ADDIS ABABA UNIVERSITY

COLLEGE OF NATURAL AND COMPUTATIONAL SCIENCES

SCHOOL OF EARTH SCIENCE

APPLICATION OF ARTIFICIAL INTELLIGENCE ON HOURLY WEATHER FORECAST TO IMPROVE THE ACCURACY OF SHORT-RANGE PREDICTION IN ETHIOPIA

A Thesis Submitted to the School of Graduate Studies of Addis Ababa University in Partial Fulfillment of the Requirements for the Degree of Masters of Science in Remote Sensing and Geo-Informatics

By

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September, 2023

Addis Ababa, Ethiopia

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Declaration

I, Atalel, declare that the work presented in this thesis which is entitled "Application of Artificial Intelligence on Hourly Weather Forecast to Improve the Accuracy of Short-range Prediction in Ethiopia "is my own original work. I have not used any sources that have not been properly cited. I have also not plagiarized any work from other sources. I have made every effort to ensure that the work presented in this thesis is accurate and complete. I am aware that any plagiarism or other form of academic dishonesty will result in a failing grade for this thesis as well as morally.

Place: Addis Ababa, Ethiopia

Date: September, 2023

Atalel Wassie

Signature -------------

ADDIS ABABA UNIVERSITY

School of Graduate Studies

School of Earth Sciences

Remote Sensing and Geo-Informatics Stream

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Approved by the board of examiners:

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Chairman Date Signature

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Finally, I would like to dedicate this thesis to the memory of my mother, whose legacy of hope and strength has been a constant source of inspiration throughout my journey. I am forever grateful for her love and guidance. It was a time when I was feeling lost and uncertain, but she gave me the strength and courage to keep going. She was always there for me, no matter what.

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List of Acronyms

ANN	Artificial Neural Network
Bi LSTM	Bidirectional Long short memory
D2M	Dew pint at 2 meters
DL	Deep learning
GRU	Gated Recurrent unit
GIS	Geographic Information System
LSTM	Long short-term memory
MAE	Mean Absolute Error
ML	Machine Learning
MSE	Mean squared error
RELU	Rectified Linear Unit
RH	Relative humidity
RMSE	Root Mean Squared Error
RNN	Recurrent Neural Network
SWVL1	Volumetric soil water layer 1
T_2M	Temperature at 2 meters
TAF	Terminal Aerodrome forecast
ICAO	International civil aviation organization

List of Appendices

Abstract

The importance of accurate weather forecast has grown in recent years, especially for those who rely on the state of the atmosphere and its phenomena in hourly, daily, monthly and yearly bases. The transportation (aviation), Agricultural activities, construction, recreational activities (sports, concerts) are particularly affected either hourly, daily or yearly bases. This study proposed a newly emerging approach to forecast the weather that can minimize economic and human losses caused by imprecision. Highly correlated input features were used for the study that was conducted on ten years of hourly data from 2013 to 2022 to forecast precipitation, temperature and fog. The proposed method used machine learning models for data preprocessing, while deep learning models are used to forecast targeted variables. Four deep learning models were built and evaluated accordingly. These were LSTM, BiLSTM, GRU, and Simple RNN. Three experiments were conducted with different hyperparameter configurations. Hence, the LSTM model was found to have the best performance comparatively, with the following error metrics. For the validation of temperature forecast: root mean square error (RMSE) of 0.136, mean squared error (MSE) of 0.018, and mean absolute error (MAE) of 0.111. The corresponding loss values for the training, testing, and validation sets were 0.018, 0.017, and 0.018, respectively. Similarly, a model also achieved RMSE = 0.023, MSE = 0.0005, and MAE = 0.008 of error metrics for the validation of precipitation. The losses for training, testing, and validation found to be 0.00094, 0.00094, and 0.00054, correspondingly. The LSTM model and the random forest classifier were compared for fog forecasting. The LSTM model achieved the following error metrics: RMSE = 0.036, MSE = 0.0013 and MAE = 0.0034. The loss values for training, testing, and validation were 0.0028, 0.0019, and 0.0013, individually. The random forest classifier achieved an accuracy of 99.96% for fog prediction. The outcomes of the study confirmed that the proposed method can be used to forecast the weather conditions accurately. This can help to minimize economic and human losses caused by forecast imprecision.

Keywords: Artificial intelligence, BiLSTM, deep learning, GRU, LSTM, loss, machine learning, model, metrics, random forest, Simple RNN, Weather forecast

CHAPTER ONE
INTRODUCTION

1.1 Background

Meteorological forecasting is the use of mathematical models**,** observational data**,** and computer simulations to predict the state of the air at a particular place and moment (Singh, Kaushik, Gupta, & Malviya, 2019)**.** Atmospheric conditions around the globe change quickly and continuously. Accurate forecasts are indispensable in today's day-to-day existence. (Jakaria, Hossain, and Rahman, 2020)**.** Weather situations include rain, snow, temperature, fog, wind, etc. Extreme heat can lead to heat stroke, while extreme cold can lead to hypothermia. Rain and snow can cause flooding and landslides, which can lead to injuries and death. Fog can reduce visibility, which can lead to accidents. Wind can cause power outages and structural damage (Ismaila,2022)**.** Refining the accuracy of weather forecasts has a dominant importance for people's wellbeing and the protection of important commercial segments, including, aviation, agriculture water, energy, and emergency response (Parker et al., 2021). Enhancing weather forecasting and more efficient communication of weather warnings can help to mitigate the impact of extreme weather. By providing prompt and precise information about upcoming weather events, we can help people to take measures to protect themselves and their property (Singh et al., 2018).

The importance of accurate weather forecasting for aviation safety is well-known, but its chaotic nature has posed many challenges to scientists around the world (Ni Huang & Chen, n.d)**.** Pilots rely on accurate and up-to-date weather forecasts to plan their flights, ensure the safety of passengers, and maintain aircraft and equipment. Weather conditions can affect the rate at which airplanes land and take off at airports (Dhal, Roy, Taylor, & Wanke, 2013)**.** Airline companies can use accurate and timely weather forecasts to improve their planning, crew scheduling, passenger notification, and reduce delays and diversions (Anaman, Quaye, & Brown, 2017)**.** The accuracy of terminal aerodrome forecasts (TAFs) can lead to saving fuel and improve the passenger experience by reducing delays and diversions (Anaman et al., 1998)**.** Fatal accidents which occurred from 1950 to 2000 in which the cause was known to be the pilot error have increased from an average of 13% in 1950 to about 19% in 2000 (Abbas, Ojo, & Igbru, 2012)**.**

The prediction of weather is not that easy due to its limitations and challenges that affect the accuracy of the prediction (Jeong et al., 2020)**.** Modern weather forecasting models are based on complex physical equations and require significant computing resources to operate. Their predictions can be imprecise, even with high-performance computing (Bochenek & Ustrnul, 2022). Weather forecasting is a difficult and demanding task because of the unpredictable and chaotic nature of the atmosphere. It requires sophisticated and computationally expensive models to produce even moderately accurate predictions. (Oshodi, 2022). The advent of big data, powerful supercomputers with Graphics Processing Units (GPUs), and scientific interest in new methods proved to be pivotal in the history of machine learning in the early 21st century. (Yang, Kristiani, Leong, & Chang, 2023). AI is a rapidly evolving field that has the potential to revolutionize many industries and aspects of our lives. It is a broad term that encompasses a wide range of technologies and approaches, making it difficult to define precisely (Russell & Norvig, 2016). Advances in technology and the growing availability of meteorological data have enabled researchers to adopt data-driven approaches in metrology. These approaches leverage machine learning and other advanced techniques to extract insights from data and identify patterns that can be used to make predictions (Ahmad, Madonski, Zhang, Huang, & Mujeeb, 2022). Deep learning (DL) is one of the most promising research areas in machine learning (ML), due to its impressive successes in a wide range of tasks (Ahsan, Imran, Khan, & Shahzad, 2021).

Paddy rice irrigation efficiency can be significantly improved by incorporating weather forecasts, especially rainfall predictions, into irrigation scheduling practices, thereby conserving valuable water resources (Cao, Tan, Cui, & Luo, 2019) and (Mishra, Siderius, Aberson, Van der Ploeg, & Froebrich, 2013). Accurate short-term temperature forecasts are essential for a wide range of applications, particularly in the energy sector. The growing adoption of renewable energy sources, such as solar power, has amplified the need for precise temperature predictions. These forecasts are crucial for maintaining grid stability, as temperature fluctuations directly influence the efficiency of solar modules and consequently the overall output of solar power plants (Green, 2003). Accurate temperature forecasts are indispensable for electric power systems, enabling precise estimations of energy consumption attributable to heating, ventilation, and air conditioning (HVAC) systems. (Kreuzer, Munz, & Schlüter, 2020). Integrating quantitative precipitation forecasting (QPF) into flood warning systems has proven to be a critical step, extending the lead time for river flow forecasts and enabling more proactive flood control measures (Toth, Brath, & Montanari, 2000).

One of the main benefits of short-range weather forecasts lies in their ability to guide irrigation scheduling, a critical aspect of crop water management (Ray et al., 2019). By anticipating rainfall patterns, farmers can adapt their irrigation practices, ensuring that crops receive the optimal amount of water for growth while minimizing water wastage and preventing waterlogging (Ray et al., 2019). This precision approach not only conserves water resources but also promotes sustainable agricultural practices (Hansen et al., 2005). The timing of pesticide and fertilizer applications is crucial for their effectiveness and environmental sustainability. Short-range weather forecasts provide valuable insights into approaching weather conditions, enabling farmers to schedule applications during periods when these chemicals are less likely to drift or wash away due to high winds or heavy rain (Zhu et al., 2020). According to Zhang et al. (2021), favorable weather conditions are crucial for maintaining crop quality and reducing post-harvest losses, which significantly influences harvesting decisions.

1.2 Problem of Statement

The unpredictable and volatile complexity of the atmosphere makes traditional weather forecasting a laborious and demanding undertaking. Due to this changeableness, it is difficult for weather forecasters to forecast the weather accurately. The conventional methods used are expensive, intricate physical and computational resources to create forecasts, which can be imprecise and have a range of catastrophic consequences for society as we observe the two extremes of flood and drought. (Gramelsberger & Feichter, 2011). The influence of weather on different sectors is likely to become more significant over time. It is common to hear daily weather forecasts in the broadcasting. Perhaps many of us have heard that what is said to be sunny is rainy, and what is said to be rainy is sunny. Such forecast inconsistency for those they require big decisions and their activities are mainly dependent on the weather, like agriculture, aviation, disaster management, water resources management, infrastructure development, public health, energy, education, and research even the condition of our clothing; entertainment programs (music concerts, sports events, etc.) will be affected. Especially the agriculture and transport sectors are the most affected by the weather and influenced in our case. Ethiopian Airlines, which I know closely and which is the starting point for this research, all the flights that are made every hour are based on the weather forecast. However, due to limitations in forecast accuracy, a number of complaints have been recorded when the actual weather conditions differed from the forecasted one. Reports shows that Ethiopian airlines lost in millions due to forecast inaccuracy. No research has been conducted to address the issue of weather forecasting inaccuracy in Ethiopia, especially in weather now casting. Additionally, researches conducted related with weather forecast has not taken into account important scientific scenarios and essential weather parameters even for other sectors to improve adequately. Applying an hourly weather forecasting system would significantly advance the current service delivery and benefit all divisions that require short-range forecasts. This improved accuracy and timeliness would lead to better decision-making and enhance the efficiency and effectiveness of various activities across Ethiopia. By investing in accurate weather forecasting capabilities, Ethiopia can unlock its full potential in all formerly mentioned sectors. This will ultimately contribute to sustainable development, economic growth, and improved well-being for all Ethiopians.

1.3 Conceptual framework

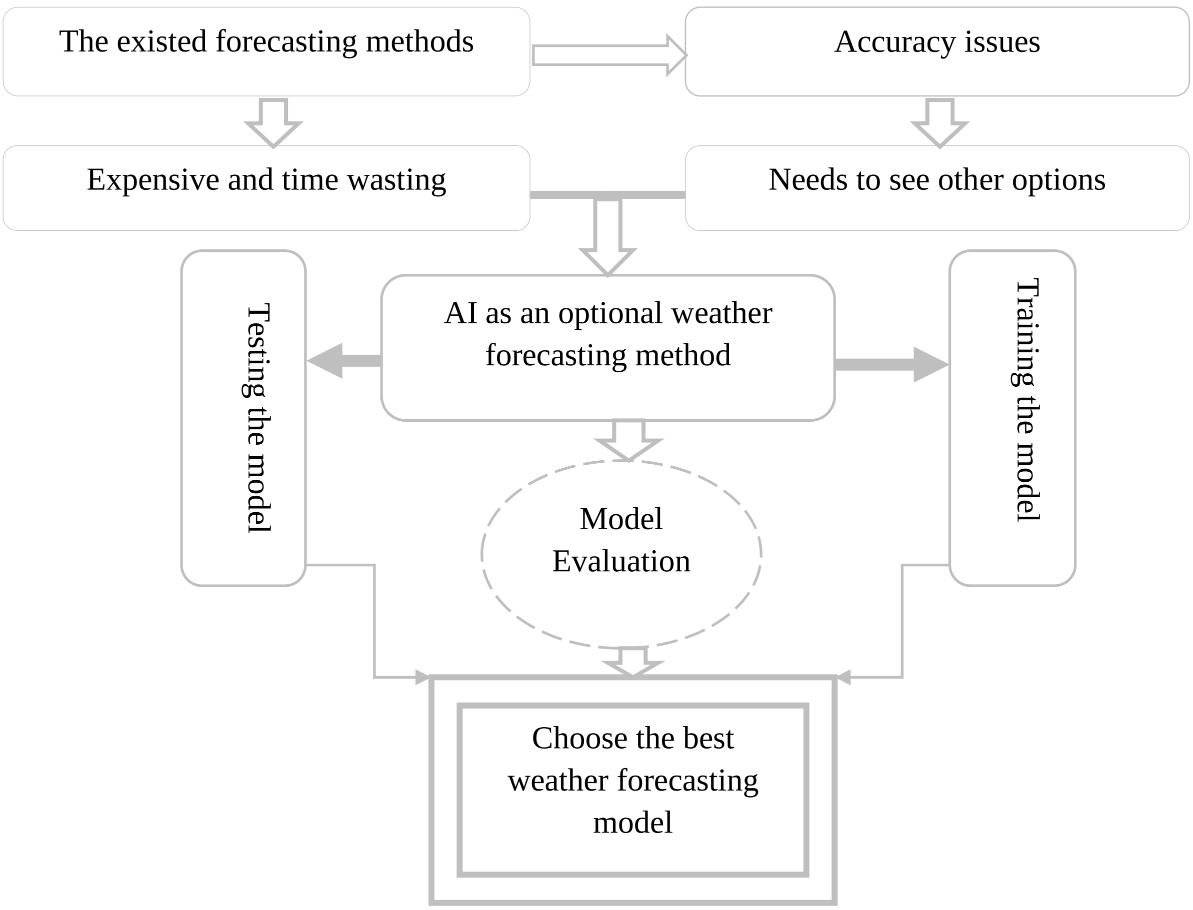

Fig.1.1 Conceptual framework flow

1.4 Objectives of the study

1.4.1 General objective

- ❖ To harness the power of artificial intelligence to create the most accurate and reliable weather forecasts.

1.4.2 Specific objectives

- ✓ To select an efficient and effective AI model for weather prediction with better performance.
- ✓ To identify and extract the unseen relationships in weather data that can be used to forecast the target variable.
- ✓ To assess various data preprocessing approaches in the footpath.
- ✓ To use remote sensing and GIS in collaboration with AI through a computational process.
- ✓ To examine the performance of machine learning and deep learning models for forecasting weather.

1.5 Research questions

- ✓ Can AI predict the weather much better than the existing one or satisfactorily?
- ✓ How do we forecast the weather using artificial intelligence?
- ✓ Which model is preferable?
- ✓ How to evaluate these models?
- ✓ Which weather variables dominantly influence the forecasting system of my target variables?
- ✓ How remote sensing and GIS applications were very important in this study?

1.6 significance of the study

It will be more impactful by demonstrating how artificial intelligence can surpass traditional methods of weather forecasting. Artificial intelligence (AI) based meteorological forecasting models have the potential to enhance the precision and dependability of weather forecasts, particularly for short-term and localized weather events. This could have a number of positive impacts, including saving lives, reducing property damage, and helping businesses and individuals make better decisions. This study will lay the groundwork for future research on the use of artificial intelligence in weather forecasting. The lack of previous research in this area makes this study especially important, as it will provide a much-needed roadmap for future work. Having this study means, it becomes the way to see further concerned stakeholders, especially those mostly affected economic sectors and that needs improvement. Since there are none and few directly related pieces of research conducted either content wise and quality in this study area and topic respectively, this will be a good input for those who want to study related issues. The research I made was very interesting and I learned a lot, keeping in mind with its little challenge. It encouraged and made me to love research.

1.7 Scope of the study

1.7.1 Thematic scope of the study

The boundaries of the research included effective ways of data preprocessing, choosing different AI models, and checking their effectiveness in prediction. In addition, the integration of remote sensing and GIS with AI was also part of the study. In this regard, the inputs were from a reanalyzed of satellite data, processed data from climate research unit, and GIS used for the identification of focusing areas. The study also explored the challenges and opportunities of using AI models.

1.7.2 Spatial scope

Despite the challenges of needing plenty of time, finance, and a suitable working environment, the study covered the entire country. The most representative locations were selected based on long-range climatic data analysis, which identified them as uniform climatic zones. Thus, Addis Ababa, Diredawa, Gode, Gondar, and Jimma were the spatial representatives of my study.

1.7.3 Temporal scope

Meanwhile the study at the same time is a partial fulfillment of a graduate thesis, it is required to completed on a specified flexible schedule (before the new academic year). The data set covers ten years of hourly data for the prediction of fog, precipitation, and temperature.

1.8 Organization of the Thesis

The research paper is organized into six sections. The first section introduces the study, including its background, problem statement, conceptual framework, objectives, research questions, significance, and scope. The second chapter summarized the previous related works in the scope of the defined study. The third chapter, which is the methodology part arranged by including the tools used, data set, and methods followed. Results and outputs are displayed accordingly in the fourth chapter of the thesis. In this section, the plots of the target variables, the actual and predicted values of the dependent variables, and tables of the metrics values are presented. The results portrayed in the former chapter are discussed well in the fifth chapter. In this portion, the dissected results are explained in detail and also the limitations of the study outlined. The ultimate chapter contains a conclusion and recommendation. This section recapitulated the overall processes and come up with a culmination.

CHAPTER TWO

2.1 Literature Review

Proposed a machine learning technique to predict and analyze rainfall efficiently. The inputs were taken from data collection and publishing websites. The study used the following features: day, place, minimum temperature, maximum temperature, wind direction and speed, gust wind direction and speed, humidity, pressure, temperature, today rain, and tomorrow rain. The classification method was conducted in four steps: collecting the database, preprocessing the data, forecasting, and obtaining the results from the estimation. The proposed system used random forest and logistic regression for comparison. A formatted data was imported into Jupiter notebook with appropriate libraries. The data was divided into two sets, a training set and a testing set. The training set consisted of 70-80% of the data, while the testing set consisted of the remaining 20-30%. The system generated the results in the form of binary digits (1/0), which represent yes or no options. Finally, a confusion matrix was created to verify the predicted outcomes with the actual values to determine the accuracy score. From the diagonal and non-diagonal elements in the test, 197 predictions were made, with 159 and 30 correct predictions for logistic regression and 8 incorrect predictions, while 159 and 26 were correct and 12 were incorrect for random forest. The accuracy of random forest was 94.4%, while the accuracy of logistic regression was 95.9%. Logistic regression was therefore considered the best model for rainfall prediction. The two approaches were compared to obtain a precise method. However, existing rainfall forecasting methods are not always accurate in complicated situations because they cannot predict the hidden patterns that are not yet fully understood. (Gowtham, Ganesh, & Ali, 2021)

A study was conducted to forecast and analyze the outcomes of rainfall using machine learning techniques. The inputs were monthly high, low, and average temperature in degrees Celsius (ºC), dew point in ºC, humidity in percentage (%), sea level pressure in hectopascals (hPa), visibility in kilometers (km), wind in kilometers per hour (km/h), precipitation in millimeters (mm), and events (rainfall, snow, thunderstorm, fog) from 1951 to 2000 for each district in India. Only average values were considered for the study. The classification algorithms of artificial neural networks (ANNs), logistic regression, naive Bayes, and random forests were experimentally implemented and compared. The results showed that random forest produced the best rainfall prediction results with an accuracy of 87.76%. It also showed the highest values for recall and F-measure, which are two metrics used to assess the performance of a classification model. The accuracy of the other models was as follows: naïve Bayes = 85.01%, logistic regression = 87.15%, and ANN = 84.70% (Mohammed, Kolapalli, Golla, & Maturi,2020). A method for forecasting fog occurrence using artificial neural networks (ANNs) was proposed in this study. A multilayer perceptron neural network with backpropagation error correction was trained using temporal series of meteorological variables from 19 years of data. The study focused on fog forecasting at the Brazilian Air Force Academy (AFA). The network was implemented with eight input variables, five neurons in the hidden layer, and one neuron in the output layer. The input variables were year, month, day, time, temperature, relative humidity, pressure, and wind speed. After training and testing the results, the proposed network achieved a reliability of 95.949% with 2/3 of the data. The network was then validated with the remaining 1/3 of the data, and it achieved a reliability of 98.107%. This suggests that the proposed method is efficient and fast, and it can be used to forecast fog occurrence with a high level of precision. The study did not compare the proposed method with other algorithms, but it is likely that it would perform better than other methods, as it was able to achieve a high degree of accuracy with a relatively simple network (Colabone, Ferrari, Vecchia, & Tech, 2015).

The study aimed to compare the performance of long short-term memory (LSTM) and bidirectional LSTM (BiLSTM) models for temperature forecasting in Semarang, Indonesia. Hourly temperature data from the ERA-5 reanalysis dataset covering the period 1979-2020 were used. Two LSTM models were trained on the data: a unidirectional LSTM model and a bidirectional LSTM model. The models were evaluated using the root mean square error (RMSE) and the correlation coefficient (CC). The RMSE of the bidirectional LSTM model was 0.6407, while the RMSE of the unidirectional LSTM model was 0.6723. The CC of the bidirectional LSTM model was 0.9768, while the CC of the unidirectional LSTM model was 0.9727. The authors concluded that the bidirectional LSTM model is a better choice for temperature forecasting in Semarang, Indonesia because it can learn from both past and future temperature data, which allows it to make more accurate predictions (Dewi, Prawito, & Harsa, 2020).

A machine learning model was created to forecast weather in Seattle. Four algorithms were used: random forest, decision tree, Gaussian naive Bayes, and gradient boosting. The algorithms were trained on data from 2012 to 2015. The models were evaluated based on accuracy, precision, recall, and F1 score. The Gaussian naive Bayes model had the highest accuracy of 84.15%. The gradient boosting model had an accuracy of 80.87%, the random forest model had an accuracy of 79.50%, and the decision tree model had an accuracy of 72.40%. The results suggest that the Gaussian naive Bayes model is the most accurate for weather forecasting in Seattle. This is because it can learn from historical data and make accurate predictions about future weather conditions (Oshodi, 2022).

A study was conducted to develop a method for forecasting weather using machine learning techniques. Three techniques were considered: support vector machines (SVM), artificial neural networks (ANNs), and time series recurrent neural networks (RNNs). The study used weather data from 2006 to 2018. The process involved collecting data, preprocessing the data, and training the models. The models were evaluated based on the root mean squared error (RMSE) between the predicted and actual values. The results showed that the RNN model had the lowest RMSE of 1.41, followed by the ANN model with an RMSE of 1.53 and the SVM model with an RMSE of 1.64. This suggests that the RNN model was able to learn the patterns in the weather data more accurately than the other two models. The study concluded that RNN is a promising technique for weather forecasting, but further research is needed to evaluate its performance on other weather datasets and to understand the reasons for its superior performance (Singh, Kaushik, Gupta, & Malviya, 2019).

In (Mathew & Mathew, 2022), a study proposed to forecast the weather using the random forest algorithm. Random forest is a machine learning algorithm that creates multiple decision trees to make predictions. It works by training a dataset with many decision trees and then aggregating the predictions of the trees. The outcome (humidity, temperature, and wind speed) was predicted using the random forest approach, which allows it to create many trees by randomly selecting parameters, resulting in a highly accurate classifier. However, the study did not show how the model worked or its accuracy.

A study proposed to use machine learning algorithms to predict the occurrence of rain the following day in Australia. Four algorithms were compared: random forest classifier, XGBoost, Light GBM, and logistic regression. The models were trained and tested on a dataset of weather data from 2009 to 2017. The dataset had twenty-three variables and 14,5459 instances. Missing values were handled using a KNN imputer, and outliers were detected using upper quartile and interquartile ranges. The results showed that XGBoost had the highest accuracy of 94.03%, followed by random forest classifier with 89%, LightGBM with 83%, and logistic regression with 77.64%. The author concluded that XGBoost performed better than the other models, but random forest can be chosen if speed is a priority (Reddy & Dinesh, 2021).

A study was conducted to evaluate the applicability of weather forecast models based on logistic regression and decision tree. The data used for the study was downloaded from the weather service website. The data consisted of weather observation data recorded by the Australian Meteorological Agency every day since 2012. The meteorological variables used for the study were recording location, daily minimum temperature, maximum temperature, rainfall, and target variables. Logistic regression was used for the classification model. The possible outcomes of the dependent variables were represented in the binary form [0, 1]. Logit transformation was performed since the value of the independent variable does not belong to [0, 1]. The accuracy of the logistic regression model on the training set and the test set reached 87.46% and 84.95% respectively. The decision tree was also used for the classification model. Unlike the results of logistic regression, only a few variables such as humidity, wind speed, and location played a decisive role in determining whether it will rain tomorrow. The prediction results of the decision tree model on the training set and the test set had 83.24% and 83.32% accuracy, respectively. The results showed that the logistic regression model was more accurate than the decision tree model. However, the decision tree model was more interpretable and had a better fitting effect (Deng, 2020).

The study aimed to use machine learning techniques to predict the weather. The data used were monthly mean maximum temperature, minimum temperature, daily global solar radiation, and wind speed for different locations in India. The most relevant input parameters were selected using correlation analysis. The random forest machine learning model was used to predict the monthly wind speed for eight cities. The performance of the model was evaluated using the performance metrics R2 and MSE. The results showed that the random forest model had an R^2 value of 0.9714 and an MSE value of 0.75, while the regression model (SVM) had an R^2 value of 0.9385 and an MSE value of 0.867. The authors concluded that the random forest model was more accurate than the regression model. They also stated that the model produced good and reasonable prediction results despite the lack of precise knowledge of atmospheric physics (Meenal, Michael, Pamela, & Rajasekaran, 2021).

