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Weather Forecasting Using Deep Learning And Seasonal Autoregressive Integrated Moving Average Model

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Abstract
A number of industries, including mining, agriculture, transportation, and disaster relief, rely heavily on weather forecasting. Time-series trends have been well-captured by conventional forecasting models like SARIMA (Seasonal Auto Regressive Integrated Moving Average). Deep learning methods have become effective instruments for identifying complex patterns and raising predicting precision in recent years. This paper suggests a method to improve the accuracy of weather forecasting by utilizing SARIMA models and deep learning. To capture spatial and temporal correlations in meteorological data, the integration of the SARIMA model and Long Short-Term Memory (LSTM) networks of deep learning architecture is investigated. The Nigeria Metrological Agency (NIMET) provided 20 years' worth of temperature, humidity, wind, and rainfall data for this study. According to the evaluation results, the LSTM had an RMSE of 41.00 for the features of the training dataset, whereas the proposed SARIMA had RMSEs of 0.59 for rainfall, 23.99 for temperature, 1.23 for wind, and 24.47 for relative humidity. This demonstrates unequivocally that SARIMA outperformed the LSTM model.

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I. Introduction

Weather forecasting is the process of predicting the atmospheric conditions for a certain location and time using science and technology. People have been predicting the weather informally for millennia, and formally since the 19th century. Scientists collect quantitative data on the atmosphere, land, and ocean as they already exist in order to produce weather forecasts. Then, they forecast future variations in the atmosphere at a particular place using meteorology. Unlike the manual computations of the past that largely took into account changes in barometric pressure, current weather conditions, sky conditions, and cloud cover, weather forecasting nowadays is based on computer-based models that take into account a range of atmospheric characteristics. Weather alerts are important because they are used to protect people and property. Temperature forecasts are used by utility companies to estimate demand in the following days.

Forecasts of temperature and precipitation are critical to agriculture and, by extension, to merchants in the commodities markets. It has a significant impact on agriculture due to changes in water availability, which cause frequent floods and droughts that inevitably affect agricultural yields in various ecological zones. A negative consequence of this could be an increase in the prevalence and severity of current weeds, illnesses, and pests as a result of the increased humidity and temperature (IFABIYI, 2023). Drought disasters are far more likely to occur now, according to analysis done by the Nigerian Meteorological Agency (NIMET). Despite the frequency of droughts, agriculture has experienced some of the slowest rates of productivity and production growth (Oluwasemire, 2012).

An important part of early weather disaster warning is a fast and accurate weather forecast. This research study follows that path but focuses on a specific method of recurrent neural networks and time series models. Weather forecasting provides analytical support for intelligent transportation-related problems, such as air visibility analysis and traffic flow prediction. The only means of monitoring and anticipating exterior environmental conditions is employed by autonomous cars. Adverse weather conditions, such as intense rain or dense fog, increase the likelihood of traffic accidents and congestion.

An artificial intelligence method called a neural network teaches computers to analyze information similarly to the human brain. Deep learning is a type of machine learning approach that imitates the structure of the human brain by using networked nodes, or neurons, arranged in a layered pattern. This adaptive strategy allows computers to grow by learning from their mistakes. In the discipline of deep learning, recurrent neural networks of the LSTM type are employed. The acronym for long-short-term memory is LSTM. An enhanced RNN is called an LSTM (Recurrent Neural Network). Time series and sequence data are the primary applications for LSTM, as RNN becomes less effective as the gap duration increases. The vanishing gradient of

RNN makes them unable of remembering long-term dependencies, which is a drawback. Long-term dependency issues are specifically avoided in the design of LSTMs.

Seasonal Auto-Regressive Integrated Moving Average, or SARIMA, is an extension of the ARIMA (Autoregressive Integrated Moving Average) model that accounts for seasonality in addition to the non-seasonal components. Time series analysis and forecasting are frequent uses for ARIMA models, whereas SARIMA models are specifically designed to handle data with seasonal trends. The purpose of this study is to examine the potential of Seasonal Auto-Regressive Integrated Moving Average (SARIMA) and Long Short-Term Memory (LSTM), two neural network (deep learning approach) features, to provide a model with better weather conditions for Nigeria.

