Precipitation Forecasting Using Artificial Neural Networks

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***Abstract*—In this paper, we investigate the use of deep learning algorithms for forecasting precipitation using artificial neural networks (ANNs) and recurrent neural networks (RNNs) as methods of predicting precipitation amounts and patterns in an area over a specific time period. We used ANNs and RNNs models that can analyze large amounts of data, including historical precipitation data, weather patterns, and other meteorological information, to make predictions about future precipitation. This method of forecasting has been found to be more accurate than traditional methods, such as statistical models, and can provide valuable information for agriculture, construction, and other industries that are affected by precipitation. Precipitation has a significant impact on agriculture, making accurate predictions and crucial forecasts, which heavily relies on the agricultural sector as a primary source of income. Our goal is to develop a model that can utilize available meteorological data to provide early and advanced precipitation predictions, thus highlighting the importance and benefits of such technology for a zone.**

Keywords—Precipitation Forecast, Artificial Neural Network, Long short-term memory.

I. INTRODUCTION

A breezy day with a good deal of dry weather and spells of sunshine, although still some showers in the west and particularly the northwest, where still fairly frequent and heavy at times. Words are usually heard on television and read in newspapers. Within this frame, you might think of what is the present likelihood of a certain amount of precipitation occurring at a particular location and time in the future? And how it is answered by a probabilistic prediction?

Weather precipitation forecast is an important part of predicting the weather. It is the process of predicting the amount of precipitation that will fall in a given area over a certain period of time. This forecast is used to help people plan their activities and to help farmers and other agricultural workers plan their crops. It is also used to help emergency services prepare for potential flooding or other weather-related events. Weather precipitation forecast is a major section of understanding the weather and how it will affect our lives.

As a crucial component of the hydrologic cycle, precipitation is important in preserving the balance between freshwater and saltwater resources around the world [1]. That's make the first thing to take as a mainspring in order to begin the investigation. The hydrologic cycle happens due to some factors defined in temparature, visibility, humidity, etc. We can examine them as basics to start a kind of a system to forecast precipitation. Within this approach, the use of an intelligent retrieval would have an extremly great impact. For downscaling and bias adjustment of precipitation, machine learning (ML) has become more and more prevalent [2]. Analysts may now train large-scale neural networks, such as deep learning models, that were previously constrained due to their high computing cost for training thanks to the development of general-purpose graphics processing units and their application in ML [1].

Since precipitation varies with time, time series forecasting is without a doubt of utmost relevance in this field as so as in many departments. In this study, we gonna drive a focal point on Recurrent Neural Networks (RNNs) as they are the most popular machine learning models for time series forecasting challenges [3]. The analysis demonstrate that the model performs well in the prediction [4].

This paper is structured in the way of following an approach to forecast precipitation, offered by Artificial neural networks (ANNs) which are considered one of the popular methodologies as they can be used to predict precipitation amounts and patterns. Because ANNs machine learning models can learn from historical data, analyze patterns and make predictions about future precipitation. This approach is based on their ability to model non-linear relationships between weather variables and precipitation. With the increasing amount of historical weather data and the advancements in technology, ANNs are becoming a more accurate and widely used method for precipitation forecasting. [5].

At last, To verify the model's performance, the constructed prediction model was further compared with the recently created deep-learning-based Long short-term memory (LSTM) algorithm [6]. Despite the fact that recent increases in processing capacity have led to the creation of more sophisticated machine learning.

II. LITERATURE REVIEW

There are many studies proposed a related work summarize system given the set of keywords arranged the paper's topic. They used the different ways based on maching learning and deep learning to extract the best results for forcusting precipitation, considerable research in Precipitation forecasting using Recurrent Neural Networks makes our research of similar search [7].

Precipitation is a quasi-periodic event in meteorology that is defined as any product of the condensation of atmospheric water vapor that falls under the force of gravity.
The precipitation predictor variables we choose are closely related to the water cycle. The predictor variables are temperature, dew point temperature, the minimum temperature, maximum temperature, atmospheric pressure , pressure tendency , relative humidity , wind speed and its maximim, wind direction , total cloud cover , height of the lowest clouds , and amount of clouds. In comparison with other studies on precipitation prediction, the approach provided in this study can select different meteorological variables to optimize the precipitation prediction results using LSTM and meteorological variables in advance for the study region are good prediction of the precipitation amount could allow for the more flexible decision-making.

The authors published articles Precipitation prediction and how it may be used in the proposed framework, consists of an advanced deep learning model (termed LSTM) to forecast continuous CTBT images, uses a precipitation estimating method (known as the PERSIANN algorithm) to determine the predicted rain rates. Three case studies are investigated over the CONUS in US, In the first part of the evaluation of forecasting skills, the results from our proposed model (LSTM/LSTM-PER) as comparing other extrapolation-based and numerical methods [8].

