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Weather Forecast Predictions using Machine Learning - Long Short-Term Memory (LSTM) networks

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ABSTRACT

This study utilizes an LSTM neural network to predict future values of various characteristics in a dataset. An LSTM model is constructed for every feature and trained using sequential historical weather data to capture temporal relationships between these data. The design of the model consists of two LSTM layers, each of which is succeeded by a dropout layer in order to avoid overfitting. After the training process, the model makes predictions continuously for the upcoming 24 hours, utilizing the latest time steps as inputs. The anticipated values are then reverted to their original scale via transformation metrics like MSE, RMSE, and R^2 are calculated for every feature to evaluate the model's precision. Additionally, the model's fitting procedure includes monitoring the training loss and visualizing it as a training curve to track the model's learning progress. The structure provides a flexible method for forecasting numerous attributes over a period by utilizing separate models for each attribute. Our results highlight the significance of choosing high-quality data and features, indicating that LSTM has the potential to improve decision-making in different industries that depend on precise weather predictions.

Keywords: LSTM, neural network, historical weather data, MSE, RMSE, R^2

1. Introduction

Precise weather prediction is crucial for numerous industries such as farming, transportation, and disaster management. Accurate weather predictions can greatly impact decision-making, resource distribution, and risk management in these industries. Conventional statistical models, though essential, frequently face difficulties in capturing the intricate temporal dependencies and non-linear relationships present in meteorological data. This restriction may cause errors, especially in short-term predictions, when quick weather changes are frequent, Machine learning methods have become increasingly popular for predicting time series data in the past few years. Out of all these methods, LSTM neural networks have become a popular choice because of their capability to understand sequential data and grasp long-term connections. LSTM models are ideal for forecasting weather due to their ability to accurately identify intricate patterns and connections among various weather variables like temperature, humidity, wind speed, cloud cover, and precipitation.

The primary goal of this study is to develop an LSTM-based model for forecasting weather conditions in the upcoming 24 hours. Utilizing historical weather data, the LSTM model can predict the weather for the next24 hours. A detailed presentation is given to help understand the method better, covering data preprocessing, model structure, and assessment criteria. The primary objective of this research is to demonstrate the enhanced precision of weather predictions using LSTM networks and examine methods to effectively fine-tune and implement them in real-world scenarios.

2. Literature survey

Recent advancements in weather forecast predictions have increasingly utilized using machine learning techniques, particularly Long Short-Term Memory (LSTM) networks, due to their ability to model complex temporal dependencies in sequential data. Arif et al. [1] compared LSTM with Adaptive Neuro-Fuzzy Inference System (ANFIS) and Autoregressive Moving Average (ARMA) models for predicting atmospheric air temperature over various time intervals. Their findings indicated that LSTM outperformed traditional methods, particularly in short-term predictions. Yu et al. [2] focused on short-term solar irradiance forecasting under complicated weather conditions using LSTM. Their study demonstrated the model's effectiveness in capturing the intricate patterns of solar radiation, which is crucial for optimizing solar energy systems. Makhamisa et al. [3] explored deep learning techniques for weather nowcasting, emphasizing the potential of LSTM networks in real-time weather prediction. Their work highlighted the importance of leveraging deep learning for immediate weather updates.

Carlos et al. [4] introduced a Convolutional LSTM architecture for precipitation nowcasting using satellite data. This hybrid approach effectively combined spatial and temporal features, enhancing the accuracy of precipitation forecasts.

Vasavi and Vasundra [5] proposed an effective weather forecasting method using a deep LSTM network based on time-series data, enhanced by sparse fuzzy c-means clustering. Their approach improved the model's robustness and accuracy in predicting weather conditions. Suleman and Shridevi [6] also utilized a spatial feature attention-based LSTM model for short-term weather forecasting, demonstrating the model's capability to focus on relevant features, thereby improving prediction accuracy.

Karevan and Suykens [7] introduced a transductive LSTM model for time-series prediction, specifically applied to weather forecasting. Their research emphasized the advantages of transductive learning in enhancing the model's performance on unseen data. These studies collectively underscore the effectiveness of LSTM networks and their variants in improving the accuracy and reliability of weather forecasts. This research aims to build upon these findings by developing a dedicated LSTM model for short-term weather prediction, focusing on optimizing performance through effective data preprocessing and model architecture.

