

A Hybrid Machine Learning Model for Short-Term Mobile Traffic Forecasting

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(Received: April 1, 2026; Revised: June 5, 2026; Accepted: August 20, 2026; Available online: October 1, 2026)

Abstract

Today, mobile networks are essential for seamless communication. As mobile subscriber numbers increase, mobile network operators must devise strategies to meet the enormous demand for mobile network resources, such as spectrum. Therefore, the need for an effective prediction mechanism for efficient resource management and planning becomes paramount. To address the challenges of non-linearity, burstiness, and hidden temporal patterns in mobile traffic prediction, this paper develops and evaluates a hybrid machine learning model for short-term forecasting of mobile traffic congestion. Real-life base-station mobile data traffic for the first quarter of 2024 from northern and southern Kaduna State, Nigeria, was used. The 40573-row, 10-column entry dataset was preprocessed to remove duplicates, outliers, and missing values. From the processed dataset, 70% was used to train various machine learning models. Long Short-Term Memory (LSTM) and Accelerated Gradient Boosting (AGB), with RMSEs 12% and 15% lower than those of other models, were selected via voting to develop the proposed hybrid prediction model. Thirty per cent (30%) of the processed dataset was then employed to test and evaluate the prediction performance of the proposed model on nine base stations with both the highest and lowest traffic using Root Mean Square (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE) as evaluation metrics. From the results, LSTM-AGB outperformed LSTM and ARIMA, achieving the lowest RMSE, MAPE, and MAE values of 2354, 8.04%, and 196, for both uplink and downlink prediction evaluations. These findings demonstrate the effectiveness of the proposed model for short-term mobile traffic prediction by enabling proactive congestion management through early identification of imminent traffic surges, thereby enabling preemptive adjustments to resource allocation and network planning. The proposed hybrid model provides a scalable, data-driven approach that can support the efficient operation of modern mobile stations, especially in resource-constrained environments.

Keywords: Mobile traffic, Long-Short Term Memory, Traffic forecasting, Traffic Congestion, Statistical models

1. Introduction

In the 21st century, mobile communication has become integral to human interaction, economic development, and the delivery of essential services. Expanding affordable, accessible, and reliable ICT infrastructure is recognized as a global priority under Sustainable Development Goal 9c [1]. Successive generations of mobile networks, from 2G to 5G [2], have delivered marked improvements in data rates, latency, and service diversity [3], [4]. The number of globally connected devices exceeded 13 billion in 2023 [5], and managing traffic increase on these devices demands mobile network operators to increasingly rely on traffic forecasting to support proactive congestion control, energy-efficient base-station operation, and dynamic radio-resource management [6], especially in situations where hidden temporal dependencies are difficult to characterize [7]. Furthermore, congestion pressures on radio access and core network infrastructure directly affect network performance, resource allocation, and operational cost [8]. This congestion is driven by the proliferation of smartphones, IoT devices, and bandwidth-intensive applications such as video streaming,

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 DOI: <https://doi.org/10.47738/jads.v7i4.1121>

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video calling, and social media [9]. This sustained growth, which is particularly pronounced across Sub-Saharan Africa [10], is projected to triple globally between 2023 and 2029 [11], [12]. Forecasting is commonly classified into short-term (days to months), medium-term (up to one year), and long-term (beyond one year) categories [13], with short-term forecasting being particularly critical for day-to-day operational optimization.

Despite its operational importance, accurate mobile traffic forecasting remains a persistent challenge. Classical statistical approaches offer low computational complexity and fast inference but assume linear temporal structure, and therefore perform poorly when traffic patterns are highly non-linear [14], [15], [16]. These shortcomings are prevalent in both Autoregressive Integrated Moving Average (ARIMA) and its seasonal variant (SARIMA) [17], [18], [19], [20]. Shallow machine learning models, including Support Vector Regression, Principal Component Analysis, Kalman filtering, and Random Forests [21], [22], [23], [24], [25], [26], [27], improve on statistical baselines but remain limited in modelling long-range dependencies and are constrained by low representational depth, resulting in weaker performance on complex traffic series. Deep learning models, particularly Recurrent Neural Networks (RNNs) and their variants, better capture sequential structure but suffer from vanishing gradients, which limit their ability to retain information over long horizons [28]. While the Long Short-Term Memory (LSTM) network [29] addresses this limitation through gated memory cells, it does so at the cost of high training complexity and reduced sensitivity to rapid, short-term residual fluctuations, a shortcoming that is particularly consequential for mobile traffic, which is characterized by sudden bursts and spikes rather than purely smooth long-term trends. This leaves a gap for a computationally efficient hybrid model that jointly captures long-range temporal dependencies and short-term traffic burstiness.

