Timeseries Forecasting of Precipitation dynamics in Africa using LSTM

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DEEP LEARNING INDABA

INTRODUCTION

- In recent years, there has been a global scientific focus on research related to rainfall forecasting, driven by the growing concern of global warming and climate change (Awan and Maqbool, 2010).
- However, conducting a detailed analysis of rainfall trends across the entire African continent using data from field-based meteorological stations poses a significant challenge due to the lack of adequate long-term and spatially representative climatic data (Pereraet al., 2021).
- Africa, being one of the most vulnerable continents to climate change and variability, has a low adaptive capacity (Gemeda and Sima, 2015).
- Despite the challenges posed by data availability, knowledge gaps, and computational complex-ity, research on rainfall forecasting and trend analysis is crucial for understanding climate change impacts, particularly in vulnerable regions like Africa (Brinkman et al., 2016).
- One of the major RNN architectures used in the field of deep learning is Long Short-Term Memory (LSTM).

Aim of the Study

The aim of this study is to provide a thorough understanding of how to analyze climate data with LSTM deep learning algorithm with respect to environmental conservation management

METHODOLOGY

STUDY AREA: .

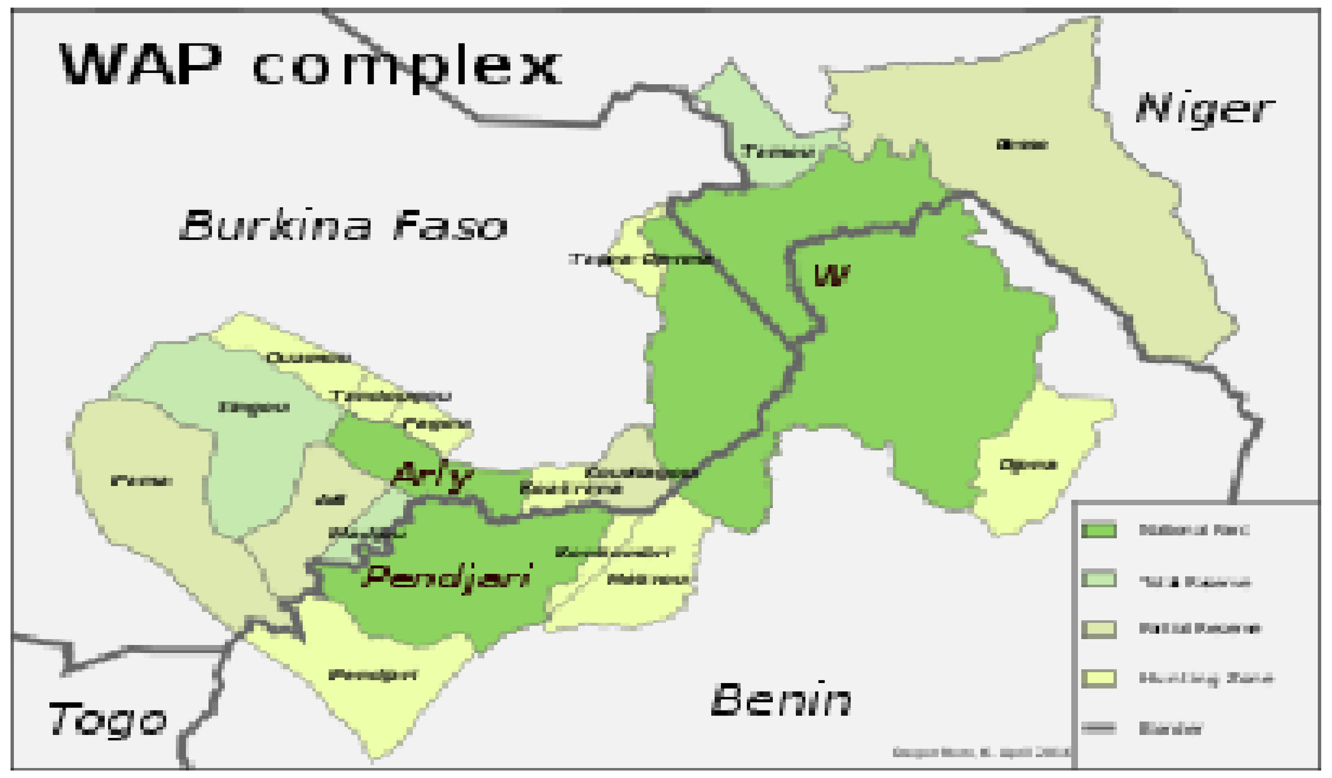


Figure 1: Map of Arli National Park, Burkina Faso

- Historical climate data of Arli National park, in Burkina-Faso was collected from NASA database over a period of 32years (1990-2022).
- Dataset was organized as a sequence, where each data point corresponds to a time step, for feature selection, input sequences that capture patterns and dependencies in the data was created.
- The dataset was divided into training, and test sets.