The authors proposed to solve the problems of existing weather forecasting systems, which were mostly implemented using statistical approaches for the Support Vector Machine (SVM). These systems were unable to provide accurate predictions as they could not capture sudden changes in weather conditions. The authors used meteorological data from Uttar Pradesh over a period of four years, from 09-08-2011 to 19-10-2016. The data set included parameters such as station, latitude, longitude, altitude, time (IST), date (IST), air temperature, wind speed, wind direction, humidity, atmospheric pressure, and rainfall recorded at random intervals throughout each day. The authors used six different machine learning algorithms to predict the weather: Support Vector Machine (SVM), Bayesian Enhanced Modified Approach (BEMA), multi-linear regression algorithm, Ranys method, BFGS, and multi-variant method. The SVM had an accuracy of 75%, the BEMA approach had an accuracy of 80%, the multi-linear regression algorithm had an accuracy of 88%, the Ranys method had an accuracy of 81%, BFGS had an accuracy of 85%, and the multi-variant method had an accuracy of 85%. The results showed that the multi-linear regression algorithm had the highest accuracy (Anusha, Chaithanya Sai, & Reddy, 2019).

The authors proposed to predict rainfall using modern machine learning algorithms for time-series forecasting. The input climate data was taken from January 1, 2000, to April 21, 2020, from five major cities in the United Kingdom. The following features were used as predictors: temperature, pressure, humidity, wind speed, wind direction, cloud coverage, time zone, latitude, longitude, snow 3 hours ago, rain 3 hours ago, snow 1 hour ago, and rain 1 hour ago. The study compared forecast models based on LSTM (Long Short-Term Memory) networks, stacked-LSTM networks, and bidirectional-LSTM networks against an XGBoost decision tree algorithm and an algorithm resulting from the use of AutoML.The results showed that a bidirectional LSTM network can be used as a rainfall forecast model with comparable performance to a stacked-LSTM network with two hidden layers. The stacked-LSTM (model four) and bidirectional-LSTM (model six) models achieved, in general, lower values in the evaluation metrics. The authors concluded that although the results are encouraging, a major drawback of using LSTM neural networks is the inability to generalize adequately. For the most part, models overfit training data and cannot record accurate predictions in test and validation sets. Future work would be directed at fine-tuning the parameters and hyperparameters of the prediction models to further close the gap between the predicted values and the observed rainfall volumes. (Barrera-Animas, et al., 2022).

propose to build an RNN and LSTM model to predict daily temperature for the next 3 days. The input parameters were temperature, rainfall, humidity, and wind speed which have been collected for 20 years (2000 – 2019). The data prepared in the preprocessing stage includes the calculation of the averages every three days for each input parameter. The temperature was divided into classes of five which were described as cold, cool, normal, warm, and hot with different values of thresholds. Tests were carried out using optimizing models SGD and Adam with a hundred epochs. Each neuron in LSTM with three gates applied to decide on input information. Calculations are also implemented in the processes. Finally comparing the two optimization models, the training and testing accuracy was evaluated according to error loss and as a result, the Adams model performs 90.92% and 80.36% respectively whereas SGD performs with an accuracy of 87.24% and 76.48% for training and testing respectively. The author found that the amount of data and sharing can affect the optimization model's results (Rahayu, Djamal, Ilyas, & Bon, 2020).

The author proposed to develop an LSTM-based weather forecasting model and evaluate its accuracy against WRF. The inputs were GFS GRIB data and historical data with ten surface parameters. This includes surface temperature, pressure, wind, humidity, rain, soil temperature, moisture, and snow water. WRF model run using the GRIB data from 1st Jan–31st May 2018 for training, 1st – 30th June 2018 for testing, and July 2018 for validation of the overall model. The proposed model (a deep network) uses a specialized Recurrent Neural Network (RNN) LSTM layers technology. The model was evaluated using MIMO (Multiple Input Multiple Output) and MISO (Multiple Input Single Output). Accordingly, the ten parameters fed into the networks. Both models were evaluated according to the ground truth and MSE was calculated to evaluate the model. Finally, the model prediction was compared with the WRF model. As a result, the proposed deep model results best comparatively in eight parameters with an efficient MIMO model (Hewage, Behera, Trovati, & Pereira, 2019).

The researchers conducted a study to enhance the accuracy of weather forecasting. They used a multiclassification tactic with machine learning techniques to forecast five weather conditions: drizzle, snow fog, sunshine, and rain. All the characteristics were used, with five of them as input to the machine learning models and one as the target class. The performance of the OAO and OAA strategies was contrasted to single classifiers k-nearest neighbors (k-NN) with k = 1 and random forest. Performance evaluation was done using accuracy, recall, F-measure, and AUC under ten-fold cross-validation. The results showed that the SVM classifier under the OAO strategy achieved the best performance in terms of all metrics. The accuracy was 96.64% and AUC was 98.5% for linear SVM, while for the OAA strategy with a polynomial of degree 3, the accuracy was 93.08%. This implies that the OAO strategy is superior to the OAA strategy. In the case of logistic regression (LR), which was used to solve the binary classification problem, the OAO strategy was also more efficient (86.92%)

than OAA (83.69%). The performance of k-NN and random forest classifiers were compared, resulting in 89.04 % & 92.60% respectively. The researchers concluded that the SVM classifier under the OAO strategy achieved more concise results and generally superior performance than the others (Dritsas, Trigka, & Mylonas, 2022).

The researchers focused on forecasting the weather in Shenzhen, China using a deep learning model. They used data from 2015 to 2019, which included the minimum and maximum temperature, air pressure, and humidity. The data was divided into three sets: training set (January 1, 2015, to January 15, 2019), verification set (January 16, 2019, to July 7, 2019), and validation set (July 8, 2019, to December 31, 2019). They proposed a model called the Empirical Mode Decomposition-Long Short-Term Memory (EMD-LSTM) combined model. They compared this model to LSTM and CNN models. The results showed that the EMD-LSTM model had the fastest convergence speed and reached a stable state in the seventh iteration with the smallest error. The mean squared error (MSE), root mean squared error (RMSE), and mean absolute error (MAE) of the designed model values were 0.0435, 0.1216, and 0.0654, respectively. The researchers also compared the EMD-LSTM model to traditional machine learning models (random forest, support vector machine) and regression models (multiple linear regression (MLR), support vector regression (SVR), polynomial regression, and ridge regression). Hence, Random Forest, Support vector machine, multiple linear regression (MLR), Support vector regression (SVR), Polynomial regression, and ridge regression are 0.1216, 0.1559, 0.1713, 0.2286, 0.2073, 0.1794, 0.1737, 0.1834 and 0.1778 respectively. The results showed that the EMD-LSTM model had the smallest MSE, RMSE, and MAE for all models. Eventually, concluded that the EMD-LSTM model is the best model for forecasting the weather in Shenzhen, China. (Chen, Liu, & Jiang, 2022).

The study aimed to develop an effective short-term forecasting model to support aviation by using machine learning techniques in the location of Malpensa Airport in Milan, Italy. The data sets were from various sources: station data (2010-2020), which included temperature, relative humidity, pressure, rain, wind speed, and wind direction; GNSS data (2011-2020), which included Zenith Total Delay (ZTD); radar data, which included coordinates, area, velocity, average, and maximum reflectivity of convective; and lightning data, which included time, location, number of lightning strikes in a covered area and time period, intensity, type of lightning, and the average height of intracloud lightning. Because the model requires continuous time series data, all possible gaps must be filled and cannot be removed. Extremes were defined by setting a threshold before forecasting. The threshold used to define extreme rainfall in the report, which was confirmed by the International Civil Aviation Organization (ICAO) and the World Meteorological Organization (WMO), is 10 mm/hr. This is very similar to the threshold of 9.6 mm/hr., which is equivalent to 1.6 mm, proposed by the study (Chkeir, Anesiadou, Mascitelli, & Biondi, 2023).

Proposed to forecast rainfall in a daily base at airport of Ercan Northern Cyprus by comparing linear and nonlinear models. Daily data including wind speed, solar radiation, rainfall, relative humidity, minimum and maximum temperature, for period of 10 years (2008 – 2018) were provided for the study with a data source NASA. In the early stages of preprocessing normalization and Statistical analysis of the raw data were performed. model calibration used 75% of the data while the remaining 25% were employed in the verification phase. They used the conventional multiple linear regression (MLR) technique and two machine learning techniques: artificial neural networks (ANNs) and adaptive neuro-fuzzy inference systems (ANFISs). The results showed that the ANN and ANFIS models outperformed the MLR model for all three linear regression models during both the calibration and verification phases. The ANFIS model was more consistent with the actual measurements than the other two models. According to error metrics MSE and MAPE values, ANFIS-M3 was found to be the best model, with corresponding values of 0.0021 and 0.0016, respectively. The paper concluded that both linear (MLR) and nonlinear (ANN and ANFIS) models could be used to predict rainfall at Ercan Airport. However, the ANFIS model had smallest values of MSE and MAPE. Hence, increased the average accuracy compared to ANN and MLR. (Abdulkadir, Ali, Abba, & Esmailia, 2020).

Proposed to forecast the weather efficiently using an artificial neural network. The proposed temperature prediction system using back propagation neural network was tested against meteorological department with the practical released of temperature forecast out puts. The inputs used were atmospheric pressure, temperature, wind speed, wind direction, humidity, and precipitation. The author followed a few steps in their approach. First, they used an ANN (artificial neural network) to generate outputs and output activations from the input data. This is called the forward propagation step. Next, they used the training patterns to generate the deltas of all outputs and hidden neurons. This is called the backward propagation step. The deltas are used to update the weights and biases of the ANN, which allows it to learn from the data. In the second phase, the weight is updated by calculating the gradient of the weight, which is the product of the activation of the input and output data. The weight is then updated in the direction of the gradient by adding a fraction of it to the weight. These two steps are repeated until the network's performance is satisfactory. In online learning, the weight is updated after each propagation. In batch learning, the weight is updated after all of the data has been propagated through the network. An algorithm of a three-layer network (only one hidden layer) was used. Finally, after testing and evaluating the performance of the Artificial Neural Network using Root Mean Square Error (RMSE) which yields a maximum error of 0.6905, 0.8005, 1.0006, and 1.2916 for 02-Jan-2009, 27-Aug-2009, 09-Jun-2009 and 29-Nov-2009 respectively (Baboo & Shereef, 2010).

Proposed to forecast the weather using random forest. Due to the less effective and time-consuming nature of traditional weather forecasts, the paper needed to see other options. The inputs used were from Kaggle which provides for research projects. These include the formatted date, summary, temperature, wind speed, wind direction, visibility, and apparent temperature. A Powerful tool WEKA used for testing machine learning approaches. The data was split into two parts of training and testing. The random forest algorithm was used to analyze the wind speed, temperature, and humidity features. The algorithm creates many trees by randomly selecting parameters, resulting in a highly accurate classifier. The outputs of each parameter are evaluated in terms of different error types. But, no comparison with models and the accuracy was not assessed accordingly (Mathew & Mathew, 2022)

The researchers sought to study and forecast temperature using support vector machines (SVMs). Maximum temperature from 2003 to 2007 has been used to build, and from January to July 2008 was used to test their models. Cleaning and transforming of data performed before dividing it into a training, validating, and testing datasets. The former was used to build the model, the second used to optimize the parameters, and the last was used to evaluate the model. Separated models created using SVMs and multilayer perceptron's (MLPs) trained with a backpropagation algorithm. A nonlinear support vector regression approach was used to train the SVMs. They applied polynomial and radial basis function (RBF) functions to sample data and discovered that RBF performed better, hence it was adopted in the study. Mean Square Error (MSE) was used as a performance metric. MLPs trained with a backpropagation algorithm and SVMs for various orders of evaluated performance in terms of MSE. The MSE for MLPs varies from 8.07 to 10.2 depending on the order, while the MSE for SVMs is in the range of 7.07 to 7.56. The performance of SVMs was compared to that of MLPs for various orders. The findings revealed that SVMs outperform MLPs trained with a backpropagation algorithm for all orders. The researchers concluded that support vector machines can replace some neural network-based models for weather forecasting applications if the parameters are properly chosen (Radhika & Shashi, 2009).

A study was proposed to estimate rainfall using machine learning algorithms. Tests were conducted on different input features, starting with the original dataset, then the under-sampled dataset, and finally the oversampled dataset. The training set and a test set data was split into a ratio of 75:25. The inputs used were cloud coverage, pressure minimum and maximum temperature, wind speed and direction, humidity. Features preprocessed to remove noise, inconsistencies, overfitting, and other factors that could degrade the model's performance. A random forest algorithm was used, which trains several decision trees and then predicts the mean of the classes using the mean of all trees. The authors created a random forest model by randomly choosing p data points from the training set and creating a decision tree for each set of p data points. They repeated this process N times, resulting in a total of N decision trees. To forecast the value of y for a new data point, the N decision trees are used to predict y for the data point. The new data point is then assigned to the mean of all the predicted y values. Finally, the user provides a location (longitude and latitude) to request weather service for the next seven days. The RMSE of the classifier for each of temperature, wind speed and humidity were 0.9755, 1.58, and 0.038 respectively (Nizar, Adytia, & Ramadhan, 2021).

Due to the significant impact of weather on the economy, accurate and timely weather forecasts are essential. Therefore, a study was proposed to investigate machine learning-based algorithms for weather prediction. The objective was to develop a machine learning model that could predict weather conditions built on past information. Publicly available data from Kaggle including precipitation, maximum temperature, minimum temperature, wind, and weather conditions from first January 2012 to 31 December 2015 used in the study. The data was preprocessed by transforming, cleaning, and removing unwanted attributes. Then data split was undertaken the ratio of 25:75 for testing and training set consequently. The four machine learning algorithms: random forest, gradient boosting, Gaussian naive Bayes, and decision tree were implemented. classifiers evaluated based on different metrics, including precision, recall accuracy, and F1 score. Out puts showed that Gaussian naive Bayes model had the highest accuracy of 84.15%, followed by random forest (79.5%), gradient boosting (80.87%), and decision tree (72.40%). Therefore, the Gaussian naive Bayes model was the most accurate of the implemented algorithms. This suggests that it is a promising approach for weather prediction (Abrahamsen, Brastein, & Lie, 2018).

A web-based weather forecasting application was developed to forecast the weather for five days ahead using linear and logistic regression models. The data used for the study was 23 years of daily weather data (observed station data), including maximum and minimum temperature, wind speed, humidity, precipitation, and the chance of rainfall. The process involved six steps: data collection, data preprocessing, processing, applying machine learning techniques, evaluating techniques and displaying the final result. Linear regression was used to analyze the relationships between the maximum and minimum temperature and rainfall in order to predict them. Logistic regression was used to forecast the probability of rainfall in categorical form. As a result, the expected outputs (maximum and minimum temperature) were within the specified range, and the probability of rain and wind speed in Kathmandu city for the next five days was predicted. The accuracy of the model was 94% for linear regression for max and min temperature forecast and 90% for logistic regression for rainfall prediction when compared to the output forecasted by Google (Sharma, 2019).

Research was conducted to develop deep neural networks to predict weather station air temperature. The data used in the study was from John F. Kennedy airport from January 1, 2009, to January 1, 2019.The study proposed three different deep neural network architectures: Multilayer perceptron (MLP), Long short-term memory (LSTM), and Convolutional neural network (CNN) with LSTM (CNN+LSTM). The data was preprocessed by standardizing the features. The features were then split into training, validation, and test sets. The models were evaluated using the mean absolute percentage error (MAPE) metric. The results showed that CNN+LSTM had the best performance for both one-day ahead and ten-day ahead predictions. The MAPE for CNN+LSTM was 97.42% for one-day ahead prediction and 71.58% for ten-day ahead prediction. MLP had the worst performance, with a MAPE of 95.03% for one-day ahead prediction and 70.32% for ten-day ahead prediction. The study concluded that CNN+LSTM is a promising architecture for air temperature prediction. However, to improve the performance of the models more research is needed for longer prediction horizons. (Roya, 2020).

The research proposes a new method for atmospheric temperature forecasting using a bidirectional LSTM (BiLSTM) model. Hourly temperature data from the Belmatit Mayo weather station in Mayo County, Ireland which covers the period from 2007 to 2020. The performance of the BiLSTM model was evaluated using two metrics: the root means square error (RMSE) and the correlation coefficient (CC). The results showed that the BiLSTM model outperformed other traditional forecasting methods, such as ARIMA and exponential smoothing, on both metrics. The RMSE of the BiLSTM model is 0.4928, while the RMSE of ARIMA is 0.5759 and the RMSE of Exponential Smoothing is 0.6487. The CC of the BiLSTM model is 0.9783, while the CC of ARIMA is 0.9729 and the CC of Exponential Smoothing is 0.9703. The authors conclude that the proposed BiLSTM model is a promising approach for atmospheric temperature forecasting (Liang, Wu, & Wang, 2021).

This study aimed to compare the performance of four different artificial intelligence models (DNNs) for predicting hourly temperatures: a simple recurrent neural network (SRN), a gated recurrent unit (GRU), a long short-term memory (LSTM), and a convolutional neural network (CNN). The study used hourly temperature data from the Beijing Meteorological Bureau in China from 2015 to 2020. The four DNNs were trained on the data and their performance was evaluated using two metrics: the root mean square error (RMSE) and the correlation coefficient (CC). Consequently, GRU-LSTM parallel network outperforms the other three DNNs in terms of both RMSE and CC. The RMSE of the GRU-LSTM parallel network is 1.691°C, while the RMSE of the SRN, GRU, and LSTM are 1.872°C, 1.775°C, and 1.796°C, respectively. The CC of the GRU-LSTM parallel network is 0.976, while the CC of the SRN, GRU, and LSTM are 0.969, 0.972, and 0.971, respectively. At the end**, the** authors conclude that the GRU-LSTM parallel network is the best DNN for hourly temperature forecasting. This is because the GRU-LSTM parallel network has the ability to acquire from past and future temperature values, which allows it to make more accurate predictions (Haque, Tabassum, & Hossain, 2021).

This study proposed a new approach to forecast precipitation using satellite data. The approach used convolutional long short-term memory (ConvLSTM) which consists of three layers: a convolutional layer to extract spatial features from the satellite data, an LSTM layer to learn temporal features from the satellite data, and a fully connected layer to output the predicted precipitation. It found that the ConvLSTM architecture outperformed other traditional methods, such as convolutional neural networks (CNNs) and LSTMs, in terms of both accuracy and robustness. The ConvLSTM architecture achieved a mean absolute error (MAE) of 0.5 mm and a root mean squared error (RMSE) of 0.7 mm. The authors concluded that the ConvLSTM architecture is a promising approach for precipitation forecasting using satellite data. (Gamboa-Villafruela, Fernández-Alvarez, Márquez-Mijares, Pérez-Alarcón, & Batista-Leyva, 2021).

This study proposed to investigate the use of deep learning techniques for weather forecasting. An hourly weather data from 1973 to 2009 were used for the investigation. In the process three deep learning techniques were used: recurrent neural networks (RNNs), conditional restricted Boltzmann machines (CRBMs), and convolutional neural networks (CNNs). The performance of each technique was evaluated using the root mean squared error (RMSE). The results showed that the RNN model had the lowest RMSE value (0.6407), followed by the CRBM model (0.6723) and the CNN model (0.7031). This suggests that the RNN model found to be the best deep learning technique for weather forecasting (Salman, Kanigoro, & Heryadi, 2015).

Summarizing and analyzing the above reviewed articles resulted as follows. Out of the 28 articles, 11 (39.29%) were used statistical models, 12 (42.86%) used machine learning models, and 5 (17.86%) were used deep learning models. The best performing statistical model become ARIMA model, with a RMSE of 0.4928 for hourly temperature forecast and the worst performing statistical model found to be exponential smoothing model, with a RMSE of 0.6487 for hourly temperature forecast. The Random Forest model was found as the most accurate machine learning model in rainfall prediction, with an accuracy of 94.4%. Decision tree model found to be the least accurate machine learning model for weather prediction, with an accuracy of 72.4%. The best performing deep learning model become the LSTM model, with a RMSE of 0.2885 for temperature prediction. Poorly accomplished deep learning model is found as the CNN model, with a RMSE of 0.6407 for temperature prediction. In the above reviewed articles, the most frequently used models are ARIMA and exponential smoothing from statistical models; Random Forest, and logistic regression from machine learning, and LSTM and BiLSTM from deep learning models. In brief, the paragraph shows that machine learning models are generally more accurate than statistical models for weather prediction but deep learning models can be more accurate for specific tasks. The most popular type of machine model for classification of sequential prediction is the random forest, following LSTM. ARIMA also best statistical model. The above articles shows that deep learning models performed best for complicated tasks like weather predictions.

CHAPTER THREE

3.1 MATERIALS AND METHODS

3.2. Study area

This research was conducted in Ethiopia, which is located between 3°00 to 15°00 N and 33°00 to 48°00 E, with an area of approximately 1.02 million square kilometers in eastern Africa **(Figure 1.1).** It is the oldest independent country and the second-largest in terms of population. It is also a country of geographical diversity, with elevations ranging from as much as 116 m below sea level in the Danakil depression to more than 4,600 meters above sea level in the mountainous regions. The country experiences three distinct seasons: Bega (October to January), Belg (February to May), and Kiremt (June to September) **(Gonfa, 1996).** The climate of Ethiopia is diverse, ranging from wet to dry. The country has a tropical climate, but the amount of rainfall varies greatly from place to place and over time.

The highlands of Ethiopia receive about 1200 mm of rainfall annually, with a narrow range of temperatures. In contrast, the lowlands receive less than 500 mm of rainfall annually and have a wider range of temperatures (Hijmans, Cameron, Parra, Jones, & Jarvis, 2005)**.** The Ethiopian highlands are regions of land that are located above 1500 meters above sea level. They are divided into two parts: the northwestern highlands and the southeastern highlands. The Ethiopian rift valley system separates these two parts (Hengl et al., 2015). Due to the high temporal and spatial variability, the representative study areas within the country were selected by considering a preliminary processing stage accordingly. In order to identify climatic homogeneity which can be typical of those regions, long-time climatic and topographic data was analyzed and mapped **(Fig. 3.5, 3.6).** As a result, five airport locations at the same time which belong to unvarying climatic regions were recognized for this study.

To make Shure this study becomes confidential, seasonal variations are also considered. Hence, from the Belg season corresponding average rainfall map **(Fig. 3.4),** five sampling points (airports) or locations became representative of rainfall distribution. Consequently, Gondar (13–64 mm), Gode (65–104 mm), Addis Ababa (105–144 mm), Jimma (145 –192 mm), Diredawa (145 –192 mm) and Mizan Teferi (193 –275 mm) has to be chosen. But more likely Jimma can replace Mizan Teferi based on its economic importance as well its location. Hence, the selected points become a good representation of the region. From the long-term annual average rainfall analysis of classes **(Fig.3.5),** we can select five representative areas. Hence, Gode (131– 455 mm), Diredawa (455–757 mm), Gondar (757–1,066 mm), Addis Ababa (1,066 – 1,405 mm), and Jimma (1,405–2000 mm). At the same time delegation is required for temperature prediction as well. Accordingly, both seasonal (Belg) and annual long-year average temperature maps **(Fig. 3.3 & 3.6)** were investigated. Simultaneously, the research-validated how the two important climatic variables are interrelated each other. Even though they are all dependent on altitude, and don't need to demonstrate a topographic map, to see multidimensional scientific scenario's and to be more supportive it was verified.

Concurrently, the elevation map of Ethiopia **(Fig.3.7)** was assessed in order to assign some homogenous regions which they will have nearly similar implications to classified climatic regions. Based on the analysis five classes were diagnosed as Gode (-189–691 m), Gondar and Diredawa can represent (691–1183 m), Gondar, Jimma and Diredawa can represent (1222 – 1,763 m) partly, Diredawa, Jimma (1,764–2,396 m), Addis Ababa and Gondar (2,397–4420). Based on the above reasonable ways of analyzing the topographic, rainfall, and temperature distribution of the country, my study has got the following destinations; keeping in mind future work is there to incorporate those negligible ignorance's of differences because of their less economic significance or less value recording.

3.2.1 Addis Ababa

It is the seat of government of Ethiopia as well as Africa with an estimated population of around 5,006,000. It extends from 38^{o} 44' 13" to 38^{o} 45' 6" longitude and 9^{o} 5' 57" to 9^{o} 6' 54" latitude. It is a high-altitude city, with an average elevation of 2,400 meters above sea level. The highest point in the city is Entoto Hill, which rises to 3,200 meters. The temperature remains relatively constant throughout the year, with average highs of 73°F and average lows of 52°F. The main rainy season runs from June to early October, when the city receives about 120mm of rain. A shorter rainy season called Belg occurs from early March to mid-April. Nearly 80% of the annual rainfall occurs during the main rainy season. (Kifaru, 2023).

3.2.2 Diredawa

DireDawa, in eastern Ethiopia, was established in 1902 as a relatively lowland (1200 m above sea level. It is far away about 500 km from the administrative center of Ethiopia, and 300 km from the international port of Djibouti (Kasim, Abshare, & Agbola, 2018). In terms of its location, the city is found in the range of 9°25′ – 9°45′N latitude and 41°40′E – 42°50′E longitude. (Erena, & Worku, 2019). The climate is characterized by extremely variable temperature conditions, with an annual average of 24.4°C and 614.7mm temperatures and precipitation respectively (Tashebo, Mekonn, & Eshete, 2021).

3.2.3 Gode

It is a distance of about 1225 km far from, the Primate city of Ethiopia, and 600 km from local center Jigjiga. The climate of the town demonstrated an average rainfall between 150-250 mm and a minimum and maximum temperature of 28° C and 40° C respectively. It is also found at an altitude of 260m above sea level (Hussein, Tsegaye, & Abdulahi, 2020).

3.2.4 Gondar

It is a momentous city in the northern of Ethiopia situated Semen Gondar Zone and geographically found between a latitude and longitude of 12°36′N and 37°28′E respectively with an elevation of 2133 meters above sea level (Moges, & Chercos, 2014). It is situated northwest of the capital around 750 km. It received annual average precipitation of 1172 mm and a temperature of 19.7°C (Awraris, Bogale, & Chanie, 2012).

3.2.5 Jimma

In terms of geography, it is situated 36°49′18″ E longitude and 7°40′49″ N latitude. The altitude of the city ranges from 1718 to 1277 m above sea level (Gemeda, Feyssa, & Garedew, 2021). The city's climate is defined by an average annual mean maximum and minimum temperature of 14°C, and 30°C; and rainfall ranging from 1138 – 1690 millimeters (Alemu, Abebe, Tsegaye, & Golassa, 2011).

