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A Deep Learning Approach for Forecasting Daily Prayer Times in Nigerian Geo-Political Zones

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Accurate determination of prayer times is essential for the daily worship practices of Muslim communities. However, many existing online and offline prayer time prediction systems are limited by regional variations, weather conditions, and complex geographical factors. Most current approaches rely on conventional algorithms or manual adjustments, which reduce accuracy across diverse locations. This study addresses these limitations by applying deep learning techniques to predict the five daily Islamic prayer times across major cities in Nigeria, including Kaduna, Borno, Abuja, Lagos, Enugu, and Rivers. Historical prayer time data were obtained from the Adhan API and subjected to preprocessing and feature engineering. Two models; Long Short-Term Memory (LSTM) and Artificial Neural Networks (ANN) were developed and evaluated using Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), and the coefficient of determination (R^2). Results show that both models achieved high predictive performance, with near-perfect R^2 values. However, ANN consistently produced lower MAE, RMSE, and MAPE for Fajr, Dhuhr, Asr, and Maghrib, indicating superior accuracy, while LSTM slightly outperformed ANN for Isha. The best-performing model for each prayer was used to forecast daily prayer times for 2025. The study demonstrated that deep learning models can significantly improve the accuracy of prayer time prediction and provide a reliable solution for faith-based timekeeping.

Keywords: Prayer Time Prediction, Deep Learning, Forecasting, Machine Learning, Nigeria.

1. Introduction

Prayer is a fundamental pillar of Islam and an obligatory act of worship for all Muslims, who constitute about 1.8 billion people globally [1]. Muslims are required to observe five daily prayers Fajr, Dhuhr, Asr, Maghrib, and Isha each performed within its specific time frame as prescribed in the Qur'an and the Hadith [2], [3]. The timing of these prayers is determined by the position of the sun relative to the Earth, signifying key astronomical events such as sunrise, noon, sunset, and twilight [4]. Accurate prediction of daily prayer times is crucial in Islamic practice because each prayer must be offered within its appointed time for it to be valid [5].

Historically, Muslims determined prayer times through direct observation of solar movements, such as the length of shadows or the disappearance of twilight [6]. However, with technological advancement, astronomical calculations have replaced manual observation, leading to the development of algorithms and digital systems that compute prayer times based on the sun's altitude and hour angle [7], [8].

Despite these advancements, discrepancies remain in prayer time calculations across different regions, particularly for Fajr and Isha, which are determined using various angular criteria ranging from 12° to 20° below the horizon, often resulting in inaccurate times at higher latitudes [9]. Although several online and offline systems provide prayer schedules, many still face challenges due to geographical variations, fluctuating weather conditions, and algorithmic limitations [10]. Existing methods typically rely on fixed astronomical formulas or manual adjustments, which do not fully capture real-time variations or dynamic environmental factors. Consequently, there is a growing need for adaptive systems that can automatically adjust to local conditions to ensure accuracy and consistency in prayer time determination.

Machine learning techniques have shown remarkable success in time-series forecasting tasks, including weather prediction, exchange rate analysis [11], and solar radiation modeling

[12]. Artificial Neural Networks (ANNs) and Long Short-Term Memory (LSTM) models, in particular, are capable of learning complex temporal dependencies and non-linear relationships within sequential data [13]. These models can therefore be leveraged to predict prayer times more accurately by analyzing historical and astronomical data patterns. Applying such data-driven approaches in Islamic contexts offers a novel pathway for enhancing precision in prayer time computation while bridging traditional fiqh-based principles with modern technological innovations [14].

Despite evidence of machine learning's predictive capabilities, limited research has explored its application in forecasting the five daily Islamic prayer times, particularly when accounting for geographical, seasonal, and environmental variations. Hence, this study seeks to develop an efficient deep learning based model using LSTM and ANN for the prediction of daily prayer times from historical data.

2. Review of Related Works

Several studies have explored various approaches to determining and predicting Islamic prayer times, ranging from astronomical calculations to the application of emerging computational methods. Razzak [2] developed a Python-based geophysical model to predict sunrise, sunset, and prayer timings using Julian date calculations. His method required geographical inputs such as latitude, longitude, and time zone and achieved accuracy comparable to online sources. However, the model relied solely on fixed astronomical equations and did not address atmospheric or input-related variations. Similarly, [10] examined the evolution from manual to digital methods, emphasizing GPS-based mobile applications that improved accessibility and educational integration but lacked empirical validation and consideration of technological limitations. Other scholars have focused on astronomical and image-based methods. Intifada and Izzuddin [14] compared celestial-mechanics-based algorithms with official Indonesian methods, highlighting scientific rigor but lacking empirical generalization across regions. Rusli *et al.* [15] introduced an image-processing approach using the Canny edge detection technique in MATLAB to determine dawn and Isha times, achieving high accuracy but remaining limited by geographical scope and weather variability.

Likewise, Saad *et al.* [16] emphasized the effect of latitude on prayer time calculations using astronomical equations, although their analysis was confined to Baghdad, limiting its generalizability. Rojak *et al.* [4] assessed the accuracy of online prayer time applications, revealing inconsistencies between the applications and official schedules, and

highlighting the need for standardized computational approaches. Research by [17] examined the influence of the Earth's revolution and rotation on prayer time variations across different global regions using accurate time software; however, the study was geographically narrow and did not account for jurisprudential differences.

In contrast, Di Piazza *et al.* [18] demonstrated the applicability of machine learning in forecasting non-religious time series using an NARX neural network to predict solar radiation and energy demand. Their model outperformed traditional linear methods, underscoring the potential of AI for temporal prediction tasks. In a more domain-specific application, Lawan *et al.* [1] employed LSTM and Non-linear Autoregressive (NAR) models to forecast prayer times in Kano State, Nigeria. The study found LSTM to be more accurate and efficient than NAR, validating the suitability of machine learning for this purpose. However, the study was limited to three prayer times (Dhuhr, Maghrib, and Isha), did not evaluate performance using standard metrics, and failed to account for variations due to geographical or atmospheric factors.

