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Short-Term Weather Forecasting Using Deep Learning Techniques

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Abstract
Weather nowcasting is the process of predicting the weather for a period of o to 6 hours. Advanced deep learning models for weather nowcasting, emphasizes precise prediction of factors such as cumulative precipitation, humidity, wind direction, etc. Deep Learning models such as LSTMs and a CNN-LSTM Hybrid and stacked LSTM were applied to the AgriMet dataset. Stacked LSTM demonstrates notable performance with low Mean Squared Error (MSE) and Mean Absolute Error (MAE), indicating effective pattern capture. These results underscore the potential of deep learning for substantial improvement in short-term weather forecasting, providing pragmatic insights for decision-making in dynamic weather conditions.
Keywords: *Weather Nowcasting, Convolutional Neural Network, Long Short-Term Memory, Stacked LSTM, Cumulative Precipitation, Short-term rainfall prediction.*

I.INTRODUCTION

Weather nowcasting has emerged as a pivotal field within meteorological research, focusing on the immediate future and playing a crucial role in mitigating the impact of rapidly changing weather conditions. With advancements in observational technologies, such as high-resolution satellite imagery, radar systems, and ground-based sensors, meteorologists are able to capture and analyze atmospheric phenomena in real-time. In the last decade, many significant efforts in weather forecasting using machine learning techniques including deep learning have been reported with successful results. AG Salman et al. [1] compared the performance of Recurrence Neural Network (RNN), Conditional Restricted Boltzmann Machine (CRBM), and Convolutional Network (CN) models. F Ahmad et al. [2] investigated the applicability of time series algorithms such as LSTM, GRU, and Bi-LSTM to develop efficient nonlinear forecasting models for automatic weather analysis. Xiongfa Mai et al. [3] introduced a Bayesian optimization XGBoost-based classification model for rain or shine weather forecasting in precipitation nowcasting, exhibiting superior performance compared to other deep learning methods
Current work aims to analyse and evaluate existing deep learning models for weather nowcasting and develop better models. By analyzing various atmospheric factors with an immediate effect on the weather and exploiting this short-term relationship through deep learning models, the paper aims to demonstrate an improvement over currently used real-time models. Specifically, the research focuses on predicting precipitation patterns based on multiple atmospheric factors, including Vapor Pressure, Wind Speed, Humidity, and Atmospheric Temperature. Models that were considered include Long Short-Term Memory networks (LSTMs), recognized for their ability to capture temporal dependencies, and a hybrid model combining Convolutional Neural Networks (CNNs) with LSTMs. These models are chosen for their prowess in handling sequential and spatial-temporal data, a crucial aspect in weather forecasting where understanding both temporal patterns and spatial relationships is paramount.

II. RELATED WORK

The usage of deep learning in short-term weather forecasting has been explored in some detail in the last decade. Many researchers have incorporated radar images in addition to atmospheric data to help predict the weather. The recent works in weather nowcasting are briefly explained below.
The paper by Xingjian Shi et al. [4] explores the application of deep learning techniques, specifically the Convolutional LSTM Network, for weather forecasting, focusing on precipitation nowcasting. The study