This study addresses this gap by combining Accelerated Gradient Boost (AGB), which uses Nesterov momentum acceleration to achieve fast convergence on non-linear, bursty patterns, with LSTM, which retains long-term temporal dependencies through its gated memory mechanism. Thus, the objective of this study is to develop and evaluate a hybrid LSTM-AGB model for short-term forecasting of mobile traffic congestion using real-world base-station data. The main contributions of this study include the following: (i) processes a large-scale, real-life, curated mobile traffic dataset from base stations in northern and southern Kaduna State, Nigeria, over the first quarter of 2024; (ii) develops and validates a hybrid model of AGB-LSTM for short-term mobile traffic; and (iii) demonstrates the performance of Hybrid models over standalone one in mobile traffic prediction, management of congestion, and resource planning in resource-constrained network environments.

2. Literature Review

2.1. Overview of Mobile Networks

Mobile network traffic refers to the aggregate volume of data transmitted over cellular infrastructure, primarily via packet-switched mechanisms. In mobile systems, traffic levels directly influence network performance, resource allocation, and operational cost [8]. A typical mobile architecture consists of the Radio Access Network (RAN), which provides wireless connectivity through geographically distributed base stations, and the Core Network (CN), where User Equipment (UE) connects to a serving base station and may transition to nearby stations via handover.

Traffic from applications over mobile networks, such as social media, audio streaming, video calling, and video streaming, has increased significantly [9]. The widespread adoption of smartphones, IoT devices, and bandwidth-intensive applications such as video streaming and social media have accelerated traffic growth. Sub-Saharan Africa alone recorded a mobile penetration and adoption [10], while global mobile data traffic is projected to triple between 2023 and 2029 [11]. Consequently, short-term traffic forecasting has become essential for proactive congestion control, energy-efficient base-station operation, and dynamic radio-resource management [12]. Traffic forecasting horizons are typically categorized as short-term (days to months), medium-term (months to one year), and long-term (beyond one year) [13]. This study focuses on short-term forecasting to support operational network optimization.

2.2. Mobile Traffic Predictive Models

A broad range of modelling techniques has been applied to predict cellular traffic. As shown in figure 1, classical statistical models [14] rely on linear temporal structures, offer low computational complexity [15], but perform poorly with non-linear and highly variable data inherent in mobile-traffic time series [16]. The Common statistical algorithms

used in traffic prediction are the ARIMA [17],[18] and its seasonal extension (SARIMA) [19], [20]. Shallow Machine Learning models [21] such as Linear Regression (LR) [22], compressive sensing[23], Support Vector Regression (SVR)[24], Principal Components Analysis (PCA)[25], Kalman filtering, and Gaussian process [26], Random Forest [27] improve flexibility but are limited in modelling long-range dependencies and highly non-linear temporal dynamics. Deep learning models can be categorized into two types: temporal and spatial-temporal. Temporal models capture the complex, non-linear interactions in traffic measurements over time steps, influenced by both short and long-term effects. For example, Das et al. [28] note that although temporal models such as Recurrent Neural Networks (RNNs) and their variants are suitable for sequential data, they are limited in capturing long-term dependencies due to vanishing gradients.

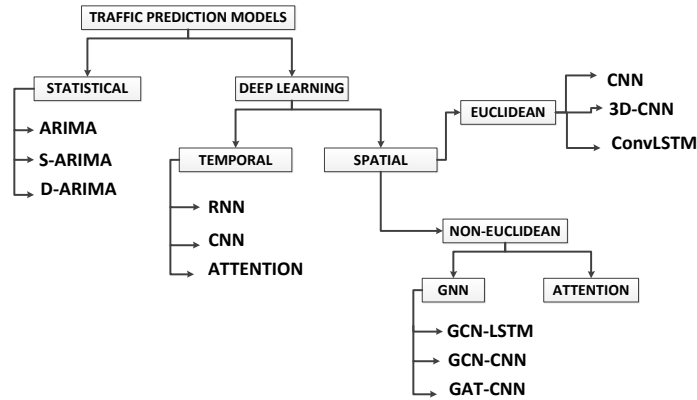


Figure 1. Classes of prediction models

To address the vanishing gradient problem in RNNs, Hochreiter and Schmidhuber [29] introduced the LSTM, which replaces RNN's simple loops with memory cells equipped with input, output, and forget gates. These gates selectively retain or discard information over long sequences, enabling effective modelling of long-term dependencies in time-series data, such as mobile traffic patterns. This architecture has proven effective for sequential tasks, such as speech recognition [30] and time-series anomaly detection [31].

The LSTM cell state is updated through the following gates and operations:

$$\text{Forget gate: } f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \quad (1)$$

$$\text{Input gate: } i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \quad (2)$$

$$\text{Candidate value: } \tilde{C}_t = \tanh(W_c \cdot [h_{t-1}, x_t] + b_c) \quad (3)$$

$$\text{Cell state update: } C_t = f_t \cdot C_{t-1} + i_t \cdot \tilde{C}_t \quad (4)$$

$$\text{Output gate: } o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \quad (5)$$

$$\text{Output: } h_t = o_t \cdot \tanh(C_t) \quad (6)$$

Note: σ = Sigmond activation function; $\tanh$ = Hyperbolic tangent activation function; $W_f W_i W_c W_o$: are weight matrices for the forget, input, candidate, and output gates, respectively.; $b_f b_i b_c b_o$ = Bias vectors for the forget, input, candidate, and output gates, respectively; h_{t-1} = Hidden state (output) from the previous time step; x_t = input at the current time step; C_{t-1} = Cell state from the previous time step; $f_t f_i f_o$ = Outputs of the forget, input, and output gates at time t; $\tilde{C}_t$ = Candidate cell state value at time t; C_t = Updated cell state at time t; h_t = Hidden state (output) at time t; $[\cdot]$ = concatenation operation.

