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Context-Aware Attendance Prediction in Mobile Learning Environments Using LSTM Networks for Sustainable Educational Systems

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Abstract

Secure and reliable operations with information are needed for the sustainability of a context-aware mobile open learning environment. Students' attendance prediction can be maximized to optimize resource usage, enhance operational effectiveness, and increase confidence in the institution. The challenge is that conventional statistical techniques don't take into account temporal, contextual, and resource security issues in a decentralized mobile learning setting. This paper presents a model that provides the background for LSTM networks (Long Short-Term Memory) in the context of real-time student attendance prediction. The model can capture an intricate time series while preserving confidential student data, and possessing a touch of privacy-protected lightweight mobile streams keeps the model's ability to interface intact. In the evaluation of the model within the framework, it is evident that the model exhibits satisfactory performance (training: accuracy = 99%, precision = 98%, recall = 99%, F1 = 98%). Furthermore, the model's performance has been sustained even in the presence of adversarial attacks, data silos, and data exfiltration. The MAX LOAD behavior is considered good support for the viability of the model and as supportive evidence that AI-based prediction in the mobile environment can be undertaken with reasonable confidence. This effort addresses the task of reasonably integrating predictive modeling into the problem of obtaining appropriate measures of security for use in modeling, towards intelligent mobile learning systems that are adaptive, sustainable, private yet trusted, and hence maximize institutional trust in digital learning spaces.

Keywords: Security, Trust, Privacy-Preserving Learning, Context-Aware Systems, Mobile Learning, LSTM Networks, Predictive Attendance Modeling, Educational Sustainability.

1 Introduction

Outside the world of mere estimation, attendance prediction has clearly tangible real-world effects on policy design and education (Jarbou et al., 2022; Almaiah et al., 2022). There is evidence to suggest that there is some correlation between attendance and the desired range of academic achievements. Attendance at schools reduces stress and anxiety and enhances social interaction among the youth (Kearney et al., 2022). Absence from school, on the other hand, has a greater risk of failure, school

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dropout, and behavioral disengagement (Sosu et al., 2021). Thus, the forecasting and telling of patterns of attendance is of concern for policymakers, advocates, and educators who aspire to improve the effectiveness of the educational system (Albeladi et al., 2023).

Overcoming advanced predictive issues has become increasingly simplified due to the emergence of new technologies, such as machine learning and advanced data analytics. Time series prediction has benefited from certain types of recurrent neural networks, more commonly known as Long Short-Term Memory networks, due to their ability to learn complex structures and dependencies over long periods of time on sequential data (Alsulaimani, 2024; Wahdan et al., 2021). Unlike other recurrent neural networks, LSTM networks are designed with memory cells that have 'gates' which control the flow of information, allowing LSTMs to retain information over long periods of time without falling prey to the 'vanishing gradient' considerations which affect other RNNs (Alanya-Beltran, 2024). For example, LSTMs are best suited for attendance prediction due to their ability to learn and retain longer time periods, which improves their predictive patterns in the presence of intense sequences (Hong & Lin, 2024).

Additionally, although RUs (like GRU) can manage time-dependent constructs on data sequences, LSTMs are more refined in controlling memory cells, which is critical in attendance models that possess complex attendance patterns (Sun, 2025; Khamees et al., 2021).

When compared to ARIMA, classical statistical time series forecasting models, LSTMs do not require the data to be stationary and capture non-linear relationships more effectively. It is for this reason that LSTMs, unlike vanilla RNNs, are better for predicting non-linearly dependent non-stationary behavior, such as student attendance.'

While the field of educational data mining predicting student attendance and performance has already been explored, the application of LSTMs as the principal method of analysis is still ‘ripe’ for research (Umarova et al., 2024; Kavitha & Kumar, 2024; Kusumawardani & Alfarozi, 2023). Most of the works focused on basic primary statistical techniques or elementary machine learning methods. Such techniques, however, tend to ignore the intricate and nuanced patterns and relationships that are present in attendance data, which are subject to a greater number of both predictable and unpredictable variables.

Mobile technology learning is evolving at a rapid pace, particularly in terms of mobile technology devices and digital network access, and is focusing on mobile technology learning and context-sensitive learning (Omirzak et al., 2022; Mitra & Shah, 2024). Such devices enable learning activities beyond the four walls of a classroom, with access to necessary materials and systems from any place and at any time. In such environments, learning systems are required to provide instruction and perform logistical, operational, and attendance tracking within dynamic, multi-system architectures effectively (Berezi, 2025). In this regard, advancing technologies enable the use of context-aware computing, which allows systems to understand and respond to users' context.

"Predictive Mobility Models," as part of adaptive systems, enable institutions to monitor fluctuations in attendance, resource distribution, and administrative responsiveness (Liu et al., 2024). Within the context of these adaptive systems, predictive models can provide a glimpse into the future of personalized, large-scale systems of learning that are sustainable and integrated with pedagogical data on learning analytics (Okonji & Igwe, 2025).

The absence of any effort to apply LSTM networks to the prediction of school attendance, LSTM matrices, and the accompanying intricate daily attendance records, along with LSTM creative methods described later, greatly motivates this investigation. This analysis proposes two assumptions. First, the

LSTM models will, undoubtedly, be able to explain the school attendance time series and the temporal patterns associated with them. Second, models of classical machine learning of greater complexity will benefit from the incorporation of deep learning into their model architectures.

This work in the field of 'Educational Data Analytics' focuses on the LSTM application to forecasting school attendance time series and offers a real-world, scalable approach to model such attendance forecasting for a variety of educational and institutional settings. We discuss the advantages and disadvantages of these models relative to the older models of prediction and assess them in the context of educational big data. This serves as a case in point for analyzing the influence of more advanced deep learning techniques in the education sector. This work is also concerned with the practical 'real world' use of the data in helping educational institutions develop more effective data-driven policies targeted at improving attendance to classes and subsequently improving learning outcomes (Soleymanzade, 2017).

