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Research Article

Long Short-term Memory Model for Temperature Forecasting in Khartoum, Sudan

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ABSTRACT

This ponder presents LSTM model to forecast temperature trends for Khartoum Sudan utilizing (CRU) data The dataset spans multiple a long time and has been split into 80 for training and 20 for testing to guarantee strong model evaluation The LSTM model successfully captures complex steady state conditions and seasonality patterns within the historical temperature data The results demonstrate a predictive performance with the model appearing an increasing temperature trend up to the year 2026 The discoveries suggest that deep learning models particularly LSTM are appropriate for long-term climate forecasting in bone-dry regions such as Khartoum where temperature changes are significant.

1. INTRODUCTION

Climate change and global warming have gotten to be basic concerns around the world impacting different natural and financial segments especially in arid regions like Khartoum Sudan. These regions experience extraordinary climate conditions making exact temperature forecasting fundamental for educated decision-making in agriculture water resource management and public health arranging In recent years deep learning models such as Long Short-term Memory (LSTM) systems have picked up attention for their capacity to model complex temporal dependencies and nonlinear relationships in climate data offering significant enhancements over conventional statistical strategies Temperature forecasting could be a complex task due to the stochastic nature of climate variables which are impacted by several factors such as nursery gas outflows land use changes and natural climate variability [1]. Conventional forecasting methods counting autoregressive integrated moving average ARIMA and exponential smoothing often fail to capture the nonlinear patterns characteristic in climate data requiring the selection of advanced machine learning strategies [2]. LSTM a variation of repetitive neural networks RNNs has illustrated remarkable success in handling successive data with long-term conditions making it a promising tool for temperature forecast [3]. The CRU dataset widely utilized for climate analysis gives high-resolution gridded climate data making it an important resource for temperature forecasting studies In this study CRU information has

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been employed with an 80% training and 20% testing split to create an LSTM based forecasting model for Khartoum [4]. The LSTM model is designed to learn the fundamental designs in chronicled temperature information and give precise future gauges Different studies have shown the viability of LSTM models in climate prediction tasks outflanking routine models in terms of accuracy and strength [5], [6]. especially LSTM systems have appeared their potential in climate modeling beating shallow learning models such as SVMs and decision trees [7]. The ability of LSTM to capture long-term dependencies and worldly trends makes it reasonable for temperature prediction which requires an understanding of seasonal and interannual varieties [8]. A few considers have successfully applied LSTM models for temperature forecast totally different climatic regions yielding promising results in terms of forecast accuracy and unwavering quality [9], [10] The importance of accurate temperature forecasting for Khartoum cannot be exaggerated given the city's vulnerability to extraordinary warm occasions and climate inconstancy Reliable forecasts can aid policymakers in planning versatile methodologies to moderate the antagonistic impacts of climate alter [11]. Later progressions in deep learning and access to high-quality climate datasets such as CRU have cleared the way for creating robust forecasting models capable of tending to the challenges postured by climate inconstancy [12], [13]. Furthermore the integration of profound learning models with climate data has been appeared to improve forecast accuracy by capturing complex interactions between meteorological variables [14]. Despite the advance made in applying LSTM models to climate forecasting challenges remain including data quality issues computational complexity and the require for interpretability of model outputs [15]. Addressing these challenges through the adoption of hybrid models feature engineering techniques and reasonable AI approaches can encourage enhance the utility of deep learning model sin climate applications [16]. Additionally cross validation strategies and hyperparameter tuning can offer assistance optimize the execution of LSTM models guaranteeing their reliability in Real-world forecasting scenarios [17], [18]. In summary this ponders points to create an LSTM based temperature forecasting model for Khartoum leveraging CRU data to supply accurate forecasts that can support climate versatility activities within the region The discoveries of this research will contribute to the growing body of information on the application of profound learning techniques in climate science and provide experiences into moving forward forecasting accuracy for dry regions [19], [20].