II. Literature Review

Tektas (2010) did a weather forecast case study of Istanbul using ANFIS and ARIMA models. The historical dataset used was gotten from the Istanbul Ataturk Airport. Statistical measures such as MAE, MSE and the RMSE were used to grade the performance of the models. However, the study did not consider other factors that could have impacted the weather forecast accuracy of the models, such as changes in climate patterns or extreme weather events. Grigonytė & Butkevičiūtė, (2016) performed a research on the need for accurate short-term wind speed forecasting using the ARIMA model. The wind speed data was gotten from a lithuanian wind farm. There was lack of consideration for other factors that may affect wind speed, such as temperature and humidity. Salman *et al* (2018) implemented single-layer and multi-long short memory model with intermediate variables for weather forecasting, due to a need to build ca robust and adaptive statistical model for forecasting univariate weather variables in the indonesian airport area. The wearher variables collected from the Hang Nadim Indonesia airport was used to train the model. The complexity of the weather and the model generalization were not considered. Thekkeppat *et al* (2018) identified the need to develop accurate forecasting models for weather parameters in Thrissur district. The study covered a six years period (2012-2017), which may not be sufficient to capture long-term trends in weather patterns. Zhou *et al* (2019) used deep learning algorithms to analyze large amounts of numerical weather prediction (NWP) data and extract patterns that are indicative of severe convective weather (SCW). The study however did not address the issue of interpretability of the deep learning model. Karavens & Suykens (2020) utilized transductive learning techniques in conjunction with LSTM for weather prediction, using historical data consisting temperature, humidity, wind, speed, and precipitation. The research paid no attention to the data quality, the computational complexity, interpretability and overfitting. Lim and Zohren (2021) addressed the problem of time-series forecasting using RNNs, CNNs and other attention based models. The research did not consider that deep neural networks typically require time series to be discretized at regular intervals. Salman and Kanigoro (2021) processed the data from the Meteorology, climatology and geophysics agency (BMKG) to develop an ARIMA model. Onyeka-Ubaka et al (2021) carried out optimal stochastic forecast models of rainfall in south-west region of Nigeria. Monthly rainfall data for the period of January 1981 to December 2016, was used to develop the SARIMA model and the fractional autoregressive integrated moving average (ARFIMA) model. The research is limited to the south west region of Nigeria. Applying it to the issue of visibility forecasting, which is crucial for various industries such as aviation transportation, and tourism. Alakkeri et al (2022) performed the modelling of weather conditions using encoder-decoder and attention based on LSTM deep regression Model. Dong *et al* (2023) analyzed and did a forecast of the monthly mean temperature of New York City using the SARIMA model. The monthly mean air and temperature was chosen as the basic data for modeling and prediction. Verma *et al* (2023) utilized deep learning architecture across various aspects of weather prediction, such as thunderstorm, lightning, precipitation, drought, heat wave, cold waves and tropical cyclones. The research was negatively impacted by data availability, model complexity and interpretability. Chen *et al* (2023) worked on improving heavy rainfall forecasting using weighted deep learning model, to improve the accuracy of heavy rainfall. The NWP data from ECMWF-IFS in the range of 2017-2022, at a resolution of 0.25º x 0.25º. Sundararaj *et al* (2023) performed probability analysis and rainfall forecasting using ARIMA model. The probability distribution of the rainfall in the Vaigai river basin and developed the forecasting model. The ARIMA model was used to forecast the average annual rainfall for the ten different sub-basins. The dataset used covered a 34 years span of the ten sub-basins, but the result did not generalize to other regions. Ahmadi *et al* (2023) trained SARIMA model on the monthly series of Sanadaj synoptic station. Indirect statistics was used to check the homogenenity of the data. The study only considered the main variables affecting the time series. Tang et al (2023) did a study to predict the changes in atmospheric water vapor (AWV) in the East Asian region. The approach used include wavelet analysis, empirical mode decomposition and Hilbert-Huang transform. The result obtained relied on the accuracy and reliability of the satellite data. Gasper (2023) applied SARIMA model to accurately forecast the consumer price index (CPI) in Tanzania. The data used was obtained from the International Monetary Funds (IMF) website. Hasanah *et al* (2023), used SARIMA model to forecast the electricity demand during religious holidays in East Kalimantan. The historical data on electricity load from