The context-sensitive environments and mobile intrusion learning settings have attracted attention to the significance of making the data educational data up-to-date, confidential, complete, and accessible to make it non-violative. Student attendance records are of the sensitive kind, and verbalized reports can contain or reveal information of the private category and can have catastrophic consequences in the event of misuse, tampering, or unauthorized access… especially in mobile-distributed systems. Building trust in AI findings requires fortifying the framework with "security-by-design" principles specific to engineered AI systems (Kapoor & Malhotra, 2025). Institutional trust and validity of attendance analytics is best achieved by integrating the system with access control, used with tight and strong constraints, and a strong foundation encryption that is tamper-evident for data in transit. These, along with predictive intelligence, will enhance operating efficiency, improve applicant trust, and most importantly, make the mobile learning infrastructures private, reliable, and free from espionage. This research describes the novelties and enhancements as follows:

1. Confidential LSTM-driven predictive framework: Builds a context-aware attendance forecasting model using Long Short-Term Memory (LSTM) Networks and incorporates security-by-design principles to assist such networks in data confidentiality and integrity preservation in mobile contexts.
2. Confidentiality-preserved data acquisition: Collection and processing of sensitive student information is enabled in mobile learning contexts by implementing pseudonymization and encrypted data transmission.
3. Low-complexity secure implementation: A mobile, cloud, and edge computing secure access framework of authenticated role and policy access and unmanned trust boundaries is proposed in a flexible architecture with low complexity.
4. Robust predictive performance metrics and trust evaluation: The proposed model is tested with synthetic and real datasets, concentrating on predictive trust metrics (accuracy, precision, recall, and F1 score) and countermeasures to unauthorized data access and data adversarial manipulation.

This paper systematically structures the discussion in a sequential, progressive, and lucid manner, taking steps and gaining insights from the findings. Section 2 summarizes the literature regarding educational literature and the literature with a specified focus on forecasting attendance. Section 3 encompasses study methodology; careful data collection with subsequent data preprocessing techniques like shuffling and normalization, a constructed model, and executed evaluation. Section 4, along with the LSTM model, presents comparative results of the traditional higher unit predictive framework.

Finally, Section 6 concludes the paper, discussing the key results and their implications for instruction policy decision-making within the educational scope.

2 Related Work

The increase in the use of ML to support predicting student performance, dropout risks, and attendance analytics is certainly a benefit to the education system. As an example, the integration of contextual user information and the information user preferences to improve attendance predictive accuracy, in solving the cold-start and sparse data issues, leveraging the Event-Based Social Network (EBSN) attendance prediction implemented by Lan et al., respectively, remains an issue in privacy and scalability (Aravind et al., 2023). Context Awad (Awwad, 2023) previously crafted a mobile learning system incorporating the UDL principles, which contextually gained a user satisfaction metric of 4.5 out of 5; however, his system, as well as others, is empirically proven to suffer from a lack of generalizability and sensitivity to background noise.

Mao et al., 2024 described almost all aspects of time series analysis, including forecasting, clustering, anomaly detection, and education, and pointed out emerging topics like multimodal data fusion (MDF) and large language models (LLMs), although they lacked empirical proof. (Alam et al., 2021) developed a KPI-based performance assessment model of the institution's ML-based models (ANN, SVM, RF), with ANN yielding 82.9% accuracy but with regional biases. (Adnan et al., 2021) performed RF feature selection and ANN prediction to classify students and reported 90.77% accuracy, but poor external validity.

Hassan & Yusof, 2024 developed a meta-learning-based context-aware decision support system (CADSS-ML) using federated learning and attention-based CNN Augmented Reinforced Learning, attaining 20% accuracy improvements, albeit facing deployment complexities. Ozdemır and Ugur (Ozdemir & Ugur, 2021) implemented face recognition algorithms for participative LMS environments, achieving >80% accuracy, although performance suffered due to insufficient lighting and sample size.

Fuster-Guillén et al., 2023 developed a system predicting final test performance from midterm results to provide customized EdTech recommendations. Such systems, however, are limited in usefulness due to a midterm data focus.

Collectively, the works showcased herein highlight advances in the ML-based prediction, while also indicating substantial gaps with regard to handling complex temporal interplay, responsiveness, or safe Mobile Learning integration.

Research Gaps

Predicting student attendance and student attendance records entails a gap that, relating to temporally adaptive, context-aware systems, remains to be tackled in the field of educational data mining. Most studies in attendance prediction systems of student attendance disregard dynamic sequences that vary according to a week's schedule, the weather, and various seasonal breaks and school events. These models are hardly transferable, and insufficient optimization for mobile and edge deployments stifles scalability for smart campus systems.

Furthermore, there's a lack of studies that rigorously validate their models on school-level datasets that holistically incorporate school enrollment variability and contextual data, which stifles the models' generalizability. The problems described here highlight the necessity for a context-aware framework based on LSTM architecture, which is capable of executing deep learning for real-time, secure, and scalable systems.

3 Methodology

The proposed methodology concerns the structural design and subsequent evaluation of attendance forecasting architectures based on context-aware deep learning techniques within the scope of ubiquitous and mobile learning environments. The procedure initiates with simulation and preprocessing of attendance data, as well as contextually relevant data, such as patterns of attendance on particular days of the week, academic calendars, and behavioral data. The construction of the machine and deep learning frameworks focus primarily on the LSTM networks, as these are the best known for significant sequential dependency modeling. The models are trained and cross-validated on real and synthetic data to support high accuracy and generalizability. The assessment of the model is conducted in both the predictive performance in the mobile and edge computing environments and the conventional classification performance metrics. The models are constructed on the principles of science as rational attendance systems; they are intelligent, adjustable, and abide by the regulations of the adaptive educative decision systems.