From the reviewed literature, it is evident that most existing studies on prayer time prediction rely on traditional astronomical or mathematical models [2], [16], which do not incorporate adaptive or learning based mechanisms to handle temporal, geographical, and environmental variations. Although emerging research, such as that of Lawan *et al.* [1], has applied machine learning to prayer time prediction, its scope was limited to specific locations and only a subset of the daily prayers excluding the more complex Fajr and Isha times that are influenced by twilight conditions. Moreover, prior studies often lack comprehensive model validation using standard statistical metrics such as MAE, MSE, RMSE, and R^2 , which are essential for ensuring reliability and reproducibility.

To bridge these gaps, this study proposes the development of Artificial Neural Network and Long Short-Term Memory models to predict all five daily prayer times across Nigeria's six geopolitical zones using historical data from 2019 to 2024. The models will be systematically evaluated using established performance metrics to determine the most accurate and efficient forecasting technique. By integrating machine learning with astronomical data, this study aims to enhance the precision, adaptability, and regional applicability of prayer time predictions.

3. Methodology

This section provides an overview of the proposed models for predicting the five daily Islamic prayer times. It outlines the sequential stages of the framework, starting with data

collection and preprocessing to ensure data quality, followed by data splitting for model training and testing. The process concludes with model development and performance evaluation using selected metrics to determine the accuracy and effectiveness of the prediction models.

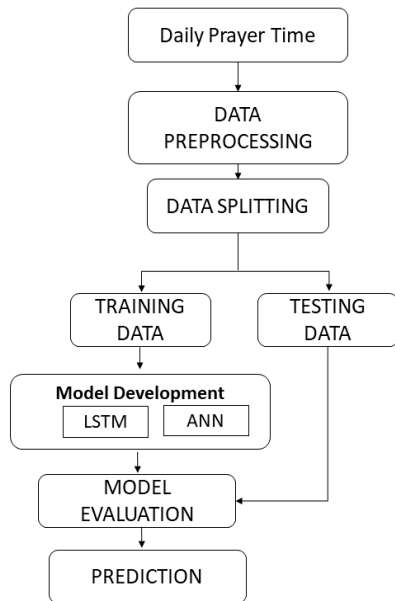


Figure 1: Proposed framework

The dataset used in this study consists of historical prayer time records for six major Nigerian cities: Kaduna, Borno, Abuja, Rivers, Enugu, and Lagos, representing the six geopolitical zones. The dataset covers the period from January 2019 to December 2024, comprising a total of 2,192 days, including leap years (2020 and 2024, each with 366 days). Daily observations were recorded for the five obligatory prayers, resulting in 10,960 data points per city (5 prayers × 2,192 days) and a total of 65,760 data points across all six cities. The data were sourced from the Aladhan API using the Muslim World League method to ensure accurate astronomical calculations.

Each record includes the Gregorian date, city name, and five prayer times (converted from HH:MM to minutes past midnight for modeling). Additional temporal (day, month) and geographical (latitude, longitude) features were engineered to capture periodic and spatial variations. Data collection was automated using Python scripts, structured into a Pandas DataFrame, cleaned, and stored in CSV format. The complete dataset comprised 65,760 samples, of which 80% (52,608 samples) were used for training and 20% (13,152 samples) for testing, ensuring robust and reproducible model development. The description of the dataset is presented in Table 1.

3.1 Data Collection

Table 1: Dataset Description

| Column Name | Data Type | Description | Example Value |
|-------------|----------------|--|-------------------|
| Date | Date | Gregorian date in DD-MM-YYYY format | 12-06-2022 |
| City | String | Name of the Nigerian city (6 geopolitical zones) | Kaduna |
| Fajr | Time (minutes) | Time of Fajr prayer (converted to minutes past midnight) | 297 (≈ 04:57 AM) |
| Dhuhr | Time (minutes) | Time of Dhuhr prayer (minutes past midnight) | 770 (≈ 12:50 PM) |
| Asr | Time (minutes) | Time of Asr prayer (minutes past midnight) | 970 (≈ 04:10 PM) |
| Maghrib | Time (minutes) | Time of Maghrib prayer (minutes past midnight) | 1140 (≈ 07:00 PM) |
| Isha | Time (minutes) | Time of Isha prayer (minutes past midnight) | 1250 (≈ 08:50 PM) |
| Weekday | Integer (1–7) | Day of the week (1 = Monday, 7 = Sunday) | 2- |
| Month | Integer (1–12) | Month of the year | 6 |
| Latitude | Float | Geographic latitude of the city | 10.52 |
| Longitude | Float | Geographic longitude of the city | 7.44 |

3.2 Data Pre-processing

Effective pre-processing is a crucial step in preparing a dataset for machine learning models, particularly when working with time-series data. In this study, multiple pre-processing steps were applied to convert raw prayer time records into structured numerical inputs suitable for model training and evaluation. These steps are outlined below:

3.2.1 Prayer Time Conversion

All prayer times were initially recorded in the standard "HH:MM" format. To facilitate numerical computation, these times were converted into minutes past midnight. For example, a time such as 06:30 was transformed into 390 (6 hours × 60 + 30 minutes). This conversion enabled the use of continuous mathematical operations required by machine learning models, such as distance calculations, normalization, and loss

computations. Furthermore, treating time as a scalar value rather than a string avoids complications with time arithmetic and improves model interpretability and accuracy.