formulates precipitation nowcasting as a spatiotemporal sequence forecasting problem and proposes the ConvLSTM network as an end-to-end trainable model. Experimental results demonstrate that the ConvLSTM network outperforms the stan- dard Fully Connected Long Short-Term Memory (FC-LSTM) network and the state-of-the-art operational ROVER algorithm for precipitation nowcasting, showcasing its ability to capture spatiotemporal correlations effectively. The paper also discusses the challenges of high dimensionality and chaotic nature of the atmosphere and shows the potential of deep learning in effectively addressing these challenges for weather forecasting.
However, with the Convolutional LSTM (ConvLSTM), challenges persist in handling location-variant natural motion. Building upon this, a novel Trajectory Gated Recurrent Unit (TrajGRU) model was proposed, actively learning location-variant structures for improved spatiotemporal correlations in precipitation nowcasting. Another paper by Xingjian Shi et al. [5] not only introduces the TrajGRU model but also establishes a benchmark dataset, HKO-7, offering a comprehensive evaluation protocol, balanced loss functions, and insights into the significance of online fine-tuning for enhancing deep learning models in the domain of short-term rainfall predictions.
The paper by Makhamisa Senekane et al. [6] introduces and compares three deep learning models—multilayer perceptron, Elman recurrent neural networks, and Jordan recurrent neural networks—for predicting sunshine and precipitation based on meteorological data from Lesotho. The models achieve high accuracies, with Elman and Jordan neural networks outperforming multilayer perceptron, showcasing the potential of deep learning in enhancing short-term weather forecasting.
Another work conducted by Georgios Kyros et al. [7] explores the application of machine learning, including Deep Learning, for short-range rainfall forecasting in Western Macedonia, Greece. Their investigation incorporates Random Forest, XGBoost, and Neural Networks (LSTM), with a significant emphasis on analyzing relationships between satellite-derived thermodynamic parameters and observed rainfall. The research showcases the effectiveness of machine learning models, particularly Random Forest, in predicting instantaneous rainfall over a 3-hour period, providing valuable insights for enhancing current forecasting methodologies.
The paper by Jihoon Ko et al. [8] contribute significantly with a novel pre-training scheme and loss function. Adapting the U-Net model for precipitation nowcasting and estimation from radar images, the study formulates these tasks as a classification and regression problem, respectively. Through comprehensive experiments on South Korean datasets, the proposed pre-training and loss function demonstrate substantial improvements in the critical success index for heavy rainfall nowcasting and reduce precipitation estimation errors. This research provides valuable insights into the effectiveness in using deep learning models for precipitation nowcasting and addressing challenges such as class imbalance in precipitation data.
In the recent years, the usage and the effectiveness of LSTMs and their variants in weather nowcasting have been explored in detail [9] [10] [11]. Therefore, LSTM model was employed for analysis and nowcasting of rainfall in this current work.

III. DESIGN AND METHODOLOGY

AgriMet dataset was extracted and preprocessed using min-max normalization and adding Gaussian noise. The dataset was split as training and testing set and further analyzed using deep learning models. The overall system architecture is shown in Figure 1.

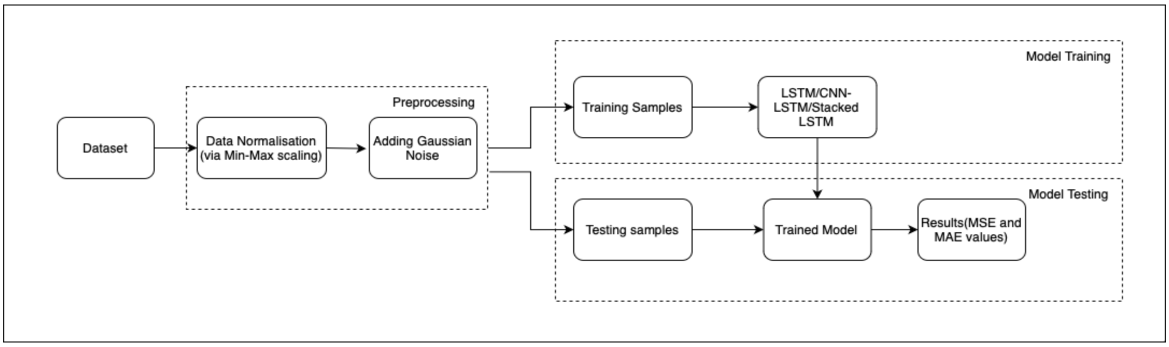


Figure. 1: System Architecture

A. Dataset

Experiments were conducted on the AgriMet dataset for the "Forest Grove, Oregon (FOGO)" weather station. (https://www.usbr.gov/pn/agrimet/webagdayread.html) This is an official weather station maintained by the United States Bureau of Reclamation (USBR), and the weather data is accessible to the public via USBR's AgriMet website. The FOGO station experiences a Mediterranean climate with dry summers and wet winters. This diverse set of weather conditions makes it ideal for testing and refining weather forecasting models across a range of scenarios. The different weather parameters available at the FOGO station and their descriptions have been tabulated in Table I. All parameters are recorded at 15-minute intervals at the FOGO station and are thus suitable for short-term forecasting experiments.