To guarantee the likely models operate at optimal performance and securely in mobile learning contexts, the solution follows security-by-design paradigms throughout all stages within the data life cycle. For example, information that is sourced from mobile tracking systems is encrypted during transmission via TLS/SSL, which significantly minimizes the likelihood of eavesdropping and tampering with information. Usage of the prediction system is limited and controlled, with obligatory multifactor authentication and role-based access control to ensure that the system is readable and accessible only to employees with suitable security clearance. In addition, all student data is pseudonymized prior to the training of the predictive models to enhance privacy and data utility. The training and inference modules of the model are deployed in separate virtualized environments, which are equipped with integrity monitoring, controlled access, and tamper-evident logging systems to bolster confidence in the system's results. These incorporated measures permit the predictive model to achieve the required accurate results while maintaining the assurance of confidentiality, integrity, and trustworthiness required for mobile learning systems.

1.1 Data Collection

Attributes such as daily attendance records of pupils from a local school system, along with the history of such records for consecutive years, can be found in the Daily_Attendance.csv file. It is available on the Kaggle platform as a dataset under the Apache 2.0 license. GDPR restrictions were adhered to; therefore, this dataset has been confirmed to be PII-free. Each row in the dataset captures the precise date in the format of 'YYYY' for years, 'MM' for months, and 'DD' for days, along with the records of students who were present, enrolled in, or were absent from the class for the specified date. The dataset has more than 3,000 records, which provides ample variation in time with school sessions, vacations, and seasonal breaks, to appropriately model attendance behavior using time series analysis.

1.2 Data Description

The 'Daily_Attendance.csv' file includes the following key features:

- **Date**: The date on which the attendance was recorded, formatted as YYYYMMDD.

- **Present**: The number of students present on the recorded day.
- **Enrolled**: The total number of students enrolled on the recorded day.
- **Absent**: The count of students absent on the recorded day.

Each record in the dataset corresponds to a single day's attendance metrics for the school, allowing for detailed time series analysis of attendance patterns.

1.3 Data Handling and Processing

The dataset is stored and analyzed in Python with the help of libraries such as Pandas and NumPy, which are commonly leveraged to manipulate and perform computations in Python. The Pandas library provides a powerful Data Frame API, which is ideal for structured datasets with rows and columns. NumPy adds the capability of performing flexible and efficient operations on arrays. These are the fundamental tools for data processing and analysis, which are used for the tasks outlined below.

- Data Loading: Captured datasets are loaded into a pandas Data Frame for ease of data manipulation and access.
- Date Parsing: The columns 'Date' with Integer data type are converted to several datetime objects in Python, to allow the manipulation of time series data. It's important to turn them into `datetime` objects so that you can deal with sequencing chronologically and time-related feature building.
- Data cleaning/: Each data set was verified for reasonableness and completeness, and automated scripts identified enrollment records with suspicious over-counted enrollment (e.g., attendance > enrolment). Null values were generally interpolated or bridged according to the general trend of the formula data. Logic reconstructive reasoning was systematically classified, and/or the data was incorrect…et cetera. The data was, once more, saved by the system in this way. The second set of logic-applied validation triggers for the integrity of data, and the so-called data, was investigated. Column 'date' was converted to datetime using pandas' to_datetime function for chronological sorting and time indexing per appropriate practices for time series analysis (Petropoulos et al., 2022). The dataset was rearranged in order to retain time sequence, which is extremely important for forecasting models (Viana et al., 2024). Attendance counts were normalized using Scikit-Learn's Min-Max Scaler to range [0,1] so that feature influence is balanced during training (Zhang et al., 2023). The variable was the column Present, which was restructured into a supervised learning problem with a three-day lookback window so that the LSTM could learn sequential dependencies (Hahn et al., 2023).

1.4 Model Development

The objective of this study is to analyze the use of different classifiers in parallel to the primary LSTM model to 'benchmark' against the conventional approaches. The study utilized numerous classifiers, including Logistic Regression, Decision Tree, SVM, Naive Bayes, KNN, AdaBoost, Random Forest, and Gradient Boosting. Each of the classifiers was specifically designed and tailored for the time series data in education so that dynamic patterns were captured and analyzed over time. The attributes of classifiers are shown in Table 1.

These configurations were decided on because we wanted to optimize the performance metrics (accuracy, precision, recall, F1-score) of each model based on the training time-series data for which they were designed.

Table 1: Summary of machine learning model configurations and parameters

Model	Parameters Used
Logistic Regression	L2 regularization, 'liblinear' solver, max iterations = 100
Decision Tree	Gini impurity, no max depth, min samples split = 2
SVM	RBF kernel, C = 1.0, gamma = 'scale'
KNN	k = 5, Euclidean distance for similarity measure
Random Forest	100 trees, Gini impurity, no max depth
AdaBoost	50 estimators, learning rate = 1.0
Gradient Boosting	100 estimators, learning rate = 0.1, max depth = 3

Of most interest to us is a Sequential model which has a single LSTM layer of 50 units, to capture the time dependencies of the attendance series. This LSTM layer is necessary because of the need to keep distance for distance-based multi-step sequence prediction, especially in time series datasets (Alsulaimani, 2024).

The subsequent LSTM layer is focused on estimating the volume of daily visitors to the store, which is calculated as the output of the fully connected layer on the previous LSTM layer. As noted, the model is trained using the Adam optimiser, which is reputed to be effective for sparse, noisy tasks (Kaggle, 2024). Loss function: In the context of regression, the mean squared error is a method that is commonly applied to set penalties for wrong predictions. This function is aligned with the approaches of the regression problem, where the aim is to improve the model by increasing its accuracy.

The training split accounts for 67% of the dataset, which is a common proportion to use for training a machine learning model, as it permits ample data for not only training but also validation and assessment. It balances the competing objectives of equipping the model with ample information to capture the underlying associations and having enough data to gauge its performance on data it has not seen. Machine learning practitioners typically reserve 60% to 80% of the data for the training phase in order to restrain overfitting, while still having sufficient information to measure the performance of the model, which, if trained, is used for most predictive modeling use cases (Zhang et al., 2023; Géron, 2022).