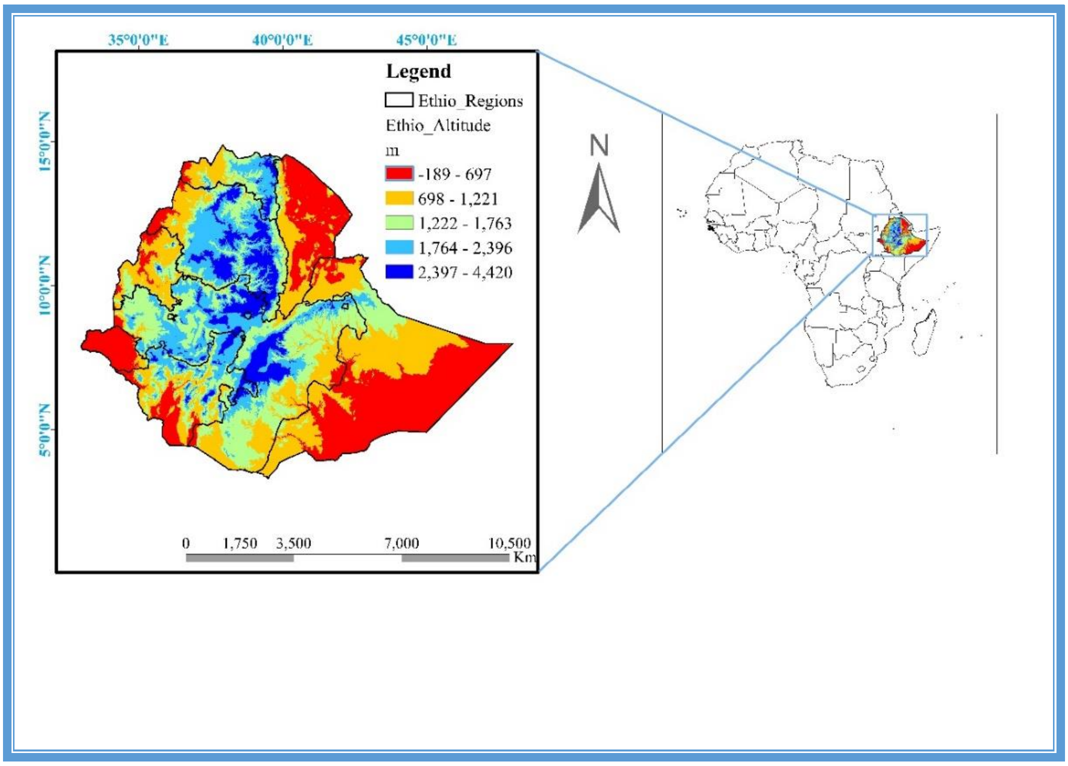

Fig. 3.1. Study area

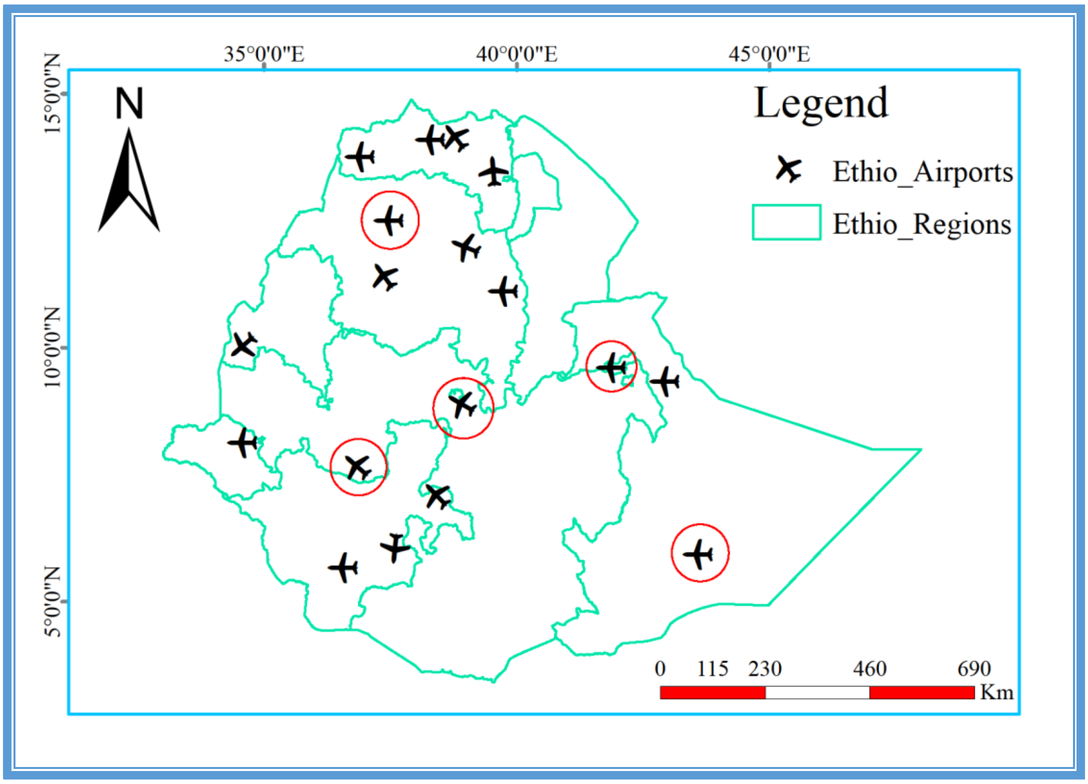

Fig.3.2 Ethiopian airports distributions

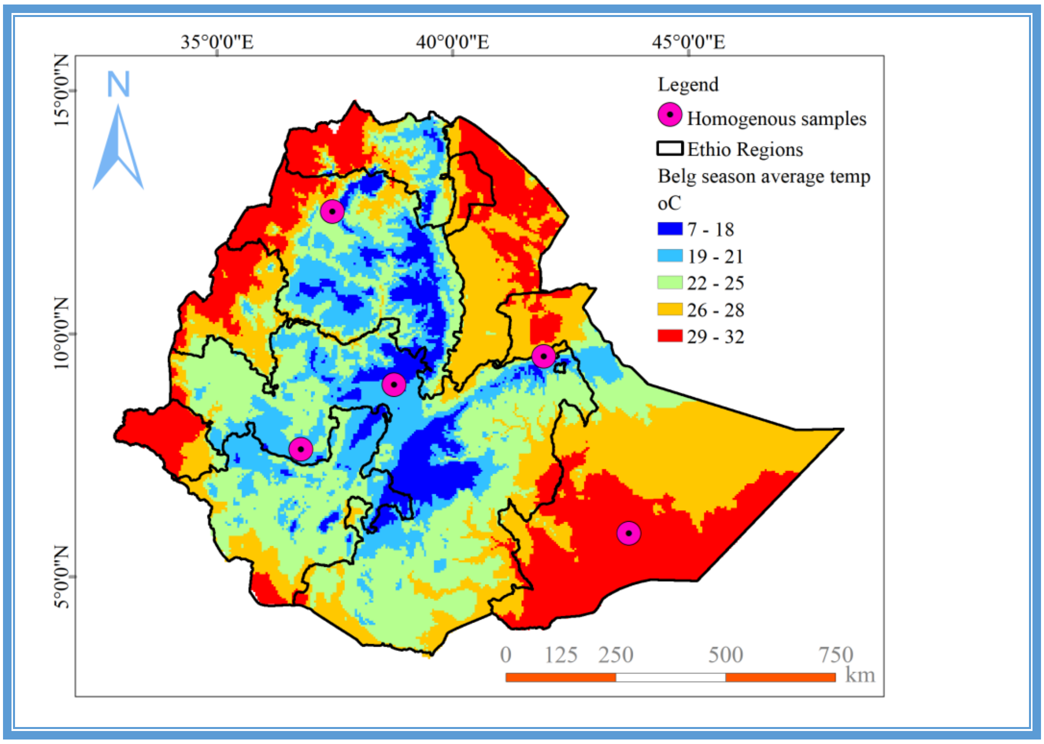

Fig.3.3 Belg season average temperature distribution

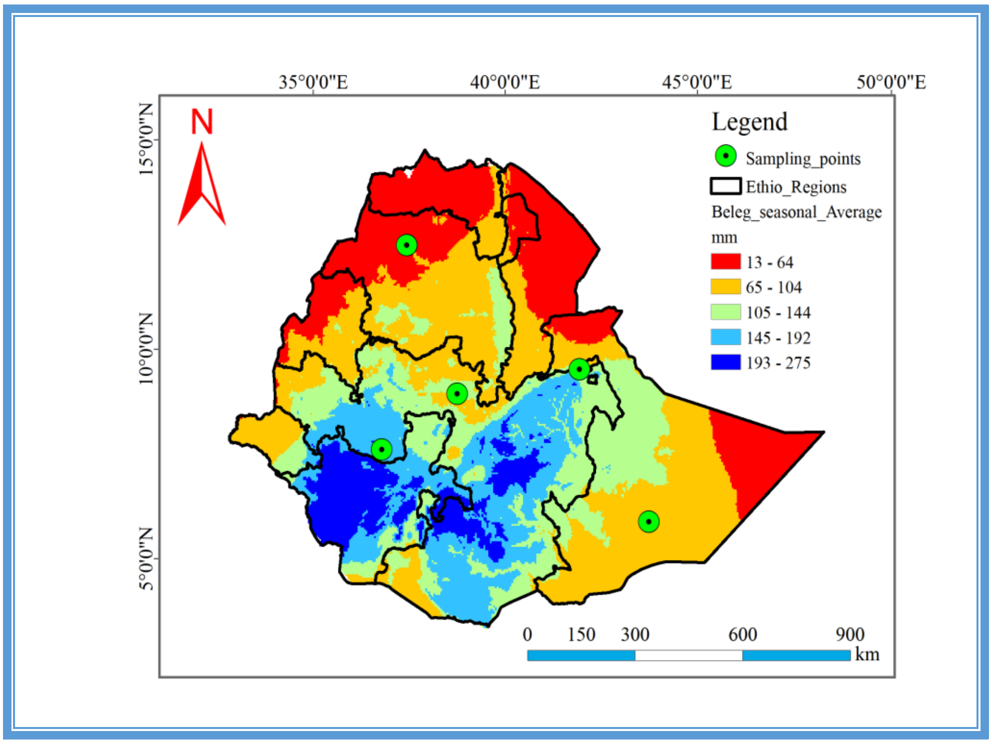

Fig.3.4. Belg season average precipitation distribution

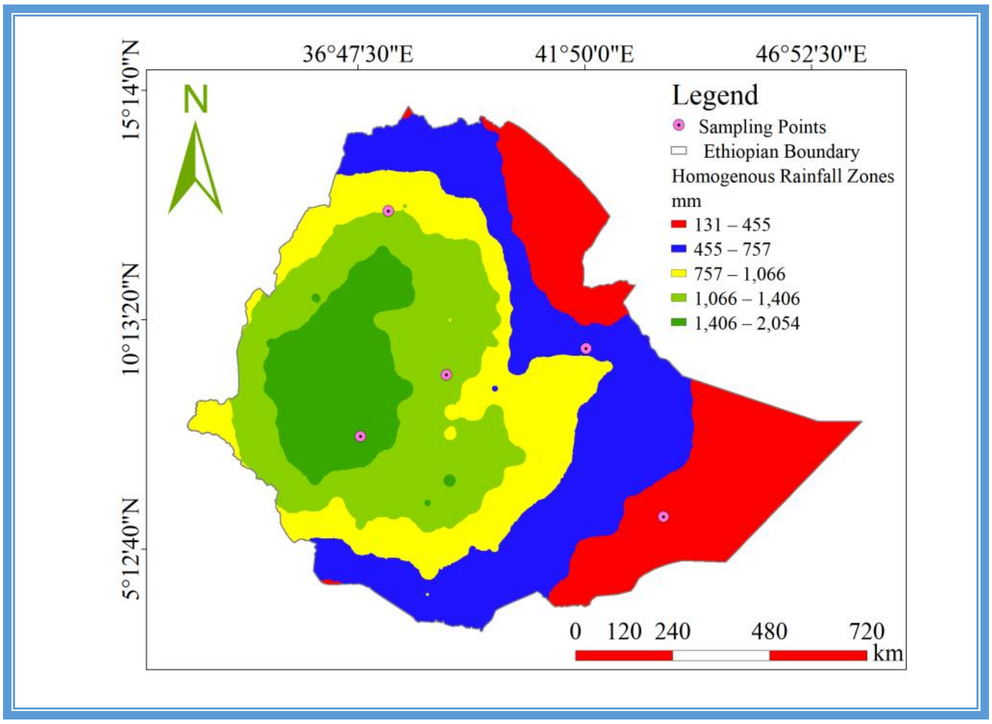

Fig.3.5 Long-year annual average precipitation distribution

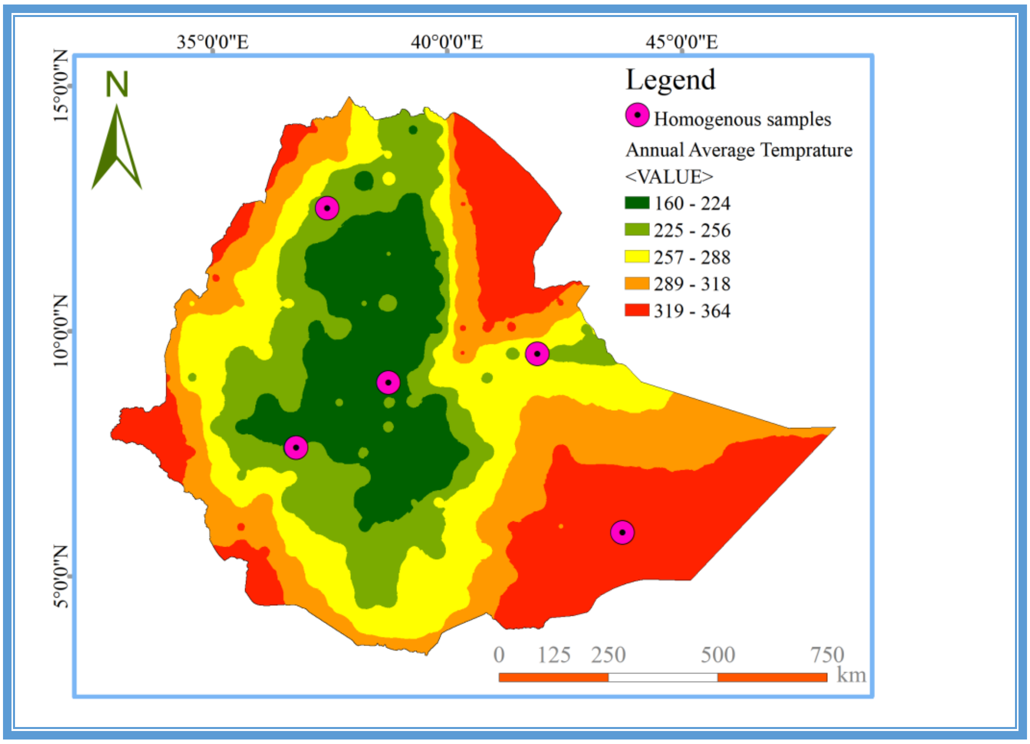

Fig. 3.6 Long-year annual average temperature distribution

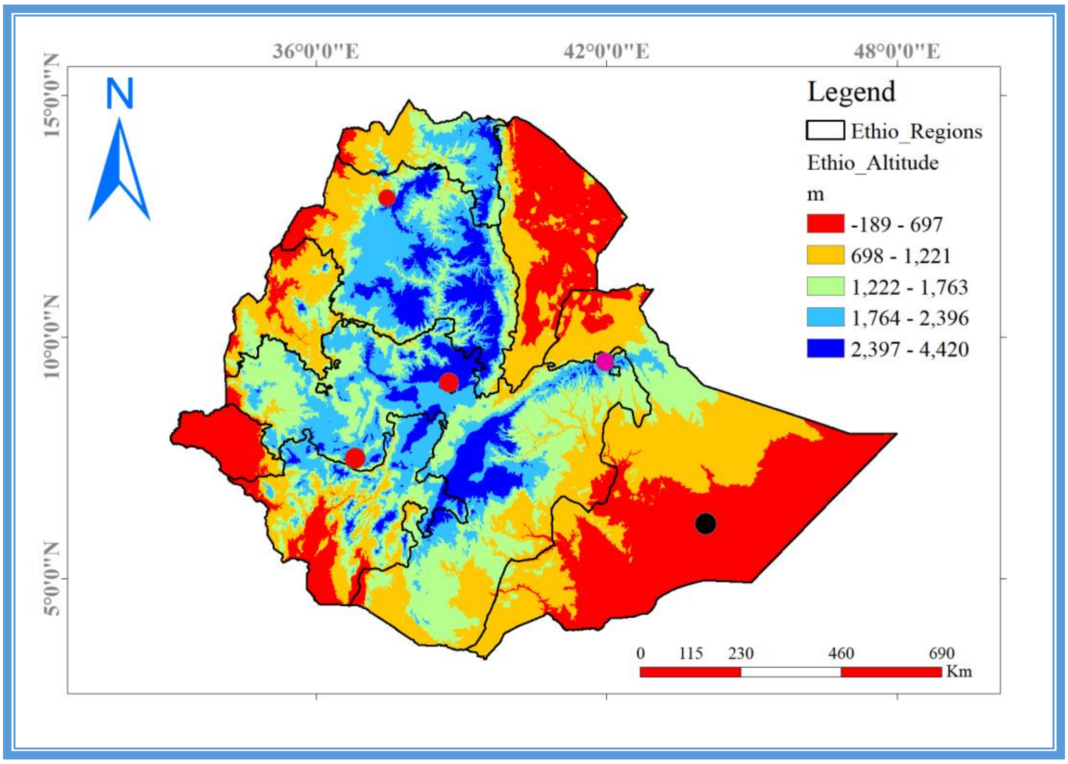

Fig.3.7 Elevation of Ethiopia

3.3 Materials

3.3.1 Data sets

The study used hourly reanalyzed and assimilated data from 2013 to 2022 and long-term climate data from the climate research unit. Both data sources are confidential and have been reprocessed to ensure high accuracy. The components of the inputted features were wind at 10m of both u and v components, volumetric soil layer temperature, cloud height, evaporation, cloud cover, potential evaporation, latitude, longitude, time, dew point, precipitation, pressure, sea surface temperature and corresponding latitude and longitude, soil temperature, relative humidity, and other factors.

3.3.2 Tools

ArcGIS, Google Earth Engine, Python, and Jupiter Notebook, google colab were the key tools that made my research meaningful.

3.4 Methods

3.4.1 Data preprocessing

Data preparation is the first stage of the data wrangling process, in which the data undergoes a number of steps, including transformation, data cleaning, and normalization.

3.4.1.1 Transformation

Data conversion is the process of changing data from one structure to another structure. The analyzed data which were obtained from the satellite and surface observations needed to transform into a suitable format before feeding to a machine.

3.4.1.2 Data cleaning

Data cleansing is the procedure of finding and modifying wrong or incomplete data. This can be done by replacing, modifying, or deleting dirty data. In this study, the input data which had null values, which will negatively impact the accuracy of the model was found to be mandatory to handle these missing values during data preparation. Three different methods were used to handle missing values: KNN, Random Forest (RF), and mean.

3.4.1.2.1 KNN imputer

K-Nearest Neighbors is a supervised machine learning algorithm that predicts missed values by finding the k most similar data points in the training set and then averaging their values. Accordingly, in my own case, I used k = 5, which means that I considered five most similar k nearest neighbors filled with the mean value of the data point when making a prediction.

3.4.1.2.2 Random Forest

Random Forest is a powerful machine learning algorithm that can be used to input missing data by training a model based on the available information and using it to fill missing values. It is also considered one of the most powerful and reliable classification model. The random forest model learns from the available data and creates decision trees that can predict the missing values based on the values of other variables. The algorithm then uses these classifiers to forecast the missing values in the evaluation set. To do this, the dataset was split into two parts: a training set consisting of the known values and the other is a holdout set used to test the model. These training and test sets are then supplied to the random forests, and subsequently, the estimated data is filled in at appropriate places.

3.4.1.2.3 Mean

Mean was also used to input null values by calculating the average value of the available data column and has been crammed**.** The formula accustomed for calculating the mean was:

Mean = (Sum of all values) / (Number of values) (1)

3.4.1.2.4 Normalization

Due to the differences in the intervals of values (in each feature), the data may become too large or too small. In order to avoid or to make the data values uniform, the data normalization process is needed (a range of between 0 and 1). The normalization can be performed by using equation (2)

$$Z = \frac{x - \min()}{\max() - \min()} \quad (2)$$

Where 'Z' scaled data, 'x' is the available data, "max" is the highest value in the column, and "min" is the minimum value in the column.

3.5 Methodology

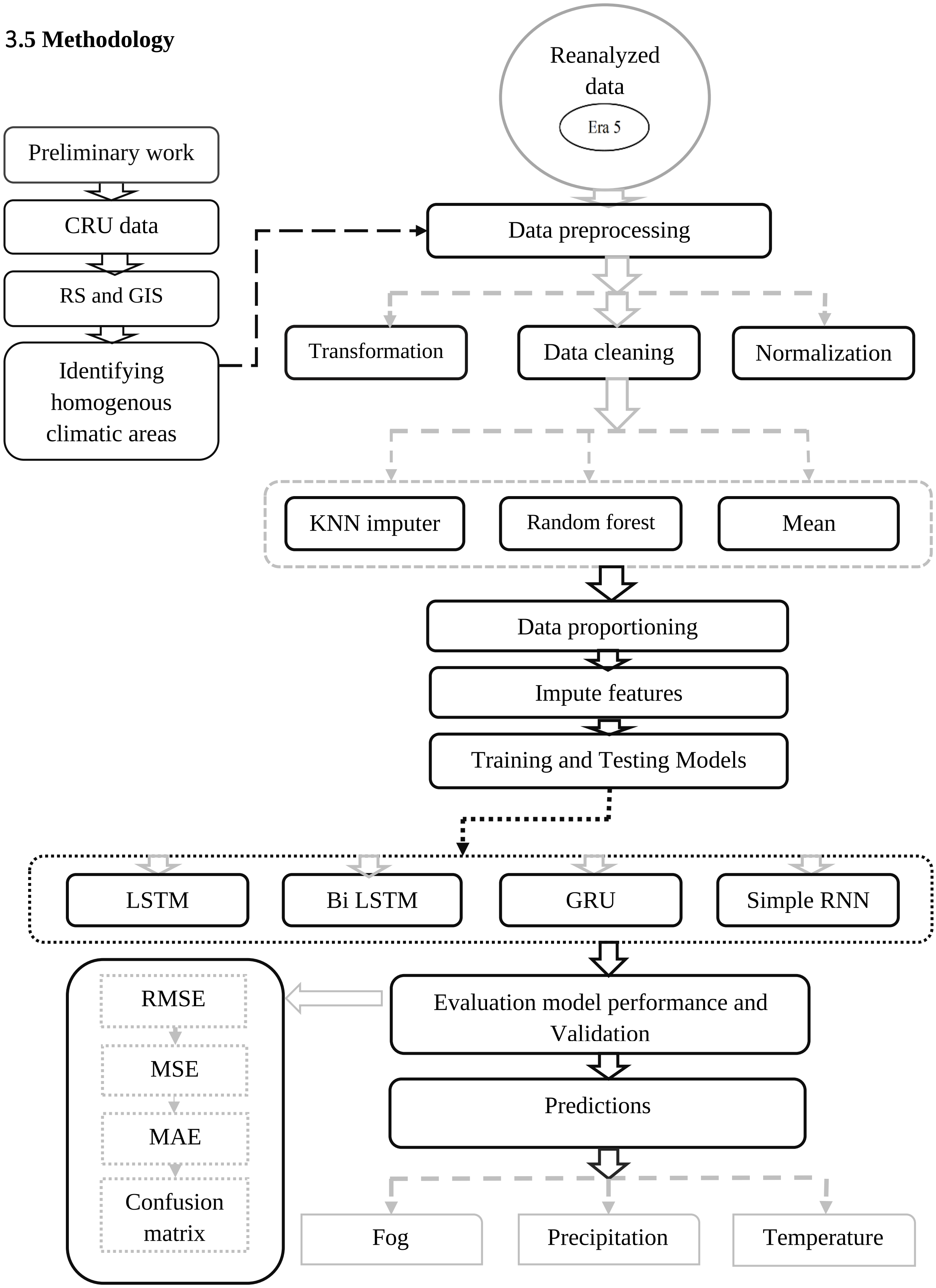

Fig.3.8 Work flow of proposed method

3.6 Machine learning models and Architectures

3.6.1. Machine learning (ML)

Artificial intelligence is the discipline of computer science that gives computers the ability to learn without being explicitly programmed. It is used to teach machines how to process data more efficiently. The goal of machine learning is to extract knowledge from data. Machine learning relies on algorithms to solve data problems. The choice of algorithm depends on the type of problem, the number of features, model type that would best fit the problem (Mahesh, 2020). For the proposed study, both machine and deep learning models applied as explained in the following sub sections.

3.6.1.1 Random Forest

An ensemble learning algorithm called random forest (RF) can be used for both classification and regression tasks. It works by building multiple decision trees and then aggregating their predictions. The individual trees are constructed from a training dataset, and each tree is trained on a separate partition of data. This helps to reduce over fitting, which is a problem that can occur with decision trees (Boulesteix, Janitza, Kruppa, & König, 2012). In the preprocessing stage, this algorithm was used to impute missing values by training it on the available data. It was also used to classify values as either foggy or not foggy, and to compare its performance with the LSTM model.

3.6.2 Deep learning (DL) models and Architectures

Sequential data consists of observations that are arranged in a logical order such that an observation at one position provides relevant information about observations at other positions. Countless supervised learning tasks require working with sequential data, and depending on the way the data is represented, one of the following three situations can arise in sequence learning (Wang, Zargar, & Yuan, 2021) and (Yadav, & Vishwakarma, 2020). In this research, my aim is to study the performance of the following neural networks: RNN, LSTM, GRU, and BiLSTM.