3. Proposed methodology

Predicting weather forecast using historical weather data for next 24 hours is challenging task, but using LSTM networks we can overcome this problem. The proposed system is shown in the below fig.1

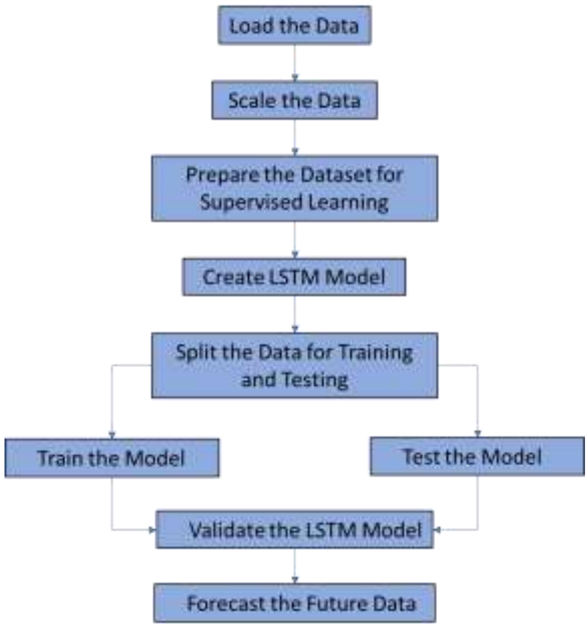


Fig.1 LSTM architecture for weather prediction

3.1 Flowchart explained

Data Collection: Historical weather data was collected from reliable sources, which contains weather attributes temperature, humidity, precipitation, cloud cover, visibility, windspeed etc..

Data Preprocessing: Data preprocessing contains normalization of weather data to machine readable format (0,1) using MinMaxScaler. The processed data further transformed into sequences, which helps LSTM model to learn temporal dependencies.

Model creation: The sequential LSTM model was designed, which contain input LSTM layer, Dropout layer and final Dense layer. The LSTM model compiled using Adam optimizer.

Splitting data into training and testing set: The weather data is splitted into training set and testing set (80%training 20%testing).

Model Training: The LSTM model was trained on training dataset. This training process involves minimizing the loss function.

Testing and Evaluation: After training the LSTM models performance evaluated using testing dataset, using evaluation metrics Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R-squared (R^2) to quantify the accuracy of predictions.

Prediction: For future predictions, last sequences in weather data are used to predict the next 24 hours using LSTM model.

Visualization: The actual and predicted values are plotted to visually asses the model's performance.

3.2 The algorithm for the proposed methodology.

STEP 1 - Data Collection: Gather historical weather data.

STEP 2 - Preprocessing: Normalize weather data and generate sequences.

STEP 3 - Model building: Creating LSTM model as per our purpose and compile model using Adam optimizer and mean squared error as loss function.

STEP 4 - Data splitting: Split weather data into training and testing.

STEP 5 - Model training: Train model using training set of data.

STEP 6 - Model evaluation: After training evaluate model using mean absolute error MAE), root mean squared error (RMSE), r-squared (R^2).

STEP 7 - Future predictions: take last sequences of observations from weather data to predict future 24 hours weather data.

STEP 8 – Visualization: Plot predicted values to visually asses models performance.