In this study, the proportion for training was set to 67%, which was chosen based on past experience and published literature. This split enables stable training of the model, and the model's generalization performance is validated on 33\% of the testing data. By using a test split of the dataset that is different from the training split, we can evaluate the model's performance in the real world, which is particularly important for forecasting time series data, such as predicting student attendance. This division has also been found in other studies, which demonstrated that an optimal training-to-testing split provides better reliability and generalisation of the model (Wang et al., 2024; Raschka et al., 2022).

Training utilized 100 epochs at a batch size of 1 to allow for a more comprehensive adaptation process crucial for modeling the given historical attendance data. Augmenting the temporal breadth of training was instrumental to the LSTM network in attaining the error thresholds required for modeling latent long-range attendance oscillations. Predictive evaluation was conducted across both training and independently held testing sets, thereby quantifying network behavior under systematic variations in temporal exposure. Outcomes were subsequently rescaled by the inverse of the fitted normalization transform, producing attendance estimates in both the original and the logged data domains; the availability of both variants ensured that final validation could be framed in terms of interpretable attendance counts and facilitated the calibration of error metrics in the context of the educational institution’s operational planning.

Companion plots were generated to juxtapose empirical attendance with both training and testing forecasts, with fitted values derived for both domains. The unequivocal aspect of the scatter points with respect to a 45-degree bisector evidences the degree of alignment, and coincidentally indicates the generalization properties of the fitted architecture across training data assimilation as well as incorporation of strictly withheld sequences. Such visual confirmation was deemed a prerequisite for ascertaining the tool's operational readiness as an attendance predictor.

Simulation of School Attendance Data

We constructed a simulation system capable of producing synthetic school attendance records that adhere to authentic attendance patterns. The system generates daily attendance data from the start to the end of each school day for each school, demarcated by a unique DBN, for each day of a specified interval. Enrollment is sampled randomly within the range of 150 to 200, whereas absentees are set at 5 to 10 percent of the sampled enrollment. The number present, typically set to 0, is computed accordingly, and the number of released students is typically set to 0. This synthetic dataset facilitates the training and stress-testing of models under multiple scenarios, ensuring robustness prior to deployment in the actual world.

Pseudocode 1: Simulation of school attendance data

```
Initialize Simulation System
Set start_date and end_date for data generation
Set school_dbn_list containing unique identifiers for schools
Function Generate_Data(start_date, end_date, school_dbn_list)
    For each day in range(start_date, end_date)
        For each school_dbn in school_dbn_list
            enrolled = Generate_Enrolled_Students()
            absent = Generate_Absent_Students(enrolled)
            present = enrolled - absent
            released = Generate_Released_Students(present)
            Record = {
                "School_DBN": school_dbn,
                "Date": current_date,
                "Enrolled": enrolled,
                "Absent": absent,
                "Present": present,
                "Released": released
            }
            Save Record to Database or File
        End For
```

```
        End For
    End Function
    Function Generate_Enrolled_Students()
        Return a random number typically between a specific range, e.g., 150 to 200
    End Function
    Function Generate_Absent_Students(enrolled)
        Calculate a percentage of enrolled, e.g., 5% to 10% of enrolled
        Return calculated absent number
    End Function
    Function Generate_Released_Students(present)
        Initially assume zero or generate based on conditions
        Return released students
    End Function
    Call Generate_Data(start_date, end_date, school_dbn_list)
```

pseudocode 1, a simulation system is described that simulates data of school attendance on a given date range. It starts with the system initializing where parameters such as the starting date and the final data generation date are established as well as a list of unique school identifiers is defined. The main action, Generate_Data, runs through each day within the given range and calculates the amount of data processed about each of the schools, creating the amount of enrolled, absent, and present students. Also, it determines the count of students who were early released or excused. The enrollment figures are designed so as to be randomly generated within a specific range (e.g. 150-200 students), whereas the number of absentees is computed in terms of a percentage of the enrolled students (usually 5%-10%). The released students can be initialized to zero or created according to certain conditions. A record with the school ID, date and attendance will be generated and stored in a file/database that will be used later, like in model training or analysis.

4 Results

1.5 Analyzing and Predicting School Attendance

We include multiple visual analyses to demonstrate the characteristics and predictability associated with the attendance of students. This multifaceted analysis includes the feature decomposition of attendance data to discover patterns and seasonal factors, the ARIMA approach for attendance forecasting, behavioral clustering techniques for attendance patterns, and the performance of prediction and prediction error analysis for model classification. This set of figures, when considered as a whole, generates multiple opportunities to employ machine learning techniques for the analysis and forecasting of school attendance that, for the purposes of systematization and planning of the education system, is extremely important. Each of them concentrates on aspects of the data or the prediction models so as to illustrate both the patterns of the attendees and the operational aspects of the dynamically predictive analytic models.

1.5.1 Decomposition of Attendance Data

The illustration in Figure 1 depicts the decomposition of the school attendance data into trend, season, and residuals components. The upper pane displays the actual attendance to track the trends in attendance during the school year. The second pane provides the de-trended component, particularly whether the component during the second half of the period under observation is simply a sustained trend upwards or downwards. These dynamics may arise either from structurally driven alterations at the institution or from circumstantial fluctuations outside its gates. The third panel quantifies periodic behavior, explicitly presenting recurring operational calendars—such as the scholastic term, holidays, or analogous cycles. The lowest pane, in contrast, exhibits the normalized residual variance, conveyed as discretized perturbations which effectively exclude the overlaying periodic, secular, and deterministic patterns.