3.6.2.1 SimpleRNN

Neurons are basic units that receive a set of real-valued inputs and produce a single real-valued output. Feed-forward neural network is the most common type of neural network, which is organized as one input, one output, and at least one intermediate hidden layer. It is limited to static classification tasks, meaning that they can only provide a static mapping between input and output. For a timeseries prediction tasks, dynamic classifier become essential. This can be achieved by extending feed-forward neural networks to allow signals from former window size to be fed back into the network. These networks with recurrent connections are called recurrent neural networks (RNNs) (Cho et al. 2014)

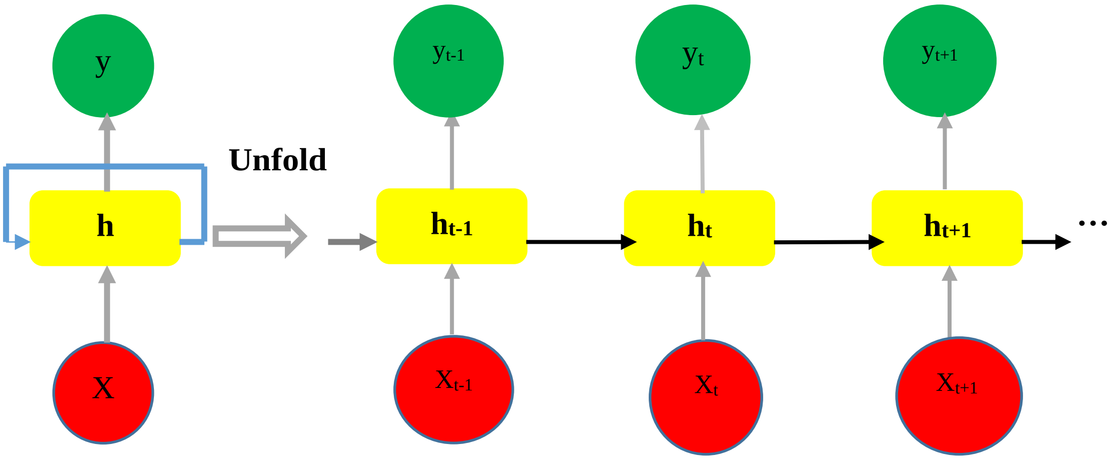

Fig.3.9. Simple RNN structural network

Simple RNN has three layers, input, hidden, and output, as shown in Figure

$$ht = \sigma\ (W\_hh\ h_{t-1} + W\_xh\ xt) \qquad (3)$$

Where:

- ht is the hidden state at time t
- h_{t-1} is the hidden state at time t-1
- x_t is the input at time t
- W_hh is the weight matrix for the hidden-to-hidden connections
- W_xh is the weight matrix for the input-to-hidden connections
- σ is the activation function

The simple recurrent neural network (simpleRNN) modifies its hidden state at each time step using the present input and the prior hidden state. The hidden state is then used to forecast the output at the next time step. The simpleRNN is a more basic version of the long short-term memory (LSTM) model. It lacks an output gate, which means that it cannot remember information from the prior hidden state.

3.6.2.2 LSTM

Long short-term memory (LSTM), a recurrent neural network structure, addresses the vanishing gradient problem by substituting the standard layers of the neural system with long-term memory cell blocks. These cell blocks are made up of four interactive layers: a cell state, an input gate, an output gate, and a forget gate **(Fig.3.9).** Feature extraction of the input sequential data x_t is combined with previous cell h_{t-1} of output data. This grouping of input data goes through the forget gate f_t (3), and the input gate i_t (4). Sigmoid activation functions to output values between 0 and 1 applied for both gates.

$$f_t = \sigma(\omega f\,[h_{t-1}, x_t] + b_f) \quad (4)$$

$$i_t = \sigma(\omega_i[h_{t-1}, x_t] + b_i) \quad (5)$$

$$C\hat{}t = \tanh(\omega_c[h_{t-1}, x_t] + b_c) \quad (6)$$

$$C_t = f_t \times C_{t-1} + i_t \times C\hat{}t \quad (7)$$

$$O_t = \sigma(\omega_O[h_{t-1}, x_t] + b_O) \quad (8)$$

$$h_t = O_t \times \tanh(C_t) \quad (9)$$

So, the forget gate (4) determines which information to discard from the cell, and the input gate (5) determines which values from the input to use to update the cell. The candidate cell state $C\hat{}t$ (6) is then computed, and the cell state Ct (7) is updated by combining the previous cell state and the candidate cell state, weighted by the forget gate and the input gate, respectively. The output gate O_t (8) determines how much of the cell state is the output. The hidden state *ht* (9) is then computed by combining the cell state and the output gate, weighted by the tanh function. Furthermore, that combination is compressed by the tanh layer, $\hat{C}_t$.Here, ωf, ω_i, ω_c *and* ω_O are weights for the respective gate neurons; b_f, b_i, b_c and b_O are biases for the respective gates. LSTM cells have an internal loop (cell state) consisting of a variable C_t (6) called the constant error carrousel (CEC). The old cell state C_{t-1} is connected to establish an effective recurrence loop with the input data. The compressed combination $\hat{C}_t$ is multiplied with the input gate data i_t **(Fig.4.9).**

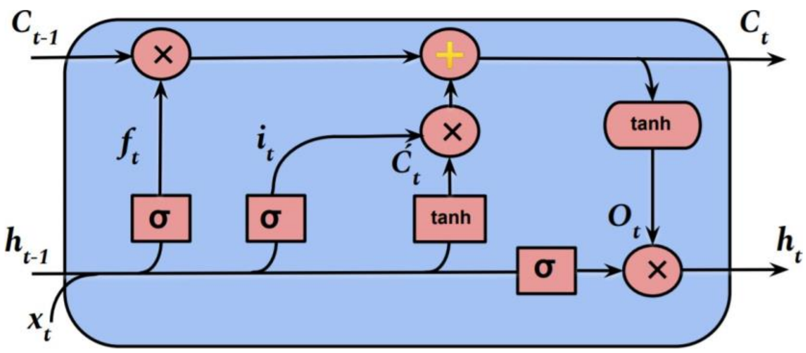

Fig.3.10 The conventional structure of an LSTM cell

The feedback loop of the LSTM network is controlled by the forget gate, determines which information to store or forget. The addition method is used instead of multiplication to reduce the risk of disappearing gradients. The tanh function transforms the cell state to values between -1 and 1, and the sigmoid gate determines how much of the cell state is output as the output value (8). H ence, this gate should control what values will be output from the h_t cell as the output value. LSTM networks are more complex than simple RNNs and require more memory and computational resources. However, they are also more powerful and can absorb long term dependencies, which is a challenge for simple RNNs (Staudemeyer, & Morris ,2019).

3.6.2.3 GRU Neural Network

Gated recurrent units are a kind of recurrent neural network which are capable of learning long term dependencies (Cho et al. in 2014). GRUs are similar to LSTMs in that they are both able to learn long-term dependencies. However, GRUs are simpler than LSTMs and have been shown to be more efficient. The flow of information through GRUs network controlled by gates. These gates are updated at each time step, and they identify how much of the previous state is kept and how much of the new input is added. While LSTM networks are known for their ability to prevent gradients from disappearing or growing too large, they need more memory because of the multiple memory cells in their design. GRU networks have fewer parameters than LSTM networks, which makes them faster to train while maintaining high accuracy. Unlike LSTM, GRU networks do not have an output gate (Fig.3.10). There are two input functions at each time step in a GRU network: the previous output vector, ht-1, and the input vector, x_t. The output of each gate is calculated by passing the input through a logical operation and exponential transformation. The association between the output and the input can be described as follows:

$$r_t = \sigma_g(\omega_r x_t + U_r h_{t-1} + b_r) \quad (10)$$

$$z_t = \sigma_g(\omega_z x_t + U_z h_{t-1} + b_z) \quad (11)$$

$$h_t = (1 - z_t) h_{t-1} + z_t \hat{h}_t \quad (12)$$

$$\hat{h}_t = \sigma h(\omega h x_t + U_h(r_t h_{t-1}) + b_h) \quad (13)$$

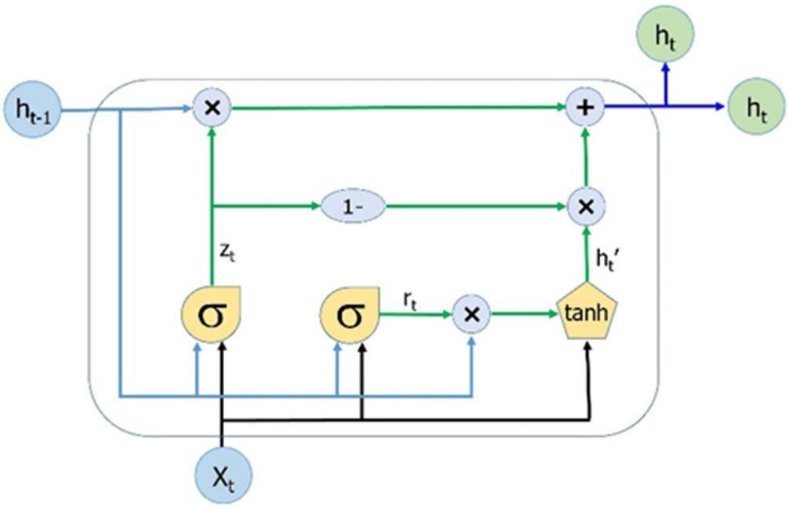

Fig.3.11 The conventional structure of a GRU cell

Where r_t is the reset gate vector, z_t is the update gate vector, $\omega_r, \omega_z, \omega h$ and U_r, U_z, U_h are weight matrices for the particular gate neurons. σ_g is a sigmoid function and σh is a hyperbolic tangent.

The reset gate in an RNN is responsible for determining whether or not the hidden state should ignore the previous hidden state and only reset with the current input when it is close to 0. This helps to eliminate irrelevant information and results in a more concise output. On the other hand, the update gate controls how much data from the previous hidden state is transferred to the current hidden state, allowing the RNN to retain long-term information like LSTM memory cells (Utebayeva, Ilipbayeva & Matson,2022).

Each hidden module in an RNN has its own reset and update gates, which enables them to capture dependencies at different time intervals. Modules that capture short-term dependencies tend to have an active reset gate, while those that capture long-term dependencies have a more active update gate.

3.6.2.4 Bi LSTM Neural Network

The BiLSTM design is a potent tool for enhancing precision in meteorological forecasting. By integrating two LSTMs, one handling the original input data and the other handling a reversed copy of it, the model can capture long-term interdependencies and consider both prior and future inputs. This approach adds more significance to the network and accomplishes faster outcomes. The idea behind BiLSTM is straightforward: it duplicates the first recurrent layer in the network and provides the input data in its initial form to one layer and a reversed copy to the duplicated layer. This resolves the issue of vanishing gradients in standard RNNs. The BiLSTM model is capable of processing input data in both forward and backward directions by utilizing a forward hidden layer and a backward hidden layer. It effectively trains on all available past and future input information within a given time frame. Overall, the application of BiLSTM in weather forecasting has the potential to transform the field by providing more precise and dependable predictions for various applications. It is essential to note that proper data pre-processing and feature engineering are critical for enhancing the model's performance (Utebayeva, Ilipbayeva & Matson,2022)

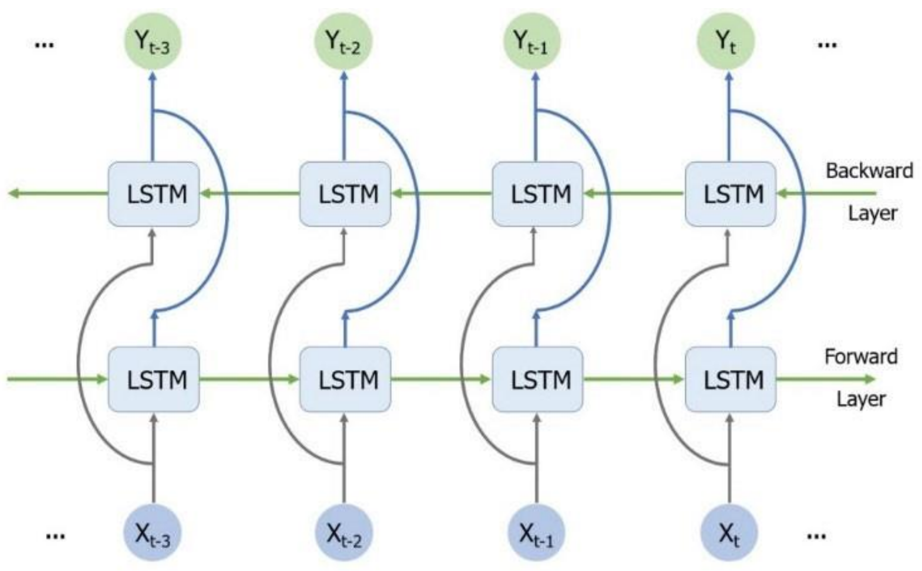

Fig. 3.12 Bi LSTM neural network structure

The methods presented above were chosen after reviewing the relevant literatures and considering the specific problem. As I have discussed and summarized in the literature, artificial intelligence is more capable than statistical methods of extracting nonlinear relationships in time series data. As a result, I have identified the appropriate approach to solve the problem.

3.7 Model evaluation metrics

Assessing the model's correctness is a critical step in the process of developing machine learning models to determine how well the model performs in its predictions. The evaluation metrics vary depending on the problem type.

3.7.1 RMSE (Root Mean Square Error)

RMSE is a widely used metric that quantifies the overall accuracy of a model by finding the square root of the average squared difference between the model's predictions and the actual values.

$$\textbf{RMSE} = \sqrt{\frac{\mathbf{1}}{\boldsymbol{N}} \sum_{i=1}^{N} (yi - y)^2} \tag{14}$$

3.7.2 MSE (Mean Square Error)

MSE is similar to RMSE, but it does not take the square root. Helps to measure the average error of the model.

$$\textbf{MSE} = \frac{\mathbf{1}}{\boldsymbol{N}} \sum_{i=1}^{N} (yi - y)^2 \tag{15}$$

3.7.3 MAE (Mean Absolute Error)

MAE is the simplest of the three metrics for measuring the average magnitude of the errors between the model's predictions and the actual values. It is calculated by taking the mean of the absolute differences between the predictions and the actual values.

$$\textbf{MAE} = \frac{\mathbf{1}}{\boldsymbol{N}} \sum_{i=1}^{N} | yi - y | \tag{16}$$

Where ‘yi’ the actual value, ‘y’ predicted values and N number of samples

3.6.2.5.4 Confusion matrix

confusion matrix is a tool that is used to assess the performance of a classification model. A table format that shows the number of true negatives (TN), true positives (TP), false positives (FP), and false negatives (FN) for a given model. The TP cell represents the number of cases that were correctly classified as positive. The TN cell represents the number of instances that were correctly classified as negative. The FP cell denotes the number of occurrences that were incorrectly classified as positive. The FN cell represents the number of instances that were incorrectly classified as negative. It can be used to calculate a number of performance metrics, such as recall, precision, accuracy, and F1 score. The accuracy of a classification model is the percentage of instances that were correctly classified. It is calculated by dividing the number of TP and TN instances by the total number of instances.

$$\text{accuracy} = (TP + TN) / (TP + TN + FP + FN) \quad (17)$$

CHAPTER FOUR

RESULTS

4.1 Correlation of impute features

More variables **(Fig.4.1)** were provided for the analyses which are suspected to contribute to the weather phenomena, among them which were highly correlated and had a threshold value greater or equal to 80 % removed based on the heat map plot **(Fig.4.2)**. As a result, some of the parameters that will bring redundancy because of their high linearity behavior are replaced and represented.

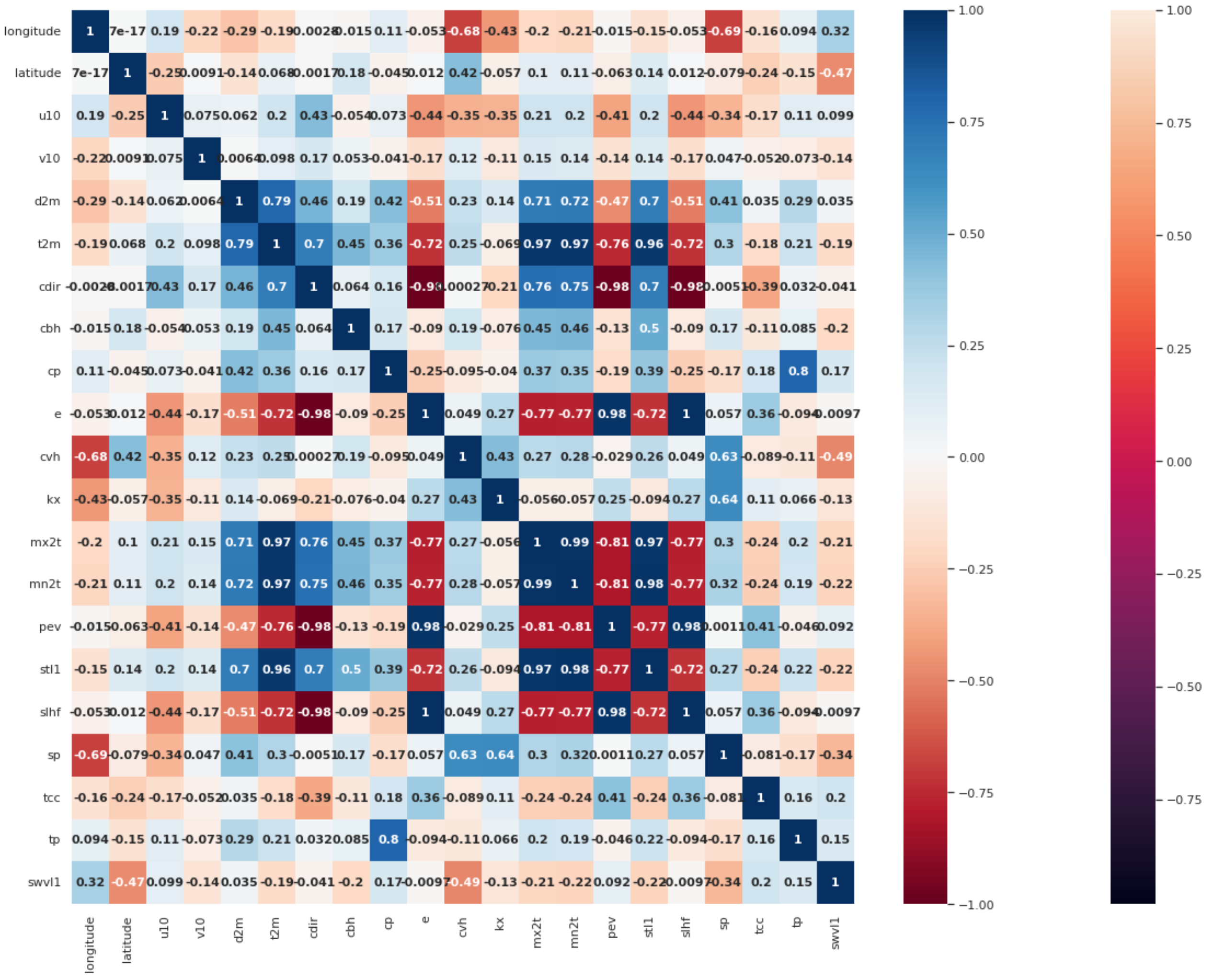

Fig 4.1 Correlation and selection of input variables

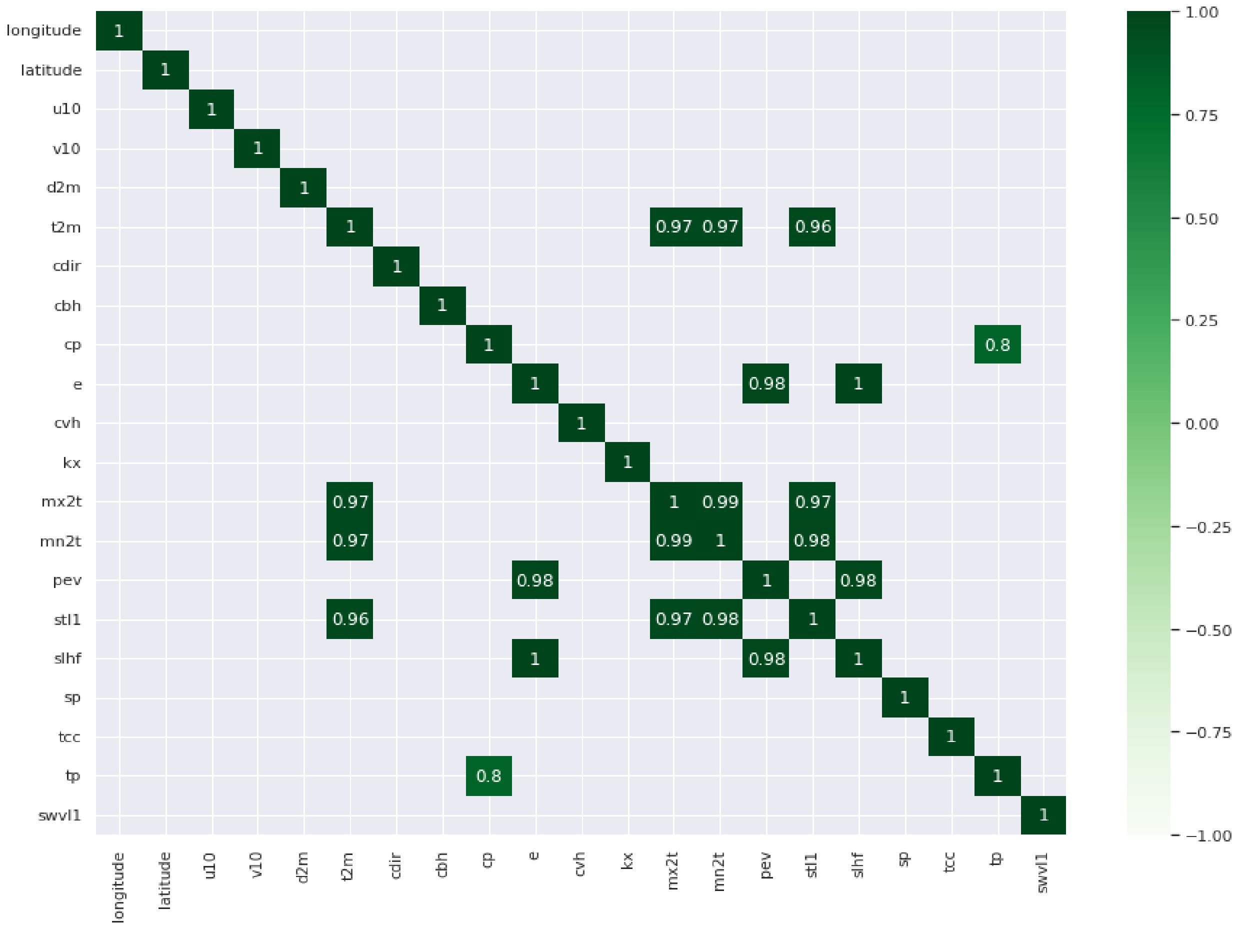

Fig .4.2. Highly correlated variables with threshold greater or equal to 0.8

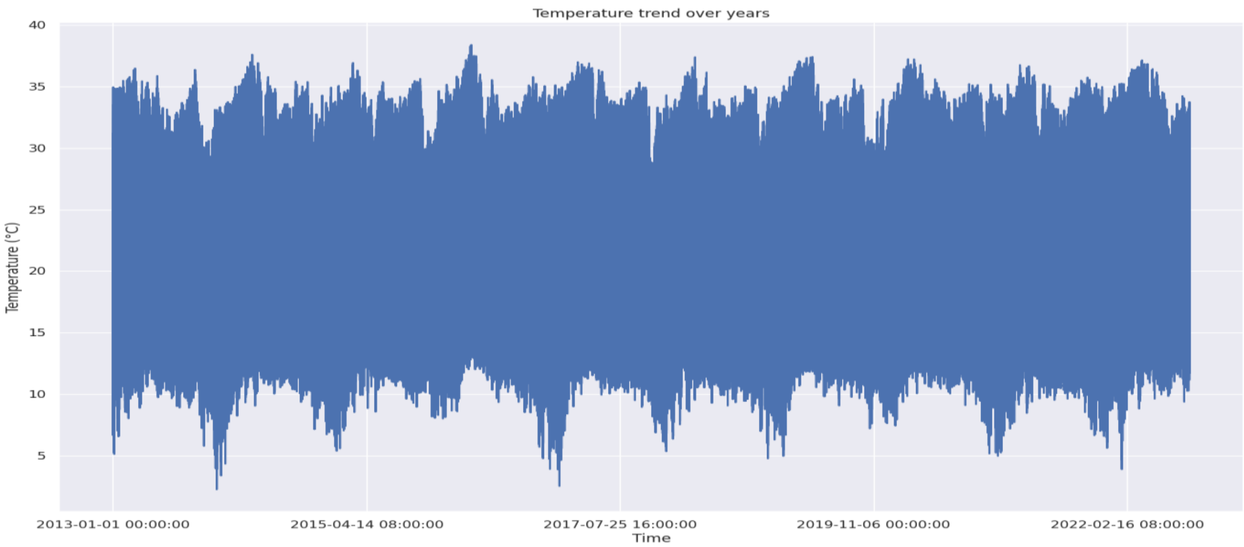

Fig.4.3A Temperature distribution over years

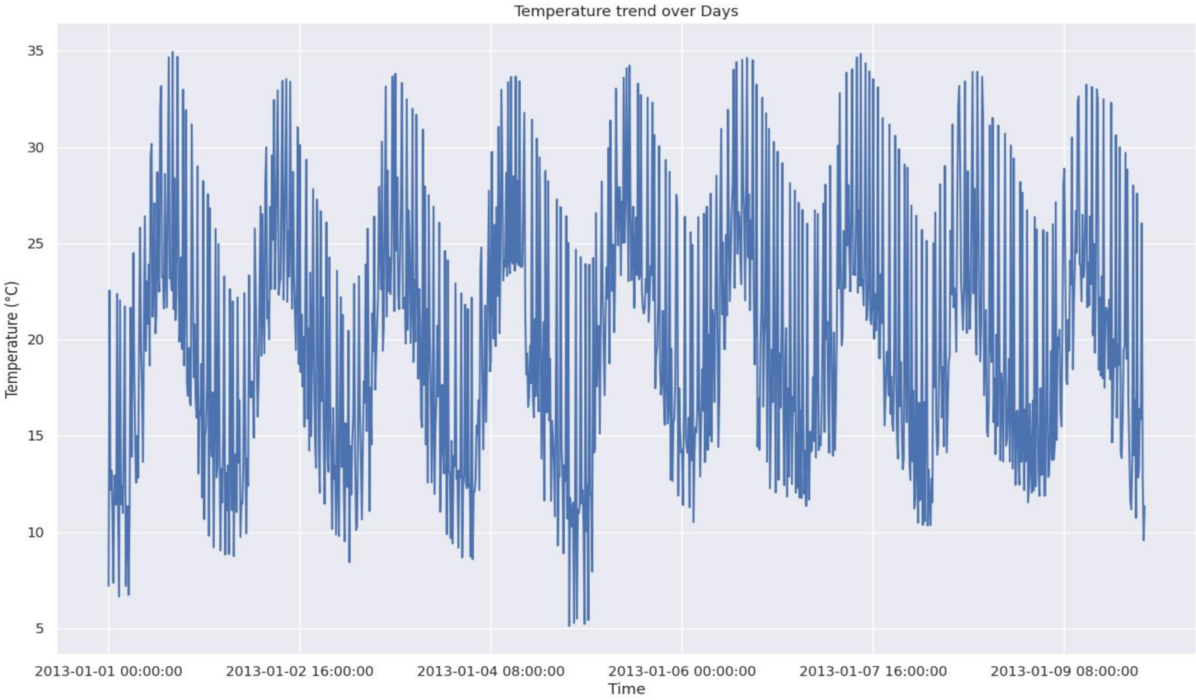

Fig.4.3B Temperature distribution over days

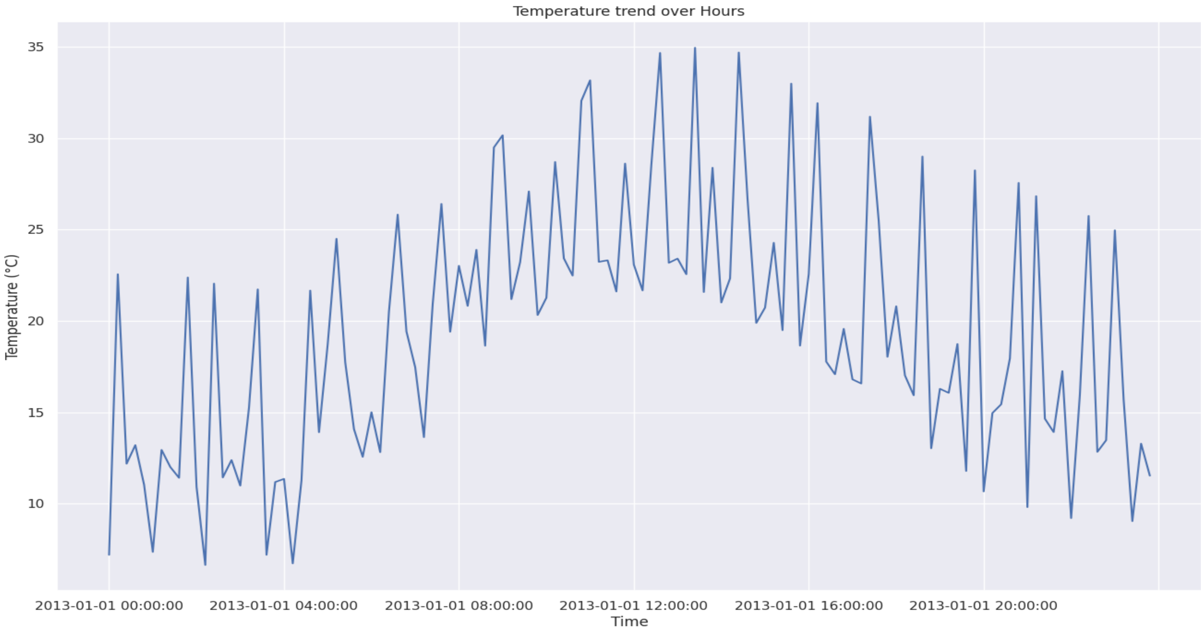

Fig.4.3C. Temperature distribution in hours

In the above figures the highest and the lowest values are demonstrations of sequential nature. The highest values of the temperature are recorded around 12:00:00 which is logically acceptable that the maximum temperature observed in the afternoon after the earth heated enough and the minimum temperature value observed at 00:00:00 before early morning where the absorbed heat released completely.