In this study, the spatio-temporal prediction of rainfall and run of time-series trends in sparsely gauged hydrologic basins are compared using LSTM neural network and wavelet neural network (WNN). Using long-term in situation observed data for 30 years (1980–2009) from ten rain gauge stations and three discharge measurement stations, the rainfall and run of trends in the Nzoia River basin are predicted through satellite-based meteorological data comprising of: precipitation, mean temperature, relative humidity, wind speed and solar radiation. Three sub-basins, which correspond to the three discharge stations, were used for the prediction modeling. The same deep learning topological structure, which consists of four hidden layers with a total of 30 neurons each, was used to build both the LSTM and the WNN [9].

This research introduces MFSP-Net, a novel multi-input multi-output recurrent neural network model
for precipitation nowcasting based on multimodal fusion and spatiotemporal prediction.
It simultaneously accomplishes 0-4 h precipitation amount nowcasting and precipitation intensity nowcasting using precipitation grid data, radar echo data, and reanalysis data as input data. The three sources of input data can be fused on a spatiotemporal scale using MFSP-Net while maintaining their spatiotemporal information flow [10].
The network is trained using the multi-task learning method. We run experiments on the Southeast China dataset, and the findings demonstrate that MFSP-Net significantly enhances the nowcasting of precipitation amounts.

When it comes to heavy precipitation nowcasting as well as the middle and late stages of nowcasting, MFSP-Net clearly has an advantage.
The authors make a further evaluation of the ARIMA daily temperature and precipitation simulations was conducted and compared with the simulations provided from one weather generator. The simulations of daily average temperatures in Phoenix and daily precipitation in Chicago from the ARIMA model and a weather generator were compared with the historical observations, the same example datasets used for other comparisons in the current study [11].

The authors use therefore forecasting methods like statistical models, machine learning, and deep learning architectures help scientists to take effective decisions to decrease the effects of natural disasters by providing decision making plans. can be forecasted using meteorological indices like the standardized precipitation evapotranspiration index (SPEI), which aid governments in taking.

In this article, we offer a large-scale infrastructure for modeling and forecasting droughts.
The proposed architecture is composed of 5 layers; Besides, we present a comparative study between three different methods ARIMA, PROPHET, and LSTM for drought forecasting. The performance evaluation uses three metrics: Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and coefficient of determination (R2) (MAE). Experiments are carried out using data from the province of Jiangsu. Results revealed that LSTM outperformed the other models, and ARIMA outperformed the PROPHET model [12].

In another research, models for predicting precipitation based on artificial neural networks (ANNs) are presented. In these models, the training parameters are modified using a parameter automated calibration (PAC) method. A multilayer perceptron (MLP) neural network, a traditional ANN-based model, was utilized to test the effectiveness of the suggested ANN-PAC method. The learning rate, momentum, and quantity of neurons in the hidden layer served as the main parameters of the MLP-based ANN.[23]

This study marks one of the first attempts to explore the usage of unified ANN methods for postprocessing medium-range ensemble QPFs (1–8 days) over a broad domain with little training datasets Two current ANN postprocessing approaches have been chosen for the experiment. In the first method (ANN-Mclass), prediction probabilities are created for discrete precipitation categories, and these probabilities are then extrapolated or interpolated to build a complete CDF. The second is the ANN-CSGD, a recently created, hybrid ANN-parametric postprocessing approach that makes use of ANN to connect a group of predictors to the parameters of a predictive censored, shifted gamma distribution. Both networks share comparable predictors and have a very basic structure (dense), but their loss functions and predictive distributions are different. These two models were really chosen to examine the possible benefits of keeping the predictive distribution's parametric shape in

In this paper, we gonna use some technologies, represented in a bunch of algorithms and mathematical background that gonna help in the accuracy of the precipitation forecasting results.

A sort of artificial neural network known a recurrent neural network is made to analyze data sequences. They are therefore perfect for jobs like time series analysis, speech recognition, and natural language processing. RNNs are based on the mathematical concept of dynamical systems, which are systems that evolve over time. This means that the output of an RNN is determined by its current state and the input it receives. In order to understand how we would work on this paper, it is important to have a basic understanding of the mathematics behind them. This includes topics such as linear algebra and ANN. Additionally, we will focal a point on the Long short-term memory (LSTM) neural network.

A. Artificial Neural Network (ANN)

In machine learning, artificial neural networks are one of the most important techniques. They are brain-inspired systems designed to mimic how humans learn, as the word "neural" in their name suggests. Input, output, and—in the majority of cases—a hidden layer made up of components that convert input into something the output layer can use make up a neural network. They work well for identifying patterns that would be impossible for a human programmer to extract and train the computer to recognize because to their complexity or sheer number.

Although neural networks (also known as "perceptrons") have existed since the 1940s, it has only been in the past few decades that they have made significant advances.