LSTM's gated mechanism provides an advantage over standard ARIMA [32] by retaining information over extended periods [33], which is critical for forecasting volatile mobile traffic sequences in our hybrid model. Another standard deep learning algorithm used within the forecasting space is Accelerated Gradient Boost (AGB). AGB enhances conventional gradient boosting by integrating Nesterov momentum, resulting in faster convergence and reduced overfitting. It maintains two sequences of functions: f^m , which follows the standard gradient boosting update, and g^m , which incorporates Nesterov's acceleration. Let L denote the loss function, and assume we minimise.

$L(f) = \sum_{i=1}^n \ell(y_i, f(x_i))$ where ℓ is a differentiable convex loss (e.g., squared error). The algorithm proceeds as follows.

Algorithm 1. LSTM–Nesterov-Accelerated Gradient Boosting (LSTM-NAGB)

Initialise $g^0 = f^0 = \arg \min_c \sum_{i=1}^n \ell(y_i, c)$ (a constant model)

For $m = 1$ to M (number of iterations)

- Compute the pseudo-residuals $r_i^m = - \frac{\partial \ell(y_i, g^{m-1}(x_i))}{\partial g^{m-1}(x_i)}$ for $i = 1, \dots, n$ (7)

- Fit a base learner (regression tree) h^m to the residuals $\{(x_i, r_i^m)\}_{i=1}^n$ (8)

- Compute the optimal step size. $\rho_m = \arg \min_{\rho} L(g^{m-1} + \rho h^m)$ (9)

- Update the standard sequence: $f^m = g^{m-1} + \rho h^m$ (10)

- Update the accelerated sequence: $g^m = f^m + \frac{m-1}{m+2}(f^m - f^{m-1})$ (11)

The final model is g^M . This formulation increases convergence by extrapolating the gradient direction using the momentum term $\frac{m-1}{m+2}$, therefore, decreases the number of iterations needed. Compared with popular boosting methods like XGBoost and LightGBM, AGB's uniqueness lies in its explicit integration of Nesterov's momentum, which empirically leads to faster training and sparser ensembles with fewer trees, thereby reducing the tendency to overfit at early iterations. XGBoost emphasises second-order Taylor approximations for loss and includes $\frac{L_1}{L_2}$ regularisation to prevent overfitting, making it robust for structured data, but computationally expensive due to greedy tree learning. LightGBM, on the other hand, utilises histogram-based approximations and a leaf-wise growth strategy for efficient processing of large datasets, achieving high speed but potentially higher memory usage. AGB sacrifices some of XGBoost's regularisation for acceleration, making it particularly suitable for time-series forecasting where rapid model updates are needed.

Convolutional Neural Networks (CNNs) [34], initially developed for image processing, have been adapted for mobile traffic forecasting due to their ability to extract local patterns via convolutional filters, offering a simpler structure and faster training than RNN-based methods. Common variants like the Temporal Convolutional Network (TCN) [35] build upon CNNs by utilizing causal and dilated convolutions to handle long-range dependencies while ensuring no information leakage, and the Fully Convolutional Network (FCN) [36] for accommodating flexible sequence lengths. ConvLSTM [37] combines convolutions with LSTM gates to capture both spatial and temporal features in grid-like data. Despite the advantages of CNNs, this model was not selected due to its poor performance in handling long-term temporal dependencies in volatile time series, such as mobile traffic. We selected LSTM for its ability to model long-term dependencies via memory cells [29], combined with AGB's acceleration to improve efficiency and better address the non-linear and bursty nature of mobile traffic.

2.3. Related Works

Early research relied on statistical models, such as ARIMA, to capture linear temporal structures with low computational overhead. ARIMA has been applied to energy-efficient base station management [38] and hybrid cluster-level prediction of cellular traffic [39]. These models provide fast inference but perform poorly in capturing non-linear patterns, resulting in higher Root Mean Square Error (RMSE) on complex datasets [40]. Shallow machine learning models, such as Support Vector Regression (SVR) [41] and Principal Component Analysis (PCA) [42], have also been employed to address non-linearity and reduce the dimensionality of traffic data. However, their limited model depth restricts their ability to capture complex relationships, resulting in relatively low R^2 scores [43].

