



Weather Prediction: Predicting Rain Using Weather Conditions

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Abstract

Weather forecasting is a major discipline that plays an important role in fields such as agriculture, transport, and emergency management, and it largely depends on accurate forecasts. Concerning this problem, this work aimed to analyze the effectiveness of recurrent neural networks, particularly the Long Short-Term Memory (LSTM), for estimating rainfall depending on precipitation, maximum temperature, minimum temperature, and wind speed. We will therefore use a large database containing recorded weather data obtained over several years to calibrate accurate predictive models designed to distinguish between drizzle, rain, sun, snow, and fog. The main idea of the work is to teach LSTM models that are capable of revealing temporal relations and patterns in sequential data, which makes them suitable to work on various time series forecasting such as weather prediction. The data is preprocessed effectively to clean it and make it ideal for our analysis to accurately compare the performance of one model against the others, we have divided the data into training, validation, and testing sets. The concurrency of the proposed LSTM model is then evaluated with the Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and the coefficient of determination (R^2) to measure the forecasting accuracy.

The findings show a better predictive performance uplift whereby the best-performing LSTM model has an MSE of 8.74, RMSE of 2.96, MAE of 2.35, and R^2 of 0.83. Such metrics represent logical dependence between the predicted and actual weather conditions, proving thus the efficiency of the model. Also, the evaluation shows how hyper parameters' optimization, features' selection, and normalization, make a huge difference in the model's performance and indicate that the precise management of weather parameters can result in better forecasts. However, the contributors of this research are not recluded to theoretical perspective; the present study can be useful for various subjects since the dependability of weather forecasts can be improved. They will be advantaged to have more precise weather data for crop growing, road networks, and other transport systems to prepare for the worst conditions, and emergency, rescue operations to be in a better position to handle certain disasters.

Consequently, this study improves the academic literature on weather peculiarities with unforeseen downpours through a demonstration and explanation of the potential of LSTM networks to analyze key meteorological characteristics for rainfall prediction. Possible future study directions are outlined, proposing the expansion of features beyond those analyzed in the existing study to improve the predictive models, the usage of continuous rather than weekly data, as well as considering the mixed-ingredients approach for increasing the prediction accuracy. This inclusive strategy seeks to enhance the realistic stages in the phased meteorological prognosis and also timely resource allocation and management tactics within climate volatility.

Keywords: Weather Prediction; rainfall; LSTM; machine learning; meteorological variables; time-series forecasting

1. Introduction

It can also be seen that the science of Weather forecasts for many fields of modern life: agriculture, transport, management of natural disasters, and others. Weather forecasts thus help users to make the right decisions on matters of operations, thus enhancing efficiency and cost-cutting. By now, weather forecasts are a necessity in activity planning owing to unstable weather conditions as a result of global warming. Organic models of prediction,

which weather forecasting has been using until now may have a lot of trouble handling the massive amounts of nonlinear information that is inherent in meteorological data [1-2].

Further improvement in machine learning, especially Deep Learning seems to hold the promise for increasing the reliability of weather forecasts Hoi and Lam 2015; LSTM 2016. LSTMs are produced to handle temporal patterns in the restricted data, which makes it appropriate for activities such as time series prediction. Because these models can ‘train’ on past weather conditions they can capture much finer detail and dependencies that other methodologies may not be able to [3].

In this study, our interest is to predict rainfall using weather data such as Rainfall, Max Temp, Min Temp, and Wind speed. These chosen features are important to define weather outcomes and their inclusion in prediction models provides a better picture of weather existence. The main goal of the LSTM-based model is to classify several types of weather, including drizzle, rain, sun, snow, and fog.

Thus, the concern of this research is not limited to academic purposes only but is vital for weather prediction since its reliability concerns many individuals with an interest in climatic patterns. The possibility of planning agricultural activities based on meteorological information will increase yields, while the relevance of meteorological information for assessing the safety of transportation will increase its efficiency. Also, the aforesaid emergency services can make their respective arrangements expecting the probability and impending disasters to save lives and properties.

