An Efficient Rainfall Prediction Model Using Deep Learning Method

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***Abstract*—Rainfall is a crucial aspect of the Earth's natural cycle and it is necessary for various activities such as agriculture, water supply and hydroelectric power generation. However excessive rainfall can lead to floods, landslides and other destructive consequences, while insufficient rainfall can cause droughts and water shortages. Therefore accurate estimation of rainfall is essential to manage and mitigate the impacts of rainfall. In this study, the dataset is collected from the NASA Power database[22] to predict the annual rainfall in Mangalore(Karnataka), India. The data is collected from January 1, 2003 to February 04, 2023 using NASA POWER API. The study used four models MLP[15],LSTM,BiLSTM,CNN to predict the daily average precipitation that contributes to the annual rainfall. The input parameters considered for the prediction are maximum monthly temperature, minimum monthly temperature, humidity, atmospheric pressure and wind speed[9]. The model's performance is measured using mean squared error (MSE) and mean absolute error (MAE) of the predicted values on training and testing ratio 80:20. CNN(Convolutional Neural Network) model outperforms and gives the MSE and MAE for the CNN(Convolutional Neural Network) model are 0.0041 and 0.0456 respectively.**

***Index Terms*—MLP,LSTM,BiLSTM,CNN,MSE,MAE**

I. Introduction

Water is a vital resource for all living beings on Earth and rainfall is one of the most critical sources of water. However, most of the water on Earth is not usable for plants and animals due to its salty nature as approximately 97% of water is found in oceans. Therefore accurate prediction of rainfall is essential for many aspects of our daily life including agriculture, flood management, and catchment management [6]. Rainfall has a huge impact on the lives of the people in and around Mangalore as it supports the agriculture sector in the region. In the agriculture sector, accurate rainfall prediction is crucial as it enables farmers to irrigate their fields and plan their crop-related activities accordingly. Varghese, L. R et.al[4] says that rubber production in Kerala needs rainfall and humidity. This prediction also helps in the management of water resources and the allocation of water for different uses. At the same time, it can save lives and property from the impacts of high-intensity rainfall which can cause flooding and landslides. Predicting rainfall is very useful in the prediction of floods and catchment management. S. Z. Ziv et. al[20] claims that precipitable water vapor helps a lot in predicting the flash floods. Accurate prediction of the rainfall is very crucial in managing the quality as well as the quantity of the water. It helps in flood warning systems which can help people to evacuate their homes and move to safer places before the flood arrives. Apart from this, rainfall forecasting can also be used for analyzing water quality problems beforehand. By knowing the rainfall prediction in a specific region water quality problems can be identified before they occur. Rainfall prediction involves the prediction of the probability of precipitation in a specific area, the amount of future precipitation, and the estimation of the amount of precipitation in a particular area. The accuracy of the forecast, the error in forecasting[7] and estimating precipitation, and the probability of precipitation in that particular region are considered. Various weather data and parameters are collected, analyzed, validated, modeled, simulated and researched to produce the forecast.

The study has collected data for the last 20 years which includes the various parameters on which the rainfall mainly depends. That is making a significant contribution to research in this field. We believe that accurate rainfall prediction is key to managing the quality and quantity of water which is crucial for both agricultural and industrial purposes. Our study aims to contribute to the development of an effective rainfall prediction model that can assist in making informed decisions related to water management and ultimately improve the livelihood of people in Mangalore and beyond.

II. Literature Review

A. Background and Related work

Chattopadhyay et al.[2] proposed a soft computing technique using a Multi-Layer Perceptron (MLP) to predict average rainfall during monsoon months in India, they used historical rainfall data from 1871 to 1999. They found that including more parameters in the model improved accuracy, with the use of an Artificial Neural Network (ANN) being particularly effective. This research highlights the potential of soft computing techniques for accurate rainfall forecasting in India, which is essential for agriculture, water management, and disaster prevention.

Abhishek et al. [3] suggested a rainfall forecasting model based on an Artificial Neural Network (ANN) for the Karnataka district of Udupi. The researchers discovered that increasing the number of neurons in the ANN layers resulted in a drop in the Mean Squared Error (MSE), suggesting an increase in the prediction model's accuracy. These findings indicate the ability of ANN for properly predicting rainfall in the Udupi district, as well as the necessity of selecting a sufficient number of neurons in the hidden layer to optimise the model's performance.