3.2.2 Input features Normalization

To ensure that all input features contributed proportionally during training, Min-Max normalization was applied. Each of the five prayer times, Fajr, Dhuhr, Asr, Maghrib, and Isha, was individually normalized to a [0, 1] range using MinMaxScaler. This was essential because raw prayer times, even in minutes, span different value ranges (e.g., Fajr may occur around 300 minutes, while Isha may be closer to 1200). Without normalization, features with larger magnitudes could dominate the learning process. In addition to the prayer times, two temporal features were also extracted:

- i. Weekday: representing the day of the week (1 = Monday, 7 = Sunday)
- ii. Month: representing the month of the year (1 = January to 12 = December)

These features were added to capture cyclical patterns in prayer times due to seasonal and weekly solar variations. Both were normalized using the same MinMax approach to keep them within a similar scale to other input features.

3.2.3 Sequence Generation

Given the temporal nature of prayer time prediction, a sliding window approach was implemented to model sequential dependencies. Specifically, a sequence length of 5 days was chosen. This means that for every prediction, the model takes as input the prayer times and temporal features from 5 consecutive previous days and attempts to predict the prayer times for the 6th day.

Each input sequence, therefore, consists of a 5-day \times 7-feature matrix (i.e., 5 days of 5 prayer times + weekday + month), while the target output consists of a single vector of 5 prayer times for the next day. This structure allowed the models, both LSTM and ANN, to capture short-term trends and temporal shifts across the week or month.

3.3 Data Splitting and Shuffling

After generating the full set of sequences, the dataset was randomly shuffled to remove any bias caused by the ordering of samples (e.g., same cities or clustered months appearing together). This shuffling helped improve model generalization during training.

The dataset was then split into training and testing sets, with 80% allocated to training and 20% reserved for testing. Importantly, while the order of samples was shuffled for learning purposes, the temporal structure within each

sample (the 5-day sequence) was preserved to maintain time-series integrity. This allowed models to learn meaningful patterns while still being evaluated on unseen data. Lastly, a label indicating the city name for each sample was retained. This metadata was later used for visual analysis of model performance across different regions, allowing for city-specific evaluations and comparisons.

3.4 Proposed Model Architecture

Two machine learning models were used and evaluated in this study: the LSTM model and the ANN. Both were designed to predict the five daily Islamic prayer times based on sequential historical input data. The choice of these models was based on their distinct learning mechanisms. LSTM was selected for this study due to its proven ability to capture long-term dependencies, non-linear patterns [19], and temporal dynamics commonly present in inflation data. ANN, specifically a fully connected feedforward Multilayer Perceptron, is included as a baseline model not only for its simplicity but also for its relatively low computational complexity, ease of implementation, and its established use as a benchmark in regression-based forecasting studies [20]. These models collectively allow for a balanced comparison across varying levels of model complexity, computational cost, and forecasting capability.

3.4.1 ANN

The Artificial Neural Network model, unlike LSTM, does not natively handle sequential data. As such, the 5-day sequences were first flattened into a single 1D input vector (i.e., 5 days \times 7 features = 35 input neurons). This transformation allows the ANN to process the entire time window as a single feature vector.

The model architecture consisted of several fully connected Dense layers activated by the ReLU (Rectified Linear Unit) function. These hidden layers allowed the ANN to learn complex, non-linear relationships within the data. The final layer was a Dense output layer with 5 neurons, each predicting one of the five prayer times for the following day.

The same training configuration was applied to the ANN model for fairness in comparison: MSE as the loss function, Adam as the optimizer, 100 epochs, and a batch size of 32. The summary table of the architecture is presented in table 2.

3.4.2 LSTM

Long Short-Term Memory networks are a specialized form of RNNs capable of learning long-term dependencies in sequential data. In this study, LSTM was chosen due to its ability to remember time-based patterns, which are critical

when predicting daily prayer times that are influenced by solar movement. The model architecture begins with an input layer that accepts a 3D tensor representing 5-day sequences of 7 features per day, five prayer times, along with the weekday and month. A single LSTM layer with 64 memory units were used, allowing the network to learn complex temporal dynamics. This was followed by a fully connected Dense layer with five (5) output units, each corresponding to one of the prayer times for the next day.

The model was compiled using the Mean Squared Error as the loss function and trained using the Adam optimizer, which provides adaptive learning rates for efficient convergence. Training was conducted over 100 epochs with a batch size of 32, using the same shuffled and normalized dataset discussed in the pre-processing stage. The model architecture and hyperparameters are summarized in Table 2.

Table 2: Summary of Model Architecture and Hyperparameters for LSTM and ANN

| Parameter | LSTM Model | ANN Model |
|---------------------|--|---|
| Input Format | 3D tensor (5 days × 7 features) | 1D vector (35 features = 7 × 5) |
| Sequence Handling | Yes (captures temporal dependencies) | No explicit sequence modeling (flattened input) |
| Input Shape | (5, 7) | (35,) |
| Hidden Layers | 1 LSTM layer (64 units) | Dense layers (64, 32 neurons) |
| Output Layer | Dense layer (5 neurons) | Dense layer (5 neurons) |
| Activation Function | tanh & sigmoid (LSTM), linear (output) | ReLU (hidden), linear (output) |
| Loss Function | MSE | MSE |
| Optimizer | Adam | Adam |
| Epochs | 100 | 100 |
| Batch Size | 32 | 32 |
| Temporal Handling | Explicit | Implicit |

4. Results and Discussion

The results of our analysis are presented in this section.

4.1 Results

4.1.1 Programming Environment

The study was implemented using a cloud-based programming environment that integrates Google Colab, Python libraries, and deep learning frameworks to facilitate machine learning experiments. Colab notebooks, linked to Google Drive, provided an accessible, collaborative platform for data analysis, model training, and evaluation. Scikit-learn was used for implementing established machine learning models, offering simplicity, ease of use, and comprehensive tools for building and evaluating predictive models. For neural network development, Keras served as the high-level API with Theano as its backend, chosen for its computational efficiency, GPU support, compatibility, and efficient implementation of deep learning experiments.