2. Literature Review

[1] Crop diseases are well known to cause substantial losses to the yields in agricultural production. This research uses CNNs for diagnosing crop diseases with the help of images, in which the model operates on the images of the leaves to determine if they are infected. The proposed system is more accurate than conventional image processing techniques to classify and detect diseases at an early stage. The developed CNN model has the potential to address a particular challenge of helping farmers conduct analyses on conditions affecting crops based on diseased and healthy leaves training data.[2] IoT is a revolutionary technology that can help in farming and other sectors by allowing several monitoring devices and technologies to feed real-time data. The research work described in this paper proposes an IoT architecture for precision farming to manage crop growth and resources via sensors for environmental and soil conditions. The machine learning models used in the system to help the farmers in their decision-making process involve trend identification to predict the best times to water crops, early identification of problem growing patterns in crops, and weather forecasting.[3]Drones are fitting more and more in the contemporary world of agriculture having the purpose of precision surveillance and data acquisition. It is within this premise that the present paper seeks to understand the use of drones that incorporate multispectral cameras to assess crop health, plant vigor, and early screening for diseases. When used to overfly fields and then capture images and video back to headquarters, drones can prove useful in determining soil variability and nutrients required for plant growth, as well as stress factors impacting the yields of a field.[4] Higher demand in the global production of food leads to advancement in smart agricultural systems. This research presents a smart greenhouse management system using IoT technology with a machine learning algorithm. It accurately controls some parameters of the external environment concerning plants, including temperature, humidity, and CO₂ concentration, and their regulation at the necessary level with minimal time delays. A machine learning algorithm training uses previous climate data to determine the best climate setting needed for the greenhouse, and make control of the environment independent, to achieve optimum crop yields.[5] It has also been seen that the use of machine learning can predict crop yields – the data is very useful in food security and production strategy. This research measures the performance of several machine learning algorithms such as random forest, support vector machines, and artificial neural networks for estimating the yield of several crops influenced by soil type, weather variables, and fertilizer application. Thus, the study establishes the superiority of the random forest model for yield prediction systems and its ability to enhance random forest model-based accuracy.[6] More so, climate change threatens agricultural productivity across the world. In this paper, the impact of temperature and changes in precipitation on plant germination, continuation, and productivity is explored with the view of developing models for effective crop management due to changing climatic conditions. Using climate information about weather conditions as well as crop models gives guidance on how climate conditions might affect future crop production and shows possible ways of how to address them by changing planting dates and crop management systems.[7] Precision agriculture technologies maintain the efficiency of resource usage and enhance production output. In this research, the authors utilize machine learning algorithms to develop a model for determining the right application of fertilizers by considering the features of the soil and the crops. The study presents a decision model that focuses on the choice of the correct fertilizer type and amount to be used to minimize waste and harm to the environment, and the promotion of plant development. Therefore field trials do show that the system helps to increase nutrient management on the farm.[8] Weed, in general, is a threat to our modern agriculture, therefore detection and control