2015 to 2018 in East Kalimantan was adopted. John and Nkemnole (2023) implemented LSTM for timely and accurate prediction of malaria incidents to enhance disease control and prevention strategies. The dataset used covered monthly malaria incidence data from January 2000 to December 2021. There were several limitations like model complexity, assumptions and uncertainties, and performance metrics. Anto *et al* (2023) implemented SARIMA to predict the sea level from PUMMA system. This was due to the need to accurately forecast sea levels to mitigate risks for coastal communities. The sea measurements were collected by Perangkat Ukur Murah untuk Muka Air Laut (PUMMA) system. The data availability, model assumptions and the sensor accuracy were part of the hindrances to the research. Ottom *et al* (2023) worked on the challenges associated with accurately forecasting rainfall amounts in the Dead Sea basin. The data used comprises daily rainfall measurements spanning from 1938 to 2022. The study's focus is on a specific area. Agyemang *et al* (2023) improved on the statistical analysis and prediction of road traffic accidents (RTAs) in Ghana. The RTA data from the Madina-Adenta highway in Ghana was used in the study. Several hindrances on the research include data collection challenges, modeling constraunts and data analysis limitations. Chakraborty (2023) evaluated the performance of RNN and LSTM models in forecasting time-series data. The artificial dataset used included characteristics typically found in long-term astronomy observations. Nugraha *et al* (2023) applied LSTM to forecast the weather accurately to support various sectors such as marine, navigation, agriculture and industry. The data used was collected from the Maritime Meteorolocy Station in Serang, Indonesia such as temperature, humidity, sunlight duration and wind speed. The external factors affecting the dataset was not considered. Guma (2024) did a comparative analysis of time series prediction models for visceral leishmaniasis based on SARIMA and LSTM. The monthly data on visceral leishmaniasis cases from January 2000 to December 2021 were used. Tejada *et al* (2024) highlighted the need to address the decreasing water level at Angat Dam in Philippines using SARIMA model. The dataset used was from January 1990 to December 2021. Amato *et al* (2023) worked on the prediction of nest weight using a SARIMA model over multivariate data. The model was used to predict microbial nest weight based on multivariate dataset. The potential presence of anomalies or outliers in the dataset was a limitation to the study. He *et al* (2024) addressed the challenges of accurately predicting oil production rates in tight reservoirs using SA-LSTM model in tight reservoirs.

III. Methodology

The Nigeria Metrological agency (NIMET) dataset was used for conducting the training of the model developed in this research. The relevant features include temperature, rainfall, humidity and wind, spanning the period of January 2013 to December 2023 for the geographical location of Oyo state. Figure 1 shows the methodology used for analyzing the NIMET dataset.