To address non-linear temporal dependencies, recurrent models such as Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks have become prominent in mobile traffic forecasting. LSTM-based approaches with normalization have been used to handle bursty traffic and reduce prediction errors by approximately 15–20% [44]. Other studies have incorporated data augmentation into LSTM-based models to improve robustness against variations in traffic patterns [45]. However, LSTM models incur relatively high training costs and remain limited in their ability

to capture rapid residual variations [48]. Convolutional neural network (CNN)-based models, including dual-channel ResNet architectures [46] and parallel CNNs [47], have demonstrated faster convergence than LSTM-based approaches while maintaining competitive accuracy for periodic traffic data. Nevertheless, Temporal Convolutional Networks may still face limitations when processing long sequences.

More recently, spatio-temporal models have been employed to improve mobile traffic prediction by jointly modeling temporal dependencies and spatial relationships. ConvLSTM-based approaches have been used as primary components for extracting complex spatio-temporal patterns from mobile traffic data, achieving higher prediction accuracy than single CNN-based models on real-world datasets [49]. Graph-based approaches, such as Graph Convolutional Network-LSTM (GCN-LSTM), integrate graph convolution with LSTM to capture both spatial and temporal information and have demonstrated improved performance compared with individual GCN or LSTM models [50], [51]. Similarly, the Spatio-Temporal fine-grained user traffic prediction mechanism (STEP) combines GCN with Gated Recurrent Unit (GRU) networks to efficiently learn from large-scale user traffic datasets [52]. Although these approaches provide improved performance in modeling heterogeneous spatial interactions, their architectural complexity increases computational requirements.

Convolution-based hybrid architectures have also been explored to balance prediction accuracy and computational efficiency. These approaches typically employ 1D CNNs to extract high-level temporal characteristics, graph convolutional layers to capture spatial features from neighboring nodes, and Gated Linear Units (GLUs) to model spatio-temporal dependencies in mobile traffic [53], [54]. Such architectures can reduce computational time compared with conventional RNN-based models while maintaining competitive prediction accuracy [55], [56]. However, existing hybrid models remain limited in their ability to simultaneously capture short-term irregularities, such as sudden traffic spikes and bursty patterns, while preserving long-term temporal stability.

Recent works on road traffic congestion prediction [57] and [54] originate from transportation and urban traffic domains, which differ from mobile traffic in scale (e.g., physical vehicle flows vs digital data packets) and granularity (e.g., road segments vs base stations); they offer valuable methodological parallels. Both domains involve time-series prediction with non-linear patterns, bursty events (e.g., traffic jams vs. data spikes), and the need for hybrid models to handle temporal dependencies. However, these models are less suited to predicting mobile traffic, which is more granular and volatile.

From prior works, it can be observed that substantial progress has been made in statistical, machine learning, and deep learning models for mobile traffic prediction over the years. However, models that address both long-term temporal dependencies and short-term burst behavior are minimal. This study proposed a unique hybrid model that integrates Accelerated Gradient Boost (AGB) with LSTM to address these limitations.

3. Methodology

This research employs the standard machine learning pipeline depicted in figure 2. This pipeline includes the data gathering, data preprocessing, model training and testing, and model evaluation. Real-world, daily-aggregated traffic data were obtained from commercial base stations in northern and southern Kaduna State, Nigeria, spanning January–March 2024. After drop_duplicates, IQR removal, and mean imputation, the dataset consists of 40,573 rows (entries) and 10 columns. For model development, 70% of the data (approximately 28,401 rows) was used for training, and the remaining 30% (approximately 12,172 rows) for testing, ensuring temporal splits to maintain sequence integrity for time-series forecasting. This daily granularity is suitable for short-term forecasting, capturing patterns like weekday peaks without the noise of sub-hourly fluctuations.

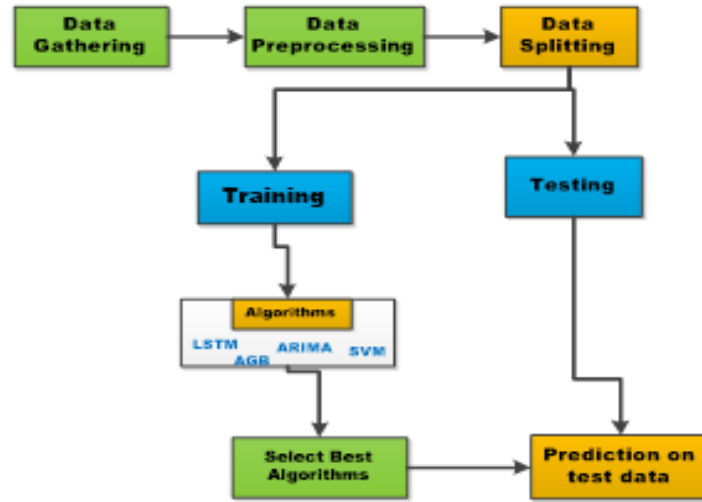


Figure 2. Model development flow

This research uses an ensemble approach to develop the prediction model. Thus, during the training phase, various algorithms were employed, and the two best-performing were selected to form the ensemble model. The various algorithms used include LSTM, AGB, ARIMA, and SVM. To select the best models for the ensemble, we employed a soft voting mechanism based on weighted averaging, which combines the predictions of the individual regressors to produce the final output. This approach was chosen over hard voting because it is better suited to regression tasks where continuous values (e.g., traffic volumes) need to be predicted, enabling smoother integration of model strengths [55], [56]. The selection criteria involved 5-fold cross-validation on the training dataset (70% of the preprocessed data), evaluating each Model (LSTM, AGB, ARIMA, SVM) based on RMSE, MAE, and MAPE. LSTM and AGB were selected because they demonstrated superior performance, with average RMSE reductions of 12% and 15%, respectively, compared to ARIMA and SVM across folds, capturing long-term dependencies (LSTM) and accelerating convergence on non-linear patterns (AGB). To formalize the hybrid prediction mechanism, the final forecast at time step t , $Y_{hybrid,t}$, is computed as a weighted average of the individual LSTM and AGB predictions:

$$Y_{hybrid,t} = w_{LSTM} \cdot Y_{LSTM,t} + w_{AGB} \cdot Y_{AGB,t} \quad (12)$$

w_{LSTM} and w_{AGB} are the non-negative weights assigned to the LSTM and AGB predictions, respectively, subject to $w_{LSTM} + w_{AGB} = 1$. The weights are derived from each model's cross-validation error such that the model with the lower error is assigned a proportionally higher weight:

$$w_i = \frac{\frac{1}{E_i}}{\frac{1}{E_{LSTM}} + \frac{1}{E_{AGB}}}, i \in \{LSTM, AGB\} \quad (13)$$

E_i denotes the average RMSE obtained for model i (LSTM or AGB) during the 5-fold cross-validation described above. During testing, the performance of the hybrid model is quantified using the following standard error metrics, where y_t and $\hat{y}_t$ denote the actual and predicted traffic values at time step t , respectively, and n is the number of test samples:

$$RMSE = \sqrt{\frac{1}{n} \sum_{t=1}^n (y_t - \hat{y}_t)^2} \quad (14)$$

$$MAE = \frac{1}{n} \sum_{t=1}^n |y_t - \hat{y}_t| \quad (15)$$

$$MAPE = \frac{100}{n} \sum_{t=1}^n \left| \frac{y_t - \hat{y}_t}{y_t} \right| \quad (16)$$

The ensembled model is then evaluated during the testing stage using Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and Mean Absolute Error (MAE).

4. Results and Discussion

Experiments were conducted on selected high-traffic base stations in Kaduna North and South. The base stations HLBE 001, HLBE 002, HLBE 016, HLBE 052, and HLBE 120 in Kaduna South, and HLBD 019, HLBE 029, HLBE 098, and HLBE 117 in Kaduna North were selected due to the enormous data traffic they generate. The samples were split into 70% for training 30% for testing. Figures 3 to figure 5 represent the total downlink data and total uplink data for HLBE 016, HLBE 120 and HLBE 019, respectively. These figures show that LSTM-AGB outperforms other models. Figure 4 presents the (a) uplink and (b) downlink traffic predictions for base station HLBE 120, the highest-traffic station among those sampled in Kaduna South. LSTM-AGB tracks the observed traffic more closely than ARIMA and standalone LSTM, particularly around the sharp uplink peaks that characterize this station's bursty traffic profile. As shown in table 1, LSTM-AGB reduced RMSE relative to ARIMA by 9.46% for downlink and 26.88% for uplink at HLBE 120, with a corresponding uplink MAE reduction of 37.12%. These gains illustrate the model's ability to adapt to high-traffic, high-variability stations, where AGB's fast convergence on non-linear fluctuations complements LSTM's long-term dependency modelling.