4.1.2 Actual Vs Predicted Prayer Times (LSTM & ANN)

Figures 2, 3, 4, 5, 6, and 7 compare actual prayer times with predictions from both LSTM and ANN models for the cities over 450 days. Across all five prayers, the predictions from both models are highly accurate, closely tracking the actual prayer times. Visually, there is very little difference between the actual data and the outputs of the two models, indicating that both the LSTM and ANN are highly effective at capturing the daily and seasonal variations in prayer times.

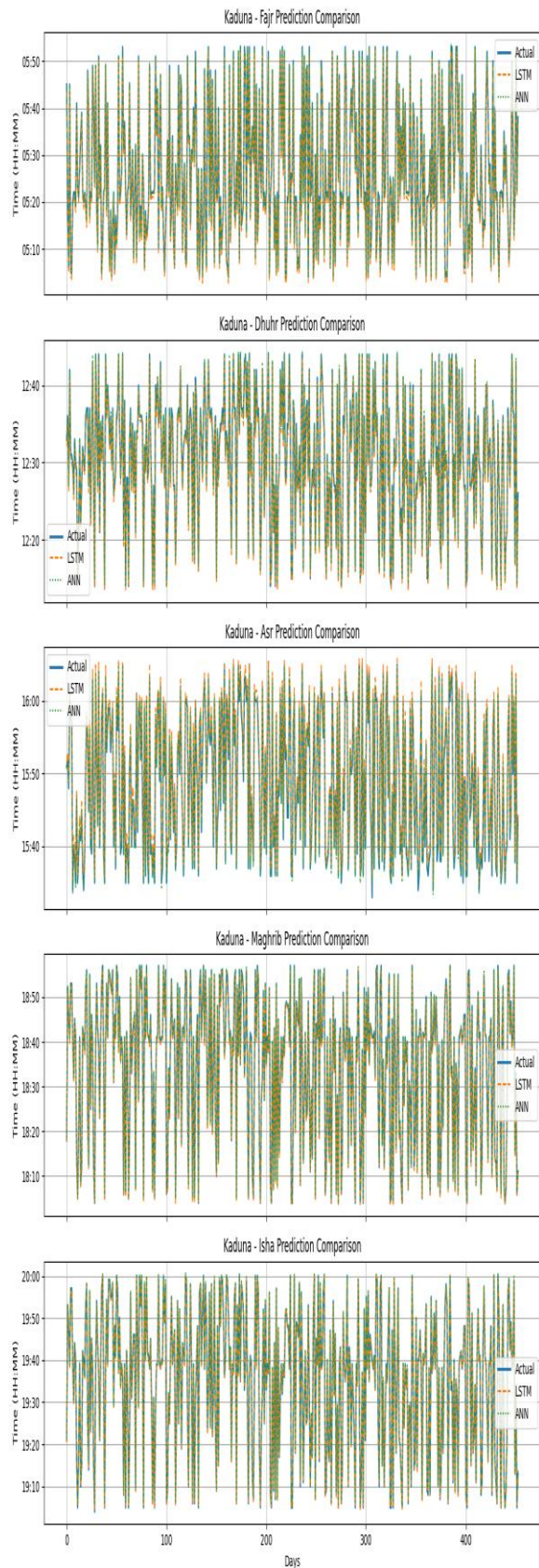


Figure 2: LSTM vs ANN Prayer Time Prediction for Kaduna

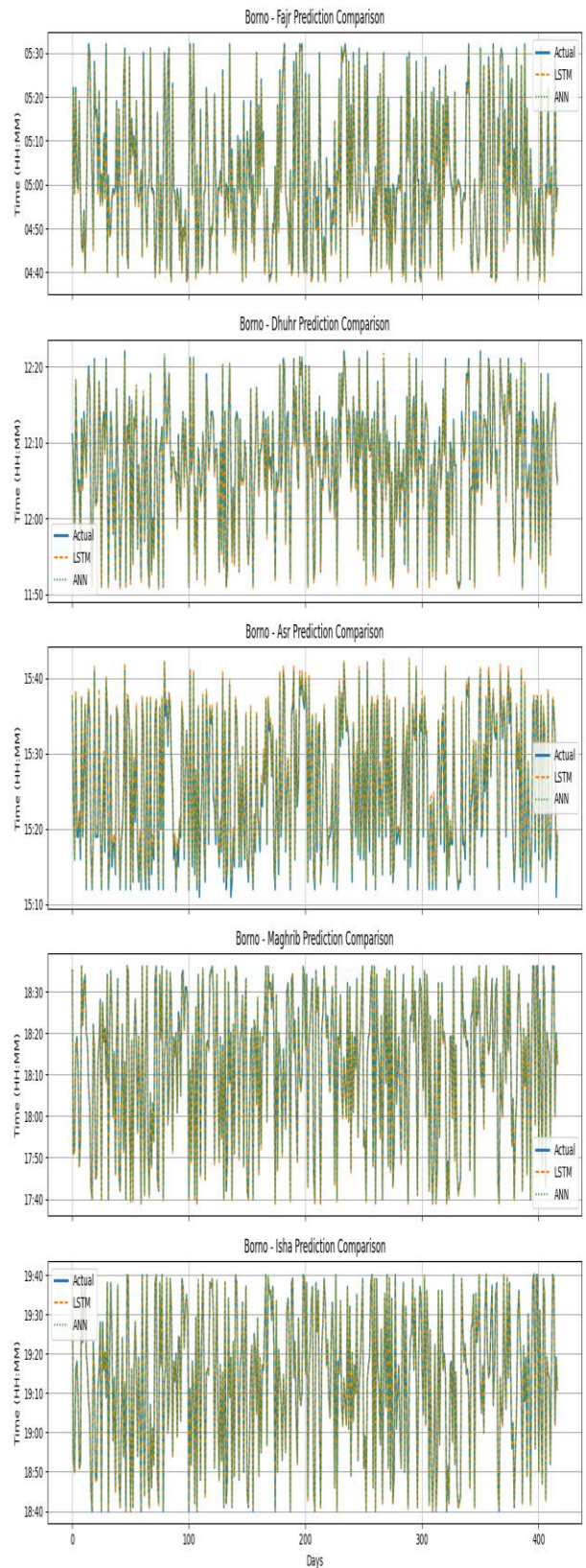


Figure 3: LSTM vs ANN Prayer Time Prediction for Borno

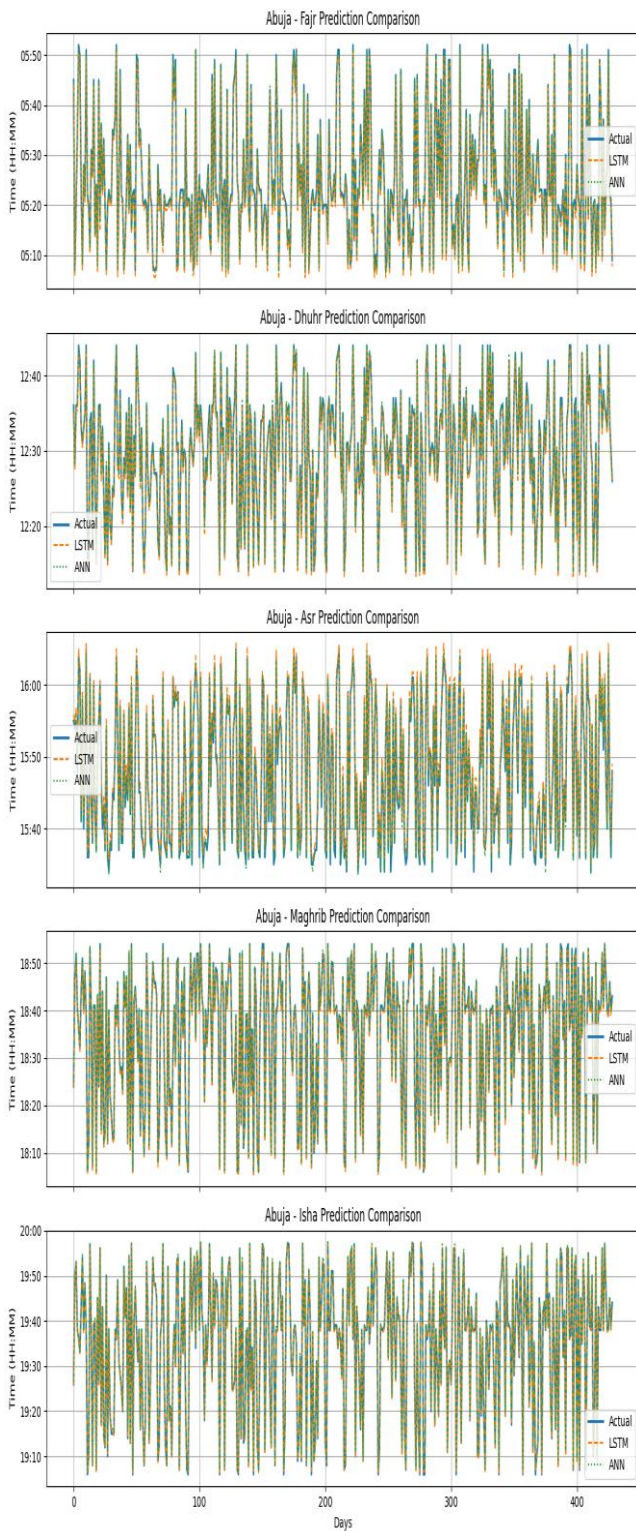


Figure 4: LSTM vs ANN Prayer Time Prediction for Abuja

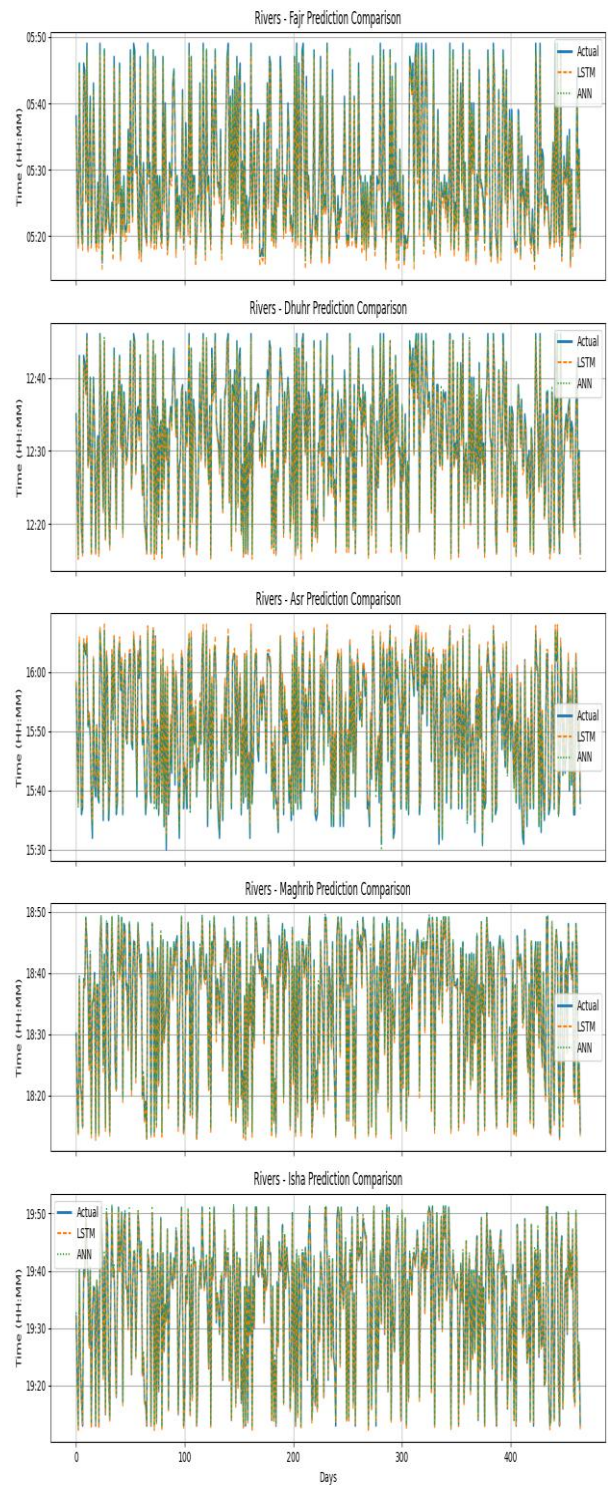


Figure 5: LSTM vs ANN Prayer Time Prediction for Rivers

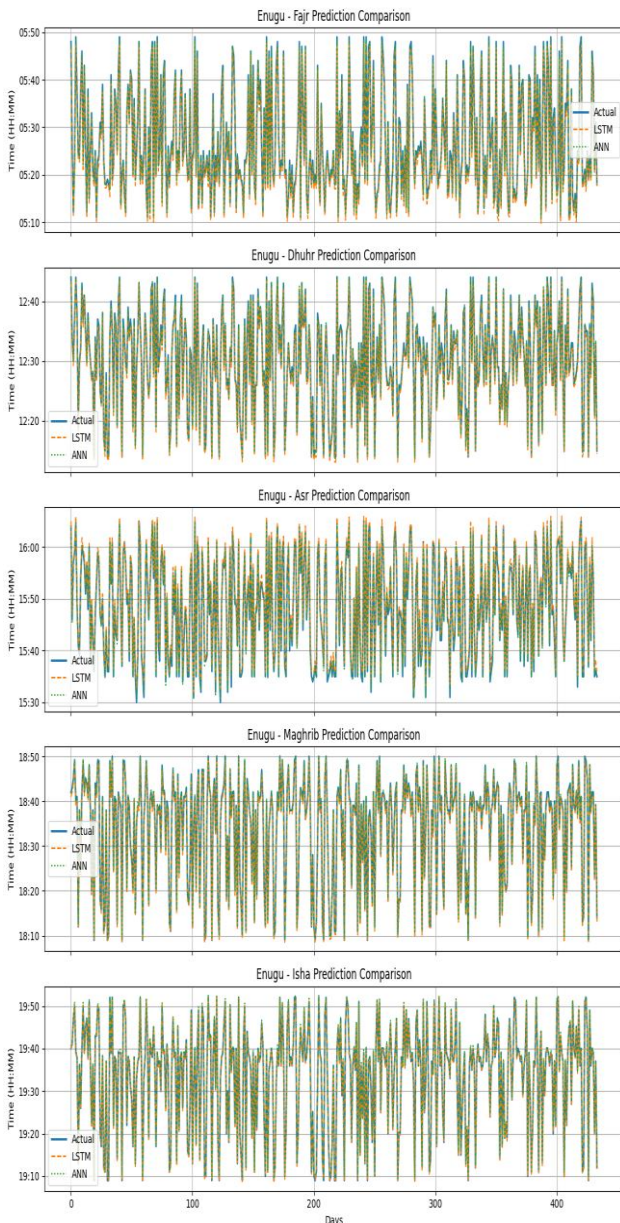