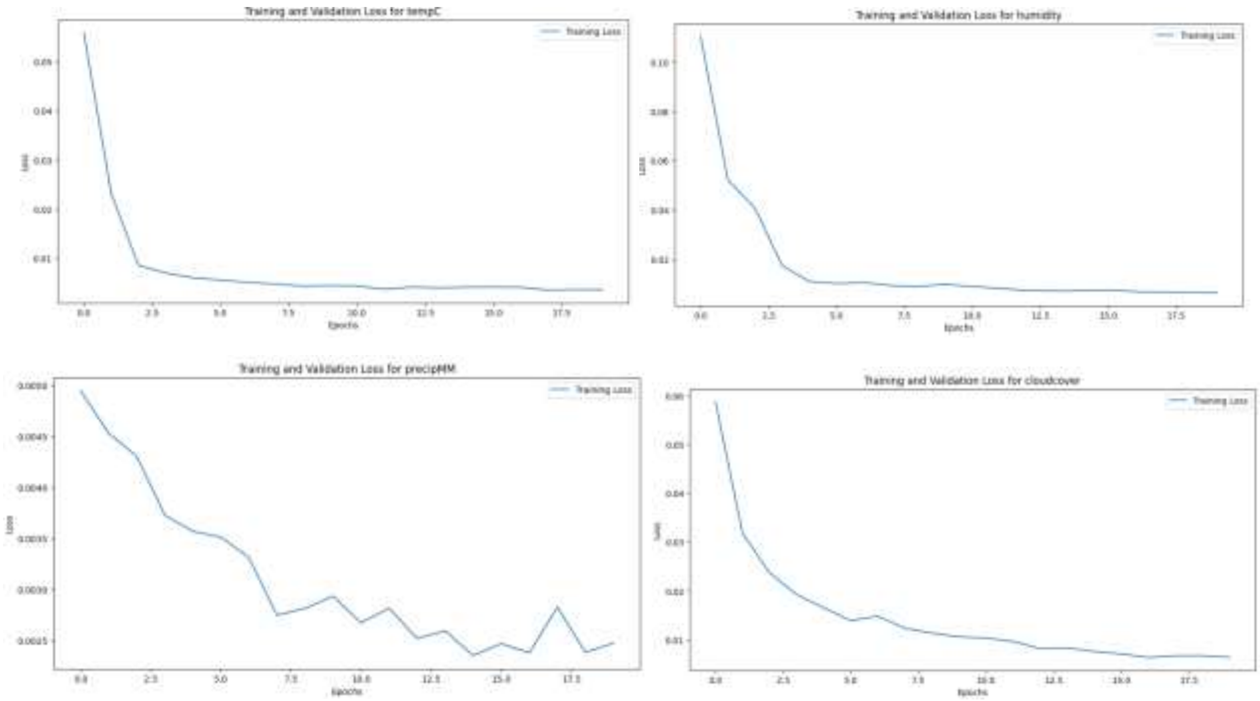
4. Results

4.1 Objectives

The objective of this study is to develop an LSTM-based model for predicting weather using past historical weather data. The model is designed to predict future values for next 24 hours weather based on historical weather data. This study aims to build robust LSTM model that captures long-term dependencies in time series data. Evaluate the performance of the LSTM model against traditional metrics like Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and the R^2 score.

4.2 System performance

The LSTM model was trained using historical weather data, where 80% of the weather data are used for training and remaining 20% for validation. During training phase, Mean Squared Error (MSE) and Mean Absolute Error (MAE) are monitored for model evaluation. And model's loss decreased across epochs (20 epochs), indicating its effectiveness in capturing temporal dependencies. Early stopping was applied to LSTM model to prevent overfitting of LSTM model. Final model achieved a balance between minimizing both training and validation losses. The training curve illustrates the reduction of training and validation losses over time, showing a steady convergence and no significant overfitting.