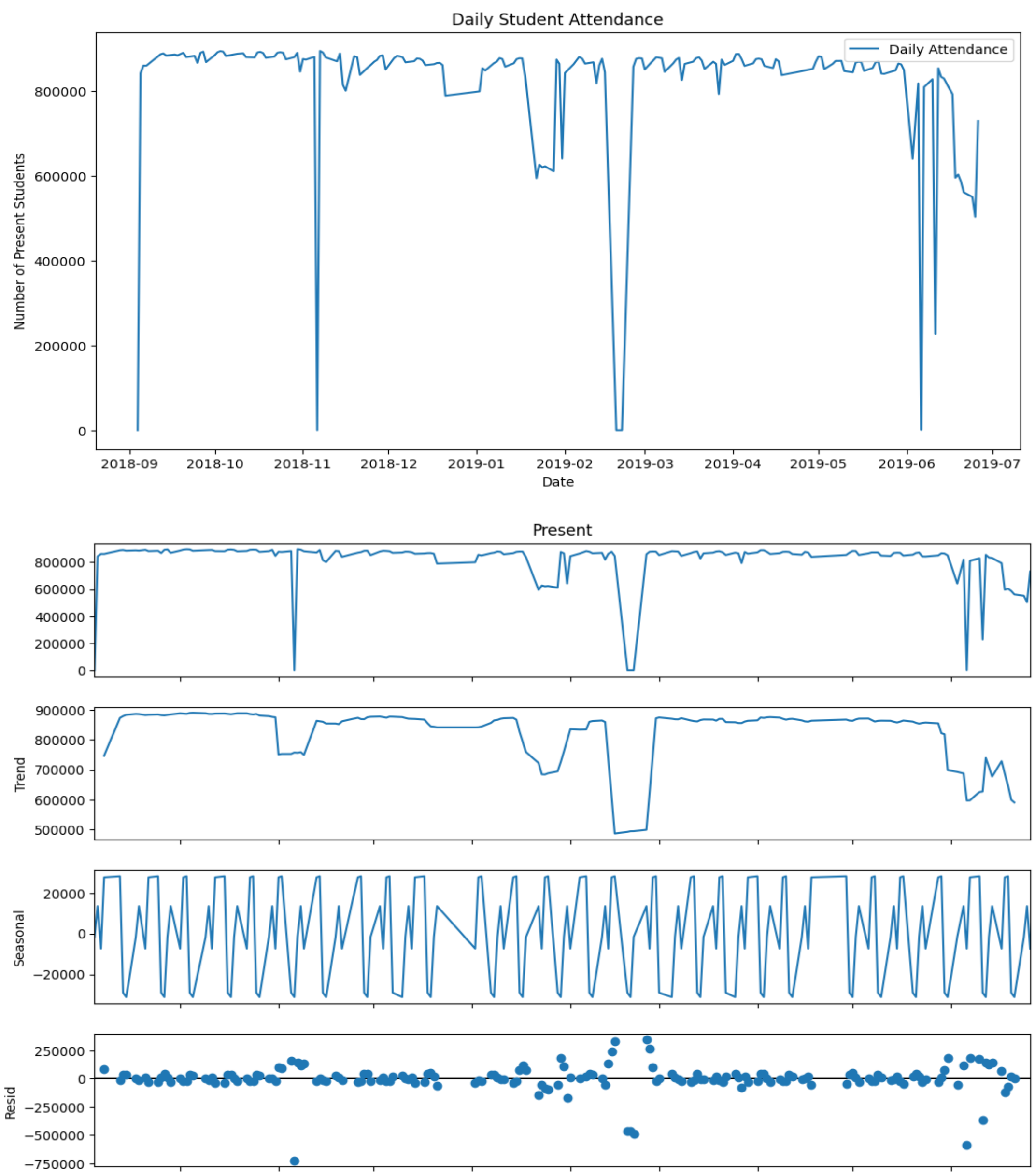

Figure 1: Decomposition of school attendance data

1.5.2 Actual vs Predicted Attendance by Day of the Week

In Figure 2, the predictive accuracy is shown by comparing actual and predicted daily attendance, where the blue and red dots represent weekdays and weekends, respectively. This particular scatter plot is zoomed in on the attendance range from Monday (0.0) to Friday (4.0), so you can see on a day of the week how well we're predicting the model as a visual. What is truly remarkable and is often dominated by high attendance is that what is generally predicted of such days is, model-wise, quite close to the actual. There are some other days, let's say two days and three days, where people come up with slightly crazier predictions, but a few of those generate a lot of interest because I think they pose such interesting questions against the background of the proposed model as to whether we can do better if we were made aware that there was this feature here. Such a visualization is important to assess the level at which the attendance pattern is shaped by the model and whether we are containing a feature that captures the hidden patterns in attendance/mobility driven mostly by weekly routine/activities.