should be done automatically. This paper provides a deep learning framework for weed detection in crop fields by feeding images from field cameras through convolutional neural networks. The model can identify between crops and weeds and herbicide application is then made on the weeds alone thus reducing chemical usage and also reducing harm to crops. The unabated performance demonstrated by the model in this study suggests the ability of the model to detect weeds irrespective of light and growth conditions.[9] Unattended water scarcity is a very important factor in the agricultural subsector, especially in the arid regions of the world. In this work, an Artificial Intelligence approach is suggested to identify estimations of needed irrigation given soil moisture status, meteorological conditions, and Crop Water Requirement. Finally, by combining the data from the sensors together with the models, the system can define when irrigation is required while saving as much water as possible and providing the crops with the necessary amounts of water. The study shows that water use can be optimized in irrigation systems through the application of artificial intelligence primarily, machine learning.[10] Deficiency of nutrients in plants causes drastic decreases in yield. This research proposes the development of a machine learning system for identifying the nutrient deficiencies in plants from leaves images. This aspect adapts color changes of the leaf images to detect diseases of nitrogen, phosphorus, potassium, and other nutrients. Ordinarily, a farmer may fail to identify nutrient deficiencies until they have severely impacted on the productivity of crops, through the early detection of nutrient issues that the system offers, farmers are well-positioned to tackle the issues before they worsen.[11] Sentiment analysis is defined as the capability to predict the sentiment polarities of a given piece of text as either positive, negative, or neutral. It falls under the niche areas of practice, including Natural Language Processing, Computational Linguistics, and Data mining. There is then the complexity of Arabic as a language together with its inherent ambiguities, and dialects, not to mention the paucity of resources. There was a high performance with BiLSTM as the model of choice which is effective in capturing contextual information outperforming state-of-the-art models. This paper focuses on applying BiLSTM for the enhancement of Arabic Sentiment Analysis since it can capture contextual information from feature sequences of Arabic improving its performance over already introduced machine learning techniques.[12] The ACL-oriented types of networks include Recurrent Neural Networks, which are typically used in handling frequent data such as language text, audio, and video. Nevertheless, ordinary RNNs have long-term dependency problems. A cell structure with gate functions in the Long Short-Term Memory (LSTM) network does not have this drawback and is therefore the object of studies of deep learning. This paper first briefly introduces LSTM cells and their types, then categorizes LSTM networks into two categories, and finally discusses the application areas of LSTM networks and provides prospects for subsequent research on LSTM networks. [13] More importantly, the reference evapotranspiration (ET₀) has to be accurately predicted to be able to determine the amount of water needed for crop irrigation. This analysis employs LSTM as well as BiLSTM models for forecasting daily ET₀ rates and multi-step prediction. Specifically, LSTM showed the highest accuracy when predicting daily total amount and BiLSTM was more efficient for forecasting multi-step total amount. The outcome established that BiLSTM models incorporate flexibility in diverse datasets pertinent to ET₀ prediction.[14] floods and Droughts are complex spatio-temporal events that are impacted by weather and physical geography. This research proposes a forecasting system based on a Long Short Term Memory (LSTM) feed-forward neural network for hydrological extreme events in the South Pacific derived from satellite rainfall and sea surface temperature anomalies. Extreme event detection is enhanced by the inclusion of eigenvector values from the SST data rather than the basic framework that employs univariate and multivariate techniques. Furthermore, the model's multivariate approach provides research hypotheses for future application in long-range weather prediction. [15] Success in the present day business world requires the use of digital marketing tools. In this study, we perform an econometric analysis and algorithms such as ExtraTreesRegressor, GradientBoostingRegressor, SVR, and CatBoost to the KPIs of the digital marketing environment. The accuracy of the predictions completed increased as providing decision-making big data tools for marketing improvements and ROI.

3. Proposed Methodology

This section provides a brief overview of the systematic approach that has been taken in this research to perform weather prediction using selected machine learning methods. Data collection and preprocessing are the first steps of our methodology aimed at providing data cleanliness and quality. Our predictors used in a dataset are past weather records, with features like precipitation, maximum and minimum temperature, and wind speed taken into account.

As the next phase in preparing data to enable their use in modeling, missing values are then insured for and the features' scale normalized, followed by – feature selection, where one seeks to identify the most impactful predictors of weather conditions. We use Long Short-Term Memory (LSTM) networks that proved to be suitable for sequential data because they address temporal characteristics.

The methodology also comprises model training, model evaluation, and validation involving the use of performance indicators like Mean Squared Error (MSE) /Root Mean Squared Error (RMSE). Lastly, the metrics are displayed in a formatted manner to ensure that the performance of the developed model is well understood at its best.