Figure 6: LSTM vs ANN Prayer Time Prediction for Enugu

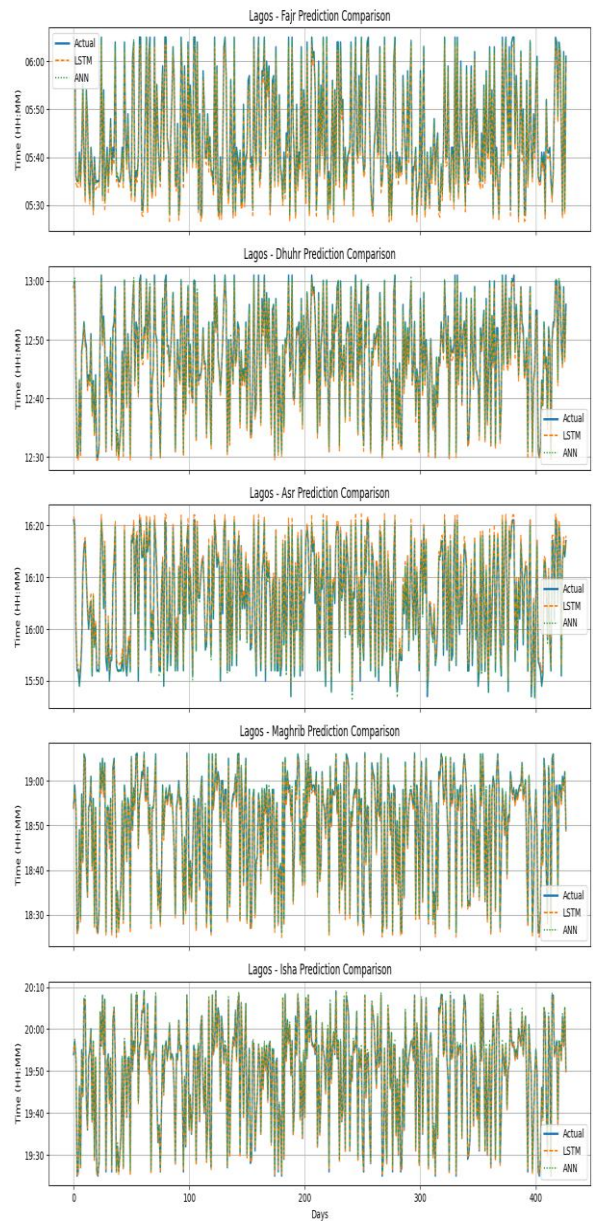


Figure 7: LSTM vs ANN Prayer Time Prediction for Lagos

4.1.3 Comparative Performance Across Metrics

The performance of the Long Short-Term Memory and Artificial Neural Network models was compared using Mean Absolute Error, Root Mean Square Error, the coefficient of determination, and Mean Absolute Percentage Error for each prayer time. The results are presented in Table 3.