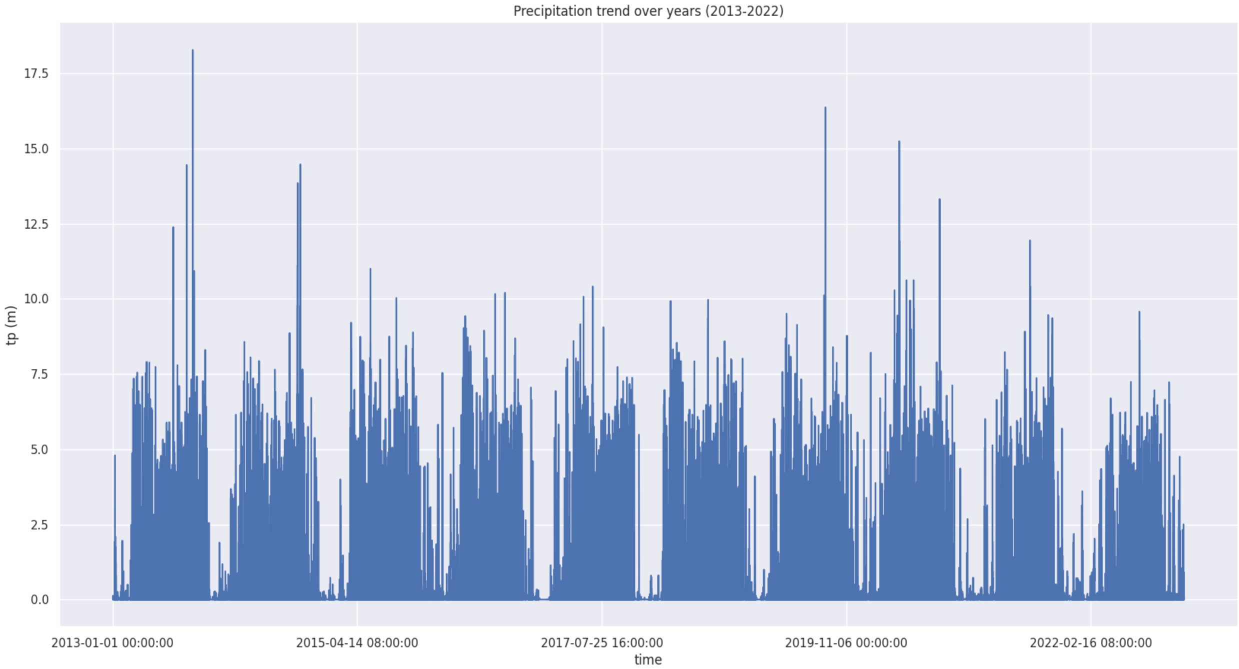

Fig.4.4A Precipitation distribution over year

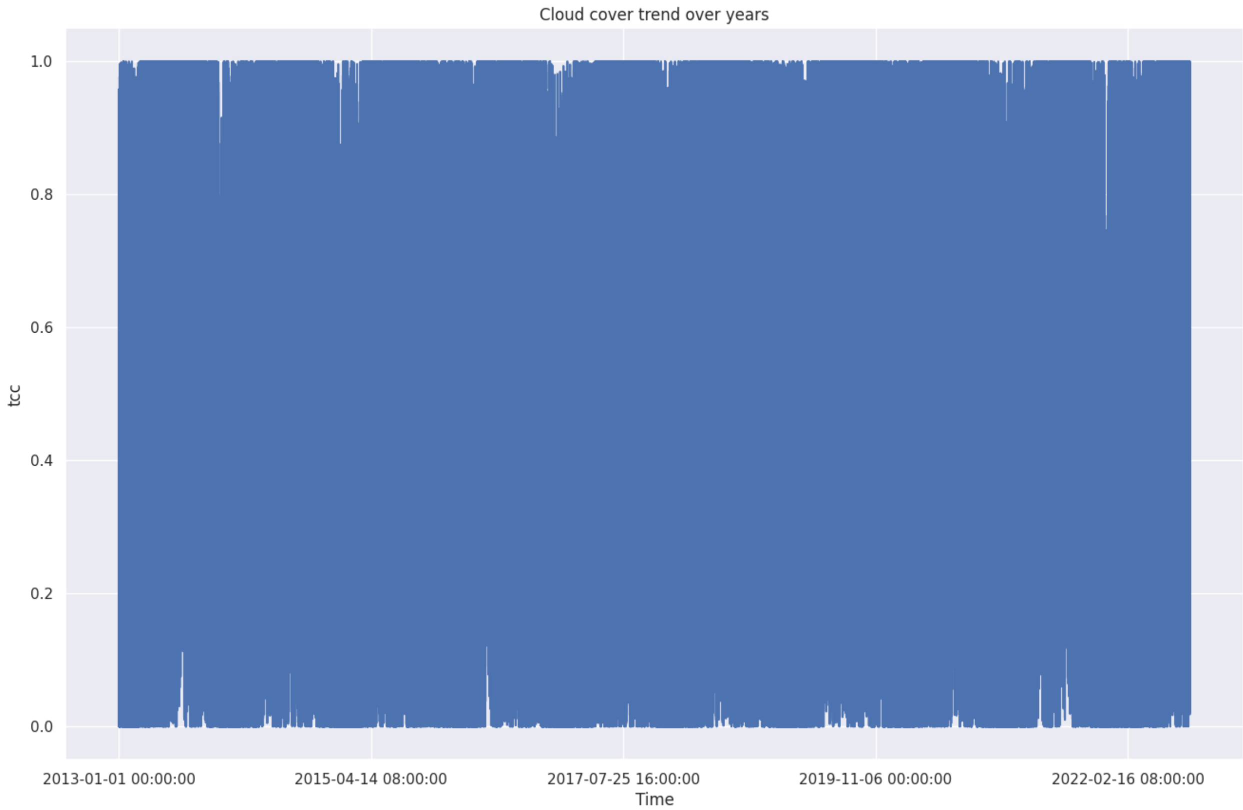

Fig.4.5A Cloud distribution over years

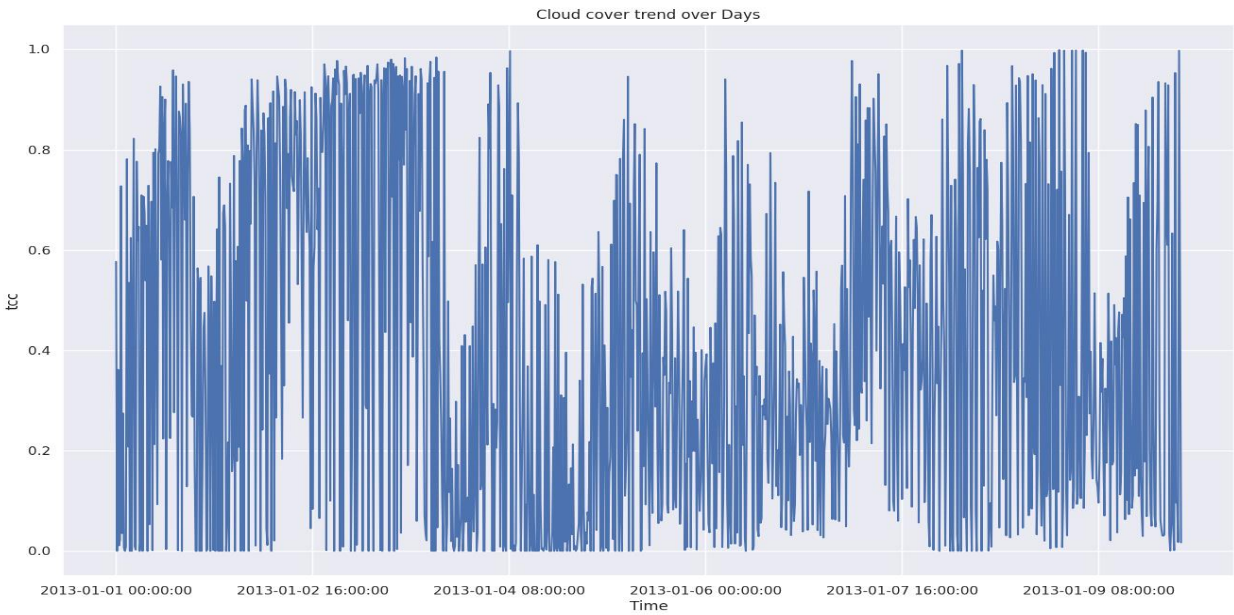

Fig.4.5B Cloud distribution over days

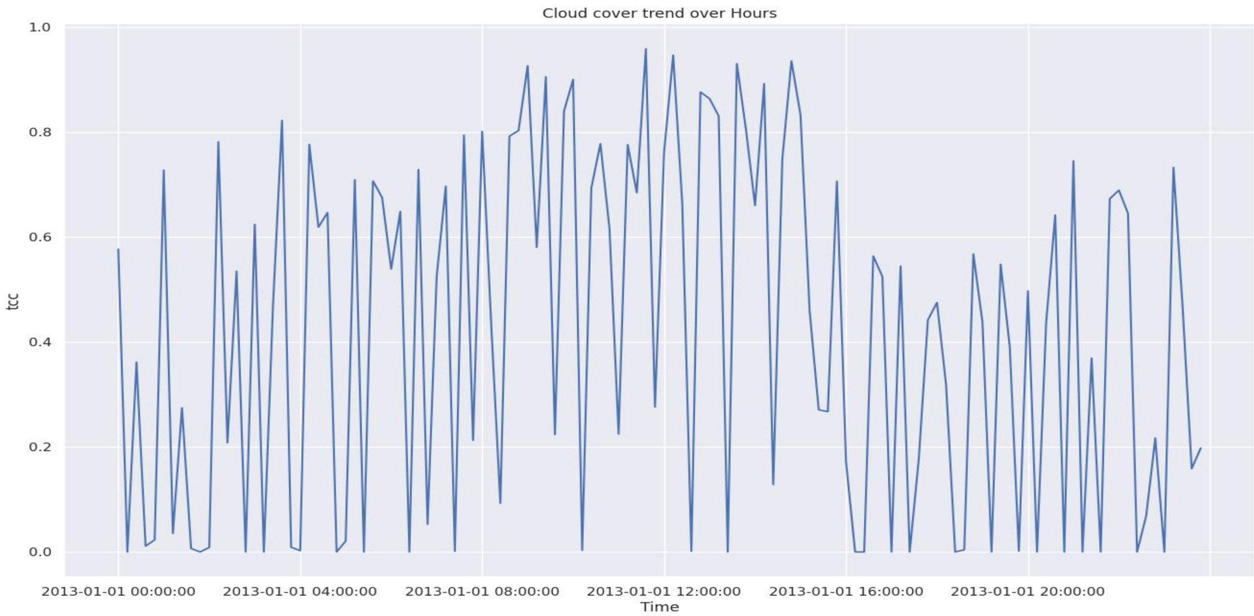

Fig.4.5C Cloud distribution in hours

The cloud distribution shows the peak and low values. The peak values shows when there is a high clod coverage and a tendency of weather phenomena while the lows indicates that the clear sky or few cloud observations. Cloudy skies observed mostly during rainy and probably in belg seasons. Similarly, it works for the corresponding precipitation (Fig.4.4A) directly related with the cloud coverage.

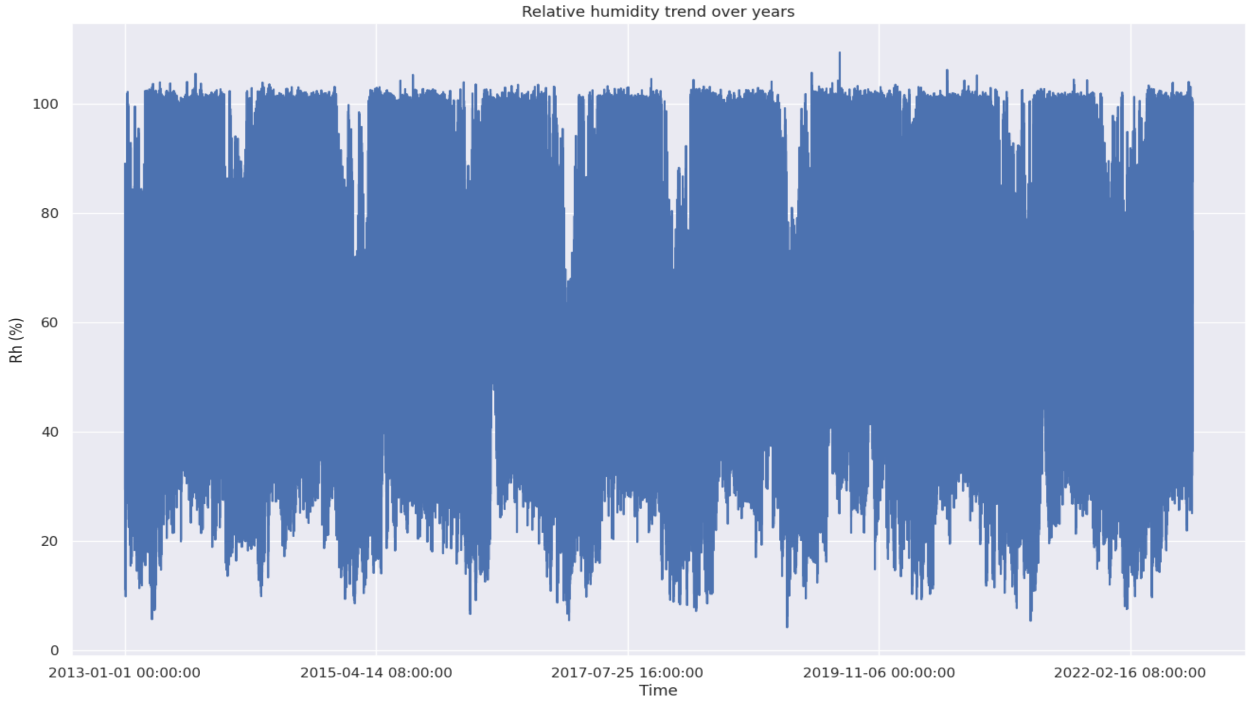

Fig.4.6A Relative humidity distribution over years

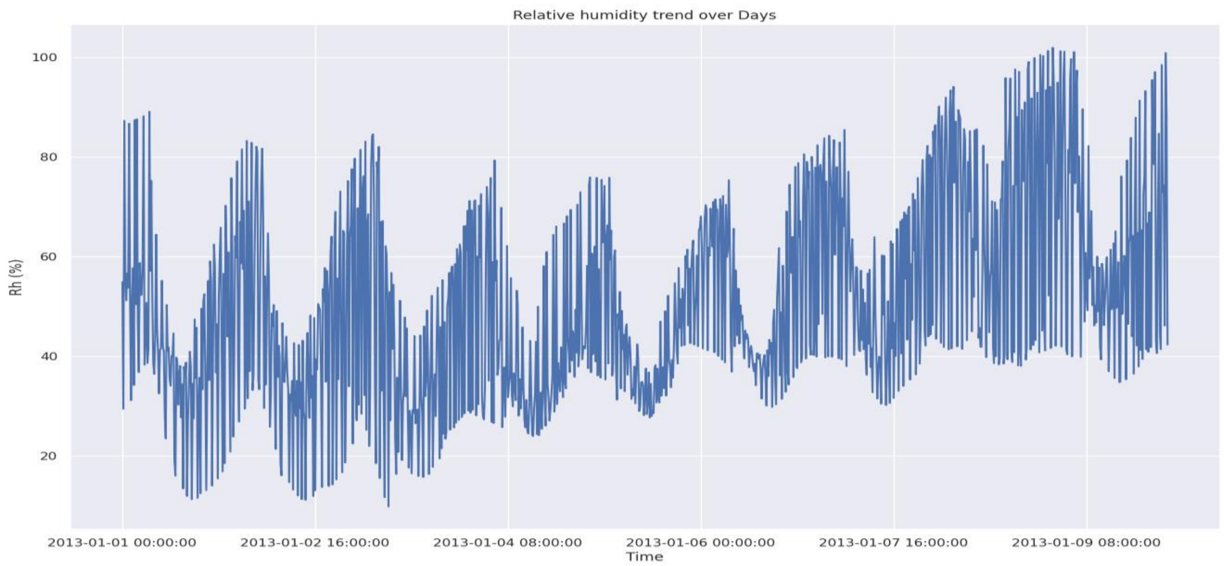

Fig.4.6B Relative distribution over days

Likewise, the relative humidity graph shows the sequential correspondence with cloud, and precipitation. The peak and lows are the reflections of cloudy skies and a tendency of precipitations. Shows a linear relationship among the displayed components.

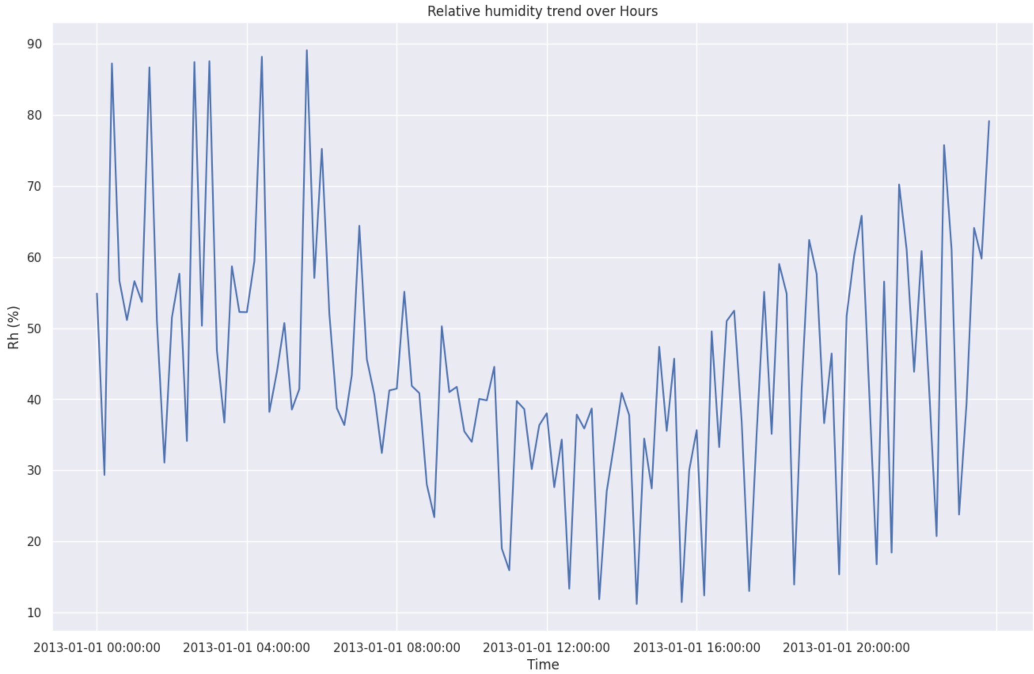

Fig.4.6 C. Relative humidity distribution in hours

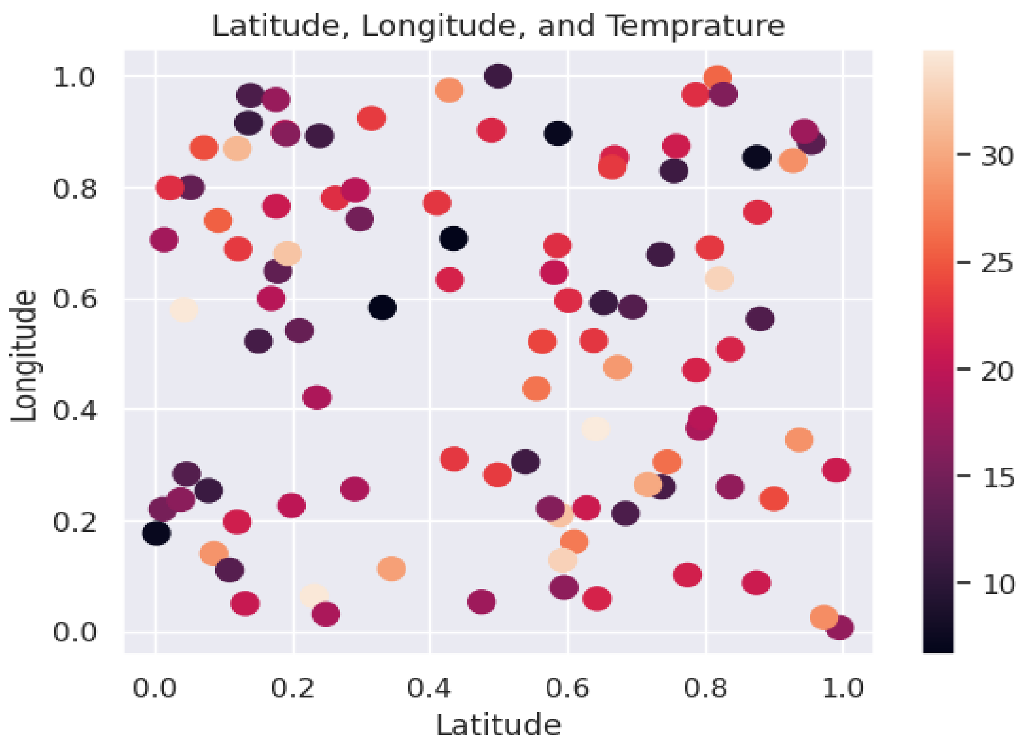

Fig.4.7. Actual temperature distribution along a scaled latitude and longitude

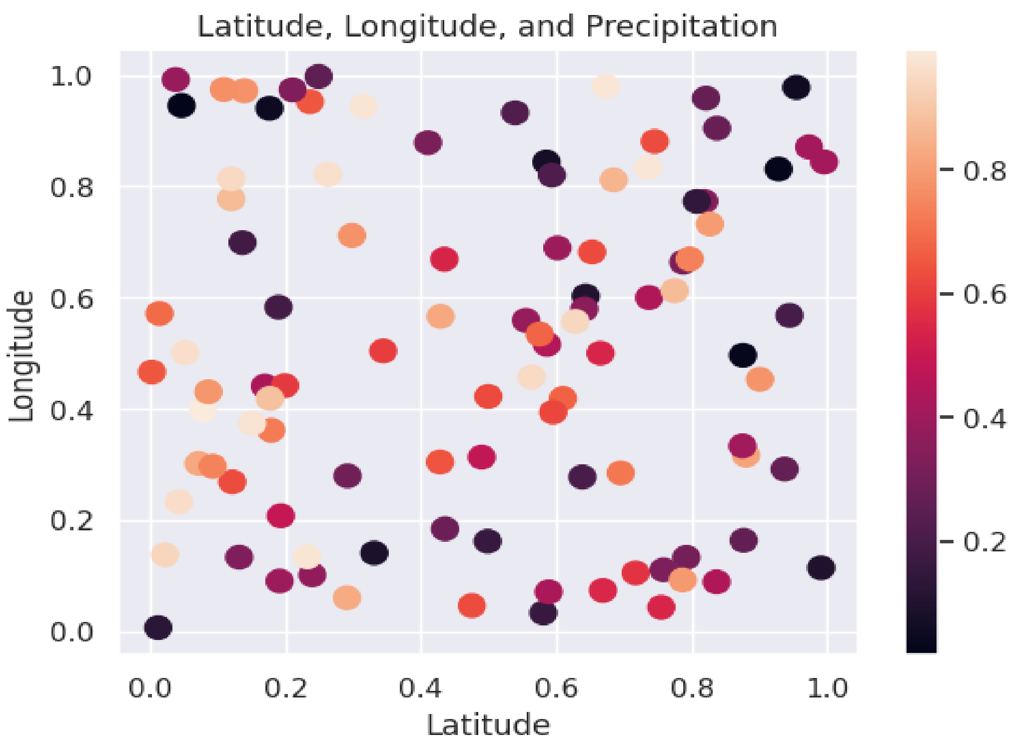

Fig.4.8 Scaled actual precipitation distribution along latitude and longitude

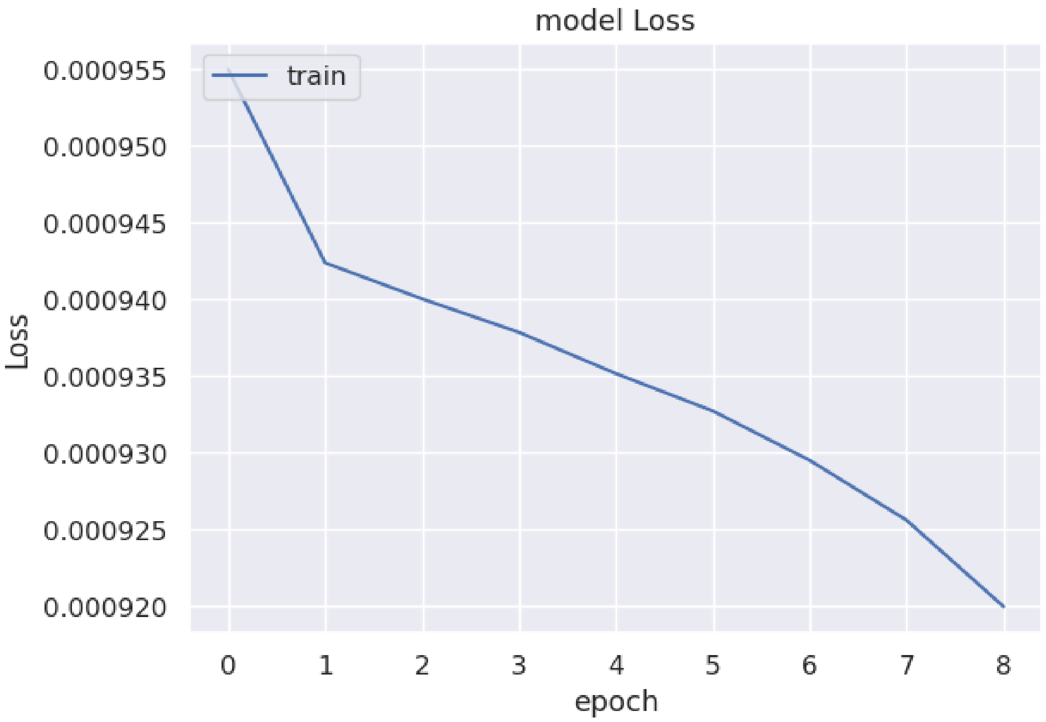

Fig.4.9 Training loss during precipitation forecast

The falling training loss line indicates that how the model works well when the learning process proceeds and came up with a value from 0.000955 to 0.000920.