Thus, the optimized routine that is suggested in the context of the present work should improve the precision of the meteorological findings and help to make a distinct contribution to the development of weather prediction methods.

3.1 Dataset Description:

The data used in this research includes historical weather data obtained from credible meteorological databases extended over different years, for seasonality analysis. It includes key features essential for predicting weather conditions:

- **Precipitation:** Expressed in millimeters (mm), this feature is used to predict rain, drizzle, and snow patterns that fall to the ground.
- **Maximum Temperature (temp_max):** This feature marked the highest temperature for the day in degrees Celsius (°C). And it affects rates of evaporation and general weather.
- **Minimum Temperature (temp_min):** Expressed in degrees Celsius (°C) it denotes the lowest temperature observed during the day mostly in the night period.
- **Wind Speed:** Given in km/h or m/s this feature reflects wind speed affecting the speed and regularity of precipitation and stability of weather.
- **Weather Condition Labels:** The input data is categorical labels, including 'drizzle', 'rain', 'sun', 'snow', and 'fog', which are the target variable or the dependent variable to be predicted.

The available dataset contains thousands of daily readings and each record includes the date and all relevant weather characteristics. To enhance the data quality motion pre-processing steps were conducted such as cleaning of the missing values as well as outliers. This all-encompassed database will be instrumental in the creation of a fairly accurate machine learning algorithm for weather prediction to provide information relevant to the meteorology sector.

3.2 Descriptive Analysis:

Here, we conduct a detailed exploratory analysis of the general description of the weather dataset to establish possible relationships and bifurcations of the variables. Knowledge of these relations is important to build relevant models for prediction. Other characteristics of interest include maximum and minimum temperatures, amount of rainfall, and speed of wind in a given period.

Figure (1) is a line type of chart or graph shown below with the label Temperature Max & Min and depicts the maximum and minimum temperature for the period of January 2012 to January 2016. On the X-axis they used the date from January 2012 to January 2016 and on the Y-axis, the temperature in the central part of Sweden tends to be between -10 and 40 degrees Celsius. The blue area represents the maximum temperature and the orange area represents the minimum temperature.

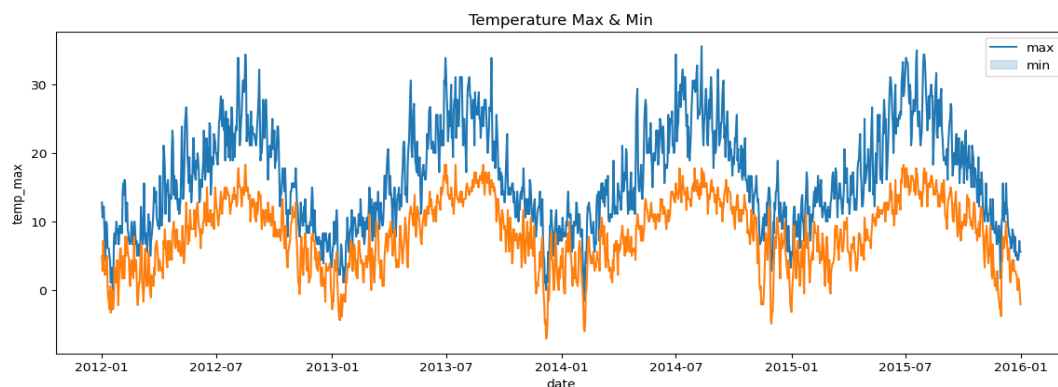


Figure 1. Temperature Max & Min

The use of the line graph shows that maximum temperatures are highest in the middle of the year, which indicates summer and the lowest is during the end or start of the year the situation which illustrates winter. In particular, the values of TMAX consistently surpass those of TMIN all over the observed period as it is characteristic of seasonal climate changes.