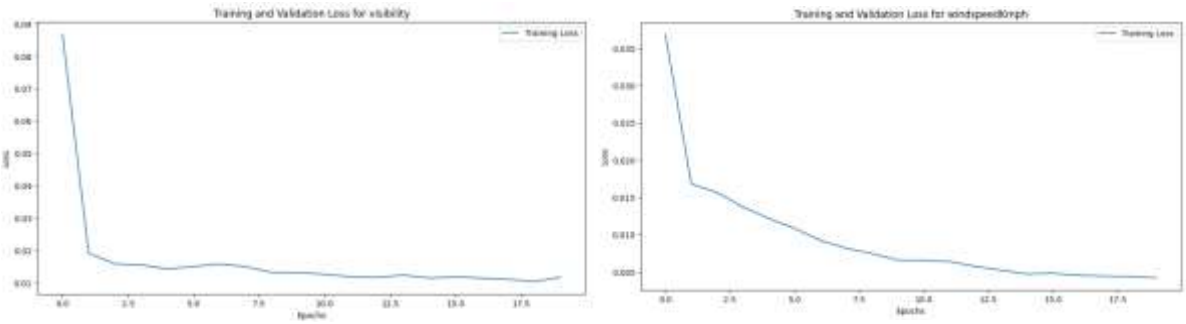


Fig.2 Training curve of LSTM model for various weather attributes

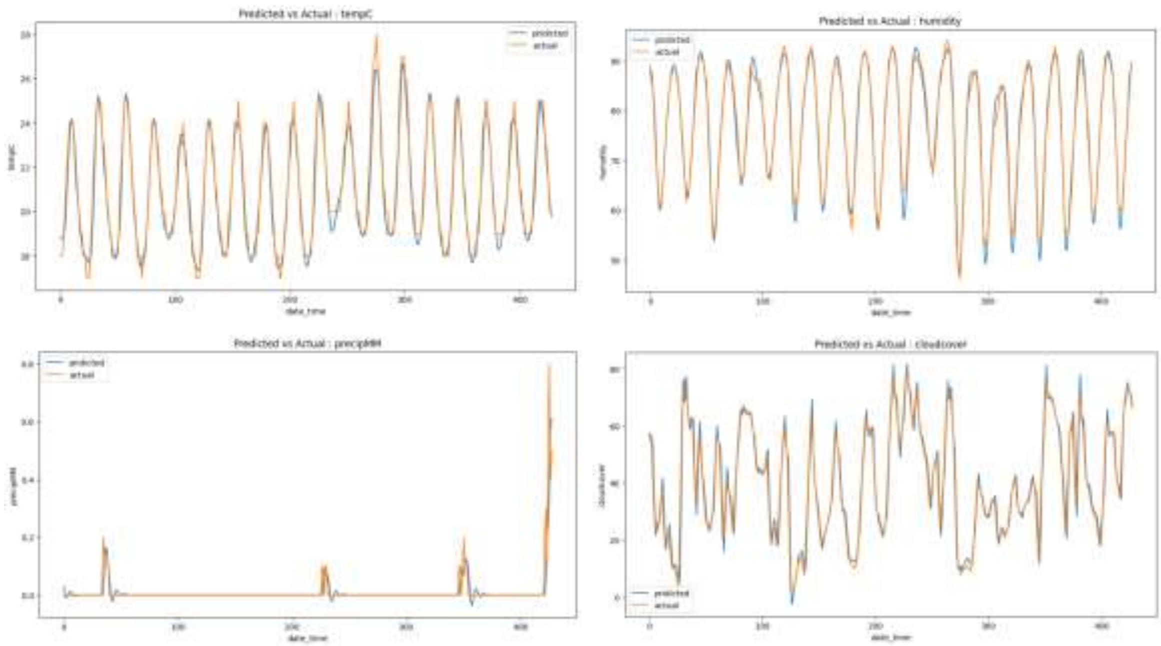
4.3 Model Evaluation

The performance of the LSTM model was evaluated using the Mean Squared Error (MSE), Root Mean Squared Error (RMSE) and R-squared (R^2) for validation of weather data. These metrics were calculated for both the training and validation sets to assess the model's accuracy and generalization capabilities. In addition, a training curve was plotted to visualize the loss across epochs.

Weather attribute	**MAE**	**RMSE**	**R^2 score**
Temperature	0.39	0.49	0.96
Humidity	0.31	0.69	0.97
Precipitation	0.008	0.03	0.65
Cloud cover	2.11	3.26	0.65
Visibility	0.15	0.29	0.63
Windspeed	0.51	0.64	0.93

Table1 Model performance metrics

The following figure demonstrates actual weather data and predicted weather data, and describes model's performance and preciseness in predicting future weather values.