4.2 Experimentation

The best model choice for time series prediction depends on various factors such as the complexity of the data, the length of the time series, and the specific problem at hand. However, LSTM and its alternatives, such as GRU and Bi-LSTM are commonly used and have shown promising results in time series prediction tasks. An experiment has been done on the four deep-learning models in the prediction of precipitation. Accordingly, they were compared based on their metrics (RMSE, MSE, and MAE) as shown in (Tables 4.1, 4.2, 4.3). This was done on a time step of 120 hours with an activation function tanh, ReLu, and optimizer of RMSprop and Adam. The experiment is done with a variation of layers, activation functions, optimizers and also time steps.

4.2.1 Experiment one

In this experiment, the four models compared based on two layers having 125 units in the first and 1 unit of an output layer, activation function of tanh, optimizer of RMSprop and an epoch of ten.

Table 4.1 Metrics for experiment one

Models	RMSE	MSE	MAE	Test Loss	Acc.
SimpleRNN	0.027	0.000	0.015	0.000	0.999
LSTM	0.026	0.000	0.014	0.000	0.999
GRU	0.027	0.000	0.015	0.000	0.999
Bi LSTM	0.026	0.000	0.015	0.000	0.999

4.2.2 Experiment two

In the second experiment, only the second layer added, and a total of three layers, the first two layers having units of 125 each, and a dense layer with one unit in the output, optimizer and activation function were not changed.

Table 4.2 Metrics for experiment two

Models	RMSE	MSE	MAE	Test Loss	Acc.
SimpleRNN	0.031	0.001	0.014	0.001	0.999
LSTM	0.031	0.000	0.012	0.000	0.999
GRU	0.031	0.001	0.014	0.001	0.999
Bi LSTM	0.031	0.000	0.015	0.000	0.999

4.2.3 Experiment three

In the third experiment, two layers possessing 125 units in the first and 1 unit of dense layer in the output were used. The activation function and optimizer used earlier replaced by relu and adam discretely**.** An epoch of 50 with early stopping also used.

Table 4.3 Metrics for experiment three

Models	RMSE	MSE	MAE	Test Loss	Accuracy
SimpleRNN	0.032	0.001	0.014	0.001	0.999
LSTM	0.031	0.000	0.012	0.000	0.999
GRU	0.031	0.001	0.014	0.001	0.999
Bi LSTM	0.026	0.000	0.015	0.000	0.999

The correspondence of the actual and predicted values of the experimented models illustrated as follows:

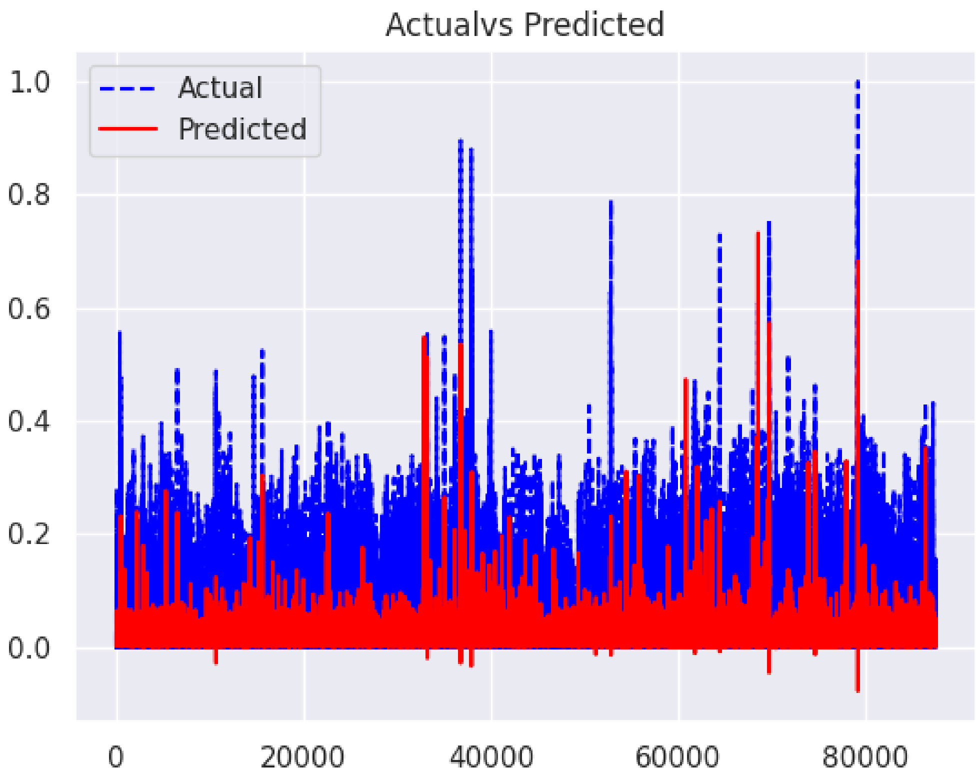

Fig.4.10 Actual and predicted values of precipitation in LSTM model training and testing

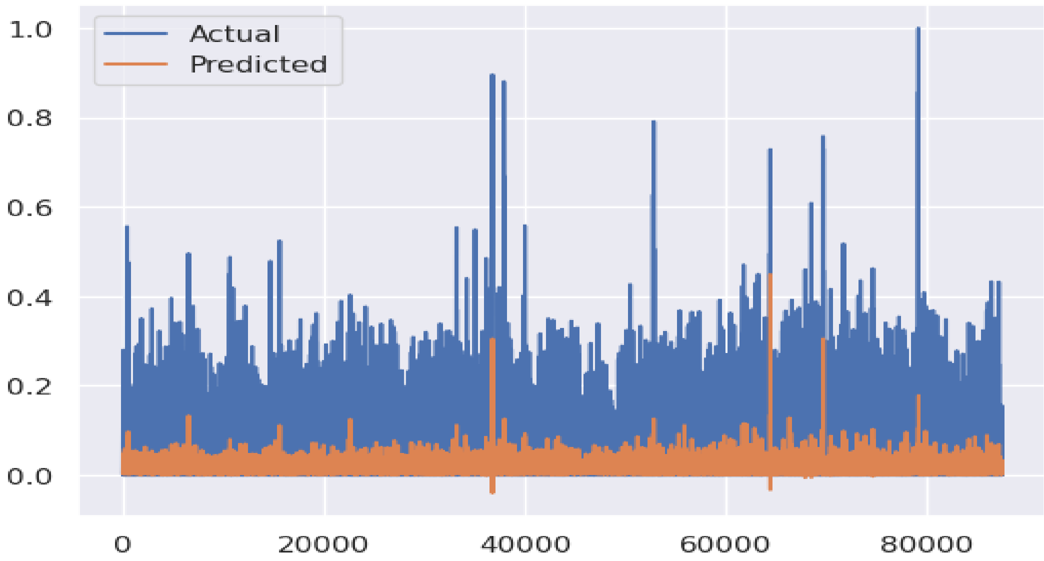

Fig 4.11 Actual and predicted values of precipitation in Bi LSTM model training and testing

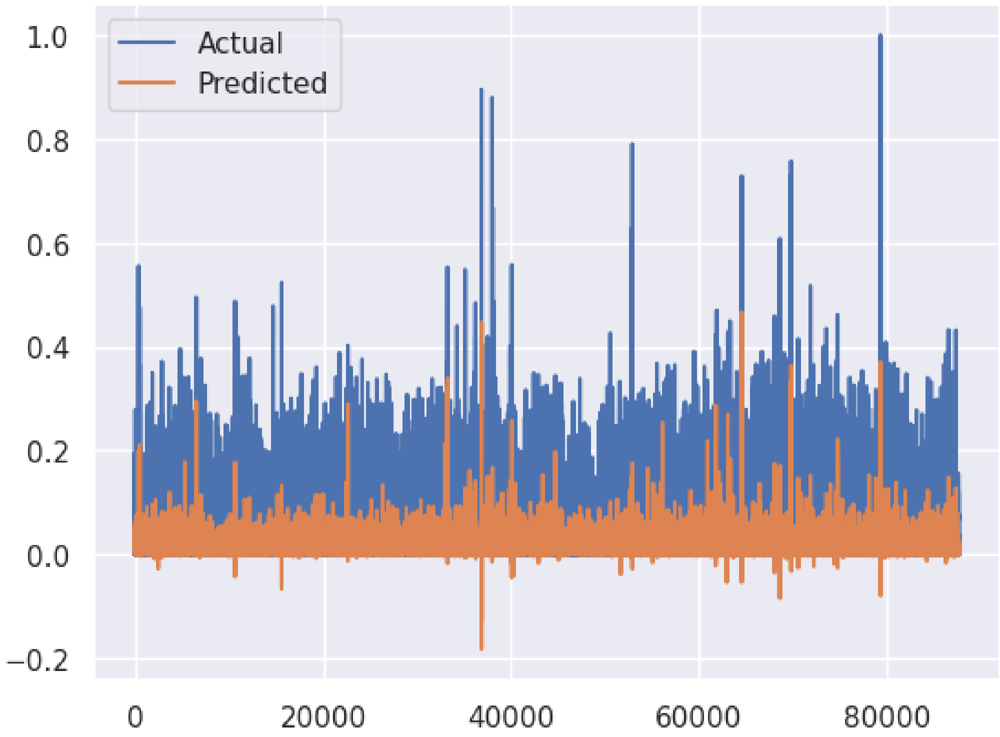

Fig.4.12 Actual and predicted values of precipitation in GRU model training and testing

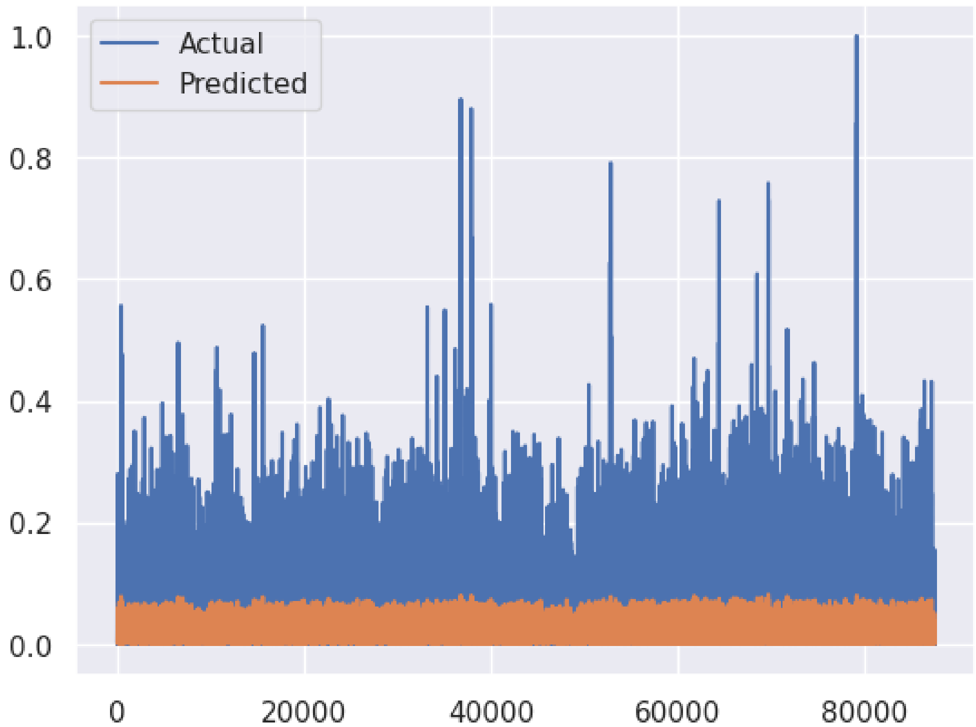

Fig.4.13 Actual and predicted values of precipitation in SimpleRNN model training and testing

4.3 Forecasting temperature, precipitation, and fog with the best model

The selected model (LSTM) with three layers of 125 neurons for the first two and one unit of a dense layer as an output layer were used. ReLu and Adam as an activation function and an optimizer has been applied separately. And also, a time step and a window size of five days were used for the prediction. Accordingly, the following results were obtained for each of the target variables.

4.3.1 Temperature

Predicting air temperature is an important research area because changes in air temperature can have a significant impact on our daily lives. Deep learning methods are well-suited for this type of forecasting, as they can learn complex patterns from data. Predicting atmospheric temperature at any given time and location has a wide range of applications, including energy production and aviation cargo. However, predicting air temperature using data-driven methods is challenging because it is part of a complex and chaotic weather system. Traditionally, this has been done using numerical weather prediction (NWP) models, which are based on physical equations. (Roy, 2020).

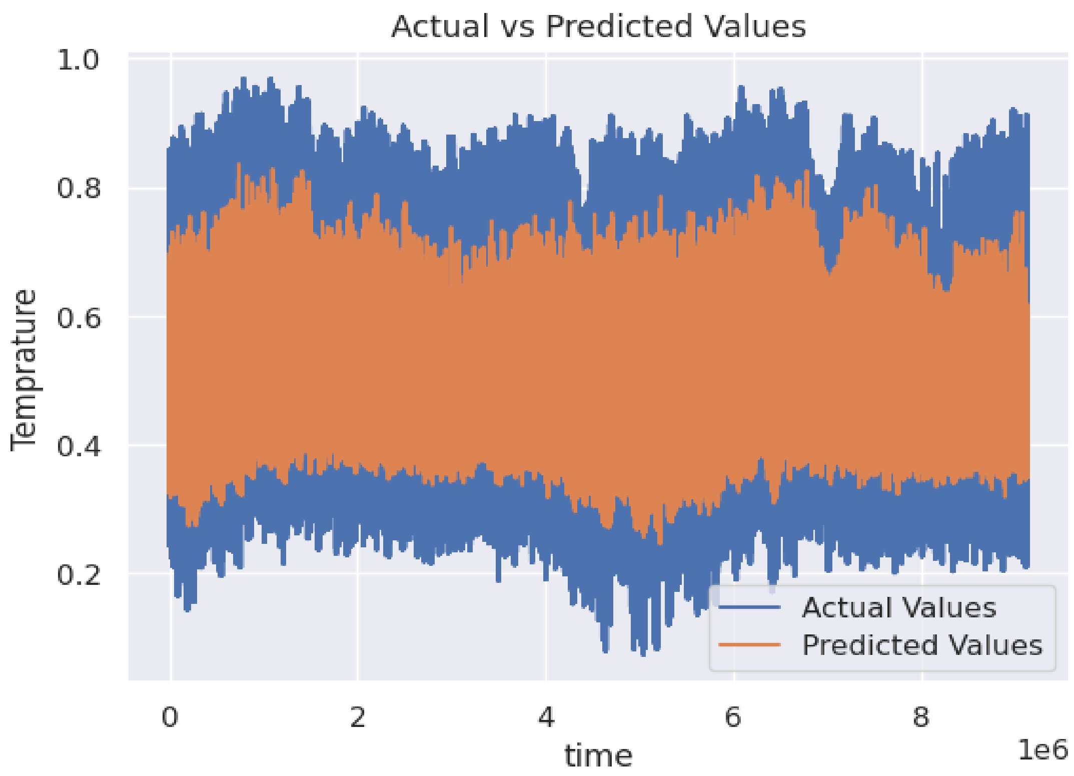

Fig.4.14A. Actual and predicted temperature value distribution

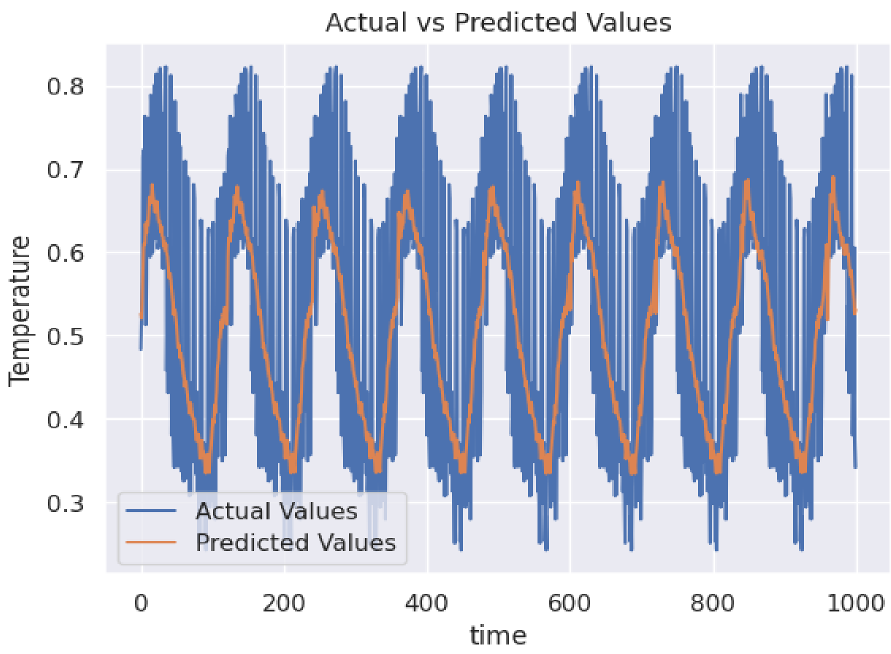

Fig.4.14 B Actual and predicted value distribution for specific sample points of testing data

The five most important features identified and used for the prediction as displayed below.

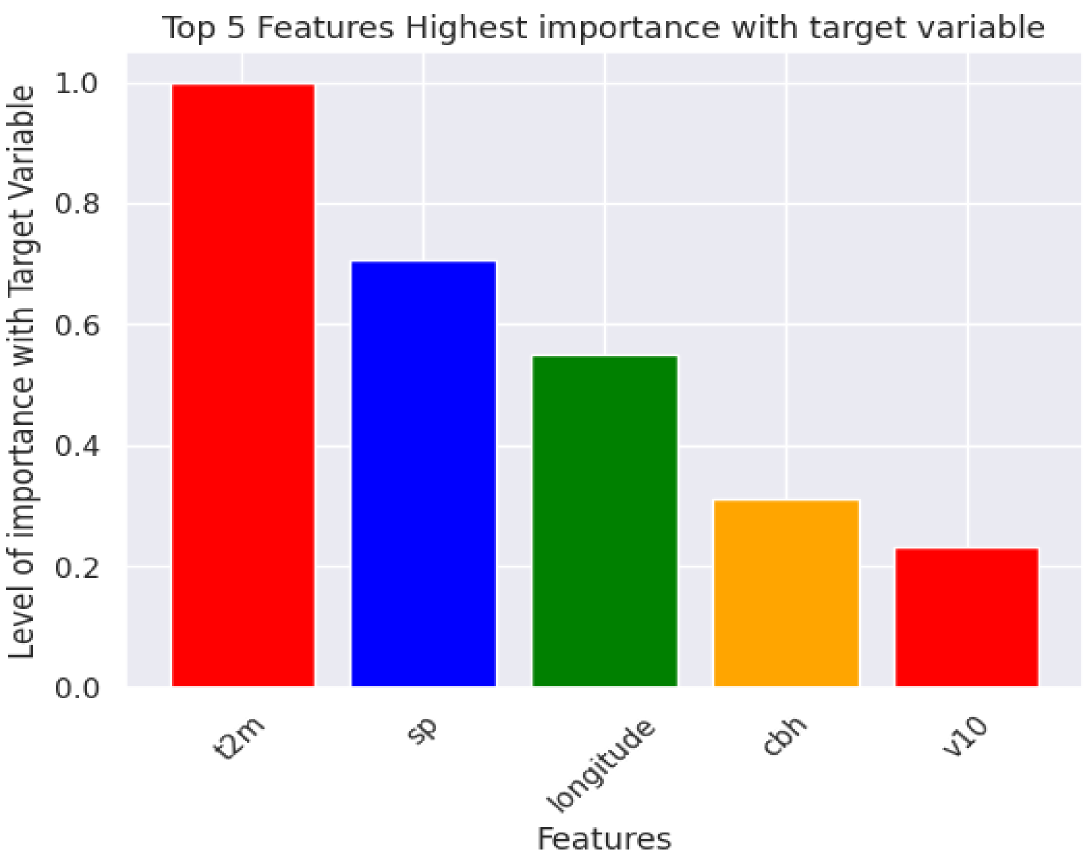

Fig.4.15. Most important features for the prediction of temperature

4.3.2 Precipitation

Rainfall is a variable that can change unpredictably in space and time, depending on the overall atmospheric circulation and local factors. (Kisi, & Sanikhani, 2015). Reliable precipitation forecast models are essential for a wide range of real-world applications, including aviation, agriculture, water resources management, and facility maintenance and control, such as airport management. Although numerical weather prediction models have made significant progress in recent years, they are still unable to provide quantitative precipitation forecasts with the spatial and temporal resolution required for some real-world applications (Ortiz-García, Salcedo-Sanz, & Casanova-Mateo, 2014).