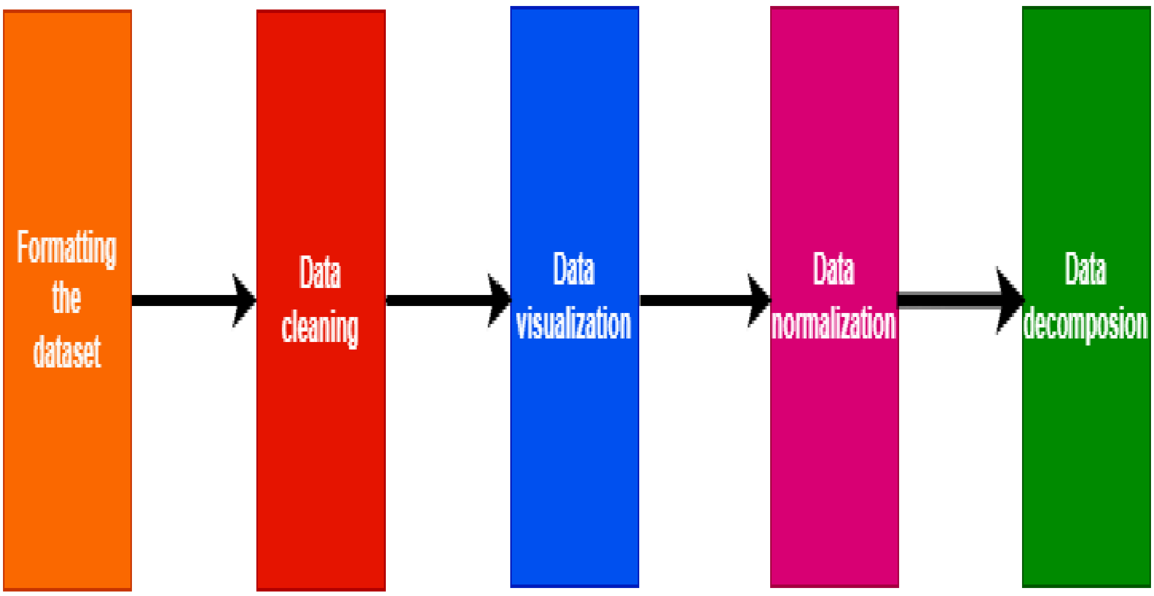

Figure 1: Methodology used for Analyzing the NIMET Dataset

The min-max method is applied to normalize the dataset, ensuring the data is within the range of 1 and 0. The min-max formular is show in figure 2.

$$X_{\text{scaled}} = \frac{X_i - X_{\min}}{X_{\max} - X_{\min}}$$

Figure 2: Min Max Method

The SARIMA Model

The SARIMA model has the same characteristics as the ARIMA, namely Autoregressive (AR), Integrated (I), and Moving Average (AR), and it also takes into account the seasonality component of the forecast. Figure 3 shows the process for training the model and the validation of the performance.

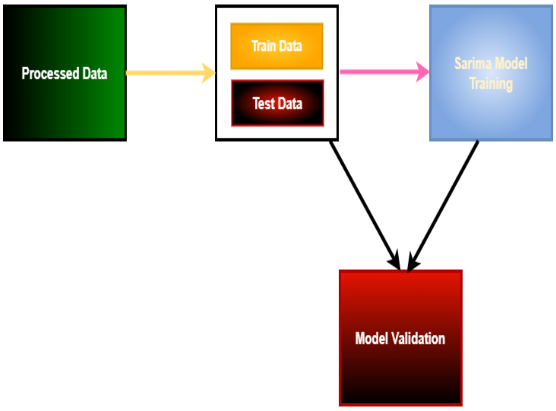

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Figure 3: SARIMA Training and Validation Process

The LSTM Model

The sea forecast is incorporated into the SARIMA model.An RNN model is a variation on the LSTM. Long time series data can be handled by LSTM, which keeps pertinent features in the cell state while removing unnecessary ones. The forget gate helps the model determine which information from the cell state should be kept or removed. LSTM consists of three units.sonality contribution and possesses the moving average (AR), integrated (I), and autoregressive (AR) characteristics of the ARIMA.

$$ft = \sigma(Wf \cdot [ht - 1, xt] + bf) \quad (1)$$

The input gate decides which values to include in the cell state (C_t) , functioning in tandem with the output gate and the forget gate to allow the LSTM to selectivel update its state. The mathematical representation for the input gate (i_t) and the candidate cell state ($\tilde{C}_t$) are as follows:

$$it = \sigma(Wi \cdot [ht - 1, xt] + bi) \quad (2)$$

$$\tilde{C}_t = \tanh(Wc \cdot [ht - 1, xt] + bc) \quad (3)$$

$$Ct = ft \cdot Ct - 1 + it \cdot \tilde{C}_t \quad (4)$$

What information is provided as the final hidden state and what percentage of the cell state is disclosed are controlled by the output gate (Ot). With the help of the input gate and forget gate, the LSTM is able to selectively update and utilize its cell state. The output gate (Ot) and candidate hidden state (ht) formulas are as follows:

$$ot = \sigma(Wo \cdot [ht - 1, xt] + bo) \quad (5)$$

$$ht = ot \cdot \tanh(Ct) \quad (6)$$

Figure 4 shows the full structure of the LSTM model , including the gates and the activation functions applied to each gates.