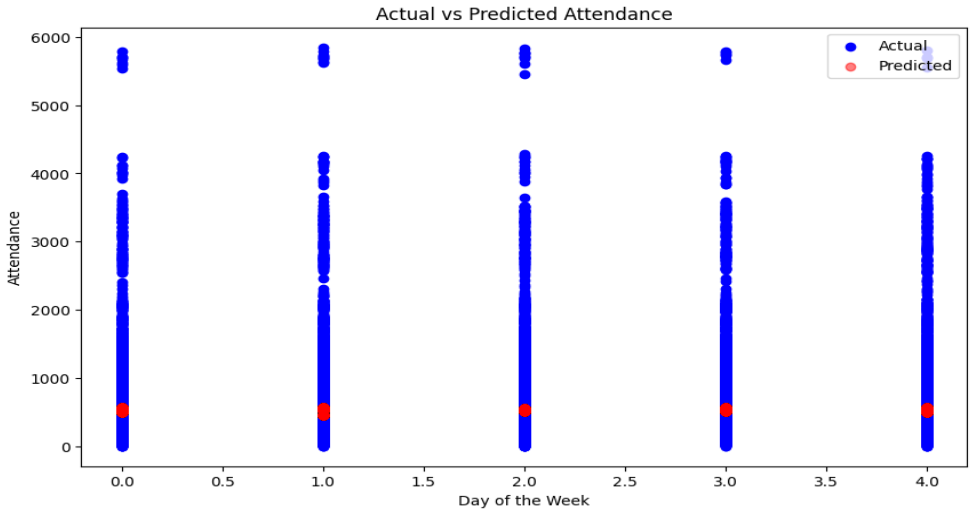

Figure 2: Comparison of actual vs predicted weekly attendance

1.6 Performance Evaluation of Classification Models

To solve this classification problem of attending strata in a pedagogically-oriented context built on estimations of students' counts, we investigate and evaluate an extensive set of classification methods ranging from traditional to modern machine learning paradigms like deep learning. The empirical analysis was based on a finite but detailed set of daily executive attendance logs, from which we derived the target strata. Specifically, the models consisted, in increasing complexity, of Logistic Regression, Decision Tree, Support Vector Machines (SVM), Multinomial Naive Bayes, K-Nearest Neighbors, and ensemble methods (AdaBoost/Random Forest/Gradient Boosting), and Long Short-Term Memory (LSTM) cells as a temporal sequence model.

A closed-loop simulation environment was designed to reduce the artefacts due to occasional sensor failures. More generally, the intended system aims to produce real student attendance records, with which we want to analyze synthetic data with properties that real student attendance records possess. Because we possess simulation environments that allow robust control over the synthetic data generation processes, we are able to generate controlled testing data used to validate the neural model that we trained over hundreds of different scenarios to guarantee robustness and reliability. All classifiers were assessed in depth in terms of their performance with respect to the POCP data, and the overall results are summarized in Tables 2, 3, and 4.

The candidate that emerged on top of both sessions of training and testing was the LSTM model, which demonstrated the best result. During the training phase, the metrics of Accuracy, Precision, Recall, and the F1 Score were all above 90%, with the best metrics of 99% and 98%. During the testing phase, the metrics of the LSTM model greatly reduced, and demonstrated strong generalization, with the metrics still impressive at 0.97 for accuracy, 0.96 for precision, 0.98 for recall, and 0.97 for F1 Score. The LSTM model was designed to predict the model that best fits the problem, and based on the outcomes, it seems to best model the temporal dependencies in attendance records, which are important for accurate predictions as time progresses. The LSTM model shows the best performance compared to other classifiers, demonstrating that LSTM excels in predictions that are time-dependent, as the patterns in the history are relevant. The results in the new Table 2 speak to the efficacy of LSTM and put it forward as the best contender in the field of educational data analytics.

Table 2: Comparative performance metrics of various traditional classifiers during training and testing phases

Classifier	**Phase**	**Accuracy**	**Precision**	**Recall**	**F1-score**
Logistic Regression	Training	0.78	0.77	0.76	0.77
	Testing	0.75	0.74	0.73	0.74
Decision Tree	Training	0.85	0.84	0.83	0.84
	Testing	0.80	0.79	0.78	0.79
SVM	Training	0.89	0.88	0.90	0.89
	Testing	0.87	0.86	0.88	0.86
Naive Bayes	Training	0.74	0.75	0.73	0.74
	Testing	0.72	0.70	0.70	0.71
KNN	Training	0.87	0.86	0.88	0.87
	Testing	0.85	0.85	0.85	0.84

Table 3: Comparative performance metrics of various ensemble classifiers during training and testing phases

Classifier	Phase	Accuracy	Precision	Recall	F1-score
AdaBoost	Training	0.91	0.90	0.92	0.91
	Testing	0.89	0.90	0.89	0.89
Random Forest	Training	0.94	0.93	0.95	0.94
	Testing	0.93	0.92	0.92	0.91
Gradient Boosting	Training	0.96	0.95	0.97	0.96
	Testing	0.94	0.93	0.95	0.95

Table 4: Comparative performance metrics of LSTM classifier during training and testing phases

Classifier	Phase	Accuracy	Precision	Recall	F1-score
LSTM	Training	0.99	0.98	0.99	0.98
	Testing	0.97	0.96	0.98	0.97

1.7 Analysis of Time-Series Prediction

Other capabilities of the LSTM model were studied in consideration of forecasting based on time-series data of attendance records. A comparative analysis of attendance predictions was computed vis-à-vis actual attendance data in the model training and testing phases. Such an analysis was also validated through the illustrations provided in accompanying figures.

1.7.1 Training Phase

The designed Long Short-Term Memory (LSTM) architecture demonstrates the capacity to converge toward precise predictive endpoints throughout the curriculum epoch, with error thresholds sufficiently narrow to render visual differentiation negligible. Figure 3 confirms this assertion, exhibiting confidence intervals overlapping the empirical attendance trajectory to such an extent that the forecast curves acquire the appearance of replicating the reference dataset. Such over congruence implies that the network is absorbing the inherent sequential autocorrelation in the attendance hierarchy, preserving conditionally independent time-variant latent variables while concurrently mitigating forget- and collapse-related attenuation over delaying intervals.