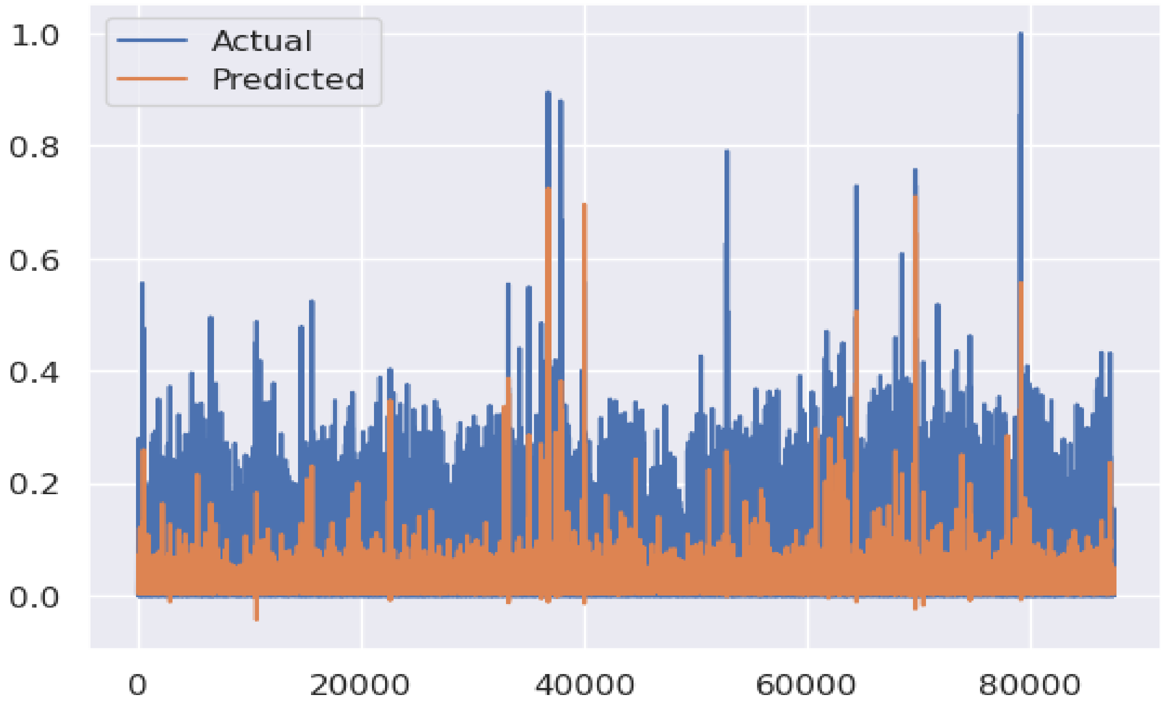

Fig 4.16A. Actual vs. predicted values for a training data set

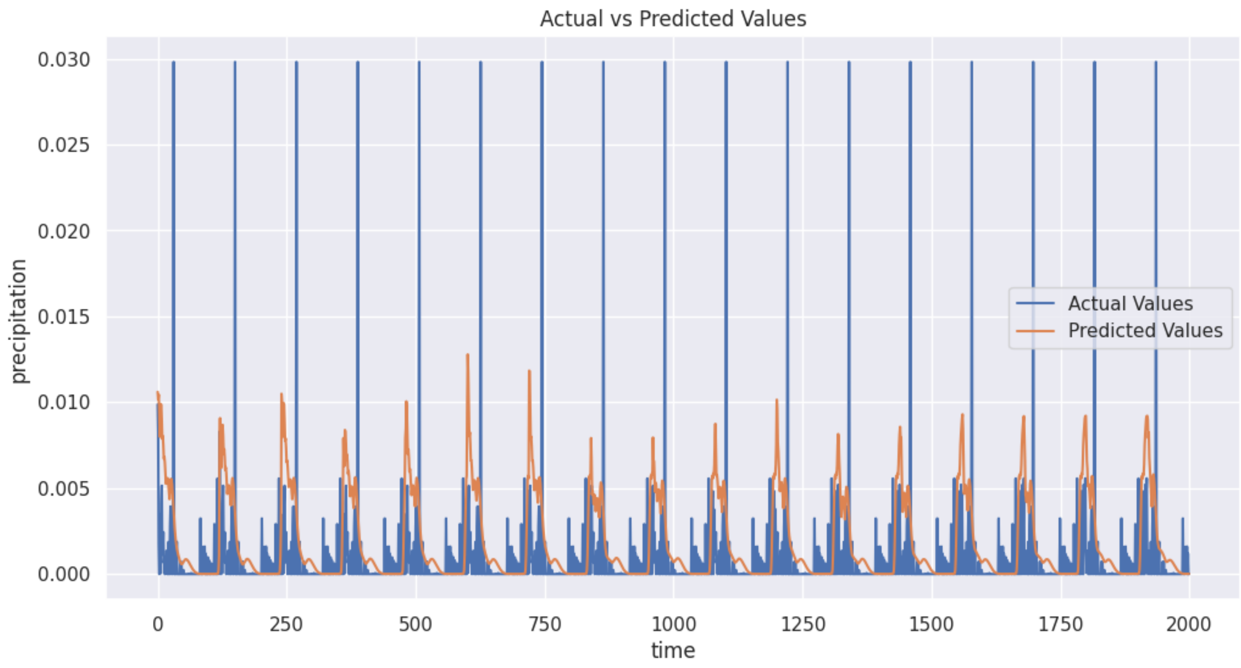

Fig.4.16 B. Actual and predicted precipitation value distribution for specific sample points of testing data

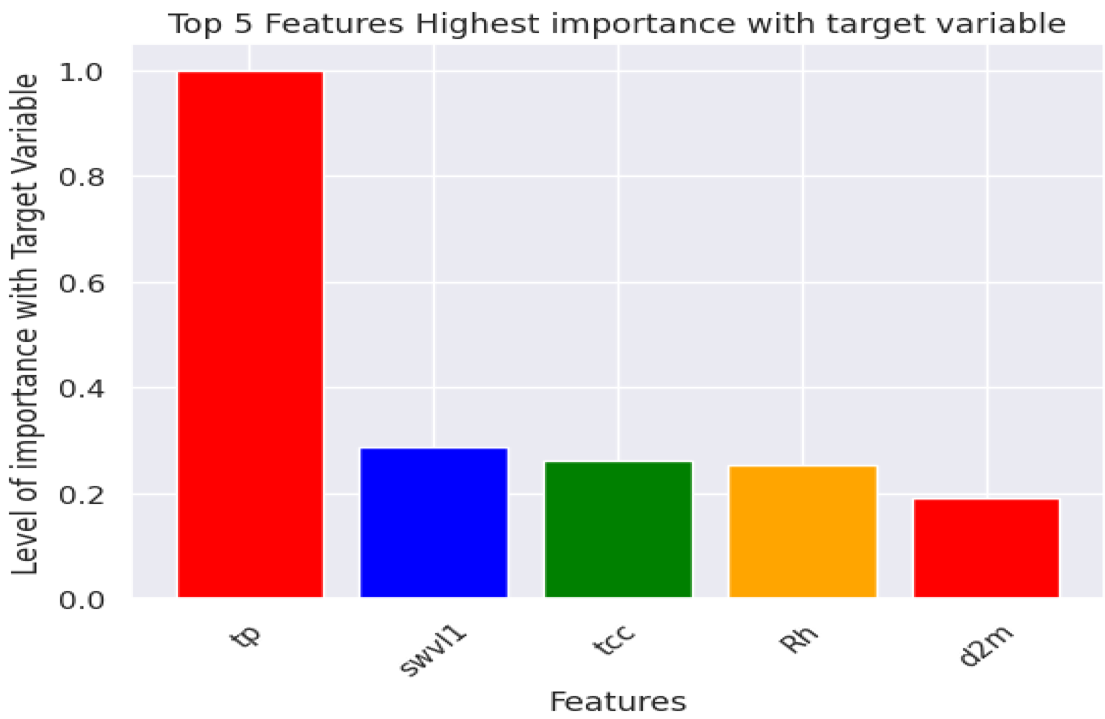

Fig.4.17 the most important features for the prediction of precipitation

As previously stated, after conducting experiments, the LSTM model was chosen for prediction of all target variables. Therefore, the model was constructed with three layers consisting of 125 neurons for the first, second layers, and a single dense layer for the output. Subsequently, the model's performance should be evaluated using metrics. The data was divided into training, testing, and validation sets with proportions of 70%, 20%, and 10%, respectively. Finally, the optimal model underwent further validation using the validation data.

```
Actual values for the last window size:
                tp
0    5.432962e-03
1    3.518030e-03
2    3.178813e-03
3    2.549596e-08
4    1.253731e-02
..            ...
115  3.824394e-08
116  5.745052e-04
117  2.549596e-08
118  2.248703e-03
119  2.549596e-08

[120 rows x 1 columns]

Predicted values for the last window size:
            tp
0    0.006772
1    0.006492
2    0.008997
3    0.009350
4    0.008936
..        ...
115  0.003747
116  0.004113
117  0.004230
118  0.004465
119  0.005205

[120 rows x 1 columns]
```

Fig.4.18 Actual and predicted values of precipitation for a period of 120 hours

4.3.2.1 Extended forecast covering 120 hours ahead

The main aim of this study was to predict specific aspects of the future with greater accuracy. The graph shown (Figure 4.19) illustrates this prediction extending beyond the available data. This graph goes beyond the limitations of the existing data, allowing us to peek into the unknown.

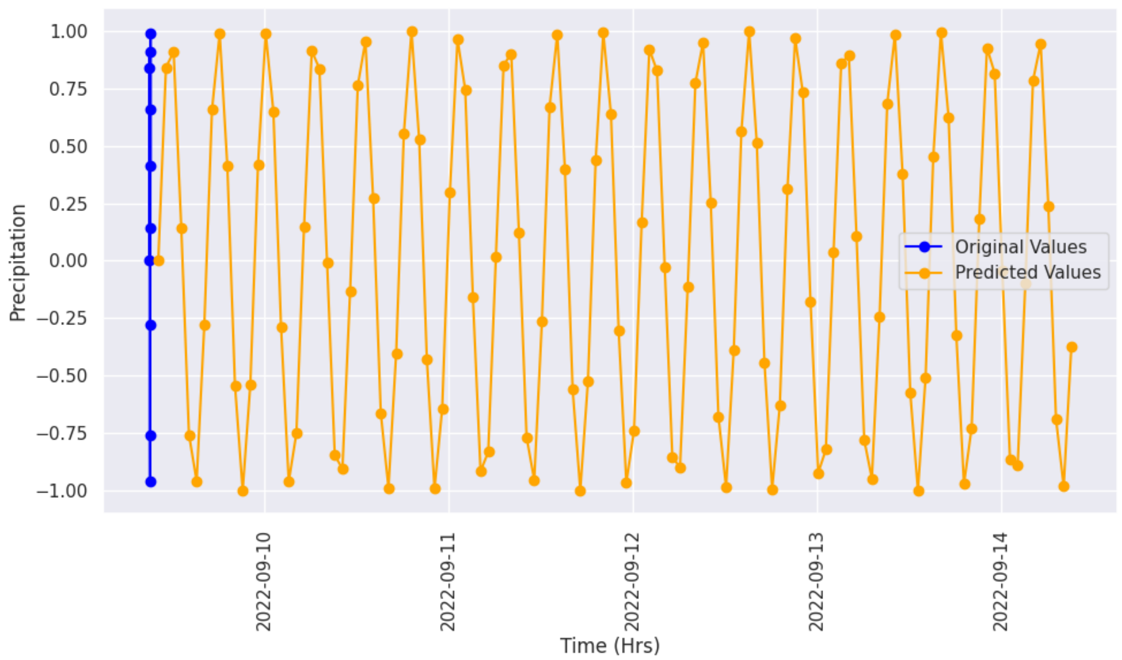

Fig.4.19 Extended precipitation forecast ahead of five days

4.3.3 Fog

Fog is a cloud of tiny water droplets that form close to the ground. It can reduce visibility to less than one kilometer, which can impact flight operations such as taxiing, take-off, and landing (Fabbian, De Dear & Lellyett, 2007) and (Miao et al., 2020). Reduced visibility resulting from fog impacts human society in numerous manners. Fog impacts transportation infrastructure such as highways, rapid transit systems, air travel hubs, and waterways. When combined with polluted air, fog can create mist that leads to various illnesses and even poses a threat to human life (Pariyar, Das, & Ferdous, 2013). The data was derived based on expertise and article references. From the data frame I have used for the above two variables (temperature and precipitation), I have set some criteria, and a new data frame was created. The best-chosen model (LSTM) and another recommended model for the classification task (RF) were used at the same time for comparisons.

4.3.3.1 LSTM

Using the LSTM model with two layers, the first layer with fifty units and the dense layer of one unit, an optimizer of adam, a batch size of 256 with the early stopping of 15, training data of 80%, and testing data of 20%, the following outputs delivered as:

Table 4.4 Metrics for test and prediction

Model	RMSE	MSE	MAE	Test Loss	Acc.
LSTM	0.051	0.002	0.005	0.002	0.997

The real and the predicted values for both the training and testing data sets are shown below (Fig.4.18, 4.19)

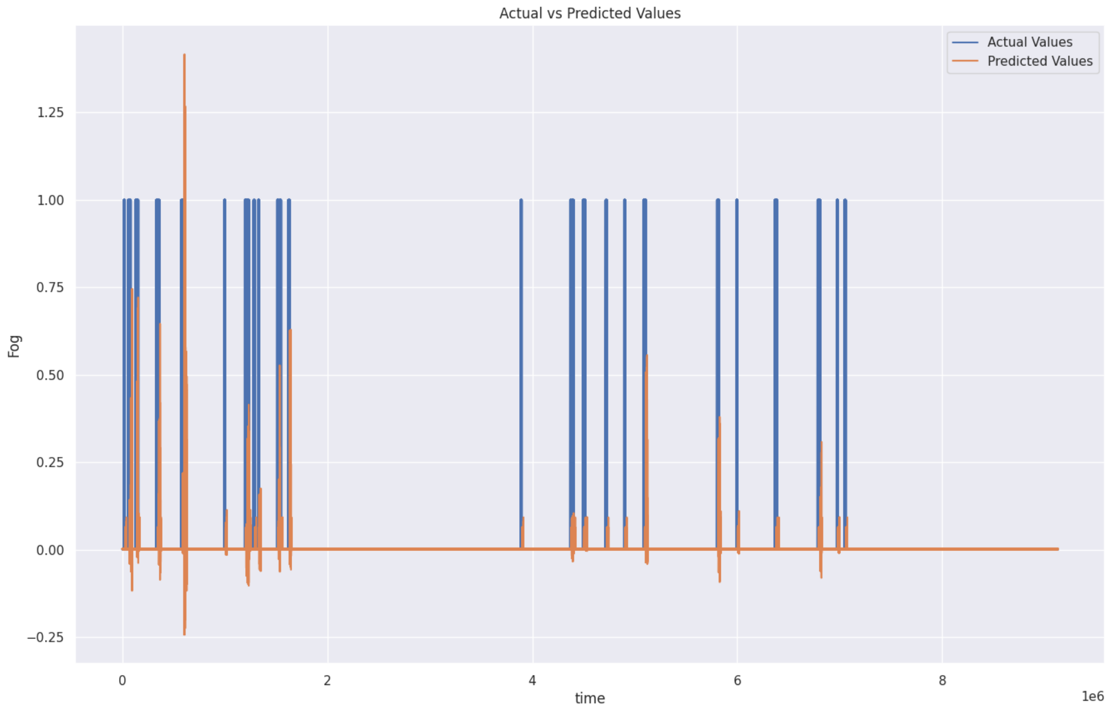

Fig.4.20 Actual vs. predicted fog for testing data

Table 4.5 Metrics for test data and prediction

Model	RMSE	MSE	MAE	Loss			Acc.	Comp time
				Test	Val	Train		
LSTM	0.043	0.001	0.004	0.001	0.001	0.002	0.998	5609.

Table 4.6 Actual and predicted values of Fog in LSTM model

	Time	actual class	predicted class
350592	2020-12-31 14:00:00	1.356998e+09	1
350593	2020-12-31 14:00:00	0.000000e+00	0
350594	2020-12-31 14:00:00	0.000000e+00	0
350595	2020-12-31 15:00:00	0.000000e+00	0
350596	2020-12-31 15:00:00	0.000000e+00	0
...	...	... ...	... ...
438235	2022-12-31 23:00:00	0.000000e+00	0
438236	2022-12-31 23:00:00	0.000000e+00	0
438237	2022-12-31 23:00:00	0.000000e+00	0
438238	2022-12-31 23:00:00	0.000000e+00	0
438239	2022-12-31 23:00:00	0.000000e+00	0

4.3.3.2 Random Forest

The following figure demonstrates the actual and predicted classes of the observed Fog in different spatial zones.

Actual vs. Predicted Fog for Specific Time

	time	Fog	Predicted_Fog
0	2013-01-01	0	Not Foggy
1	2013-01-01	0	Not Foggy
2	2013-01-01	0	Not Foggy
3	2013-01-01	0	Not Foggy
4	2013-01-01	0	Not Foggy
...	...	...	...
424560	2022-09-09	0	Not Foggy
424561	2022-09-09	0	Not Foggy
424562	2022-09-09	0	Not Foggy
424563	2022-09-09	0	Not Foggy
424564	2022-09-09	0	Not Foggy

Fig.4.21. Actual and predicted classes of Fog using Random Forest

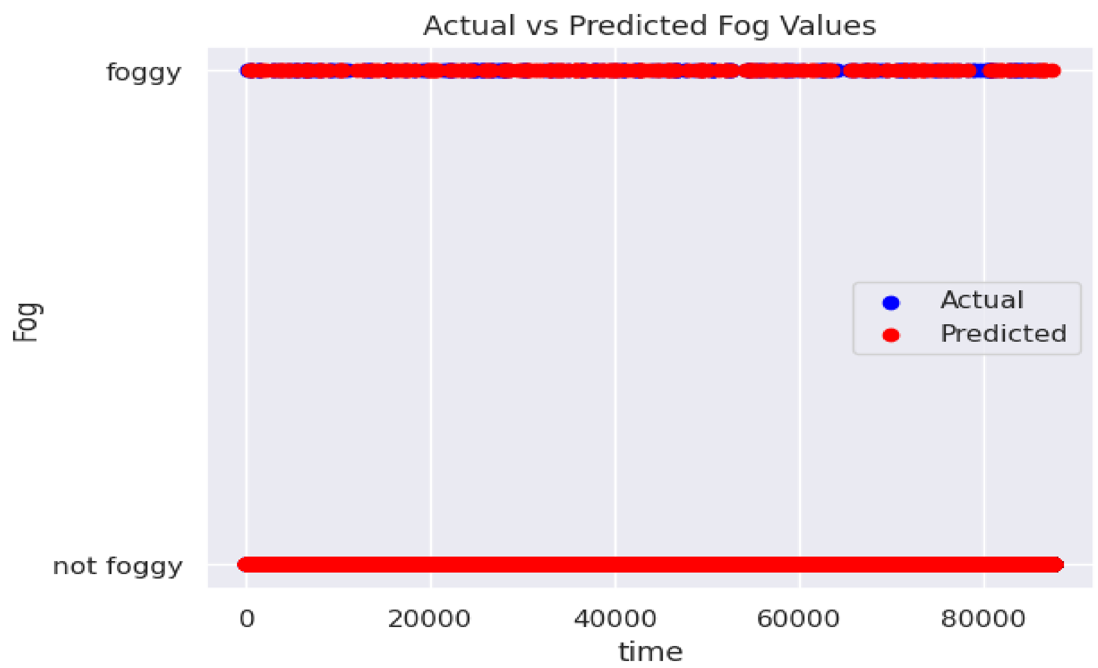

Fig.4. 22. Actual and predicted fog using Random Forest

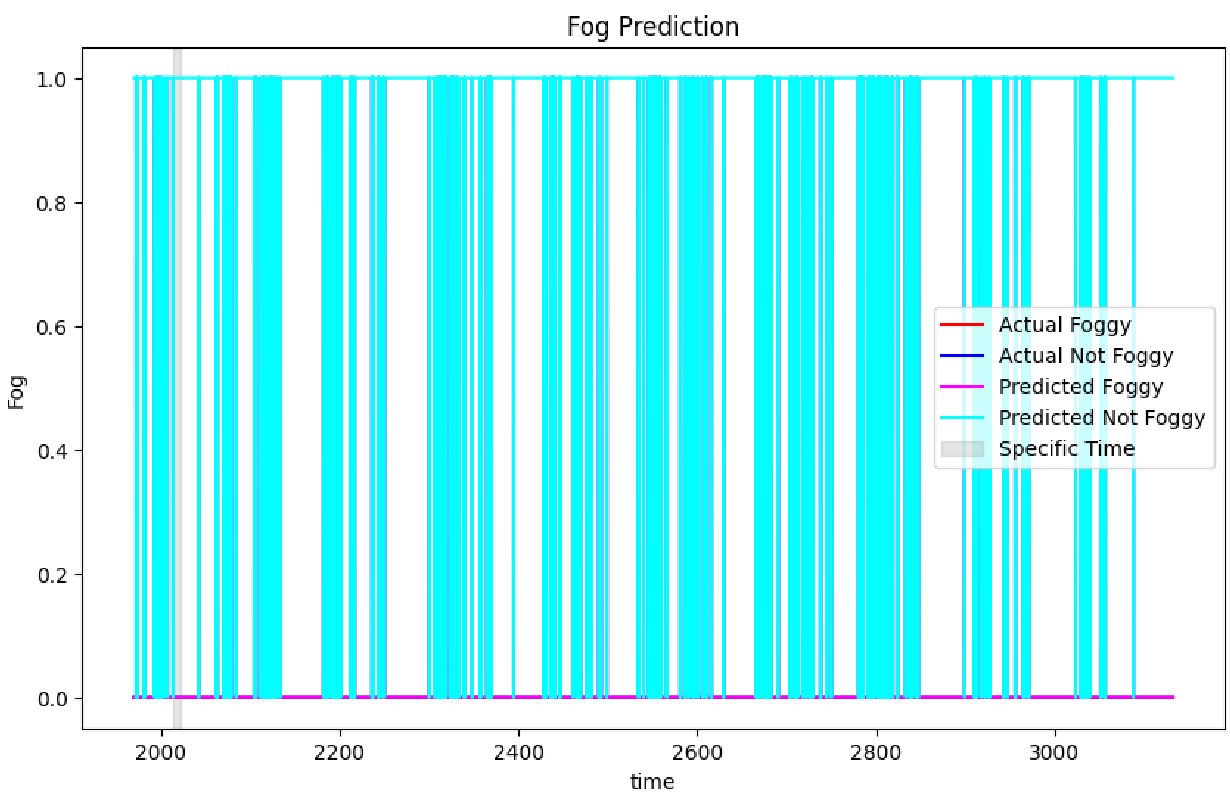

Fig.4. 23. Actual and predicted fog classes using Random Forest

4.3.3.3 Extended Fog forecast

The main thing that was wanted to show was that after the prediction model was well trained, I could predict the future without the data provided for training. Hence, the following graph shows that no foggy conditions will be observed for the next twenty-four hours

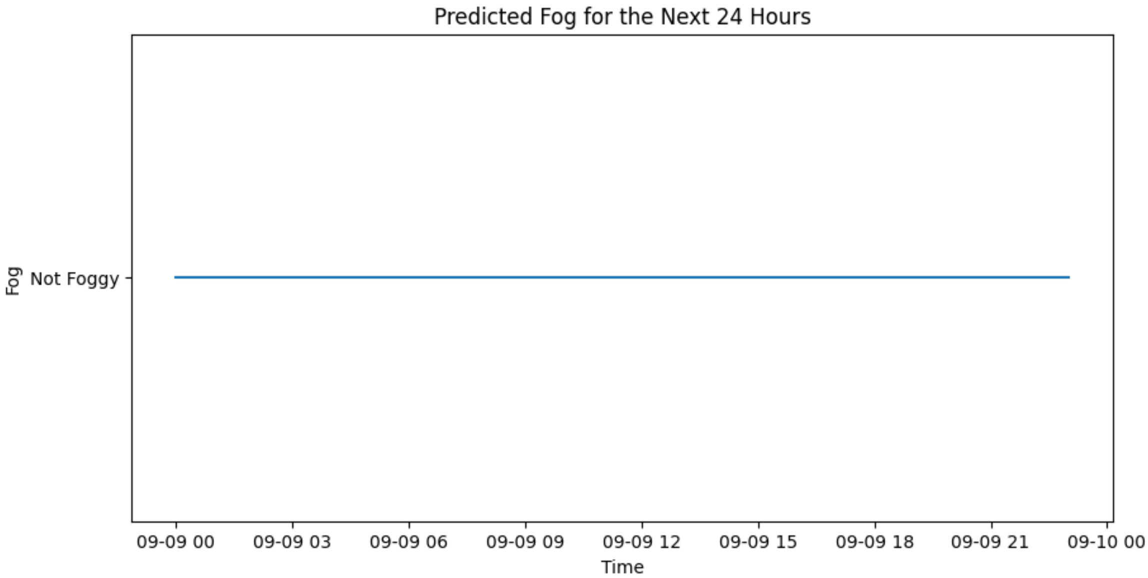

Fig.4.24 Extended Fog forecast ahead of 24 hours

4.3.4 Accuracy and performance evaluation

Accuracy: 0.9996234939759037 (model output)

Confusion Matrix:

[[87410   5]

[28   205]]

$$\frac{(87410 + 205)}{87410 + 205+5+28} = 0.9996234939 \text{ (calculated)}$$

4.4 Validation

4.4.1 Temperature validation

Table 4.7 Metrics for testing and Prediction

Model	RMSE	MSE	MAE	Loss			Comp time
				Test	Val	Train	
LSTM	0.133	0.017	0.110	0.017	0.018	0.016	6984

Table 4.8 Metrics for validation and prediction

Model	RMSE	MSE	MAE	Loss			Comp. time
				Test	Val	Train	
LSTM	0.136	0.018	0.111	0.017	0.018	0.016	6984

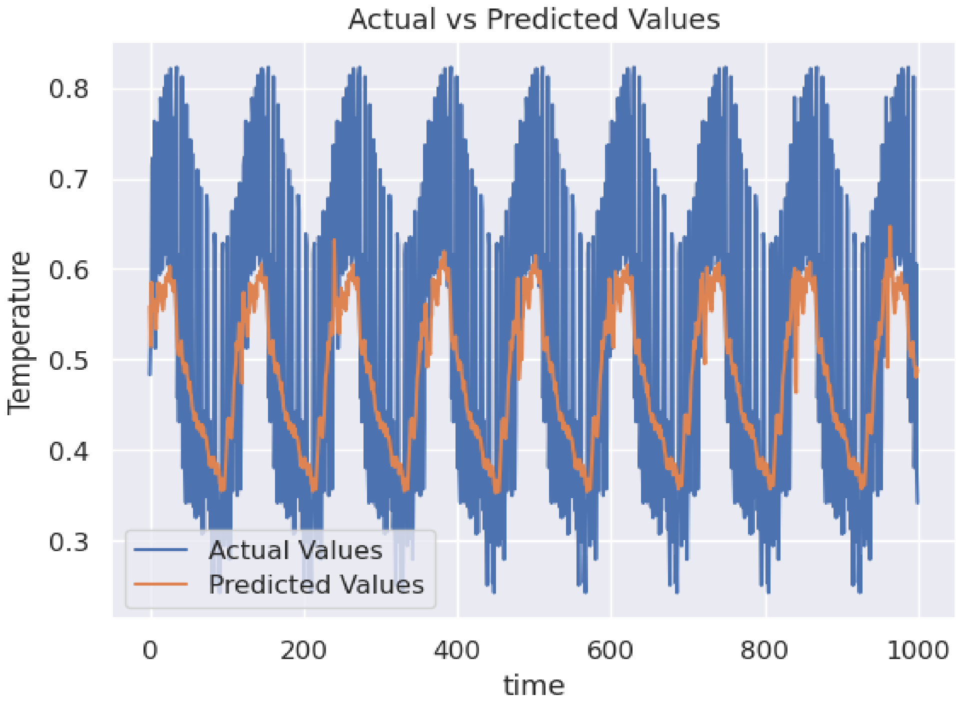

Fig.4.25 Actual and predicted value distribution for specific sample points of validation data

4.4.2 Precipitation validation

Table 4.9 Metrics for testing and prediction

Model	RMSE	MSE	MAE	Loss			Acc	Comp time
				Test	Val	Train		
LSTM	0.030	0.000	0.011	0.018	0.018	0.016	0.999	15607.

Table 4.10 Metrics for validation data and prediction

Model	RMSE	MSE	MAE	Loss			Acc	Comp time
				Test	Val	Train		
LSTM	0.023	0.000	0.008	0.000	0.000	0.000	0.999	15607.