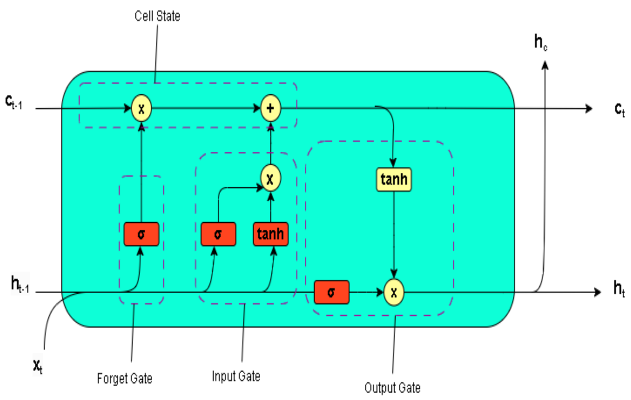

Figure 4: Full structure of the LSTM Model

Methodology Validation and Evaluation

The dataset was divided 60:20:20 into training, validation, and testing subsets. The prediction models' accuracy was evaluated using the Root Mean Square Error (RMSE). RMSE is more sensitive to outliers than Mean Square Error (MSE) since it penalizes greater mistakes more severely. A low RMSE number indicates that the model fits the data well and generates more accurate predictions, whereas a higher value suggests that there are more major errors and fewer accurate forecasts.

IV. Results

MEASUREMENT METRICS PREDICTION FOR DECEMBER 2023					
	LONG SHORT TERM MEMORY (LSTM)	**SEASONAL AUTOREGRESSIVE INTEGRATED MOVING AVERAGE (SARIMA)**			
		RAINFALL	**WIND**	**TEMPERATURE**	**RELATIVE-HUMIDITY**
MEAN ABSOLUTE ERROR **(MAE)**	**25.4989**	**0.212283**	**0.889176**	**23.3579**	**15.7036**
MEAN SQUARRED ERROR **(MSE)**	**1681.0514**	**0.351675**	**1.5281**	**575.5767**	**598.8361**
ROOT MEAN SQUARED ERROR **(RMSE)**	**41.00018**	**0.593022**	**1.236170**	**23.9911**	**24.4711**

The recommended metric for accuracy is the Root Mean Square Error (RMSE). Because it offers an error measure in the same unit as the target variable, the root mean square error (RMSE) is favored because it facilitates easier interpretation and comparison. RMSE is a metric used to evaluate prediction models' accuracy. It is more sensitive to outliers since it penalizes greater errors more severely than Mean Square Error (MSE).

A low RMSE value indicates that the model fits the data well and produces more accurate forecasts; on the other hand, a greater value suggests more substantial errors and fewer accurate forecasts.

Considering that the errors are squared prior to being averaged. Large mistakes are given a comparatively high weight by the RMSE. Therefore, when significant mistakes represent undesired weight, the RMSE is most helpful.

V. Conclusion

As a time-series model that can only be trained using a single feature, the Seasonal Auto-Regressive Integrated Moving Average (SARIMA) model developed in this study performed exceptionally well in predicting the weather condition for Oyo State, with each weather element having its own metric for measure of accuracy. The results demonstrate that the SARIMA model performed much better than the LSTM model with an RMSE of 41.00018. This is because separate models were built for the execution of all four elements (temperature, relative humidity, rainfall, and wind).

VI. Recommendations

For future improvement on weather forecasting using LSTM and SARIMA models there is a need for combination of technical advancements, model enhancements and operational considerations by development of ensemble models that combine the predictions of LSTM and SARIMA models, investigate the possibility of developing hybrid models that will integrate LSTM and SARIMA components in a more seamless manner, explore transfer learning techniques to leverage pre-trained models on large datasets for similar geographical regions or climate types, enhance the models by integrating real-time data sources such as satellite imagery, weather station updates, and other relevant data streams also to improve the interpretability of the models to make it easier to understand the factors influencing the predictions.

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