring its accuracy and reliability in predicting student attendance. The prediction system's effectiveness is determined by how well it predicts attendance while maintaining efficiency. A comprehensive evaluation typically involves using both time-series analysis and cross-validation techniques.

User Interface
The user interface development of the web-based student attendance prediction system is divided into frontend and backend components, ensuring an integrated and scalable platform that delivers real-time predictions.

Frontend Development
The frontend of the system is developed using only HTML and CSS, providing a simple yet effective interface for users to interact with the ARIMA-based predictive model. This lightweight architecture prioritizes usability and accessibility, ensuring that users can easily engage with the system to forecast student attendance. Despite being a static site in design, the frontend provides real-time feedback, showing users predictions and insights based on input data.

Backend Development
The backend of the system is built using Flask, a Python web framework known for its lightweight and modular approach. Flask handles all server-side operations, including data processing, API management, and communication with the ARIMA model. The ARIMA model with exogenous variables is trained and serialized into a `.pkl` file for easy access and quick predictions. When a user inputs data through the frontend, Flask processes these inputs, passes them to the serialized model, and returns the prediction results to the frontend in real-time.

Web Interface Deployment
Deployment is a critical phase in the development of a web-based student attendance prediction system, ensuring that the system becomes available for user access. Before making the system publicly accessible, rigorous testing is required to validate its functionality, accuracy, and stability. The development of this predictive modelling system was carried out using a variety of tools and software to facilitate both frontend and backend development. Visual Studio Code (VS Code) was the primary Integrated Development Environment (IDE) used for writing and debugging the code. VS Code's flexibility and support for multiple programming languages made it an ideal choice for this project. For the backend, Flask (version 2.3.2) was employed due to its lightweight nature and ability to efficiently manage server-side operations. The

handling of datasets and data manipulation was powered by pandas (version 2.0.3) and numpy (version 1.25.1), both widely-used libraries in Python for managing data and performing numerical computations.

The predictive model itself was built using scikit-learn (version 1.3.0), a versatile library that supports machine learning algorithms and statistical modelling, including the ARIMA model used for forecasting. Flask interacted with the predictive model, which had been serialized for deployment. To ensure smooth communication between the frontend and backend, the requests library (version 2.31.0) was utilized to manage HTTP requests. By integrating these tools and software, a scalable and efficient web-based system was developed, capable of delivering real-time attendance predictions with a user-friendly interface.

RESULTS AND DISCUSSION

The performance of the attendance prediction model is critical in ensuring the accuracy and reliability of the web-based student attendance prediction system. To develop a robust model, it is essential to evaluate not only the model's performance but also the factors that influence its accuracy.

In this study, the historical attendance data from SESE provided the foundation for model development, ensuring that the dataset had enough variability to account for different attendance trends. A sufficient dataset helps identify patterns, including rare events or outliers, that could affect attendance predictions. This variability improves the model's ability to generalize across different contexts and student populations, a key factor in the practical deployment of the system in real-life educational environments.

To ensure generalizability, cross-validation techniques were used to train and test the model on various subsets of the data. The dataset was randomly split into training (80%) and testing (20%) sets, allowing for an unbiased assessment of the model's performance on unseen data. This division helps detect overfitting, where a model performs well on the training data but poorly on new data. In addition, hyperparameter tuning was applied to models like ARIMAX to further improve performance. Figure 5 shows a screenshot of the training dataset sample.

	Day of the Week	Time	department
1422	1	13.0	1
1872	4	13.0	3
1913	0	12.0	3
57	2	15.0	0
2630	1	9.0	4
...	...	...	...
1638	2	15.0	3
1095	2	15.0	1
1130	1	13.0	1
1294	3	11.0	1
860	4	13.0	2

2153 rows × 3 columns

Figure 5: Screenshot of the Training Dataset Sample

The key machine learning algorithms applied in this study include:

i. ***Linear Regression:*** Used as a baseline model for comparison, Linear Regression provides insights into the impact of predictors such as the day of the week, time, and department on attendance. The evaluation metrics for this model, such as Mean Squared Error (MSE) and Mean Absolute Error (MAE), indicated that it consistently delivered reliable results, making it the most accurate model. Figure 6 shows the evaluation metrics for linear regression model.

```
=== Training Set Metrics ===
Linear Regression MSE (Train): 277.89395939124597
Linear Regression MAE (Train): 13.690095083991718
Linear Regression RMSE (Train): 16.67015175069639
Linear Regression Relative MSE (Train): 99.00%
Linear Regression Relative MAE (Train): 98.61%
Linear Regression Relative RMSE (Train): 99.50%
Linear Regression R² Score (Train): 0.8814048056398495

=== Test Set Metrics ===
Linear Regression MSE (Test): 290.1528413980957
Linear Regression MAE (Test): 14.077041606375676
Linear Regression RMSE (Test): 17.033873352766708
Linear Regression Relative MSE (Test): 99.83%
Linear Regression Relative MAE (Test): 98.71%
Linear Regression Relative RMSE (Test): 99.92%
Linear Regression R² Score (Test): 0.8334367328098771
```