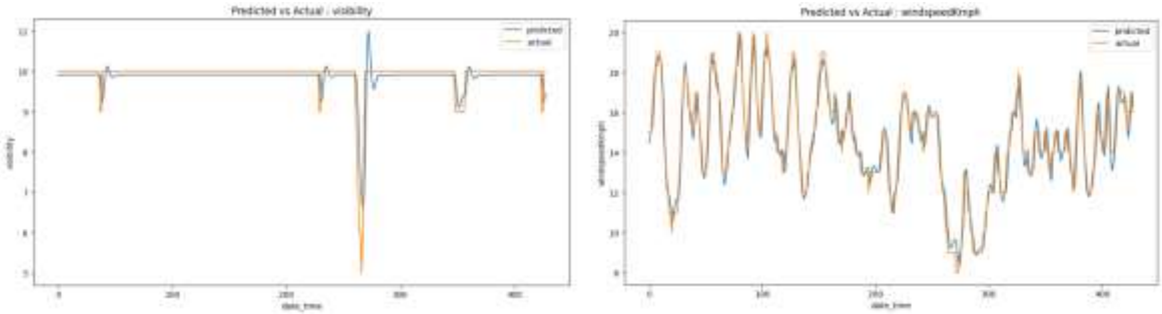


Fig.3 Actual vs predicted weather attributes

4.4 Future Predictions

The model was tested on unseen data to predict weather conditions for the next 48 hours. The predicted values aligned closely with the actual values, as shown in **fig.3**, demonstrating the model's effectiveness in short-term weather forecasting.

The following table demonstrates models predicted weather attributes for next 24 hours.

	temp	humidity	precip	cloudcover	visibility	windspeed
2024-09-09 00:00:00	20.149664	97.931061	0.181870	96.384529	12.412757	11.207985
2024-09-09 01:00:00	19.965727	98.979462	0.183269	95.598412	9.793468	10.744649
2024-09-09 02:00:00	19.865429	99.653900	0.184529	94.857231	7.792431	10.405890
2024-09-09 03:00:00	19.862940	99.944229	0.185646	94.318153	6.506737	10.276468
2024-09-09 04:00:00	19.980068	99.699890	0.186632	93.899452	5.898688	10.390079
2024-09-09 05:00:00	20.247116	98.748726	0.187542	93.408318	5.292821	10.770176
2024-09-09 06:00:00	20.682495	97.392479	0.188491	92.722992	5.034392	11.395064
2024-09-09 07:00:00	21.340889	95.256554	0.189648	91.910065	4.858284	12.385700
2024-09-09 08:00:00	22.249071	92.379829	0.191242	90.917061	5.632408	13.815344
2024-09-09 09:00:00	23.308920	89.185509	0.193547	89.700356	6.550900	15.421097
2024-09-09 10:00:00	24.418297	86.292267	0.192552	88.230179	7.545757	16.932579
2024-09-09 11:00:00	25.445831	84.118416	0.195663	86.747566	8.712293	18.399652
2024-09-09 12:00:00	26.276394	82.724068	0.200365	84.881203	10.151021	19.697496
2024-09-09 13:00:00	26.825186	82.175972	0.202780	83.169670	11.523713	20.632076
2024-09-09 14:00:00	27.010910	82.463547	0.210336	84.403458	12.783840	21.079556
2024-09-09 15:00:00	26.835297	83.505356	0.211684	86.441490	13.884057	21.063536
2024-09-09 16:00:00	26.353889	85.006485	0.199322	88.668304	14.758284	20.656200
2024-09-09 17:00:00	25.662113	86.796349	0.198156	89.917435	15.082447	19.865637
2024-09-09 18:00:00	24.830519	88.926895	0.196132	90.459351	14.853097	18.767422
2024-09-09 19:00:00	23.955992	91.370369	0.192981	90.883507	14.089983	17.571121
2024-09-09 20:00:00	23.172274	93.361984	0.192766	91.932739	12.854917	16.417709
2024-09-09 21:00:00	22.489960	95.267525	0.192536	92.770905	11.242157	15.297467
2024-09-09 22:00:00	21.906685	97.205475	0.192289	92.970680	9.648327	14.087534
2024-09-09 23:00:00	21.418310	99.128433	0.192028	93.970718	7.993043	12.814561

Table 2 predicted weather attributes for next 24 hours

The following line graph demonstrates predicted weather attributes for next 24 hours over the time