TABLE I: FOGO Station Meteorological Data

Variable	**Code**	**Description**
OB	Air Temperature	15 Minute Instantaneous (°F)
OBX	Air Temperature	15 Minute Maximum (°F)
OBM	Air Temperature	15 Minute Average (°F)
OBN	Air Temperature	15 Minute Minimum (°F)
TU	Relative Humidity	15 Minute Average (%)
TUX	Relative Humidity	15 Minute Maximum (%)
TUN	Relative Humidity	15 Minute Minimum (%)
EA	Actual Vapor Pressure	15 Minute Average (kPa)
TP	Dew Point Temperature	15 Minute Average (°F)
WD	Wind Direction	Mean of Wind Vector (°azimuth)
WG	Peak Wind Gust	Last 15 minutes (mph)
WS	Wind Speed	Hourly Average (mph)
UI	Wind Run	Cumulative (miles)
SQ	Global Solar Radiation	Cumulative (langleys)
SI	15 Minute Solar Radiation	Cumulative (langleys/hour)
PC	Precipitation	Cumulative (inches of water)

B. Preprocessing

All rows in the weather data with NaN values were identified and removed. Further, precipitation (PC) values at the FOGO station are reset whenever they reach a threshold of 50 inches. To make PC values consistent across the dataset, they were modified to reflect precipitation in each 15-minute interval rather than its cumulative value over time. All columns (weather parameters) were then normalized using min-max scaling. To decrease overfitting, small gaussian noises were added to all weather parameters using their respective means and standard deviations. For model training, 3-year weather data from Jan 1, 2019 to Jan 1, 2022 was used. For testing, 6-month weather data from Jan 1, 2021 to July 1, 2021 was used. The following models were used to predict the weather paramaters: Long Short-Term Memory network (LSTM), Convolutional Neural Network LSTM Hybrid (CNN LSTM Hybrid),
and Stacked LSTM.

C. DEEP LEARNING MODELS

i. LSTM

LSTMs [12] are a type of recurrent neural network designed to overcome the limitations of traditional RNNs in capturing long-term dependencies in sequential data. LSTMs introduce a memory cell with a gating mechanism, including input, forget, and output gates. These gates regulate the flow of information, allowing the network to selectively remember or forget information at each time step. The cell state serves as a long-term memory, while the hidden state acts as a short-term memory or output. Due to LSTMs' excellent ability to learn and retain temporal patterns, they are well-suited for time series prediction tasks.

To build an LSTM for forecasting task, TensorFlow v2.15.0 was used. Along with the input layer, one LSTM layer with 50 memory cells, and an output layer were added. The model was compiled with the Adam optimizer and the Mean Squared Error (MSE) loss function. The Adam optimizer is commonly used for training neural networks, and MSE is suitable for regression tasks where the goal is to minimize the squared difference between predicted and actual values.

The first paramater that was predicted is cumulative precipitation (PC) for a 6-hour lead time. Therefore, 25 steps of 15-minute intervals (excluding PC) were used as inputs, and the cumulative precipitation (PC) over the next 25 steps of 15-minute intervals was predicted. The previously defined LSTM model was trained for 50 epochs with a batch size of 32 and a validation split of 20 percent was taken. Figure 2 shows the actual and predicted Cumulative Precipitation values of LSTM model.

ii. CNN-LSTM Hybrid

A CNN LSTM Hybrid combines the strengths of CNNs and LSTMs, providing a powerful architecture for tasks involving both spatial and temporal dependencies, such as spatiotemporal forecasting. CNNs excel at capturing spatial features through convolutional layers, which analyze local patterns in data, while LSTMs specialize in modeling sequential dependencies over time. In a hybrid architecture, CNNs are typically employed as the initial layers to extract spatial features from input data, and the extracted features are then fed into LSTMs to capture temporal dependencies.

To build a CNN LSTM Hybrid, TensorFlow v2.15.0 was used. Along with the input layer, a 1D convolutional layer with the ReLU activation function, a MaxPooling layer, an LSTM layer with 50 memory cells, and an output layer were added. The model was compiled with the Adam optimizer and the Mean Squared Error (MSE) loss function.