Varghese, L. R et.al[4] proposed to use time series forecasting for the prediction of rainfall in Kerala, India. They have classified the seasons into 4 parts like summer, winter, the northeast monsoon, and northwest monsoon. Their study didn't show anything about the dependency of the rainfall on other parameters like humidity and temperature

Akash Dutt et.al[5] in their research, Artificial Neural Network (ANN) models for rainfall prediction in coastal Puducherry, India have been proposed. Three ANN models were developed each with a distinct training technique and a set number of 20 neurons. The highest accurate result was obtained by using the feed-forward distributed time delay Algorithm. The study emphasises the significance of selecting the best training strategy to optimise model performance in coastal areas.

Devanshi Shukla et. al[8] proposed a prediction model for rainfall using neural networks. They analyzed monsoon season data in India and considered various factors like humidity, vapor pressure, rainfall, temperature, evaporation, wind direction, wind speed, rainy days, cloud cover, soil temperature and bright sunshine. The researchers used two methods Feed Forward Back Propagation and Cascade Back Propagation and found that the Cascade algorithm performed better for larger datasets compared to the Feed Forward network.

Xiaobo Zhang et.al[10] proposed two models for Annual and Non-Monsoon Rainfall Prediction in Odisha, India using Support Vector Regression (SVR) and Multi-Layer Perceptron (MLP) neural networks. In this model whole year is divided into four seasons: monsoon, pre-monsoon, post-monsoon, and winter monsoon and the model is used to predict the rainfall during these four seasons. The researchers found that SVR outperformed MLP in predicting annual rainfall in Odisha.
Moreover they found that using SVR was more accurate for predicting future rainfall for five non-monsoon months while MLP was more accurate for the remaining three non-monsoon months.

Sai Saran Ravi et. al[11] proposed a deep learning model for predicting rainfall and used parameters such as average rainfall, month, year, and date. Their aim was to predict whether it would rain on a given date or not. Two deep learning methods Long Short-Term Memory (LSTM) and Artificial Neural Network (ANN) were employed and compared for accuracy. The study found that the LSTM outperformed the ANN in predicting rainfall.

Y. H. Lee et. al[12] have done research on the dependency of rainfall based on the parameters like temperature, humidity, and Precipitable Water Vapour(PWV) [13],[18],[19] in the atmosphere, they concluded that PWV can be an accurate way to predict rainfall and using the remaining parameters can reduce false alarms.

Y. Kim et. al[14] have used ConvLSTM for the short-term prediction of rainfall. They claim that their model is efficient for light and moderate rainfall over a short period of time but it's not efficient when it comes to heavy rainfall because of the short life cycles of the heavy floods.

Feng Lyu et. al[21] Proposed an idea of using triple collocation to merge the datasets since there are chances that the dataset is not optimal and having errors and null values usually. They have conducted studies on mainland China and have used PERSIANN and CMORPH. Triple collocated datasets have given best results than individual datasets.

B. Problem Statement

To propose an efficient method for rainfall prediction using deep learning models that will predict the daily rainfall over Mangalore, a city of Karnataka.

III. METHODOLOGY

In this section, we will describe the detail about our rainfall prediction models and the various step involves in this process. Since we are predicting the rainfall over Mangalore whose latitude and longitude are 12.8698N and 74.8430E respectively. Mangalore is a coastal region where the Monsoon season starts in June and lasts till September. So through our model we will predict the next day rainfall from the previous day's data.

A. Data Collection:

- In this step historical weather data for Mangalore is collected from the NASA Power database[22] using the latitude and longitude coordinates obtained from geopy library of python.
- The data is collected for the specified start and end date range, which is from January 1, 2003 to February 04, 2023. The API used for collecting the data is the NASA POWER API and the Pandas library has been used to store the data in CSV file format.
- The collected data includes various meteorological variables such as Maximum Temperature, Minimum Temperature, Atmospheric Pressure, Relative Humidity, Wind Speed and Precipitation and data is stored in a CSV file format.