The second visualization Figure (2) is a pair plot that explores relationships among four key weather variables: rainfall, maximum temperature, minimum temperature, and wind speed. The scatter plot within the matrix represents a regression of one variable on another and the diagonal illustrates the distribution of each variable. The coordinates are also color-coded according to the type of weather, namely: blue for drizzle, red for rain, green for sun, purple for snow, and orange for fog weather type.

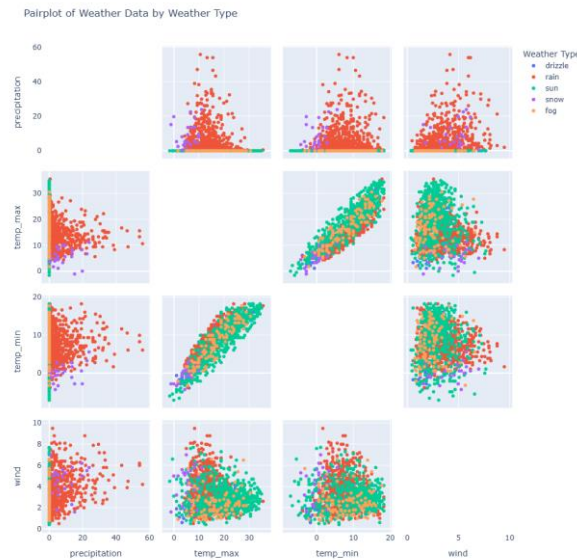


Figure 2. Pair plot of Weather Data

This specific kind of visualization is very useful for showing trends and relationships between various aspects of weather depending on several factors. For instance, it would be observed that in conditions where precipitation level is high; there is low maximum and minimum temperature in the following rainy and snowy weather conditions. This at least can help us in our effort to build the weather predictions model and to find out what can be a potential predictor with the help of this pair plot.

By way of descriptive statistics, we get an idea about the nature of the data set which would be helpful in the subsequent modeling stage. Not only do these visualizations enlighten the viewer on key trends, but understanding these trends is an essential first step in accurately modeling the relationships between weather conditions.

3.3 Data Preprocessing

Cleaning and transforming the weather dataset is very important as it involves breaking down and structuring the data for further analysis. For this study, we have used several processing methods to improve the quality of our data set, which includes precipitation, maximum temperature, minimum temperature, and wind speed [4].

1. Handling Missing Values :

The pre-processing steps we carried out initially involved filling in missing values from the data set. For this purpose, it became necessary to address gaps that may exist in the dataset for numerical features namely temperature and wind speed. This approach replaces lost values relating to specific factors with nearby values thus preserving the structure of the data set. Of course, if there were some rows with missing values higher than the established limit, we would exclude such records from the dataset.

2. Normalization and Scaling :

Thus, normalization was applied to the feature values so that the model could train from the data provided in the best possible way. The ranges of the features varied from millimeters in case of precipitation to degrees Celsius; therefore, we used Min-Max scaling to scale the features into the [0, 1] range. Rem edition, this normalization avoids features of large-o oscillation ranging from dominating the learning process.

3. Feature Engineering :

Feature engineering was most crucial to building a model with better predictive accuracy. This had the effect of giving additional meaning to existing features to capitalize on parameters that are related to the state of the climate. For instance, the average temperature was arrived at by using the arithmetic mean of, the highest and the lowest temperature readings. Thus, this new feature delivers a broader vision to appreciate the fluctuations of temperature to make better estimations about the climate.

4. Data Splitting :

After preprocessing the data, we decided to divide the database into the train, validation as well as test data. The training set includes 80% of the total records and it is used for model training the validation set should contain 10% of the references to test the model performance and tune the hyper parameters. The final 10% was used as the test set where its function was to test the model's predictive accuracy irrespective of training.