Model Architecture:

- The LSTM model for precipitation forecasting was designed, and the input, LSTM layers, and output layers configured.
- Appropriate activation functions and optimization algorithms were defined.
- **Training Process:**
- The input sequences were fed into the LSTM model during training.
- Backpropagation through time (BPTT) was used to update weights and optimize the model.

Hyperparameter Tuning:

- Hyperparameters such as the number of LSTM units, batch size, learning rate, and sequence length. Were adjusted.
- Afterwards, the parameters were finetuned to enhance model performance.

Forecasting:

- After training, the LSTM model was used to make predictions on unseen data, and historical sequence data was provided as input to forecast future precipitation values.

Evaluation:

- The model's performance was evaluate using Mean Squared Error and Root Mean Squared Error.
- Finally, the forecasted values was compared against actual precipitatio observations.

RESULT

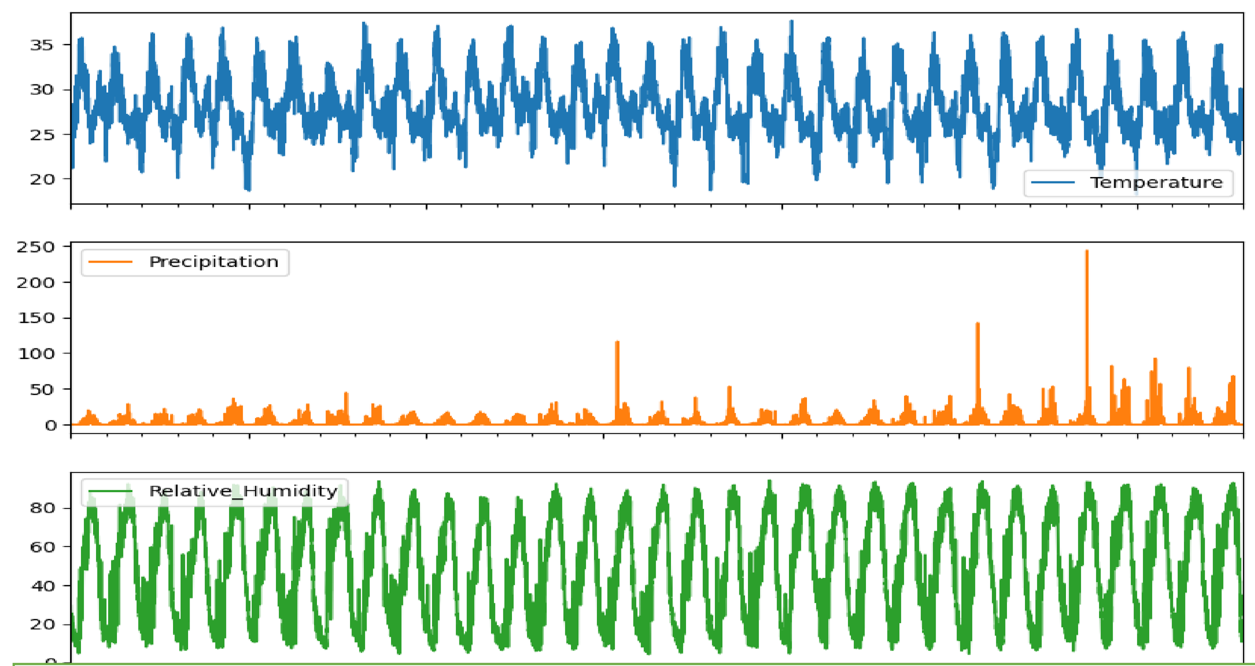


Fig 1: Showing the time series data for "Temperature," "Precipitation," and "Relative Humidity" over the "Date" timeline. Each subplot provides insights into how these variables change with time.