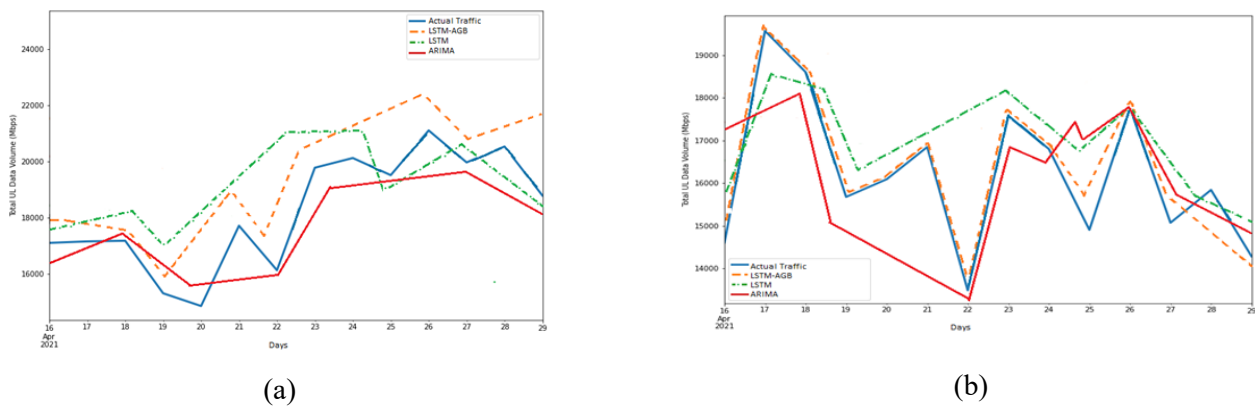


Figure 3. Prediction (a) HLBE 016 uplink data (b) HLBE 016 downlink data

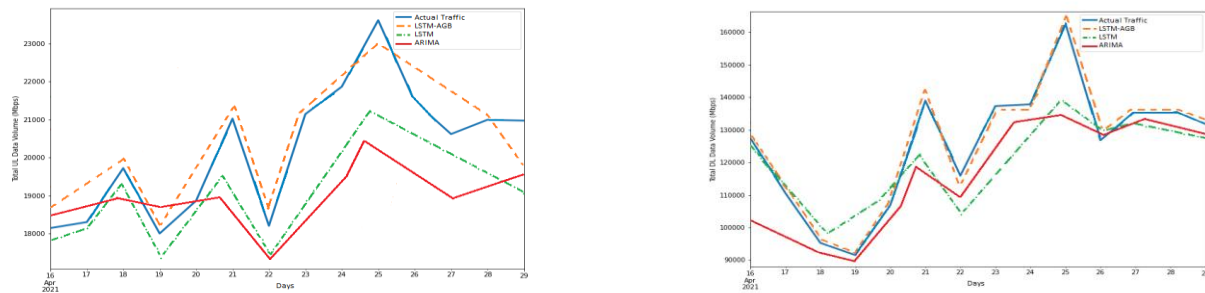


Figure 4. Prediction for (a) HLBE 120 uplink data (b) HLBE 120 downlink data

Figure 5 shows the (a) uplink and (b) downlink traffic predictions for base station HLBE 019 in Kaduna North. Unlike the other sampled stations, HLBE 019 exhibits a comparatively quasi-linear downlink traffic pattern, and as Table 1 shows, LSTM-AGB's downlink RMSE (24,184) is marginally higher than that of ARIMA (22,315) and LSTM (23,208) at this station; this is visible in Figure 5(b), where the LSTM-AGB curve deviates slightly more from the observed downlink trend than at the other base stations. Despite this, LSTM-AGB still achieves the lowest MAPE and MAE for both uplink and downlink traffic and the lowest RMSE for uplink traffic at HLBE 019, indicating that its overall predictive accuracy remains competitive even at a station whose relatively stable traffic pattern favors the simpler linear structure of ARIMA

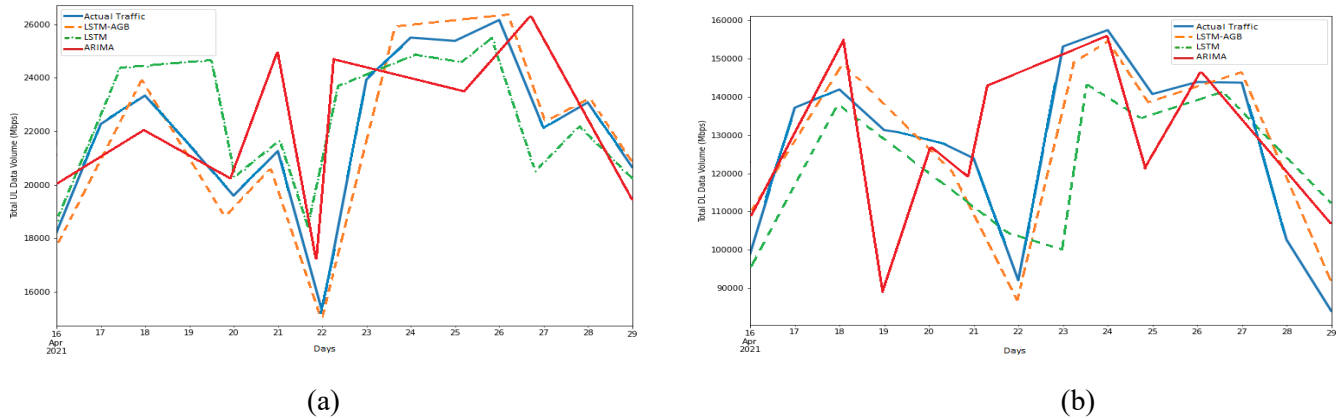


Figure 5. Prediction for (a) HLBE 019 uplink data (b) HLBE 019 downlink data

Table 1 shows the Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and Mean Absolute Error (MAE) comparisons of LSTM-AGB, ARIMA, and LSTM at various base stations. To facilitate a quantitative synthesis, we computed average error values across the base stations and analyzed each model's performance. The mean results across nine base stations reveal that average RMSE, MAPE, and MAE values for LSTM-AGB were significantly lower for both total downlink (TDL) and total uplink (TUL) traffic. Compared to ARIMA, LSTM-AGB reduced RMSE by 9.11% (TDL) and 25.80% (TUL), and MAE by over 22%. Improvements over LSTM were also observed, particularly for bursty uplink traffic. These mean values reveal notable percentage improvements. However, at base station HLBE 019, ARIMA outperforms LSTM. This base station exhibits relatively quasi-linear short-term patterns, which the ARIMA model is well-suited to, given its linear autocorrelation structure. Furthermore, the performance discrepancy may arise from data sparsity or lower traffic variability at HLBE 019, which can reduce the effectiveness of deep learning models.