3.4 Artificial Neural Networks (ANN)–LSTMs:

A forgotten artificial architecture of RNN is the LSTM [5] which was proposed by S. Hochreiter and J. Schmidhuber in 1997. They operate a gated mechanism (input, output, and forget gate) to regulate the flow, storage, and dependency of information in sequence training over time. Long – short-term memory eliminates issues of long-term dependencies, vanishing gradient, and exploding gradient in the traditional setting of Recurrent Neural Networks. LSTM networks give the nice prospect to cope with the long-time sequences employing the gates that regulate the interaction with the inputs [6]. An LSTM cell unit consists of an input with an activation vector, an output with an activation vector, and a forget with an activation vector [6]. LSTM for instance, is better suited for noisy and nonlinear data, unlike methods such as ARIMA which handle linear time series prediction [7]. According to the prior work, LSTM is superior in large-scale data while ARIMA may be superior to LSTM in smaller-scale data due to inadequate sample data [7]. Other models like LSTM-RNN have been deployed with higher accuracy than other models [8], and herein we use LSTM to capture temporal weather patterns to make predictions bore on its aspect of learning long-term dependencies with memory units [9-12].

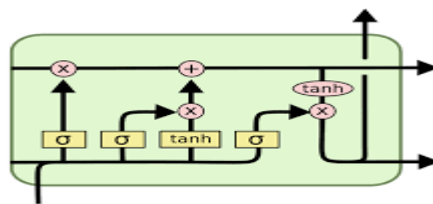


Figure 3. LSTM Architecture

3.5 Performance Metrics:

The performance of the models developed in this study was then measured through various statistical evaluation criteria to evaluate the proposed models [13]. The performance of the same model in both the training and only the independent test set was assessed [14]. This study computed RMSE, MSE, and R^2 at three-time intervals, with averages obtained from 30 repeated trials. Furthermore, the RMSE for each grid cell of the entire training and testing phases was calculated as well.

Table 1: Criteria for evaluating regression result.

Metric	Formula
MSE	$\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2$
RMSE	$\sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2}$
MAE	$\frac{1}{n} \sum_{i=1}^n y_i - \hat{y}_i $
R ²	$R^2 = 1 - \frac{\sum_{i=1}^N (y_i^{actual} - y_i^{predicted})^2}{\sum_{i=1}^N (y_i^{actual} - \bar{y}^{actual})^2}$

- **Mean Squared Error (MSE):** This is referred to as the mean of the squared differences between the forecasted and actual values. It is used as a measure through which the model's probability can be tested with lower MSE values being construed as an indicator of a good model [15].
- **Root Mean Squared Error (RMSE):** RMSE is the square root of MSE, which means that it is directly an average measure of the magnitude of approximations. We know that low RMSE is better than MSE [15].
- **Mean Absolute Error (MAE):** MAE estimates the average size of errors which represents the error range [15].
- **R² (Coefficient of Determination):** R² refers to the measure of the dependent variable variance that was accountable to the independent variable. The fact that higher R² values correspond to better model-fitting has been asserted by previous research [15].

4. Results

The performance of the model was further measured using Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and the Coefficient of Determination (R²). These metrics provide complete insight into how accurately the model is capable of predicting results in case of testing. The results are summarized as follows: Mean squared error (MSE) of 8.74, root-mean-squared error (RMSE) of 2.96, mean absolute error (MAE) of 2.35, and a 0.83 coefficient of determination. These values further substantiate that the model has high accuracy in giving the right predictions, the model establishes a high likelihood of the correlation between predicted and actual values, and relatively low error rates.

Table 2: The Model Results

MSE	RMSE	MAE	R ²
8.741861	2.956664	2.353954	0.827729

However, to further elaborate the performance as shown in TABLE 4, the actual and predicted values of the validating and testing data sets are illustrated in Figure 4. This figure shows how close the actual values were captured by the model explaining the trends, and very little discrepancy is observed between the actual values and the predicted values. The correlation between these values is rather high, which is evidence of good generalization to unseen data within the confines of the model. There are small variations in a couple of areas which could be explained by other factors outside the meantime features. However, these deviations are not beyond reasonable limits and therefore have no serious implication on the quality of the resultant predictions.