To predict PC values for 6-hour lead times, the CNN LSTM Hybrid model was trained for 50 epochs with a batch size of 32 and a validation split of 20 percent was taken. Figure 3 shows the actual and predicted Cumulative Precipitation values of CNN-LSTM Hybrid model.

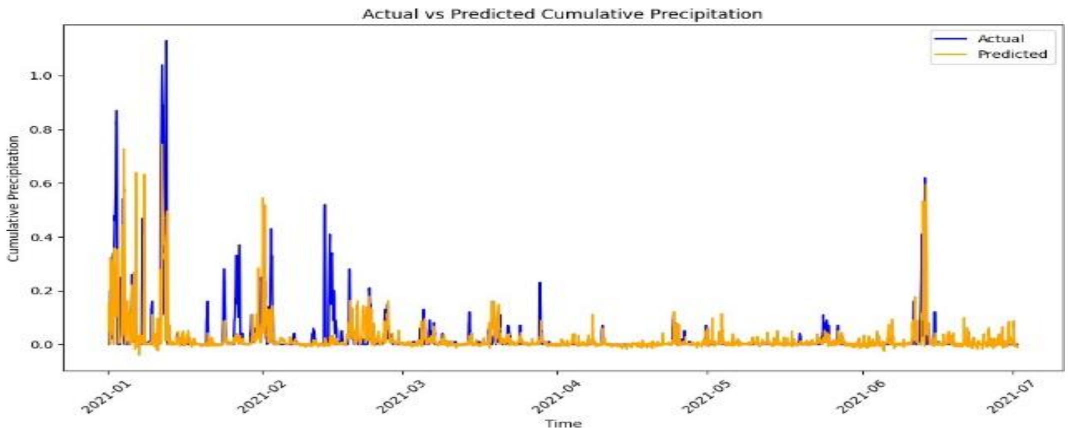
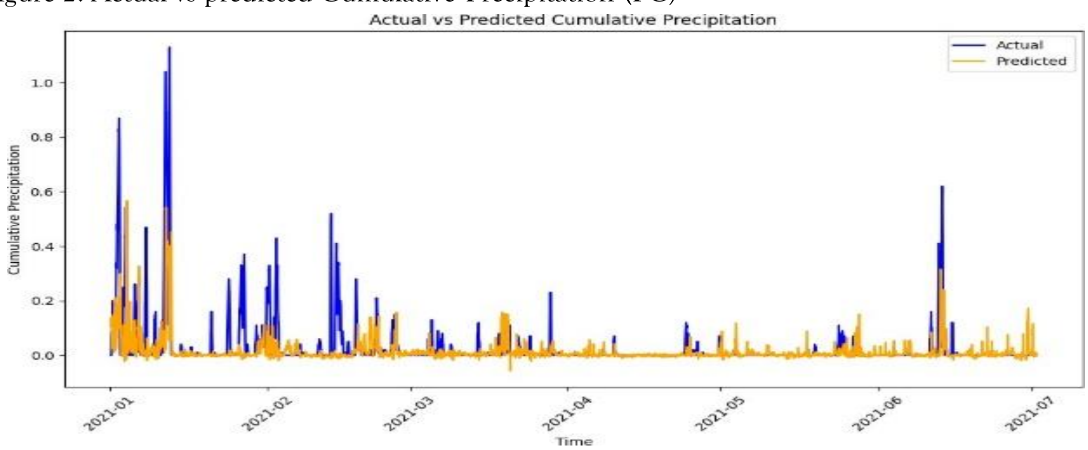
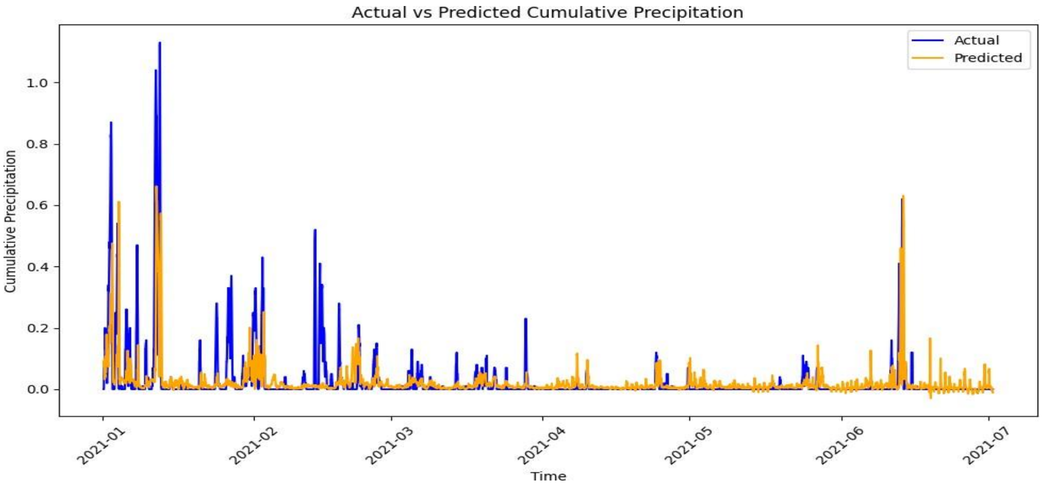