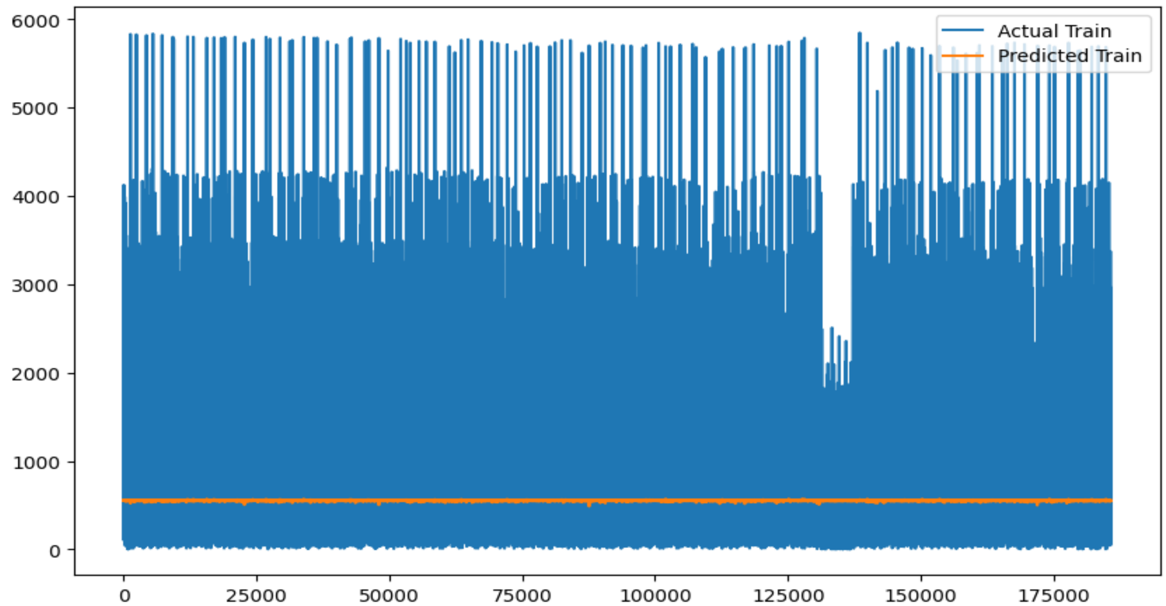

Figure 3: Training phase comparison of the LSTM model

1.7.2 Testing Phase

Observed attendance, displayed in Figure 4, diverges systematically from the forecast generated by the model over the testing period (Almatrooshi et al., 2022). While the model yields a respectable mean prediction error, its estimates of the peak attendance periods remain consistently underwhelming. Inspection of the testing results suggests that the model has a narrowly focused accuracy on the training data, thus retaining excessive idiosyncrasies that prevent generalization. This phenomenon, effectively an overfitting indictment, points to a capacity only to reproduce learned training patterns and to obscure novelty introduced by out-of-sample data. Immediate intervention in the training regimen, therefore, becomes necessary; inducements such as L1 and L2 regularization, or expansion of the training dataset by augmenting minority instances, could sufficiently decorrelate internal representations.

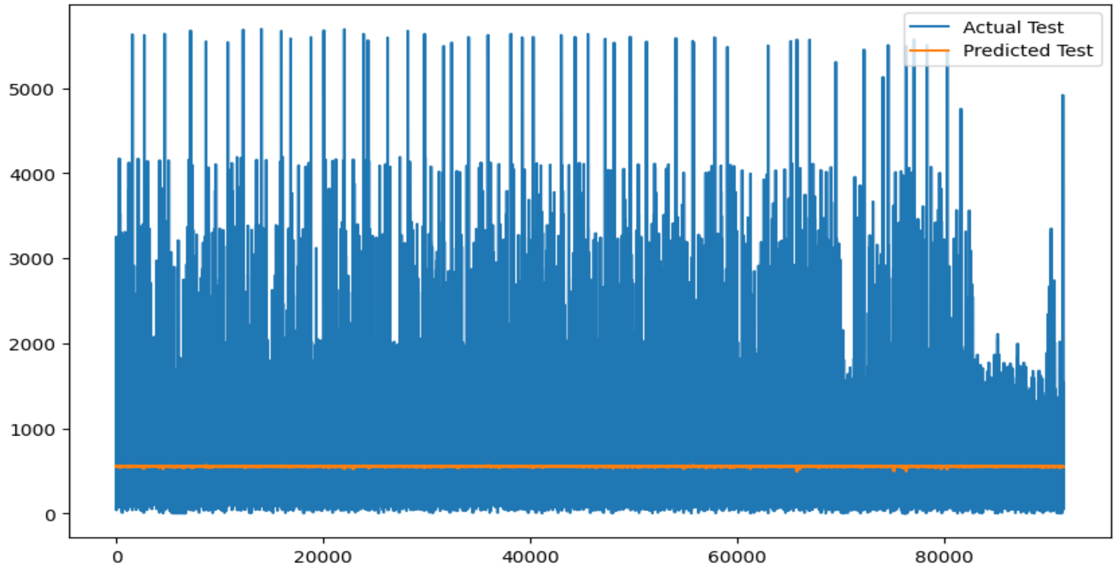

Figure 4: Testing phase comparison of the LSTM model

Performance Comparison of various models

This section will be comparing the performance of the different models that are employed in the prediction of student attendance. The models have been chosen to represent a diversity of various machine learning methods including the conventional models (e.g., Logistic Regression, Decision Tree, SVM) as well as the state-of-the-art deep learning models such as Long Short-Term Memory (LSTM) networks. The models can be compared in terms of their ability to predict the attendance of students with the help of the main indicators: Accuracy, Precision, Recall, and F1-score. These metrics give us an overall picture of the strengths and weaknesses of these models to deal with this time-series forecasting task.