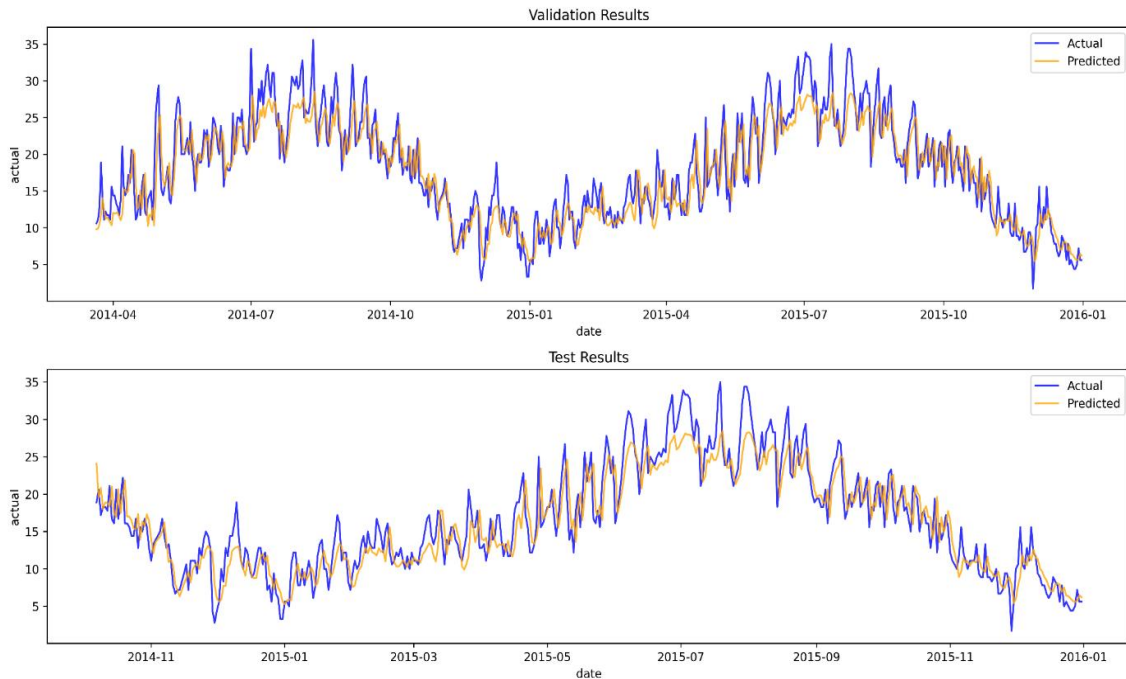


Figure 4. Comparison of Predicted and Actual Values.

Aside from comparing the predictions with the actual values, the training is shown in Figure 5 in terms of the loss and RMSE throughout the epochs. The curves that show that there is a reduction in the training and validation losses depict that the model is learning from the data provided. At ‘Validation Loss’ it is still slightly higher than ‘Training Loss’ as usual but the difference between these two curves is extremely small, which indicates that the model did not overtrain. The progressive decline and continuous fluctuation of a loss further suggest the excellent convergence of the model, increasing its credibility and its capacity to perform well with other datasets.