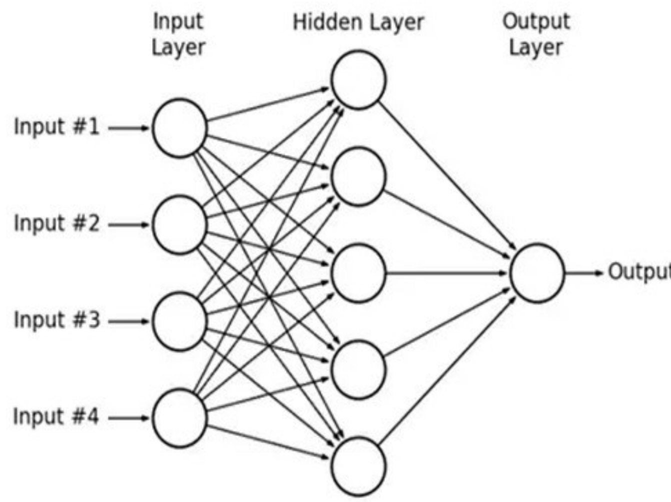

Figure 1: "The architecture of an artificial neural network", commons wikimedia, wiki, Neural_Network

The artificial neural network receives input, computes the weighted total of the inputs, and incorporates a bias. A transfer function is used to visualize this calculation. What is an artificial neural network? In order to create the output, it passes the weighted total as an input to an activation function. A node's activation functions decide whether or not it should fire. The output layer is only reached by those who are fired. Depending on the type of work we are undertaking, several activation functions are accessible.

The mathematical formula for the computation performed by an artificial neuron in an ANN can be represented using the following format:

$$y = f(\sum(w_i * x_i) + b)$$

Where:

y is the output of the neuron

x_i is the i-th input to the neuron

w_i is the weight of the connection between the i-th input and the neuron

b is the bias term of the neuron

$\sum$ is the summation operator

$f(x)$ is the activation function applied to the sum of the weighted inputs and bias.

It's worth noting that this representation is a simplification of the formula and in practice, the weights and inputs are represented by matrices and vectors, and the dot product is used instead of the summation operator. But this is the general idea behind the math.

B. Recurrent Neural Network

Many academics aim to develop recurrent neural network (RNN) algorithms because they are useful in solving time-variant problems across a range of areas [13].

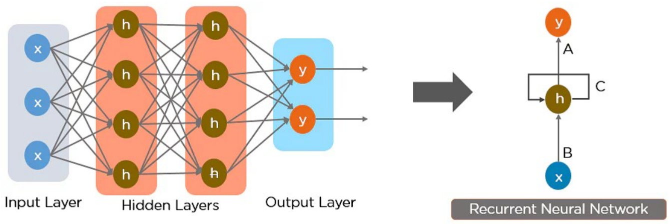

Figure 2: "a Simple Recurrent Neural Network", simplilearn, tutorials, deep-learning-tutorial, rnn

The fundamentals of recurrent neural networks can be learnt , including the tasks they can be used for, to create the objective functions for these tasks, and backpropagation through time, by using their variants as long short term unit and grated recurrent unit on which we'll go into more details.

According to IBM, a recurrent neural network is a type of artificial neural network which uses sequential data or time series data [14]. These deep learning algorithms are included into well-known programs like Siri, voice search, and Google Translate. They are frequently employed for ordinal or temporal issues, such as language translation, natural language processing (nlp), speech recognition, and image captioning.

Recurrent neural networks use training data to learn, just like feedforward and convolutional neural networks (CNNs) do. They stand out due to their "memory," which allows them to affect the current input and output by using data from previous inputs. Recurrent neural networks' outputs are dependent on the previous parts in the sequence, unlike typical deep neural networks, which presume that inputs and outputs are independent of one another. Unidirectional recurrent neural networks are unable to take into account future events in their forecasts, despite the fact that they would be useful in deciding the output of a particular sequence.

The question that can come to mind, following all the algorithms and knowing their methodologies, is what can differ them. In our study, we may use Convolutional neural network. Instead, we chose RNN a simple why is asking itself! As we have already said in the introduction, several circumstances load to forecast precipitation. For example, the temperature data map processes the geographical correlation using CNN, while the subsequent temperature data map processes the time correlation using RNN [15].

In our case, analysis depends on time only and lets the study area fixed, which means we only need to use a model well-suited to time series data which is RNN, based on historical temperature data or on whatever the factor is.

C. Long Short-Term Memory(LSTM)

Long Short-Term Memory (LSTM) networks are a type of Recurrent Neural Network (RNN) that are specifically designed to handle sequential data, such as time series, text, and speech. They are widely used in tasks such as natural language processing, speech recognition, and time series forecasting.

LSTMs have a more complex architecture than traditional RNNs, which allows them to better handle long-term dependencies in the data. They consist of memory cells, gates (input, forget, and output gates), and fully connected layers. The memory cells are responsible for maintaining information over a long period of time, while the gates control the flow of information in and out of the cells.
One of the main advantages of LSTMs is their ability to handle long-term dependencies, which is a common problem in traditional RNNs. They are able to selectively remember or forget information based on the input data, which helps to prevent the vanishing gradient problem. Additionally, LSTMs have been shown to be highly effective in a wide range of tasks such as natural language processing, speech recognition, and time series forecasting.[16]
However, LSTMs also have some limitations. One of the main drawbacks is that they are computationally expensive, which makes them harder to train and run than other RNNs.