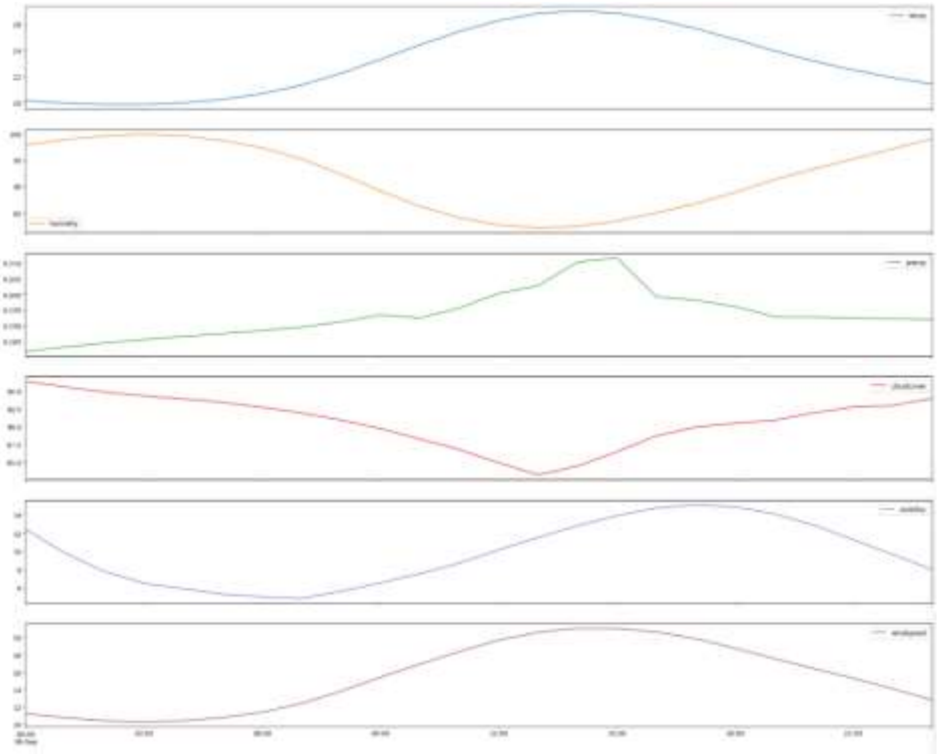


Fig.4 Line graph for predicted weather attributes for next 24 hours

The experimental results showed that LSTM model can efficiently deals with complex and non-linear characteristics of weather data. The model demonstrated enhanced accuracy compared to traditional statistical models by capturing temporal dependencies between weather attributes. Furthermore, incorporating dropout layers also useful in reducing overfitting, ensuring the LSTM model's reliability for practical use in weather predictions.

4.5 User interface

The following fig.5 represents the simple user interface for weatrher prediction using Long Short-Term Memory (LSTM) networks, which displays previous 7 days weather data with line graph to easily understand weather patterns.

Fig.5 User interface

Fig.6 User interface-predictions

The following fig.7 represents the predicted weather data for next 24 hours using LSTM model , with line graph for every weather attribute(temperature, humidty, precipitation, cloudcove, visibility, windspeed)

Fig.7 Final output with next 24 hours predicted weather data

5. Conclusion

This research showcased the capabilities of LSTM networks in short-term weather prediction. By making good use of past weather information, our models were able to predict temperature, humidity, precipitation,cloudcover, visibility and windspeed with great accuracy for the upcoming 24 hours. The strong agreement between observed and forecasted values demonstrated the LSTM's ability to capture complex weather patterns. And provide accurate weather predictions for next 24 hours.

Our study results indicates that precise weather predictions can help industries such as farming and disaster management, and urban planning. In general, this study highlights how LSTM networks are useful in predicting weather and opens the door for upcoming research to incorporate live data and extra characteristics, enhancing the accuracy of forecasts.

Future work

Future devlopments in LSTM-based weather forecasting systems should prioritize enhancing forecast accuracy and scalability of model. Improving the LSTM model to handle complex meteorological patterns like such as sudden weather changes, will improve predictions for temperature, precipitation, and wind speed. Incorporating external data sources like satellite imagery and IoT sensor data will offer more comprehensive real-time predictions. Future versions should investigate hybrid models that merge LSTM with methods such as attention mechanisms to enhance performance. Increasing the system's capacity to predict for various regions and timeframes, while also guaranteeing data security and confidentiality, will be essential for wider acceptance and dependability.

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