Figure 6: Linear Regression Evaluation Metric

i. ***Gradient Boosting (XGBoost):*** This ensemble method was used to capture nonlinear relationships between variables. Although it improved performance, it did not outperform Linear Regression in terms of accuracy for this specific task. Figure 7 shows the evaluation metrics for Gradient Boosting (XGBoost) model.

```
=== Training Set Metrics ===
XGBoost MSE (Train): 247.32740529512517
XGBoost MAE (Train): 12.774362900990516
XGBoost RMSE (Train): 15.726646346094427
XGBoost Relative MSE (Train): 88.11%
XGBoost Relative MAE (Train): 92.01%
XGBoost Relative RMSE (Train): 93.87%
XGBoost R² Score (Train): 11.890615647348046

=== Test Set Metrics ===
XGBoost MSE (Test): 268.8946563869744
XGBoost MAE (Test): 13.558307046545755
XGBoost RMSE (Test): 16.39800769566152
XGBoost Relative MSE (Test): 92.52%
XGBoost Relative MAE (Test): 95.08%
XGBoost Relative RMSE (Test): 96.19%
XGBoost R² Score (Test): 7.48090717688955
```

Figure 7: XGBoost Evaluation Metric

ii. **ARIMAX:** This model, which accounts for time series dependencies and external factors, was trained to capture temporal trends. While ARIMAX handled temporal variations in attendance well, its overall performance metrics, compared to Linear Regression, showed that it was more suitable for capturing specific trends rather than general attendance predictions. Figure 8 shows the evaluation metrics for ARIMAX model

```
=== Training Set Metrics ===
ARIMAX MSE (Train): 307.71694426862143
ARIMAX MAE (Train): 14.329669842699332
ARIMAX RMSE (Train): 17.541862622555833
ARIMAX Relative MSE (Train): 91.35%
ARIMAX Relative MAE (Train): 86.01%
ARIMAX Relative RMSE (Train): 95.18%
ARIMAX R² Score (Train): 9.622912519682437

=== Test Set Metrics ===
ARIMAX MSE (Test): 660.0106896855278
ARIMAX MAE (Test): 19.76087609247521
ARIMAX RMSE (Test): 25.690673204210274
ARIMAX Relative MSE (Test): 75.70%
ARIMAX Relative MAE (Test): 81.51%
ARIMAX Relative RMSE (Test): 79.31%
```

Figure 8: ARIMAX Model Evaluation Metric Result

The performance evaluation used metrics such as MSE and MAE to assess how well each model generalized to unseen data. The results indicated that Linear Regression was the most reliable model, offering a balance of accuracy and simplicity in predicting student attendance. In comparison, ARIMAX provided detailed insights into time-based trends, and XGBoost captured complex, non-linear relationships, but neither consistently outperformed Linear Regression. Table 1 shows the evaluation metrics for the three models used in this study.

Table 1: Evaluation Metrics for Attendance Prediction Models

		Training Set Metrics		Test Set Metrics	
Linear Regression	MSE	277.894	99%	290.153	99.32%
	MAE	13.69	98.61%	14.077	98.74%
	R^2Score	0.8814		0.8514	
XGBoost	MSE	247.327	88.11%	268.895	92.52%
	MAE	12.774	92.01%	13.558	95.08%
	R^2Score	11.891		7.481	
ARIMAX	MSE	307.716	91.335%	660.01	75.70%
	MAE	14.329	86.01%	19.761	81.51%
	R^2Score	9.6229		13.213	

The findings show that while advanced models like XGBoost and ARIMAX have their advantages, particularly in handling complex and time-based data, Linear Regression remains the most effective for predicting student attendance based on its accuracy, consistency and ability to generalize across different contexts. This makes it a valuable tool for institutions looking to manage student engagement and attendance proactively. The results highlight the importance of further research and model validation to continue improving the accuracy and generalizability of the system across different educational contexts.

CONCLUSION

The development of a web-based student attendance prediction system using machine learning has profound implications for various stakeholders in the education sector. This system's ability to predict attendance trends and provide real-time insights can transform how schools monitor and manage student attendance, leading to more proactive interventions and improved educational outcomes. For teachers, especially in large classrooms, manually tracking attendance trends and identifying students with attendance issues can be challenging. The predictive system offers an automated solution that highlights students who are at risk of poor attendance early on. Teachers can leverage this information to intervene before absenteeism becomes a larger issue, providing tailored support to students who may need it. School administrators can benefit from the system by gaining insights into attendance patterns across different grades, departments, or student groups. By analyzing this data, administrators can make data-driven decisions about resource allocation, policy adjustments, or targeted interventions.

For students, the system offers real-time visibility into their attendance records, empowering them to take ownership of their academic progress. Students who may not realize their attendance patterns are slipping will be able to see this data and take corrective action. Regular attendance correlates strongly with academic success, and having access to this data will help students maintain regular attendance and achieve their academic goals.

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