Table 3: Comparative Performance across metrics

| Prayer | LSTM _E _{MA} | ANN _E _{MA} | LSTM _E _{RMS} | ANN _E _{RMS} | LSTM ₂ _R | ANN ₂ _R | LSTM _E _{MAP} | ANN _E _{MAP} |
|---------|---------------------------------|--------------------------------|----------------------------------|---------------------------------|--------------------------------|-------------------------------|----------------------------------|---------------------------------|
| Fajr | 1.10 | 0.32 | 1.18 | 0.39 | 1.00 | 1.00 | 0.34 | 0.10 |
| Dhuhr | 0.63 | 0.29 | 0.72 | 0.35 | 1.00 | 1.00 | 0.08 | 0.04 |
| Asr | 1.07 | 0.39 | 1.20 | 0.49 | 0.99 | 1.00 | 0.11 | 0.04 |
| Maghrib | 0.62 | 0.32 | 0.70 | 0.39 | 1.00 | 1.00 | 0.06 | 0.03 |
| Isha | 0.34 | 0.51 | 0.41 | 0.62 | 1.00 | 1.00 | 0.03 | 0.04 |

The results showed that the ANN model generally outperformed the LSTM model in predicting Fajr, Dhuhr, Asr, and Maghrib prayer times. For these four prayers, ANN consistently achieved lower MAE, RMSE, and MAPE values, indicating higher prediction accuracy and better stability. For instance, in Fajr, ANN achieved an MAE of 0.32 compared to LSTM's 1.10, and a MAPE of 0.10 compared to 0.34, while maintaining an identical R² value of 1.00. Similar patterns were observed in Dhuhr, Asr, and Maghrib, where ANN's errors were significantly smaller than those of LSTM. However, for Isha, the LSTM model performed better, with an MAE of 0.34 and a MAPE of 0.03, compared to the ANN's 0.51 and 0.04, respectively. Despite these differences, both models achieved near-perfect R² values for all prayers, demonstrating an excellent fit to the dataset. The ANN generally provided more precise and consistent predictions.

4.2 Discussion

The evaluation results for both LSTM and ANN models across the five daily prayers show that, although both achieved near-perfect R² values (approaching 1.00), ANN consistently recorded lower MAE, RMSE, and MAPE for Fajr, Dhuhr, Asr, and Maghrib, indicating superior precision in these periods. LSTM, however, slightly outperformed ANN for Isha, likely due to its ability

to capture sequential nightfall patterns. This variation in performance can be attributed to the distinct temporal and solar characteristics associated with each prayer time. ANN's stronger performance in predicting Fajr, Dhuhr, Asr, and Maghrib arises from its ability to effectively capture stable and repetitive daily patterns influenced by consistent solar transitions such as sunrise, noon, and sunset. These prayer times exhibit smoother and more predictable variations throughout the year, making them well-suited for ANN's nonlinear mapping capabilities. In contrast, LSTM's superior performance for Isha stems from its inherent ability to model long-term temporal dependencies and sequential dynamics. Since Isha occurs after sunset and is influenced by gradual changes in twilight duration and atmospheric light scattering, LSTM's memory structure enables it to better learn these evolving nightfall patterns.

Based on these results, the best-performing model was selected and applied to forecast daily prayer times for the period 1st January 2025 to 31st December 2025. This approach ensures that the forecast benefits from the highest possible accuracy for each prayer, thereby maintaining consistency and reliability throughout the prediction period. Table 4 presents an excerpt of the forecasted daily prayer times for the year 2025 using the ANN model.

Table 4: Excerpt of ANN Forecast for 2025 (First 7 Days per City)

| | Date | city | Fajr | Dhuhr | Asr | Maghrib | Isha |
|----|------------|--------|-------|-------|-------|---------|-------|
| 0 | 2025-01-01 | Kaduna | 05:46 | 12:34 | 15:52 | 18:19 | 19:22 |
| 1 | 2025-01-02 | Kaduna | 05:46 | 12:34 | 15:52 | 18:20 | 19:22 |
| 2 | 2025-01-03 | Kaduna | 05:46 | 12:35 | 15:53 | 18:21 | 19:24 |
| 3 | 2025-01-04 | Kaduna | 05:46 | 12:36 | 15:53 | 18:22 | 19:25 |
| 4 | 2025-01-05 | Kaduna | 05:47 | 12:36 | 15:54 | 18:23 | 19:25 |
| 5 | 2025-01-06 | Kaduna | 05:47 | 12:36 | 15:55 | 18:24 | 19:26 |
| 6 | 2025-01-07 | Kaduna | 05:48 | 12:37 | 15:55 | 18:24 | 19:26 |
| 7 | 2025-01-01 | Borno | 05:25 | 12:11 | 15:27 | 17:54 | 18:56 |
| 8 | 2025-01-02 | Borno | 05:25 | 12:11 | 15:28 | 17:55 | 18:57 |
| 9 | 2025-01-03 | Borno | 05:26 | 12:12 | 15:29 | 17:56 | 18:59 |
| 10 | 2025-01-04 | Borno | 05:26 | 12:13 | 15:29 | 17:56 | 18:59 |
| 11 | 2025-01-05 | Borno | 05:27 | 12:14 | 15:30 | 17:57 | 19:00 |
| 12 | 2025-01-06 | Borno | 05:29 | 12:23 | 15:43 | 18:16 | 19:16 |
| 13 | 2025-01-07 | Borno | 05:29 | 12:23 | 15:43 | 18:17 | 19:17 |
| 14 | 2025-01-01 | Abuja | 05:43 | 12:33 | 15:53 | 18:22 | 19:24 |
| 15 | 2025-01-02 | Abuja | 05:44 | 12:34 | 15:53 | 18:22 | 19:24 |
| 16 | 2025-01-03 | Abuja | 05:44 | 12:35 | 15:54 | 18:23 | 19:26 |
| 17 | 2025-01-04 | Abuja | 05:44 | 12:36 | 15:54 | 18:24 | 19:27 |
| 18 | 2025-01-05 | Abuja | 05:46 | 12:36 | 15:55 | 18:24 | 19:26 |
| 19 | 2025-01-06 | Abuja | 05:45 | 12:36 | 15:55 | 18:26 | 19:27 |
| 20 | 2025-01-07 | Abuja | 05:45 | 12:36 | 15:56 | 18:26 | 19:28 |
| 21 | 2025-01-01 | Rivers | 05:38 | 12:35 | 15:58 | 18:30 | 19:33 |
| 22 | 2025-01-02 | Rivers | 05:39 | 12:36 | 15:58 | 18:31 | 19:33 |
| 23 | 2025-01-03 | Rivers | 05:39 | 12:37 | 15:59 | 18:32 | 19:34 |