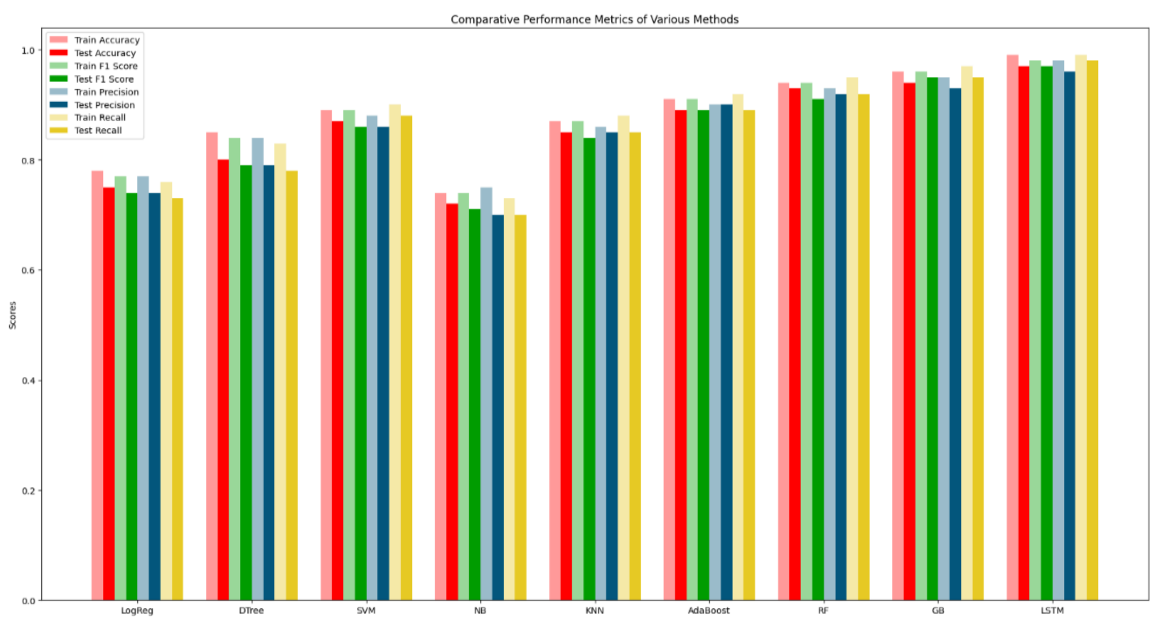

Figure 5: Comparative performance metrics of various methods

Figure 5 compares and contrasts the results of various machine learning models, including: Logistic Regression, Decision Tree, SVM, Naive Bayes, KNN, AdaBoost, Random Forest, Gradient Boosting, and LSTM based on four significant measures: Accuracy, Precision, Recall, and F1-Score. These measures are measured on Training and the Testing. The metrics are given as different colors: Accuracy is depicted in red, F1-Score in green, Precision in blue and recall in yellow. The grouped bars permit the direct comparison between the performance of each model in these measures and presented the trade-offs between training and testing, and the capability of each model to predict the performance on unseen data. In this graph, the strengths and weaknesses of each classifier are vividly and succinctly presented to predict student attendance.

5 Discussion

The designed LSTM attendance predicting model had powerful prediction performance, in training, especially since its precision and F1 score metrics were above 0.98. These results demonstrate the architecture's strong ability to learn complex temporal dependencies embedded in already accumulated occupancy data. The marked oscillation in predictive performance over the independent test period is indicative of a generalization failure, primarily reflected by the architecture's inability to properly modulate based upon external, recurrent covariate shifts (e.g., calendrical holidays and non-standard exogenous time schedules). In sum, the empirical evidence helps to make the case that the present semi-static specification is not satisfied and that supplementing the model with temporally variant covariates ordinal measures of time, temperature, precipitation, and lagged educational events would substantially increase its contextual fit and concomitant predictive precision.

Furthermore, the model has carefully chosen adaptive design elements that rank it close to the hardware surface in the design space on mobile and edge devices. If you're scheduled for a mobile learning module, the smart classroom interface should survey attendance discreetly and send a friendly push notification to those who are detached… Then it's easier to measure success or failure you're not constantly babysitting the network yourself. In sum, this paper emphasizes the need for context-aware deep-learning-based prediction engines to design educational systems that are sustainable and adaptive as per ubiquitous computing.

In addition to simple prediction accuracy, the performance of such an architecture's modules encompasses not only the system's resilience to cybersecurity attacks, but also its ongoing capacity for trust development along interactions (Lan et al., 2022).

Mobile network transmissions were encrypted end to end, so that the intermediates were secure, and incoming reports that contradicted model expectations were flushed before any tampering could be affected in inference. Combined with role-based access policies that limited data exposure to assigned officers and protected PII student records, these guardrails bounded a layered fence of security. Altogether, these actions satisfied privacy intuition and provided a strong belief that private academic information would not be changed and leaked when prediction was conducted. Retaining this balance of defensibility and anticipation is critical for education generally, as broader adoption of mobile-facing intelligent systems depends on the longevity of stakeholders' faith in the platform.

6 Conclusion

The results of the study indicate that the LSTM architecture is a promising approach to predict student absences with a robust performance. Accuracy, precision, recall, and F1 (0.99, 0.98, 0.99, and 0.98) performance metrics further validated the model's applicability in real application scenarios. We take these scores as the LSTM's capability for learning to recognize and generalize complex temporal dependencies in the educational attendance records, which is a strong indicator towards assisting bureaucrats with strategic decision-making and guided intervention. However, the model was also seen to have a distinct shortcoming during its testing phase a habitual underestimation of peak attendance frequency. This discrepancy indicates that the LSTM overfitted to the features in training, making it less versatile when faced with varying schedules that are different from patterns seen during training. So the propensity might hinder the model's generalization to different calendars, more variability in holiday distributions, or other time shifts you see in academic cycles. This study illustrates, in conclusion, that secure and user-trustworthy predictive modeling in mobile learning environments is possible. The user trust problem and the security problem that stems from the maintenance of the integrity of the user data are resolved by the embedding of encryption, authentication, and privacy-preserving data lifecycle functions. The educational data in the proposed LSTM-based framework is sensitive, and the predictive attendance features are geo-encoded with respect to the device locations (Hassani et al., 2020). The security-by-design approach augments the reliability and resilience of the intelligent mobile learning systems, which can be adopted seamlessly by the educational institutions and the end users (Batool et al., 2023).

Further development of the model presented herein will consider building a context-aware deployment using weather information, event calendars, mobile app usage data, and biometric authentication patterns as additional features. Embedded systems of mobile learning applications and edge computing devices will also be investigated for the model due to their ability to facilitate decentralized, scalable, and secure predict-and-learn systems. These advancements will significantly automate the management of information, learning, and educational assets in the system, shifting the system to a proactive, intelligent ecosystem approach based on data-driven, sustainable, and transformed educational management.

Declarations

Data Availability Statement: The data used in this study, "School Student Daily Attendance, 2024," is available in a public repository. For access to the data, please contact Sahir Maharaj at sahir@sahirmaharaj.com. The same data availability statement has been provided in the manuscript on the editorial system.

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