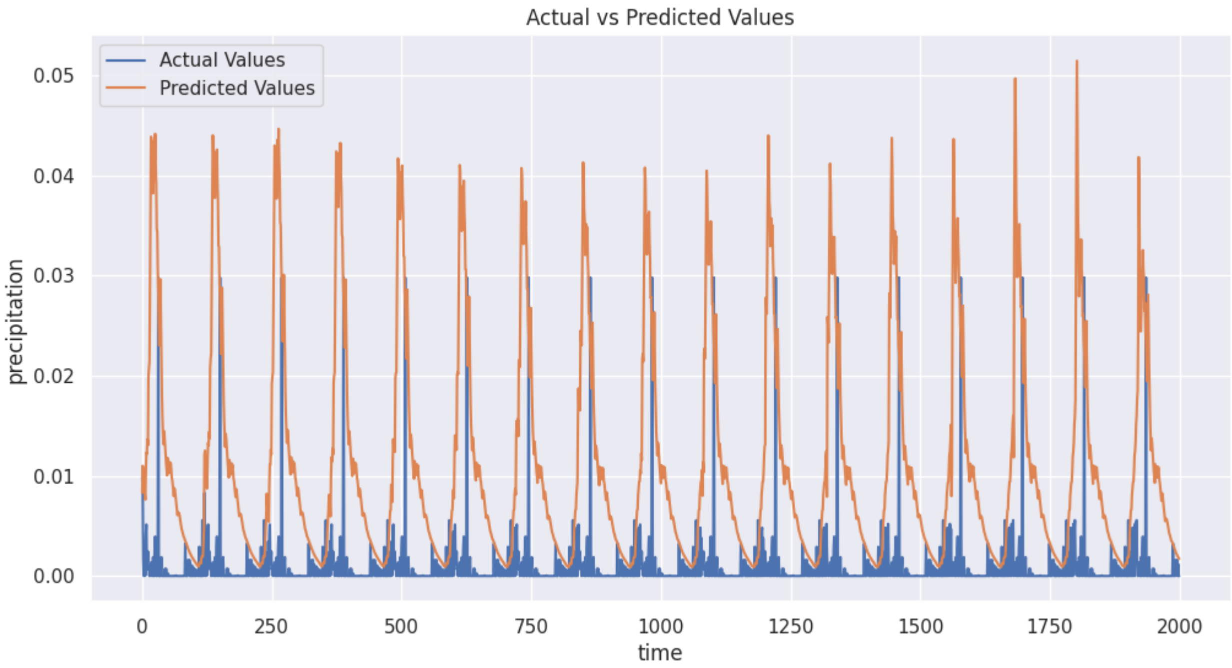

Fig.4.26 Actual and predicted value of precipitation for specific sample points of validation data

4.4.3 Fog validation

Table 4.11 Metrics for test data and prediction

Model	RMSE	MSE	MAE	Loss			Acc.	Comp time
				Test	Val	Train		
LSTM	0.043	0.001	0.004	0.001	0.001	0.002	0.998	5609

Table 4.12 Metrics for validation and prediction

Model	RMSE	MSE	MAE	Loss			Acc.	Comp. time
				Test	Val	Train		
LSTM	0.036	0.001	0.003	0.001	0.001	0.002	0.998	5609

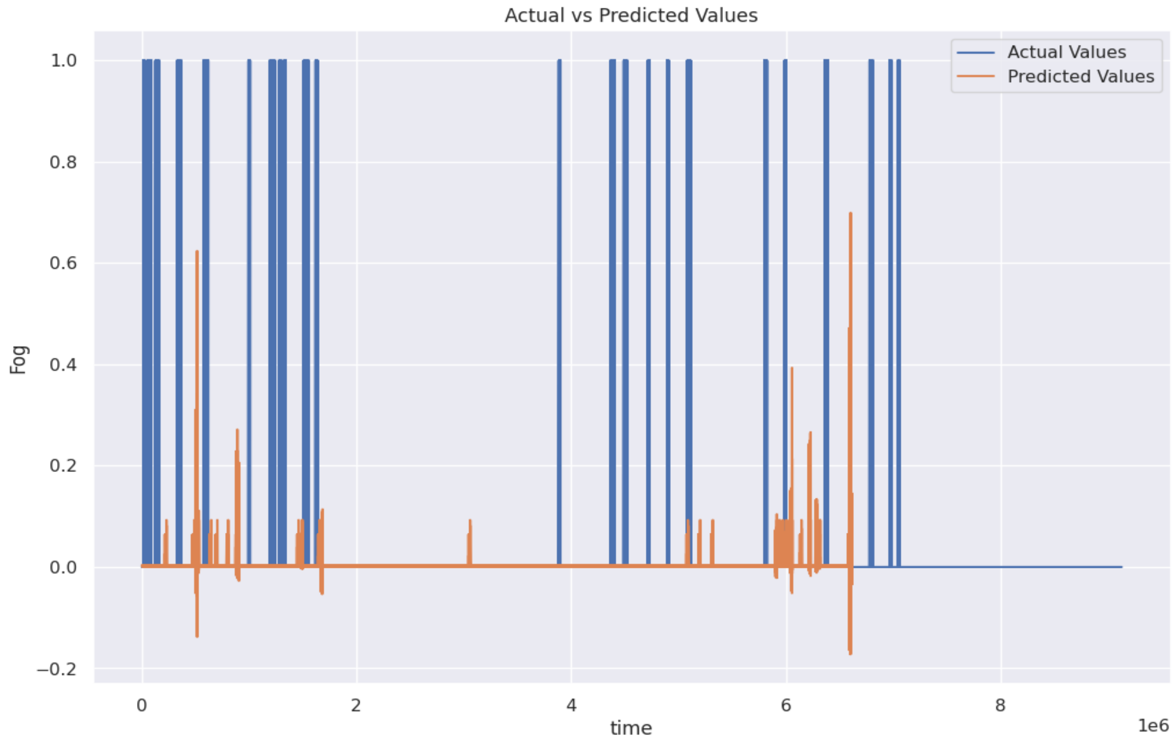

Fig.4.27 Actual and predicted fog levels for the validation data set in LSTM model

4.5 Demonstrating actual and predicted values using GIS

Actual and predicted values for precipitation

```
start_time = '2021-01-01 00:00:00'

end_time = '2021-01-05 00:00:00'
```

Th following maps well demonstrated the actual and predicted precipitation distribution across the country. It is the reflection of where and what happens and what will happen at present and in future conditions orderly. This helps to visualize and understand events spatially.

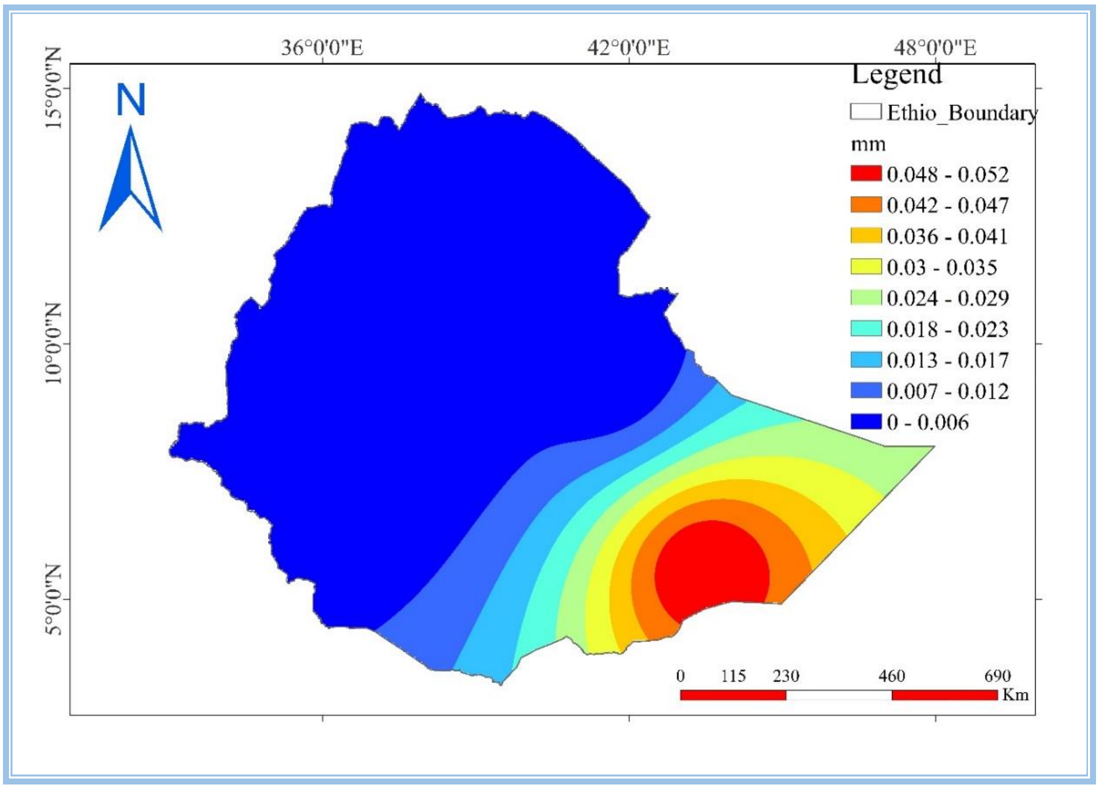

Fig.4.28 Map of Actual classes of precipitation

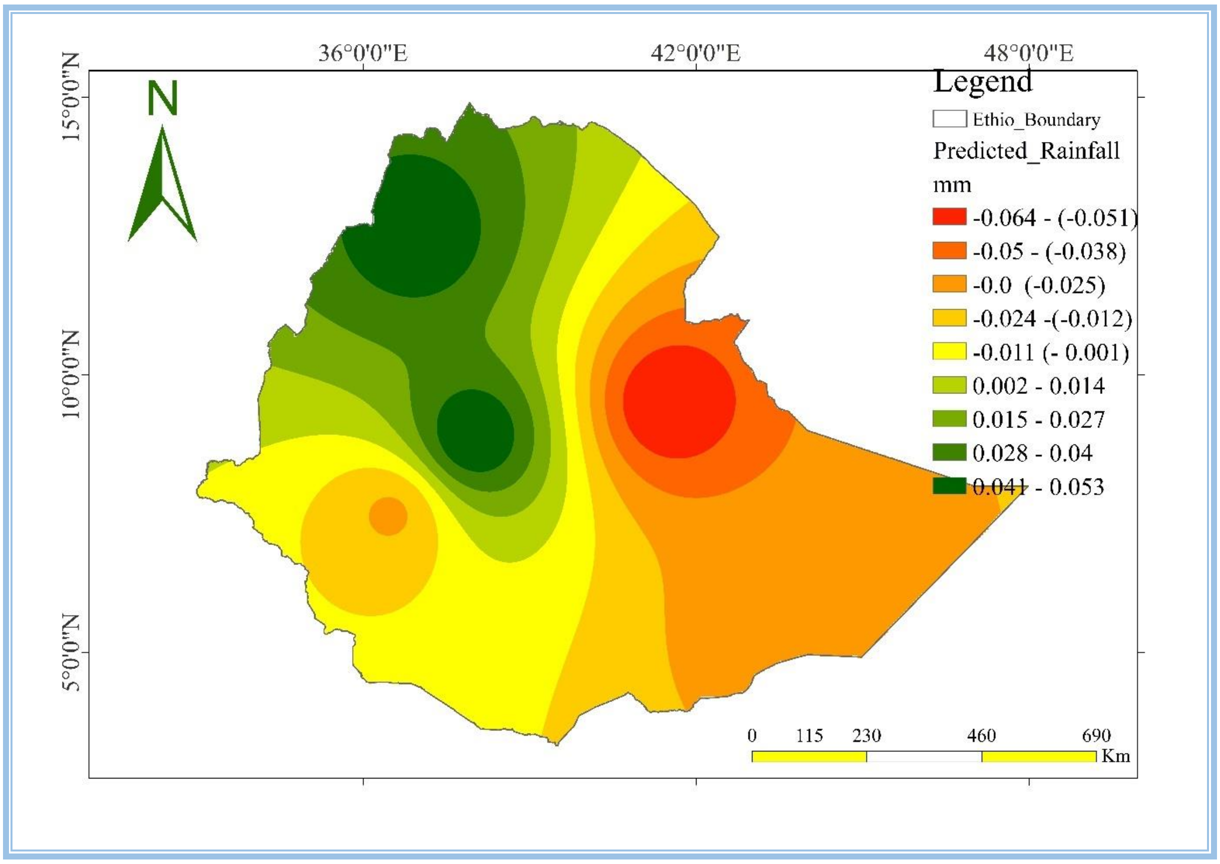

Fig.4.29 Map of predicted classes of precipitation

CHAPTER FIVE

5.1 Discussion

The analysis section of the paper started by identifying highly correlated variables using a heat map (Fig.4.1). Accordingly, variables that have a threshold greater or equal to 80% were segregated to avoid redundancy of contributions (Fig.4.2). Most important weather parameters displayed to demonstrate their timely trend either annually, daily or hourly basis to show how they are time series or sequential. This helps to consider models which are appropriate for such kind of scenarios. As we have observed on plots (Fig.4.3A – 4.6C), they all have shown a series manner and proved well. The scaled data which lies between 0 and 1 demonstrated to show its spatial distribution in correspond with precipitation and temperature values respectively (Fig.4.8 and 4.7). Selecting the best model was a big issue and needed to experiment duly. This has been done with different hyperparameter configurations in different experimentations. In the first experiment (Table 4.1), two layers having 125 units in the first, and 1-unit dense layer in the output with an activation function tanh and an optimizer of RMSprop experimented. Hence, LSTM, BiLSTM, GRU, and Simple RNN have got smaller values of error metrics (RMSE, MSE, MAE) in order of the list. In the second experiment (Table 4.2), three layers having 125 units in the first and second, 1 unit of the dense layer in the output together with a similar activation function and optimizer of the previous experiment. Thereupon, LSTM, BiLSTM, GRU, and Simple RNN have got smaller error metrics and losses. The last experiment (Table 4.3) was done using two layers, 125 neurons in the first layer and 1 dense layer in the last. The activation function and optimizer were seated as relu and adam respectively which yields nearly similar results to former experiments. But Bi LSTM in some trials gives a promising and best result than all the rest. Since the computational time is greater than LSTM and GRU, it was difficult to come up with a clear difference because of interruptions while processing. It was found to be processed without any disconnections in order to exactly know the outputs they resulted. Obviously, the results I have got for all models are approximately equal and we can use one of the three ordered models for the time series prediction.

The actual and predicted values of variables using each of the above models presented in the figures (Fig.4.10 –13). As we have seen from the plots, precipitation prediction using LSTM, BiLSTM, GRU, and Simple RNN is demonstrated well. Consequently, LSTM seems more illustrative but others are also not bad. All my dependent variables were predicted using the preferred model. Fittingly, the temperature predictions using the designated model are illustrated in (Fig 4.14A – 14. C) For the training data and some specific values apiece. In addition to prediction, one of the research goals was to identify the most critical variables that significantly impact the target. Thus, temperature, surface pressure, longitude, cloud height, and wind were the top five important variables (Fig.4.15). Likewise, precipitation was predicted using LSTM, and actual and predicted values were manifested using plots for both testing, some specific values (Fig.4.16A – 4.16C) respectively. The most important features for the prediction of precipitation were identified. Subsequently, precipitation, volumetric soil water layer 1, cloud cover, relative humidity, and dew point in their order of importance (Fig.4.17).

For the experiments I conducted, the data set was split into training and testing sets with a proportion of 80% and 20%, respectively. But it was important to see the validation of the selected model for a ratio of 10% data. The error measuring metrics like root mean squared, mean squared, and mean absolute errors were used for the outcome evaluation. Consequently, the validation of the model and correlative metrics were (Table 4.4, 4.5) 0.136, 0.018, and 0.111 for RMSE, MSE, and MAE respectively. The loss values in accordance with the provided training, testing, and validation order have been 0.0185, 0.017, and 0.0186 separately. These very less results in both blueprints insured that the model performed well. Identically, for the prediction of precipitation (Table 4.8, 4.9) error metrics for validation data arose as 0.023, 0.0005, and 0.008 for RMSE, MSE, and MAE specifically. The losses for training, testing, and, validation were 0.000940, 0.000944, and 0.00054 respectively. These are pieces of evidence to show how it performed optimally for the validation data as well. The third most decisive and challenging weather phenomena were fog. For the prediction of the target variable, an appointed deep learning model (LSTM) and the most known machine learning classifier, random forest were used. The actual and the predicted values offered for both training and validation data (Fig.4.19 and 4.24). The actual and predicted value of precipitation and fog presented (Fig.4.18 and Table 4.6) confirmed that both the actual and predicted (5.432962e-03 = 0.005432962,0.006772) of the first rows indicated nearly equal precipitation values lined each other and the model performed well. In the case of random forest classifier (Fig.4.21,4.22,4.23) the predicted classes presented as “foggy” and ‘not foggy”. Almost all of the predicted and actual values visualized as “not foggy” since the fog phenomena is a rare occasion. Hence, it is forecasted satisfactory.

More or less without any observed data, having such kind of promising results was found to be rewarding. The classified values (actual and predicted) for random forests were shown in (Fig.4.21) either ‘foggy’ or ‘not foggy’ for the next 24 hours with a window size of 12 hours. This delivered an accuracy of 99.96% which was inspiring. The confusion matrix was used as a way of model evaluation. Consequently, a 2x2 confusion matrix represents the performance of a classification model. Here's how to interpret it. True Negative (TN): The model correctly predicted 87410 instances as "not foggy”. False Positive (FP). The model incorrectly predicted 5 instances as "foggy" when they were actually "not foggy”. False Negative (FN): The model incorrectly predicted 28 instances as "not foggy" when they were actually "foggy”. True Positive (TP): The model correctly predicted 205 instances as "foggy”. In this case, the model has a high number of true negatives and true positives, indicating good performance. However, there are a few false positives and false negatives, suggesting some misclassifications. Overall, the model seems to perform well, but further analysis may be needed to understand the reasons behind the misclassifications.

For the prediction of fog using an LSTM model like the antecedent predictions, error metrics, and loss values are also presented as follows. This was done for both testing and validation data (Table.4.11– 4.12). Hence, the metrics for testing data were 0.043, 0.0019, and 0.0041 in respect order of RMSE, MSE, and MAE. Again, the metrics for validation data and corresponding forecast were 0.036, 0.0013, and 0.0034. The loss values respective of training, testing, and validation were found as 0.0028, 0.0019, and 0.0013. In all circumstances of evaluation of model accuracy, satisfactory and uplifting outputs were obtained. My research seems different from previously conducted studies in Ethiopia in the area of artificial intelligence for weather forecasting especially, prediction of fog is the first in Ethiopia even for using observed data is not available. perhaps as well, the globally prediction of fog by using derived data techniques which were scientific and expertise judgments in addition of article references. The validation for all dependent variables i.e., temperature **(Fig.4.22),** precipitation **(Fig.4.23),** and fog **(Fig.4.24)** insured that the model predicted well even for the validation data likewise.

Research which was conducted in 2022 for the prediction of daily rainfall in Jimma considered five parameters as input including maximum temperature, minimum temperature, relative humidity, solar radiation, wind speed, and precipitation. Most of the parameters which have been used are directly related. The challenge in weather prediction is exponential relationship. The linearity can be addressed by statistical techniques. And also, the study doesn't contemplate global scenarios that can affect the weather conditions of the area (Endalie, Haile, & Taye, 2022).

Another study was conducted to forecast and model risky weather and flood for upper Blue Nile of the eastern Tana sub-basin, Ethiopia. In this study, the outputs from the WRF model temperature and precipitation are used for the SWAT model input to forecast the flood. The inputs for the WRF model prediction were wind speed at two meters, air temperature, solar radiation, precipitation, relative humidity, geopotential height, and sea surface temperature. The weather components have been forecasted at a six-hour time step and changed to daily for SWAT model input. The ascribe didn't include thunderstorm potential based on the vertical temperature lapse rate, and the amount and vertical extent of low-level moisture in the atmosphere, since we can't see extreme weather events in isolation from the occurrence of a thunderstorm. Cloud as well a more important parameter for extreme weather prediction. A six-hour time step may not be enough to capture the causal effects. If failed to include these parameters, the built flood forecast model will be faced accuracy issues.

Furthermore, the WRF model is a numerical weather prediction model that uses a physical model of the atmosphere to predict the weather. Perhaps, due to the continuous change of the atmosphere (climate change), the physical processes or principles that govern the weather may alter and it might be failed to extract relations. In addition, WRF takes more computation time and deep learning models are faster (Desalegn, Demissie, & Admassu, 2016). In consideration of fundamental atmospheric parameters, global scenarios and an hourly based forecast made my study more relevant and unique. Additional research was carried out in 2021 to predict daily rainfall using machine learning techniques. The data used for this study was collected from a single station (Bahirdar city) and the data points were a year, month, date, sunshine, maximum temperature, minimum temperature, humidity, wind speed, and evaporation. According to the authors, variables in which their correlation coefficient is greater than 0.2 were selected based on Pearson. Accordingly, evaporation, relative humidity, sunshine, maximum daily temperature, and minimum daily temperature selected. First, Pearson correlation is a statistical measure that assesses the strength of the linear relationship between two variables. Hence, doesn't consider nonlinear relations. Second, rainfall is a time series weather phenomenon, which requires observational time for its prediction. Keep in mind the preferred parameters are very small, and wind speed, dew point, and any other relevant parameters were not included. Here, we can say even though this study aimed to predict daily rainfall, what it really did was comparing the performance of machine learning algorisms (RF, MLR, and XGBoost). Astonishingly, the authors blamed how most researchers did not show the prediction of the daily rainfall amount rather predicting whether it will rain or not. But nothing is different with this even whether it will rain or not rain likewise (Liyew, & Melese, 2021).

The findings obtained have been strongly supported by numerous publications. Deep learning models of BiLSTM and LSTM were used for temperature prediction and results RMSE of 0.6407 and 0.6723 respectively (Dewi, Prawito, & Harsa, 2020). In my own case LSTM value for the validation data of temperature prediction were 0.1339 which has a difference of 0.5 and hence it performs good. Machine learning techniques like support vector machine, ANN, and RNN were used and their RMSE was 1.64, 1.53, and 1.41 respectively (Singh, Kaushik, Gupta, & Malviya, 2019). Deep learning models EMD LSTM, LSTM and CNN compared and have got RMSE of 0.1216, 0.1527 and 0.2885 respectively. The results shows that neural networks performed better than machine learning techniques (Chen, Liu, & Jiang, 2022). Hourly temperature forecast using statistical and deep learning models of BiLSTM, ARIMA, and Exponential smoothing with RMSE of 0.4928, 0.5759, and 0.6487 (Liang, Wu, & Wang, 2021). Temperature forecast using deep neural networks of Simple RNN, GRU, LSTM, and GRU-LSTM parallel network with RMSE of 1.872, 1.775, 1.796, and 1.691 respectively (Haque, Tabassum, & Hossain, 2021). Hence, neural networks outperform machine learning and statistical models focusing and comparing among they were felicitous.

5.2 Limitations of the Study

The practice of artificial intelligence (AI) for weather prediction is a promising area of research, but it is also challenging. AI models require more resources and facilities to achieve satisfactory results. They are also computationally expensive to train and run, and they can take a long time to produce a forecast. The accuracy of AI models is also reliant on the quality and accessibility of data. The surface observed data that accessed was not in a suitable format, and it was also incomplete. In general, the availability of data, high-performance computing machines, internet access, and a suitable working environment are all important factors that can influence the accuracy of AI operations.

CHAPTER SIX

6.1 Conclusion and Recommendation

6.2 Conclusion

In this study, four deep learning models, namely LSTM, BiLSTM, GRU, and Simple RNN have been compared and the best model selected based on the error metrics and losses during training, testing, and validation. I also used machine learning techniques for data preprocessing and filling missing values. More important variables used to come up with the relevant ones in the procedure. This enabled me to identify the most vital relationships between the variables that I was interested in, and to make predictions that are relevant to a wide range of activities in Ethiopia, such as agriculture, aviation, water resource management, leisure, and business hours. I also took into account global factors that can affect Ethiopian weather, such as sea surface temperature. I found that the deep learning model (LSTM) outperformed the statistical model, which is commonly used for weather forecasting. A time step of five days and a horizon of the same length produced satisfactory results for both target variables, even for fog prediction.

To ensure reliable results, analyzing and mapping appropriate sampling points that represent the region well using long-term average climatic data were found to be substantial. The error metrics and losses for both training, testing, and validation were the most significant measures of model performance. The smallest loss values indicates that the model was able to predict the correct output for data that it has not seen before. This showed that the model was built satisfactorily and can predict accurately. The overall accuracy of the LSTM and other compared models resulted best performance for the prediction. Eventually, deep learning models have shown great promise in weather prediction, particularly for short-range forecasts. This is significantly better than the accuracy of traditional numerical weather prediction models, which typically have an accuracy of around eighty to ninety percent. The improved accuracy of deep learning models is due to their ability to learn long-term dependencies in the data. This is important for weather prediction, as the atmosphere is a complex system with many interacting components. Artificial intelligence able to capture these interactions and make more accurate predictions than existed ones.

6.3 Recommendation

The proposed study found that artificial intelligence, especially deep learning models, can be used for a short-range weather prediction with improved accuracy. These models have been shown to outperform statistical models, which are commonly used for weather forecasting tasks. The findings of the entire experiment confirmed that deep learning algorithms were significantly more accurate than traditional numerical weather prediction models, as reported in various publications and in my own experiment. Deep learning models can learn long-term patterns in data, which is essential for weather prediction. The atmosphere is a dynamic system with many interconnected parts, and these models can capture these relationships to make more accurate forecasts.

The LSTM model has been demonstrated to be effective in predicting both rainfall and temperature. It can also be used to predict fog, which is a critical consideration for transportation and other activities. Using appropriate and efficient mechanisms to have accurate forecasts lead to better decision-making by stakeholders, such as aviators, farmers, water management, flood warnings, businesses, and government agencies, and increased preparedness which would allow stakeholders to be better prepared for weather events. This would help to reduce the impact of these events on people and property and improve economic development by providing appropriate information. Confidentially, this constructed LSTM model would be a beneficial tool for weather forecasting in the short term with a better performance and can be used for seasonal weather events with some adjustments. More precise forecasts provide a number of specific advantages, such as, enhanced readiness, and improved economic development by providing appropriate decision-making for most sectors. Restricted resources, time, expertise, and suitable working conditions are constraints to achieve the desired outcome. Based on the results obtained; it is possible to recommend that the model can be used for a short-range weather forecasting with better accuracy than usual.

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Appendices

Appendix I

The model experimented with three layers to check what if for validation data as follows. The first two layers with 125 neurons and the output layer with one neuron, adam and tanh as an optimizing and activation functions.

Table 1 Experiment of validation data for different hyper parametrization

Model	RMSE	MSE	MAE	Loss			Acc.	Comp time
				Test	Val	Train		
LSTM	0.13456809435679573	0.018108572018881948	0.11107263491105998	0.018108565360307693	0.01875683292746544	0.016878489404916763	0.7193714949176305	4316.621766090393

Two layers having 125 units in the first and 1 unit of an output layer, activation function of tanh, optimizer of RMSprop and an epoch of ten.

Table 2 Metrics for validation data and prediction

Model	RMSE	MSE	MAE	Loss			Acc	Comp time
				Test	Val	Train		
LSTM	0.13695562502010977	0.018756843224648916	0.11194423195681227	0.018108565360307693	0.01875683292746544	0.016878489404916763	0.72696730722744595	4316.621766090393

Appendix II

Statistical Model

ARIMA

```
RMSE: 0.03225426882773921
MAE: 0.01449396880617605
MSE: 0.0010403378576120696
                    Time  Latitude  Longitude        Actual
6    2013-01-01 01:00:00  1.000000   0.071429  2.549596e-08
13   2013-01-01 02:00:00  0.275362   0.000000  8.592389e-05
21   2013-01-01 04:00:00  0.478261   0.214286  2.549596e-08
23   2013-01-01 04:00:00  0.000000   1.000000  2.549596e-08
28   2013-01-01 05:00:00  0.275362   0.000000  5.526203e-04
...                  ...       ...        ...           ...
```

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