| | | | | | | | |
|----|------------|--------|-------|-------|-------|-------|-------|
| 24 | 2025-01-04 | Rivers | 05:39 | 12:37 | 15:59 | 18:33 | 19:35 |
| 25 | 2025-01-05 | Rivers | 05:40 | 12:37 | 16:00 | 18:33 | 19:35 |
| 26 | 2025-01-06 | Rivers | 05:40 | 12:38 | 16:00 | 18:34 | 19:36 |
| 27 | 2025-01-07 | Rivers | 05:40 | 12:38 | 16:00 | 18:35 | 19:36 |
| 28 | 2025-01-01 | Enugu | 05:39 | 12:33 | 15:55 | 18:26 | 19:29 |
| 29 | 2025-01-02 | Enugu | 05:39 | 12:34 | 15:55 | 18:27 | 19:29 |
| 30 | 2025-01-03 | Enugu | 05:40 | 12:35 | 15:56 | 18:28 | 19:29 |
| 31 | 2025-01-04 | Enugu | 05:40 | 12:35 | 15:56 | 18:28 | 19:30 |
| 32 | 2025-01-05 | Enugu | 05:41 | 12:36 | 15:57 | 18:29 | 19:31 |
| 33 | 2025-01-06 | Enugu | 05:41 | 12:36 | 15:57 | 18:30 | 19:31 |
| 34 | 2025-01-07 | Enugu | 05:41 | 12:36 | 15:58 | 18:31 | 19:32 |
| 25 | 2025-01-01 | Lagos | 05:55 | 12:50 | 16:11 | 18:42 | 19:45 |
| 26 | 2025-01-02 | Lagos | 05:56 | 12:51 | 16:11 | 18:43 | 19:45 |
| 27 | 2025-01-03 | Lagos | 05:56 | 12:51 | 16:13 | 18:44 | 19:46 |
| 28 | 2025-01-04 | Lagos | 05:57 | 12:52 | 16:12 | 18:45 | 19:47 |
| 29 | 2025-01-05 | Lagos | 05:57 | 12:52 | 16:13 | 18:45 | 19:47 |

The excerpt above presents a sample of the daily prayer time forecast for selected cities in Nigeria from January 1st to January 7th, 2025, generated using the best-performing model from the study. The results show that prayer times vary by city, reflecting geographical and astronomical differences. For instance, Fajr occurs earliest in Borno (around 05:25) and latest in Lagos (around 05:55–05:57), while Maghrib ranges from approximately 17:54 in Borno to 18:45 in Lagos.

5. Conclusion

This study successfully developed and implemented a predictive framework for forecasting daily prayer times across six Nigerian cities: Kaduna, Borno, Abuja, Rivers, Enugu, and Lagos for the year 2025. Utilizing historical prayer time data from the Adhan API, along with rigorous preprocessing, feature engineering, and normalization techniques, the models were trained under optimal conditions to ensure accuracy and reliability. Both LSTM and ANN models achieved near-perfect R^2 values, demonstrating strong predictive capabilities. However, ANN consistently produced lower MAE, RMSE, and MAPE for Fajr, Dhuhr, Asr, and Maghrib, while LSTM slightly outperformed ANN for Isha. The final forecasts effectively captured seasonal variations and geographical differences across regions, providing a precise schedule for the entire year 2025. Overall, the results underscore the potential of machine learning and deep learning techniques in time-sensitive religious scheduling, offering a scalable, data-driven solution that could be extended to other regions or adapted for real-time updates.

Future research could focus on integrating live astronomical data, accounting for weather influences, and expanding coverage to more

cities and years to further enhance prediction accuracy and applicability.

Authors' Contributions

Conceptualization: Abubakar Tukur and Philip O. Odion; Methodology: Maaruf M. Lawal; Software: Abubakar Tukur; Validation: Abubakar Tukur, Philip O. Odion and Maaruf M. Lawal; Formal analysis: Abubakar Tukur; Investigation: Abubakar Tukur; Resources: Abubakar Tukur; Data curation: Abubakar Tukur; Writing—original draft preparation: Abubakar Tukur; Writing—review and editing: Abubakar Tukur, Philip O. Odion and Maaruf M. Lawal; Visualization: Abubakar Tukur; Supervision: Philip O. Odion and Maaruf M. Lawal; Project administration: Philip O. Odion and Maaruf M. Lawal; funding acquisition: Abubakar Tukur. All authors have read and agreed to the published version of the manuscript”.

Conflict of Interest

The authors declare no conflict of interest.

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