Additionally, LSTMs may struggle to handle high-dimensional or complex input data.[17]
Overall, LSTMs are a powerful technique for handling sequential data and can be used for a wide range of tasks such as natural language processing, speech recognition, and time series forecasting[18]. They are known to handle long-term dependencies in the data, which makes it an ideal algorithm to use in the context of sequential data. However, it's important to consider the computational complexity of the model and the nature of the task and data before choosing LSTM. [19]

The LSTM algorithm consists of several key steps, starting from the input gate that controls the flow of new information into the cell state. It is responsible for determining which values from the current input should be added to the cell state.
Down to the output of the LSTM which is generated by the output gate, and it is used as the input for the next time step.
By and by, repeat from the first step. The step is done for each time step until the end of the sequence.

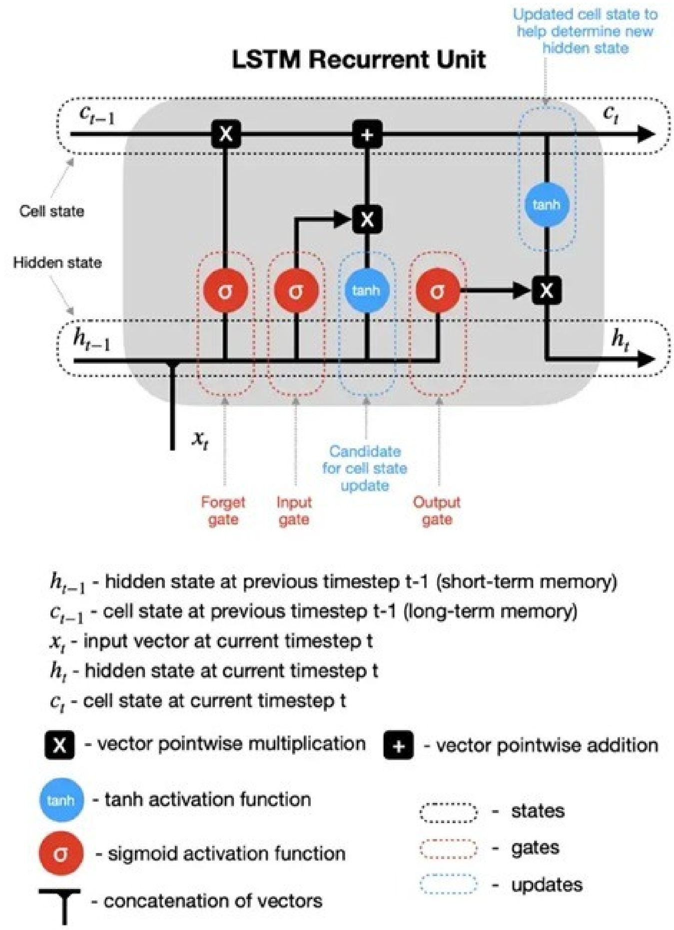

Figure 3:"The structure of the Long short-term memory, Saul Dobilas, Demystifying Data Science and ML"

D. Time Lagged Neural Networks (TLNNs)

Time Lagged Neural Networks (TLNNs) are a variant of Artificial Neural Networks (ANNs) that are specifically designed to handle time series data. They incorporate the concept of time lags, which means that the inputs are delayed by a certain number of time steps. This allows the network to take into account the temporal dependencies and patterns within the data, which is important for tasks such as prediction and forecasting.

The architecture of TLNNs is similar to that of traditional feedforward ANNs, with an input layer, one or more hidden layers, and an output layer. However, the input layer includes not only the current values of the time series but also the previous values, which are lagged by a certain number of time steps. The number of lags used in the input layer is typically determined by analyzing the data and determining the optimal number of lags that capture the most relevant temporal dependencies.

One of the main advantages of TLNNs is their ability to capture temporal patterns in the data, making them suitable for tasks such as prediction and forecasting. They can also handle missing values and non-stationary data, which is common in time series data.

However, one of the main limitations of TLNNs is the high computational complexity of the model, which increases with the number of lags used in the input layer. This can make it difficult to train and run the model efficiently. Additionally, TLNNs may struggle to handle long-term temporal dependencies and patterns that span across many time steps.