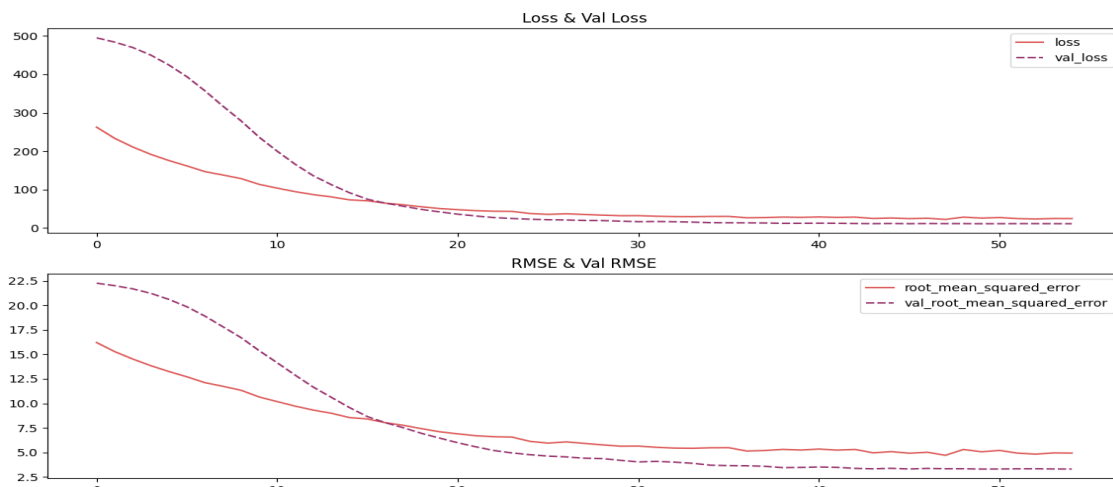


Figure 5. Training and Validation Loss Curves.

Still, on the evaluation metrics, in combination with these visualizations, it is clear that the model is quite efficient in its ability to make precise predictions with comparatively small errors' rates. The pinpointed high value of R^2 (0.83) reflects the idea that the model indeed investigates a specific part of the target data variances. The values prove that the model has captured significant characteristics of the data and applies them effectively to unknown data points with minimal discrepancies between actual and estimated futures. Also, the fact that the predicted values do not tally perfectly with the actual ones, as depicted in Figure 4, is negligible, when better tuning is made from features added or hyper parameters adjusted, the difference identified will improve. The trajectories of the training and validation loss presented in Figure 5 show that the model did learn properly and did not over fit. These results suggest that the model is indeed reliable for downstream analyses and is capable of capturing target effects, assuming finer-grained feature extraction or the optimization of hyper parameters. Moreover, a brief of descriptive captions will be given for both; Figure 4b will depict the comparison between the predicted and actual values Figures 5a and 5b will illustrate the loss and RMSE curves.

5. Conclusion

The purpose of this paper was to research how climate variables and climate models can be included in a model to improve recommendations for crop yield with the use of different inputs agricultural. The evaluation of the proposed model suggested a good performance based on the Mean Squared Error (MSE 8.74), Root Mean Squared Error (RMSE 2.96), and Coefficient of determination (R^2 of 0.83). As these results show, the model is realistic in capturing all of the climate-dependent variables, soil conditions, and crop yields and in generating accurate and realistic predictions that can assist farmers and stakeholders in the field of agriculture. The findings also supported the model by providing graphical illustrations of the predicted and actual values (Figure 4) as well as the training and validation loss (Figure 5). The small discrepancy between the prediction and actual data shows the model's ability to apply well on data that has not been seen before while the two loss curves indicate that learning was accomplished without overfitting. This balance of training and validation loss is very important in the sense that users of the model are confident of it when applied in the real practice of agriculture. Nevertheless, including learning opportunities for more detail with reference to climate variability, it is worth noting the potential for the extension of the work. It may in the future address more developed climate data and more factors such as weather change and storms to improve the predictive ability. Extending the article with research on more sophisticated forms of machine learning and performing ambitious hyper parameter optimization can also result in better accuracy and speed up. As a result, this work advances knowledge in climate data and forecasting and their application within crop-recommended systems. Through the use of big data, actors in the farming value chain can best select their crops, improve standards for adaptability to climate change, and increase food productivity. These insights highlight the need for more cutting-edge technologies in farming activities to improve on the farming mechanisms that are likely to be affected by climate change.

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