Figure 2. Actual vs predicted Cumulative Precipitation (PC)



values from LSTM model.

Figure 3. Actual vs predicted Cumulative Precipitation (PC)



values from CNN-LSTM Hybrid model.

Figure 4. Actual vs predicted Cumulative Precipitation (PC)
values from Stacked LSTM model.

iii. Stacked LSTM

Stacked LSTMs refer to the use of multiple LSTM layers in a neural network, allowing for hierarchical learning of sequential patterns. The output of one LSTM layer serves as the input for the next, creating a stacked architecture. This stacking enables the network to learn hierarchical representations of temporal features, with lower layers capturing short-term patterns and higher layers capturing longer-term dependencies.

To build a Stacked LSTM model, TensorFlow v2.15.0 was used. Along with the input layer, two LSTM layers with 50 memory cells each, and an output layer were added. The model was compiled with the Adam optimizer and the Mean Squared Error (MSE) loss function.

To predict PC values for 6-hour lead times, the Stacked LSTM model was trained for 15 epochs with a batch size of 32 and a validation split of 20 percent was taken. Figure 4 shows the actual and predicted Cumulative Precipitation values of Stacked LSTM model.

IV. RESULTS AND ANALYSIS

To evaluate the goodness of different models, Mean Squared Error (MSE), and Mean Absolute Error (MAE) metrics were used. The results from different models are rounded to the nearest ten thousandth and given in Table III.

TABLE III: Performance Metrics

Model	MSE	MAE
LSTM	0.0069	0.0295
CNN-LSTM Hybrid	0.0073	0.0304
Stacked LSTM	0.0065	0.0281

The relatively low MSE and MAE values of the LSTM model from Figures 3 and 4 indicate that it is performing well on the task, capturing the patterns in the data effectively. The slightly higher MSE and MAE of the CNN LSTM Hybrid compared to LSTM alone may be due to the added complexity of the hybrid architecture. The MSE and MAE values of the Stacked LSTM model are comparable to that of the LSTM model, indicating that the additional layer may not significantly impact or improve performance.

V. CONCLUSION

Deep Learning models such as LSTM, CNN-LSTM Hybrid and Stacked LSTM were applied on AgriMet dataset. It is observed that Stacked LSTM performed better when compared to other two models at predicting Cumulative Precipitation (PC) values. Furthermore, these models tend to excel at predicting low values of PC, and struggle with accurately predicting the PC values beyond the threshold value of 0.3. Based on the above results, improvements could be done by incorporating various boosting models to extract the spatial features. Additional pre-processing methods could have been employed such as subsampling the dataset to eliminate class imbalance via clustering of the features.

Applications of deep learning weather nowcasting models include emergency response planning where deep learning models enable accurate short-term weather predictions, aiding emergency response planning for events like heavy rainfall, storms, or floods. Timely forecasts assist authorities in preparing for and mitigating potential disasters.

Another application is public health management where timely weather predictions contribute to anticipating conditions conducive to the spread of diseases. For example, predicting heavy rainfall helps authorities prepare for potential flooding and the associated health risks. Other applications include urban planning and infrastructure maintenance, tourism and event planning, and agricultural decision support.

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