Overall, Time Lagged Neural Networks (TLNNs) is a powerful technique for handling time series data and can be used for a wide range of tasks such as prediction, forecasting, and classification. However, it is important to carefully consider the suitability of the algorithm for a specific task and to properly choose the number of lags to ensure that the model captures the most relevant temporal dependencies and patterns. [20]

E. Feed Forward Neural Network (FNN)

Feed forward Artificial Neural Networks (ANNs) are a type of machine learning algorithm that consist of layers of interconnected nodes or neurons. These neurons process and transmit information from input to output, simulating the way the human brain works. Feed forward ANNs are called as such because the information flows in a single direction, from the input layer to the output layer, without any loops or feedback. The input layer receives the input data, which is then processed and transformed by the hidden layers before reaching the output layer where the final prediction or classification is made. One of the main advantages of feed forward ANNs is their ability to learn and adapt to new data and patterns, making them suitable for a wide range of tasks such as image recognition, natural language processing, and prediction. They also have a large number of parameters that can be tuned to optimize performance. However, feed forward ANNs also have some limitations such as the need for a large amount of training data and being susceptible to overfitting. They also may struggle to model complex, non-linear relationships and temporal data. Overall, feed forward ANNs are a powerful and versatile machine learning technique that can be used for a wide range of tasks and have been widely used in many fields. However, it is important to carefully evaluate the suitability of the algorithm for a specific task and to properly tune and regularize the model to avoid overfitting. [21]

F. Seasonal Artificial Neural Networks (SANNs)

*S*easonal Artificial Neural Networks (SANNs) are a type of neural network that are specifically designed to model and predict seasonal patterns in time series data. They are a variation of traditional Artificial Neural Networks (ANNs) that incorporate a term to account for the seasonal component in the data. This can be done in a variety of ways, such as by adding a seasonal term to the input layer, by incorporating a seasonal component in the network's architecture, or by adding a separate module for modeling the seasonal component.

SANNs are used in various fields such as finance, economics, weather forecasting, and more. They are particularly useful for modeling and predicting patterns that repeat at regular intervals, such as monthly or yearly patterns.

One of the most famous example of SANN model is SARIMA (Seasonal AutoRegressive Integrated Moving Average) model, which is widely used in time series forecasting[22]

G. The Root Mean Squared Error (RMSE)

The Root Mean Squared Error (RMSE) is a measure of the

difference between predicted values and actual values. It is a common evaluation metric used in regression problems, and it calculates the square root of the average of the squared differences between the predicted values and the actual values.

In mathematical terms, the RMSE for a set of predictions is calculated as:

$$RMSE = sqrt((1/n) * \sum(predicted\_i - actual\_i)^2)$$

where n is the number of predictions made, predicted_i is the i-th predicted value, and actual_i is the i-th actual value.

The RMSE value is always positive, and it is in the same units as the original data. It is widely used to measure the model performance, the lower value of RMSE indicates that the model is good fit for the data. The common thresholds for RMSE is depend on the data you are dealing with, but it is common to see values below 10% of the range of the target variable considered good fits, while values above 20% are considered poor fits.

It is important to note that the RMSE is sensitive to outliers and doesn't consider relative errors, so other metrics like Mean Absolute Error (MAE) or R-squared (R2) are recommended to be used as well in conjunction.

H. Mean Absolute Error (MAE)

Mean Absolute Error (MAE) is a commonly used measure of forecast accuracy for continuous variables. It is a measure of the average absolute difference between the predicted and actual values. The MAE is calculated by taking the absolute value of the difference between the forecasted and actual values for each data point, and then taking the average of these absolute differences.

MAE is often used to evaluate the performance of a forecasting model because it is relatively easy to interpret and understand. It is also relatively robust to outliers in the data, as the absolute value function "pins" large errors to the same level regardless of their direction.

A lower MAE value indicates that the forecast errors are small, while a higher value indicates that the forecast errors are large. It's important to note that MAE alone is not enough to evaluate the performance of a model, and it is a good practice to also consider other metrics such as mean squared error, root mean squared error and correlation coefficient. Aditionally, it's important to keep in mind that MAE is a scale dependent metric, meaning that it's interpretation can change depending on the scale of the variable being forecasted. It's a good practice to scale the variable and normalize the error metric, so it can be compared across different forecasting scenario.

The mathematical formula for MAE is as is as follows :

$$MAE = (1/n) * \sum(|y - \hat{y}|)$$

Where:

y is the actual value

$\hat{y}$ is the forecasted value

$|y - \hat{y}|$ represents the absolute value of the difference between the actual and forecasted values

$\sum$ denotes the summation of the absolute differences for all n data points

n is the total number of data points

III. METHODOLOGY

In this work, we attempted to study a sample of data related to the Pune region to form a dataset containing more than 37 years of data. This data includes the main factors that contribute to predicting and measuring rainfall, such as monthly temperature, rainfall amount, wind speed, and visibility. The date range of this data is from 1965 to 2002 and it contains various connected data that are considered appropriate for their studies using deep learning and time series analysis techniques. The Artificial Neural Networks (ANNs) approach has been suggested as an alternative technique for time series forecasting and has gained immense popularity in recent years. It tries to recognize regularities and patterns in the input data, learnt from experience, they have been applied in many different areas, especially for forecasting and classification purposes.