B. Data Preprocessing:

In this step, the collected data is preprocessed and prepared for further analysis.
The preprocessing steps involve:

- Converting the 'date' column to date time format using the Pandas library.
- All the invalid values were replaced by null values and we then removed all rows containing null values using the dropna() function from the Pandas library.

- Scaling the data between 0 and 1 using MinMaxScaler from the Scikit-learn library by applying the equation :

$$Y_{norm} = \frac{Y - Y_{min}}{Y_{max} - Y_{min}} \quad (1)$$

a) where Y is the original value.
b) Y_{max} is the feature's highest value.
c) Y_{min} is the feature's lowest value.
d) and Y_{norm} is the normalized value.

Scaling the data is a necessary task to make all the features fall in the same range and that helps the model to converge faster during the training. Rainfall, wind speed, and other parameters are not on the same scale so we used a min-max scaler to do all parameters on the same scale.

- Data was split in an 80:20 ratio for training and testing using the functions from the Scikit-learn library.

C. MLP(Multilayer Perceptron) Architecture

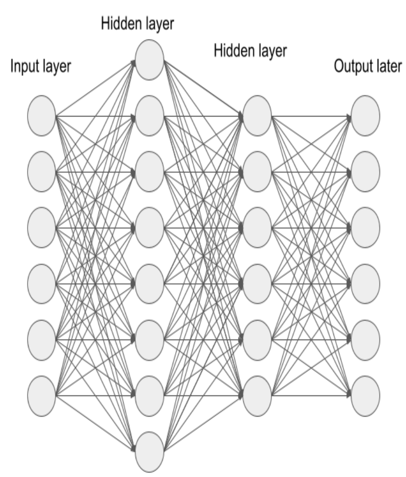

Fig. 1. MLP architecture

- In this step, a neural network model is developed using the Keras library.
- The model architecture consists of an MLP[2](Multilayer perceptron). It is a popular neural network that is widely used in regression tasks with 4 dense layers.
- Model is having four layers in it which include one input layer, one output layer and two hidden layers.
- Input layer is a dense layer with 6 neurons specifying the input dimension to be 6 and activation function as ReLu.
- The second and third layers are also dense layers with 8 and 6 neurons respectively and activation function as ReLu.
- The output layer adds a dense layer with 6 neurons but without any activation function specified means the function is linear by default.

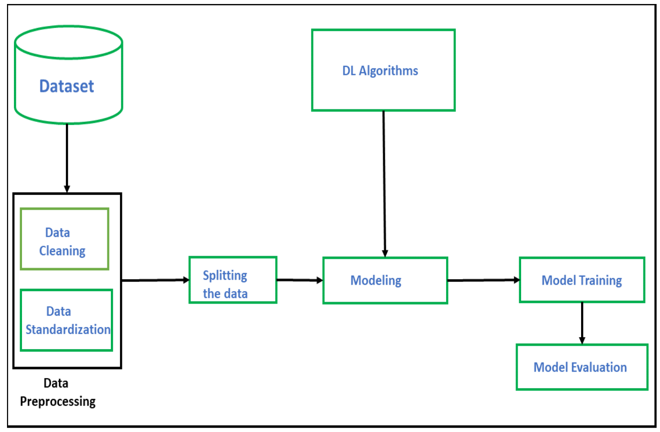

Fig. 2. Methodology Diagram

In Fig 2, we can see that, we are cleaning the dataset and then using a min-max scaler for standardization then for training purposes, we are splitting the dataset and we are using different DL models, and after that we are training and evaluating the model. In the compilation of the model Mean Squared Error(MSE) loss function, and Adam optimize are used for each model.

D. LSTM(Long Short-Term Memory) Architecture

- The model architecture consists of two LSTM layers[11] with 6 and 8 units respectively followed by two fully connected Dense layers with 6 units in each layer.
- The input shape to the model is (1,6) indicating that the model expects input sequences of length 1 with 6 features per time step.
- The activation function used for the LSTM and Dense layers is ReLU which introduces non-linearity into the model.
- The model is built to predict 6 output values and is compiled using the default optimizer in Keras (Adam).