Table 1. Comparison of LSTM-AGB performance with ARIMA and LSTM at various base stations

HLBE	Algorithm	RMSE TDL	RMSE TUL	MAPE TDL	MAPE TUL	MAE TDL	MAE TUL
001	ARIMA	14,615	2,808	26	33	12,593	1,975
	LSTM	13,203	1,963	24	31	10,725	1,875
	LSTM-AGB	12,884	1,502	21	29	10,674	1,523
002	ARIMA	18,457	4,537	18	17	15,014	2,764
	LSTM	17,717	3,376	15	14	13,901	2,676
	LSTM-AGB	17,245	2,947	12	12	11,452	2,123
016	ARIMA	14,253	2,941	13	9	11,325	2,036
	LSTM	13,031	2,057	12	8	10,723	1,724
	LSTM-AGB	11,457	1,527	10	8	8,456	1,205
052	ARIMA	3,245	864	37	39	2,015	534
	LSTM	3,354	752	34	37	1,927	456
	LSTM-AGB	2,354	654	32	35	1,536	364
120	ARIMA	20,142	2,946	12	12	17,364	1,964
	LSTM	19,274	2,405	9	10	15,369	1,798
	LSTM-AGB	18,236	2,154	9	9	12,459	1,235
019	ARIMA	22,315	2,858	19	11	20,492	2,296
	LSTM	23,208	2,897	17	10	22,549	2,337
	LSTM-AGB	24,184	2,802	15	8	18,316	2,258
029	ARIMA	16,352	2,945	16	16	15,452	2,931
	LSTM	14,342	2,808	15	14	13,482	2,642
	LSTM-AGB	13,264	2,546	13	13	1,235	2,210
117	ARIMA	4,523	453	27	26	3,564	260
	LSTM	4,009	339	25	22	3,154	241
	LSTM-AGB	3,846	301	23	18	2,956	220
146	ARIMA	36,351	4,194	40	34	25,222	3,132
	LSTM	33,109	4,456	38	32	24,761	3,401
	LSTM-AGB	33,100	3,781	36	28	22,519	2,677

To enhance interpretability, Figure 6 (a) - (c) presents a bar plot comparing the average RMSE, MAE, and MAPE across all models for Total Downlink (TDL), aggregated over the nine base stations. The plot clearly illustrates LSTM-AGB's consistent error reductions, with notable improvements over ARIMA. A comparative analysis of station-based traffic patterns shows varying error magnitudes across base stations, indicating heterogeneous mobile traffic across different geographical and demographic contexts. For example, at base station HLBE 001 of Table 1, LSTM-AGB reduces downlink and uplink RMSE by 11.86% and 46.50% over ARIMA, with MAPE drops of 19.23% and 12.12%, and MAE reductions of 15.23% and 22.89%. At base station HLBE 002, LSTM-AGB shows significant improvements over ARIMA, achieving 6.61% RMSE for downlink, 35.05% RMSE for uplink, 33.33% MAPE for downlink, and 29.41% MAPE for uplink. Furthermore, at HLBE 016, it achieves an RMSE reduction value of 19.62% for downlink and 48.08% for uplink, and MAPE drops of 23.08% and 11.11%, respectively.

These differences stem from factors such as location, population density (which is more variable in urban areas), time-of-day peaks, user mix (residential vs. commercial), and special events. The LSTM-AGB's ability to sustain lower error levels across these diverse conditions demonstrates its robustness and generalizability. Additionally, TUL predictions show substantially lower errors than TDL across models and stations, with TUL RMSE often an order of magnitude smaller (e.g., at HLBE 146, LSTM-AGB yields 33,100 for TDL vs. 3,781 for TUL—a ratio of 8.8:1). This persistent asymmetry reflects intrinsic differences in traffic profiles: download traffic is higher in volume and more volatile due to content consumption, whereas upload traffic is comparatively stable and dominated by signaling and modest user-generated activity. The lower variability of upload behavior naturally yields more accurate TUL predictions across models.