ANNs are inherently non-linear, which makes them more practical and accurate in modeling complex data patterns, as opposed to various traditional linear approaches such as ARIMA methods, we will use the FNN (Feedforward Neural Network) model as it is widely used for predicting problems, in addition to another type of FNN called TLNN (Time Lagged Neural Network) which its input structure is a time series at certain specified time delays.

A SANN (Seasonal Artificial Neural Network) structure is also suggested to improve the performance of ANNs for seasonal time series data.
SANN can identify the seasonal pattern in the time series without removing it, in contrast to some other traditional methods such as SARIMA. In this model, the seasonal indicator "s" is used to determine the number of neural cells for inputs and outputs. The seasonal notes i and (i+1) are used consecutively as the value for input and output neurons in the network structure. Therefore, when forecasting using SANN,

the number of neural cells for inputs and outputs should be considered as 12 months and 4 for the quarterly time series.

The appropriate number of hidden layers can be determined by conducting appropriate experiments on training data. Furthermore, Recurrent Neural Network (RNN) / Long Short-term Memory (LSTM) can also be used to analyze time series data due to their ability to store and remember important information from the previous inputs, which makes them very accurate in predicting the next value.

LSTM is a powerful model that is particularly suitable for sequential data as it has the capability to store long-term dependencies in its memory. During prediction, the model considers both the current input and what it has learned from previous inputs as it processes the information in a loop. The number of hidden layers and output units can also be increased to improve the performance.

We always try to divide the data in a sequential way, 80% for training and the rest for testing in order to extract the relationship between the percentage of precipitation, temperature, visibility and wind speed. After that, we compare and analyze the results obtained by using the forecasting performance measure RMSE (Root Mean Squared Error) and MAE (Mean Absolute Error).

IV. Results and Discussion

Through the available data samples and knowledge of four different variables such as temperature, wind speed, vision, and direction, which are monthly average values for 37 years divided randomly into 80% for training and 20% for testing. As for the deep learning algorithm, each algorithm uses different variables from the best variables obtained and gives the best results for each model, Table 1 shows the parameters used per algorithm.

Table 1: Algorithms and their parameters.

Algorithm	Parameters used
FNN	Number of combinations: 28 Input nodes(p): 12 Hidden nodes: 5 Output nodes: 1 Number of epochs: 500 Batch size: 20 Number of future steps forecasted: 60
TLNN	Number of combinations: 16 Input nodes(s): 12.0 Hidden nodes: 5 Output nodes: 12 Number of epochs: 500 Batch size: 20 Number of future steps forecasted: 60
SANN	Number of combinations: 8 Input nodes(s): 12 Hidden nodes: 5 Output nodes: 12 Number of epochs: 500 Batch size: 20 Number of future steps forecasted: 60
LSTM	Number of combinations: 52 Input nodes(p): 12 Hidden nodes: 4 Output nodes: 1 Number of epochs: 300 Batch size: 20 Number of future steps forecasted: 60

whether from the results obtained by MAE or RMSE. The table below contains the results obtained for each of them. Through the above table,

Table 2: Algorithm's MAE and RMSE values

Algorithm	MAE	RMSE
FNN	85.691	118.387
TLNN	88.99	126.365
SANN	100.3	138.594
LSTM	56.037	94.24

We see that the MAE and RMSE values are lower in the LSTM model. The value has become 94.24 in RMSE while the value of MAE is 56.03 when compared to the SANN model this MAE become 100,3, and the RMSE 138.

When comparing this models of forecasting models, the experimental findings show that the LSTM model has the best prediction performance on percipitation forecasting.

Based on these findings, if we compare DL algoritms to A nother ltechnique , we can clearly conclude that DL algorithms provide better understanding of the correlations between the chosen weather parameters.

Among the four deep learning algorithms LSTM, had better results as it has the lowest MAE and MAPE, proves by itself that temperature has a correlation between wind speed, visibility, precipitation and dewp. The importance of this result resides in the fact that instead of predicting pricipitation using only pricipitation values form the past.
Lets show the performance of the trained models figures provides a visual demonstration of its.