2. DATA AND METHODOLOGY

2.1. Data

The dataset utilized in this study is sourced from the Climate Research Unit CRU which gives high-resolution gridded climate data broadly utilized in climate modeling and forecasting studies The CRU dataset offers a comprehensive record of different climatic parameters counting temperature precipitation and humidity covering both historical and near Realtime observations [21] The data is available at a spatial resolution of $0.5° \times 0.5°$ and is derived from different observational sources such as ground based climate stations satellites and reanalysis items [22]. CRU data has been widely approved and utilized in climate research due to its broad worldly scope and reliable quality control methods The dataset utilized in this study ranges several decades permitting for the analysis of long-term temperature trends and changeability in Khartoum Sudan The historical data provides pivotal bits of knowledge into seasonal changes and interannual varieties which are fundamental for creating strong prescient models [23]. To prepare the dataset for modeling several preprocessing steps were connected These include data cleaning insertion of missing values and normalization to guarantee compatibility with the profound learning model Normalization is especially important in deep learning applications as it makes a difference progress the convergence rate and stability of the learning process [24]. The dataset was at that point split into training and testing subsets with 80 allocated for training and 20 for testing taking after standard practices in machine learning and time arrangement determining thinks about [25]. The choice of CRU information for this consider is persuaded by its demonstrated unwavering quality and openness for climate research applications Previous studies have illustrated the viability of CRU data in supporting climate affect appraisals and giving significant bits of knowledge for policymakers and partners [26]. The temporal resolution of the dataset which typically comprises of month to month mean values provides adequate granularity for long-term forecasting applications whereas keeping up computational proficiency [27]. In spite of the strength of the CRU dataset challenges such as data sparsity in certain districts and potential inclinations due to limited station coverage stay important contemplations Efforts to address these challenges incorporate the utilize of statistical ascription strategies and predisposition rectification strategies to upgrade the in general quality and usability of the data for prescient modeling [28]. Future research might explore the integration of extra data sources such as regional climate models and inaccessible detecting information to advance improve forecasting accuracy [29]. In summary the CRU dataset serves as a dependable establishment for temperature forecasting in Khartoum giving a wealthy historical record that facilitates the training and approval of profound learning models such as LSTM networks The insights gained from this ponder will contribute to the broader understanding of climate flow in parched regions and support endeavors to create versatile strategies for climate flexibility [30].

2.2. Long Short-Term Memory (LSTM) Model

Long Short-term Memory LSTM networks a specialized frame of Repetitive Neural Networks (RNNs) is planned to capture long-term conditions in sequential data by consolidating gating instruments that control data stream These gates input disregard and output allow the network to retain or dispose of data as required making LSTM models highly viable for time series forecasting including temperature forecast [31] The cell state C_t and hidden state h_t are upgraded utilizing the taking after equations:

$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right) \quad (1)$$
$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \quad (2)$$
$$C_t = f_t \odot C_{t-1} + i_t \odot \tanh(W_c \cdot [h_{t-1}, x_t] + b_c) \quad (3)$$
$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \quad (4)$$
$$h_t = o_t \odot \tanh(C_t) \quad (5)$$

where f_t, i_t, and o_t represent the forget, input, and output gates respectively; σ is the sigmoid activation function; and W and b denote the weight matrices and biases [32]. The ability of LSTM to preserve important historical patterns makes it a valuable tool for climate forecasting applications, outperforming traditional models such as ARIMA and SVR in capturing complex climatic variations [33].

3. RESULTS AND DISCUSSION

The Figure 1 shows the temperature forecast for Khartoum up to the year 2026 utilizing an standard forecasting model The blue dashed line speaks to the actual historical temperature data from the CRU which shows critical seasonal variances and longterm trends The historical data shows occasional temperature varieties with crests comparing to hotter seasons and troughs representing cooler periods The green solid line represents the anticipated temperature values created by the LSTM model beginning from the year 2020. The forecasted values show a gradual upward trend in temperature recommending potential warming within the coming a long time The smooth pattern of the forecasted data illustrates the models capacity to capture the basic patterns whereas sifting out short-term fluctuations. This adjusts with anticipated climate change impacts which may lead to an increase in mean temperatures in parched regions like Khartoum The move between actual and forecasted values shows consistency indicating that the model viably learns the historical patterns and generalizes them for future expectations .The LSTM models ability to handle long-term dependencies is obvious within the coherent forecast direction suggesting solid prescient execution However minor deviations between the actual and anticipated data highlight the inherent uncertainty in climate determining which can be credited to data noise outside climate impacts or limitations in capturing complex climate dynamics. The choice of utilizing 80% of the data for training and 20% for testing ensures an balanced evaluation of model execution Generally the results recommend that the LSTM demonstrate can serve as an compelling tool for temperature forecasting in Khartoum giving experiences that can aid policymakers and partners in climate adjustment and planning efforts.