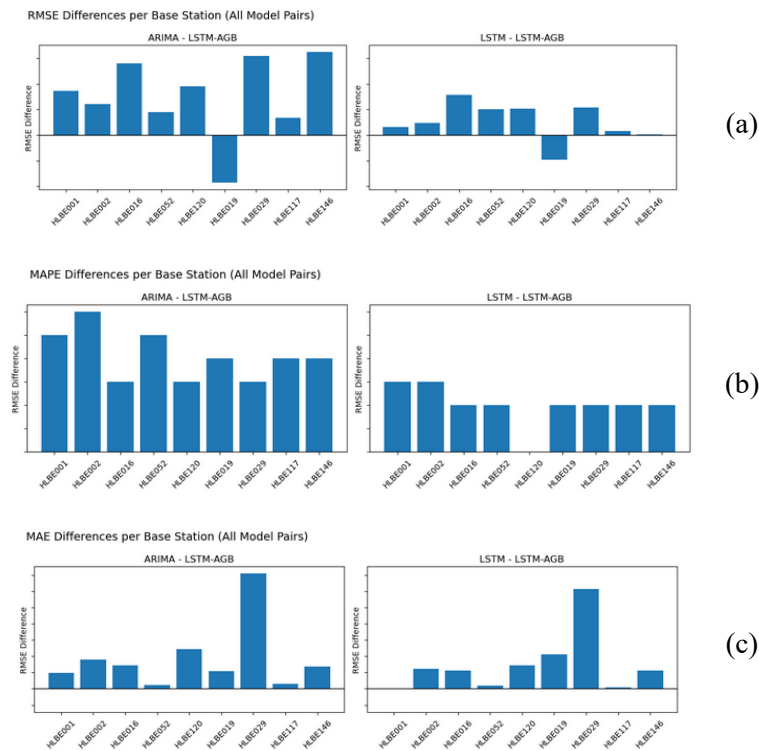


Figure 6. Average error differences for (a) ARIMA-LSTM-AGB downlink data (b) ARIMA-LSTM-AGB downlink data (c) ARIMA-LSTM-AGB downlink data

To assess the statistical significance of these improvements, paired t-tests were conducted on the error metrics (RMSE, MAE, MAPE) across the nine base stations, with Cohen's d values indicating the effect sizes. All paired t-tests were conducted using 9 paired observations from repeated experimental runs under identical conditions. Two-tailed tests were employed at a 5% significance level. From table 2, the statistically significant improvements observed in RMSE, MAPE, and MAE relative to ARIMA confirm that linear models cannot capture the non-linear, bursty, and highly dynamic characteristics of mobile traffic at short time scales. Compared with LSTM, LSTM-AGB achieves significant gains in MAPE and MAE, with large effect sizes, indicating better control of relative and absolute forecasting errors,

which directly influence resource provisioning and congestion management. This improvement is driven by the adaptive gradient-boosting component, which refines residual prediction bias and enhances responsiveness to transient fluctuations. However, the RMSE comparison is not significant, suggesting that the LSTM captures temporal dependencies. Overall, these results demonstrate that LSTM-AGB provides a robust and practically relevant improvement for short-term mobile traffic forecasting in dynamically evolving network environments.

Table 2. Paired t-test of LSTM-AGB and baseline models

Error Metric	Model A	Model B	Sample Size	df	t-statistic	p-value	Cohen's d	Significance(p<0.05)
RMSE	ARIMA	LSTM-AGB	9	8	2.8873	0.020283	0.9622	Yes
RMSE	LSTM	LSTM-AGB	9	8	2.0581	0.073574	0.6852	Moderately
MAPE	ARIMA	LSTM-AGB	9	8	11.7004	0.000003	3.7947	Yes
MAPE	LSTM	LSTM-AGB	9	8	6.9282	0.000121	2.3094	Yes
MAE	ARIMA	LSTM-AGB	9	8	2.6721	0.028268	0.8906	Yes
MAE	LSTM	LSTM-AGB	9	8	2.4064	0.042750	0.8019	Yes

5. Conclusion

This study proposed a hybrid LSTM-AGB model for short-term mobile traffic forecasting using real-world base-station data from urban locations in Kaduna North and South. The findings show that LSTM-AGB consistently achieves lower RMSE, MAE, and MAPE than ARIMA and standalone LSTM models, demonstrating its effectiveness in modelling the non-linear and bursty characteristics of short-term mobile traffic. The findings indicate the potential of hybrid deep learning models to support short-term, traffic-aware decision-making at the base-station level. The scope of these conclusions is limited by the dataset's temporal and spatial coverage. The analysis is restricted to Q1 2024 and is biased toward urban base stations in Kaduna, which may not reflect traffic dynamics or conditions in rural areas or other regions. As such, comparisons beyond urban areas will require further validation. Future work will extend the dataset across longer time horizons and more diverse geographic areas to assess seasonal effects. It will evaluate the feasibility of integrating the proposed model into practical network monitoring frameworks by assessing architectural design, data ingestion, and computational scalability requirements before any application-level deployment.

6. Declarations

6.1. Author Contributions

Conceptualization: A.A.A., J.E.P.; Methodology: A.A.A., J.E.P.; Software: W.O.C., M.M.; Validation: A.A.A., J.E.P.; Formal Analysis: M.M.; Investigation: W.J.S., W.O.C.; Resources: J.E.P., M.M.; Data Curation: W.O.C.; Writing – Original Draft Preparation: W.J.S.; Writing – Review and Editing: W.J.S., A.A.A.; Visualization: M.M.; All authors have read and agreed to the published version of the manuscript.

6.2. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

6.3. Funding

The authors acknowledge INTI International University, Malaysia, for funding the journal publication through a Research Fellowship award to the Lead author.

6.4. Institutional Review Board Statement

Not applicable.

6.5. Informed Consent Statement

Not applicable.

6.6. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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