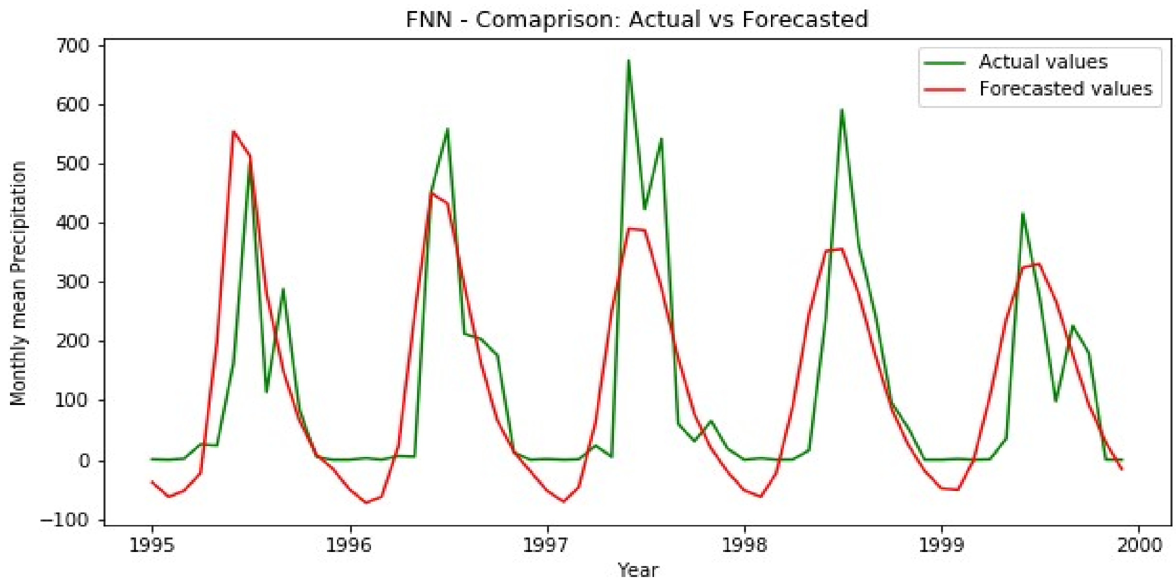

Figure 5:FNN comparaison actual and forecasted

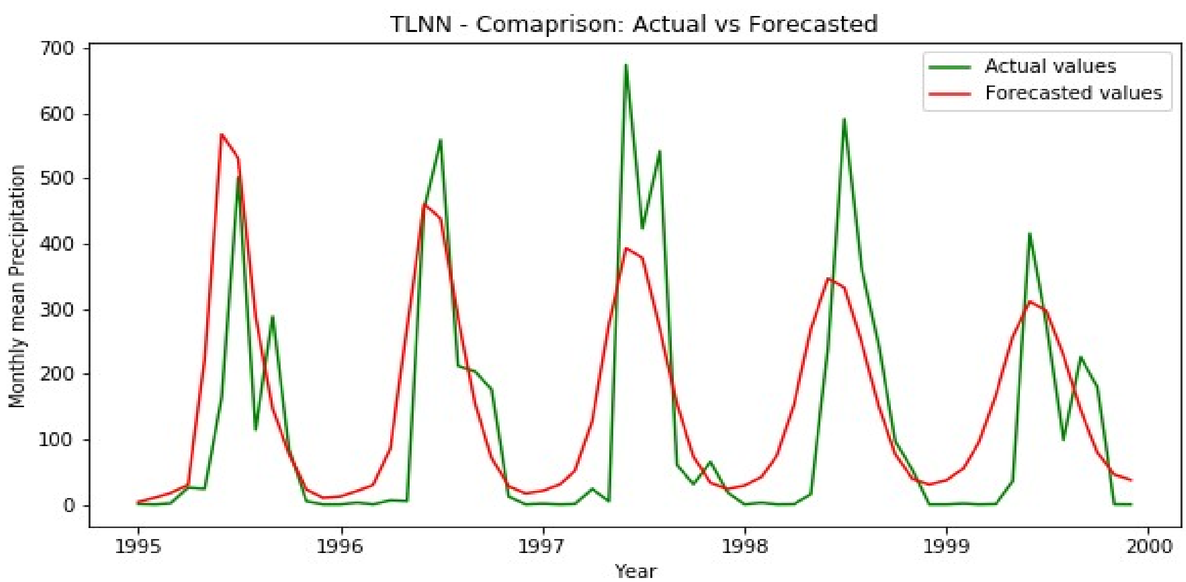

Figure 6:TLNN comparaison actual and forecasted

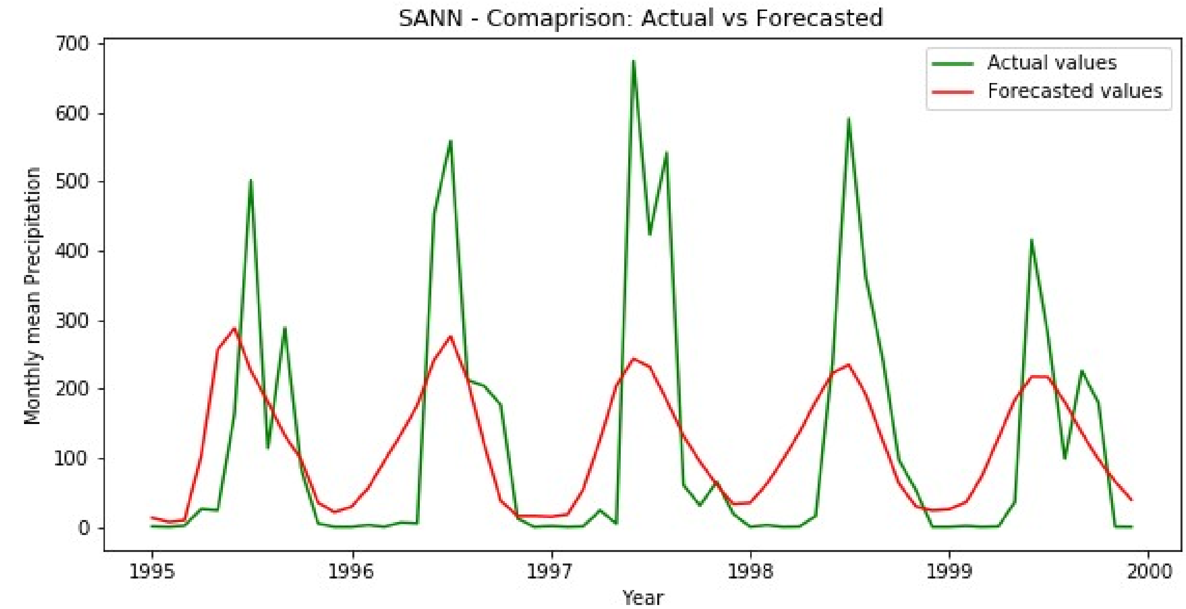

Figure7:SANN comparaison actual and forecasted

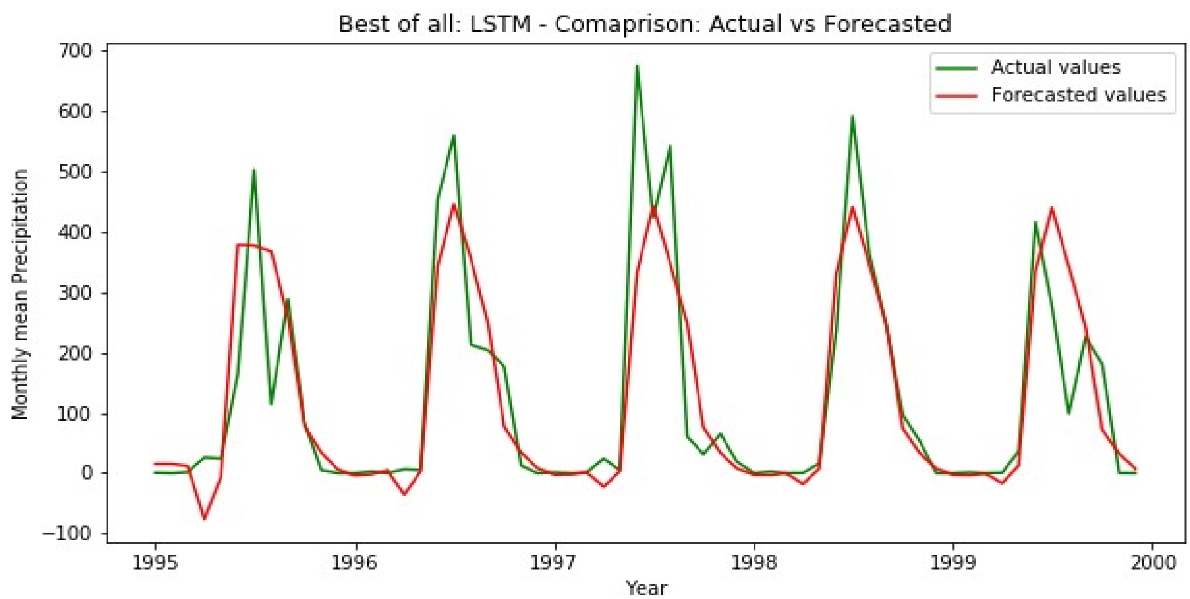

Figure8:LSTM comparaison actual and forecasted

Precipitation forecasting is the Long Short-Term Memory (LSTM) model, as it has the lowest Mean Squared Error (MSE), Mean Absolute Error (MAE), and Root Mean Squared Error (RMSE) among the models compared. The LSTM model has a MSE of 9327.699, MAE of 63.982, and RMSE of 96.58. In another hand, the FNN model has slightly higher MSE, MAE, and RMSE than LSTM model, with a MSE of 13385.58, MAE of 80.698, and RMSE of 115.696. But we can clearly notice the Time Lagged Neural Network (TLNN) model has a performance worse than the FNN model, with a MSE of 15870.466, MAE of 85.863, and RMSE of 125.978.
In last, The Seasonal Artificial Neural Network (SANN) model has the worst performance among the models compared, with a MSE of 19049.922, MAE of 101.188, and RMSE of 138.021.

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CONCLUSION

In conclusion, this study demonstrated the potential of using deep learning techniques, specifically Artificial Neural Networks and Recurrent Neural Networks, for forecasting precipitation. Our results showed that these methods can provide accurate predictions, surpassing traditional methods in certain cases. The LSTM model appears to be the best choice for precipitation forecasting based on the performance metrics presented. However, it is recommended to also consider other factors such as model interpretability, computational cost, etc In the futur work, the development of LSTM would be better for our living region using more parameters or the best of them, because they can differ from an area to another, which makes it a challenge in deciding the best way of using the algoritm and makes it another open project.

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