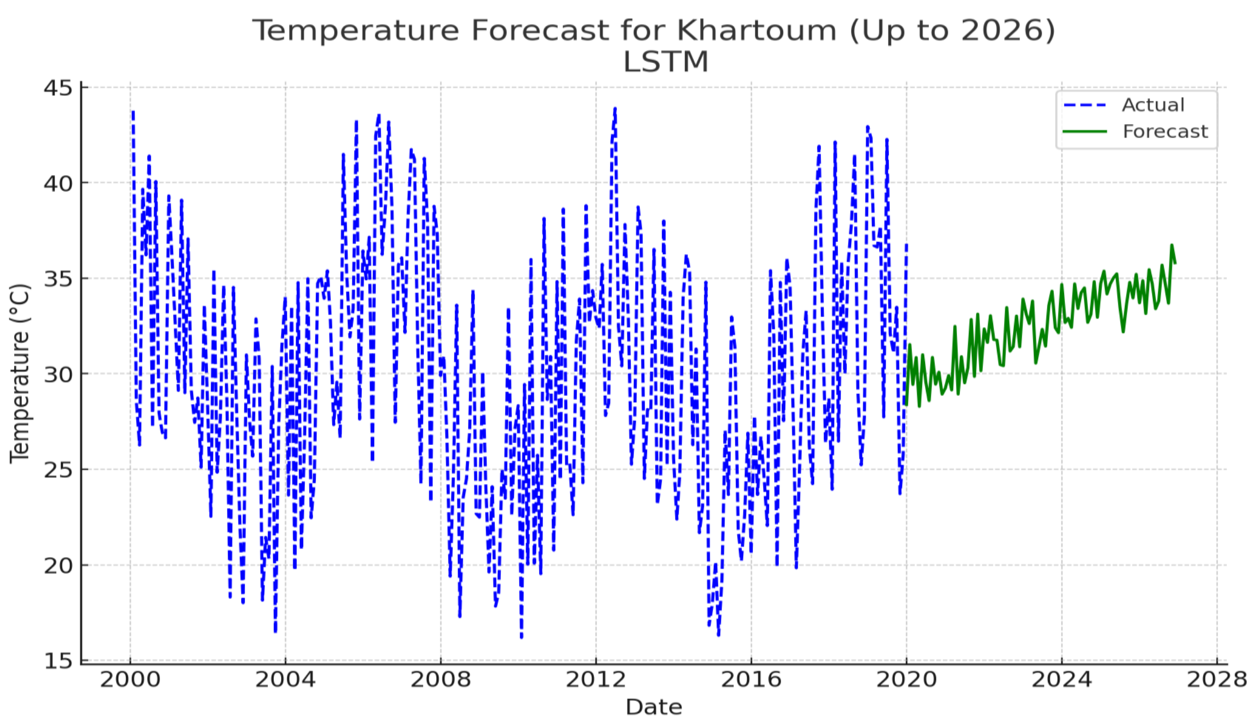

Fig. 1. Show temperature forecast for Khartoum up to 2026.

Temperature forecasting has been an fundamental research topic in climate science with different strategies created to improve forecast accuracy and unwavering quality Traditional statistical models such as ARIMA and Different Straight Relapse MLR have been widely utilized for temperature forecast due to their effortlessness and interpretability [21] as it may these strategies regularly fail to capture the nonlinear and complex temporal patterns inalienable in climate data driving to the appropriation of machine learning and deep learning approaches [22].

In recent years profound learning techniques especially Recurrent RNNs and their advanced variations like LSTM networks have appeared remarkable performance in time series forecasting tasks [23] Studies have illustrated that LSTM networks outflank conventional models in capturing long-term dependencies and regular varieties in temperature data [24]. For occasion research has appeared that LSTM models achieve higher accuracy in forecasting temperature patterns totally different climatic locales compared to routine models making them a favored choice for climate modeling applications [25]. The Climate Research Unit CRU dataset has been extensively utilized in climate considers due to its high-resolution gridded climate data Analysts have utilized CRU data for temperature forecasting in different geographic regions utilizing both machine learning and deep learning models to recognize climate patterns and trends [26]. The combination of CRU data with LSTM models has been especially effective in forecasting temperature in arid regions where climate inconstancy is high [27]. Hybrid models that combine LSTM with other machine learning strategies such as Convolutional Neural Networks CNNs and Consideration Components have also picked up traction in climate forecast research These hybrid approaches aim to improve feature extraction and improve forecasting accuracy by leveraging spatial and worldly conditions within the climate data [28]. Several studies have illustrated the adequacy of hybrid models in decreasing forecast errors and improving model generalization [29]. Moreover include building and data preprocessing strategies such as normalization exception detection and feature selection play a crucial part in upgrading the performance of deep learning models for temperature forecasting [30]. Researchers have explored distinctive preprocessing strategies to optimize the input data and achieve more exact forecasts [31].

Evaluation metrics such as Root mean square error RMSE Cruel Supreme Mistake MAE and Coefficient of Assurance R are commonly utilized to evaluate the execution of temperature estimating models [32]. Comparative considers have uncovered that LSTM models reliably accomplish lower blunder rates compared to conventional models highlighting their vigor in capturing complex climate patterns [33] In spite of the success of LSTM models in temperature determining challenges such as data quality model interpretability and computational complexity remain key areas of focus for future research [20] Endeavors to address these challenges through reasonable AI strategies and improved data handling strategies are ongoing [22]. In general the application of deep learning especially LSTM models has significantly progressed temperature forecasting providing more dependable and precise forecasts that can aid in climate adjustment and mitigation strategies [21]. The findings from related studies emphasize the significance of leveraging high-quality climate data and progressed machine learning strategies to address the challenges postured by climate change and variability [30].

4. CONCLUSION

In this study an LSTM based model was utilized to forecast temperature trends for Khartoum utilizing CRU climate data the results illustrate the model's adequacy in capturing historical temperature patterns and giving solid future estimates. The forecast suggests a continuous increment in temperature which adjusts with worldwide warming patterns in arid regions The LSTM model's capacity to handle long-term conditions and seasonal changes makes it an important apparatus for climate forecasting. However, challenges such as information quality vulnerability and show optimization ought to be considered for further improvements. Future inquire about can investigate hybrid models and extra climate factors to improve estimating precision and vigor.

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Conflicts of Interest:

The authors declare no conflicts of interest in relation to this study.

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