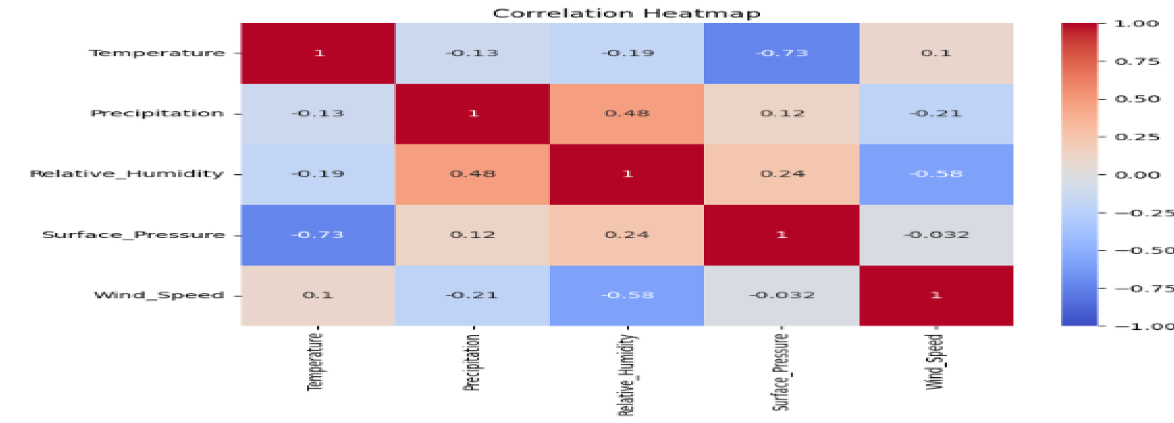
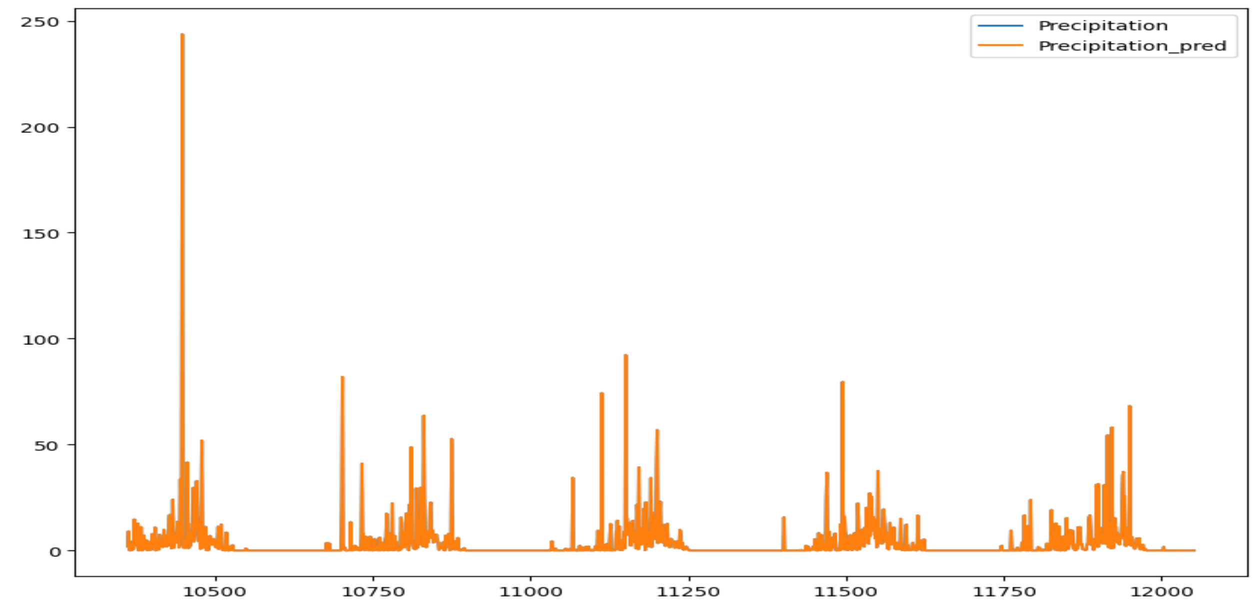


Fig 2: shows that Temperature has a moderate negative correlation with Surface Pressure (-0.734), suggesting that higher temperatures are associated with lower surface pressures., Precipitation and Relative Humidity have a moderate positive correlation (0.476), indicating that higher relative humidity is associated with higher precipitation levels.

Wind Speed has a strong negative correlation with Relative Humidity (-0.579.



CONCLUSION

- The final training loss was 0.0043.
- MAE of 0.0513 and validation loss of 0.0033, and validation MAE of 0.0453. Overall, results suggested good model performance with low loss and small MAE values.

REFRENCES

Awan, J. A. and Maqbool, O. (2010). Application of artificial neural networks