E. BiLSTM(Bidirectional Long Short-Term Memory) Architecture

- The model architecture consists of two BiLSTM(Bidirectional Long Short-Term Memory) layers with 6 and 8 units respectively followed by two fully connected Dense layers with 6 units in each layer.
- The input shape to the model is (1,6) indicating that the model expects input sequences of length 1 with 6 features per time step.
- The activation function used for the BiLSTM and Dense layers is ReLU which introduces non-linearity into the model.
- The output of the final Dense layer is the model's prediction for the next 6 values.

- Overall BiLSTM model is designed to capture bidirectional dependencies in the input data.

F. CNN(Convolutional Neural Network) Architecture

- The model architecture consists of two Conv1D layers with 6 and 8 filters respectively followed by a MaxPooling1D layer with pool size 2.
- The input shape to the model is (1,6) indicating that the model expects input sequences of length 1 with 6 feature per time step.
- The activation function used for the Conv1D layers is ReLU which introduces non-linearity into the model. The model is built to predict 6 output values and is compiled using the default optimizer in Keras (Adam).
- The model is designed to learn features from the input data using convolutional layers and downsample those features using pooling layers.
- The output of the last Conv1D layer is flattened and fed into two fully connected Dense layers with 6 units in each layer with ReLU activation in the first and linear activation in the second.

G. Model Evaluation

- In this step, the trained model has to be evaluated. So for that various evaluation metrics have been used like Mean Squared Error (MSE) and Mean Absolute Error (MAE) [10].

- MSE is calculated using the formula:

$$MSE = \frac{1}{num}\sum_{i=1}^{num}(x_i - \hat{x}_i)^2 \qquad (2)$$

a) x_i is the actual value of the i-th data point
b) num is the total number of data points
c) $\hat{x}_i$ is the predicted value of the i-th data point

- MAE is calculated using the formula:

$$MAE = \frac{1}{num}\sum_{i=1}^{num}|x_i - \hat{x}_i| \qquad (3)$$

a) where num is the number of observations.
b) $\hat{x}_i$ is the predicted value of the i^{th} observation.
c) x_i is the actual value of the i^{th} observation.
d) The absolute value $|\cdot|$ is used to ensure that the error is always positive and the average of all the absolute errors is taken to give the overall Mean Absolute Error (MAE).

- The evaluation is done on both the training and testing data to ensure that the model is performing well on both datasets.
- The evaluation results are then used to tune the hyperparameters of the model to improve its performance.

- Training data has been used for training the model and testing data has been used to evaluate the model using K-fold cross-validation with 10 folds to check for overfitting.

Results and Analysis

H. Dataset Description

The data has been collected from the NASA Power database[22] (using the latitude and longitude coordinates obtained from geopy library of python)which has the weather data of every place.
The dataset primarily consists of daily data from January 01, 2003 to February 04, 2023. We collected common parameters like temperature, both high and low, precipitation, humidity and wind speed.In the data set missing values are also there and the missing values are represented by -999. The collected data is stored into csv format for the further use.

	YEAR	MO	DY	T2M_MAX	T2M_MIN	RH2M	PRECTOTCORR	PS	WS10M_RANGE
7335	2023	1	31	27.69	23.56	80.56	5.13	99.19	2.28
7336	2023	2	1	31.38	21.66	70.31	0.04	99.12	2.05
7337	2023	2	2	31.43	20.71	70.69	0.00	99.13	2.92
7338	2023	2	3	31.30	22.55	69.00	0.00	99.20	3.01
7339	2023	2	4	32.20	22.76	70.94	0.03	99.12	2.67

Fig. 3. Dataset

Here in Fig 3, T2M_MAX is the maximum temperature of the day(°C), T2M_MIN is the minimum temperature(°C) of the day, RH2M is the average relative humidity(%), PRECTOTCORR is the daily rainfall(mm/day), PS is the surface pressure(kPa) and W10M_RANGE is the wind speed(m/s)[1].

I. Data Visualization

We have used various plots for better data visualization like in which month the maximum rainfall happens, in which month the temperature is maximum and minimum and also humidity is maximum. We have plotted the correlation matrix to check the parameter that we are using are correlated to rainfall or not.

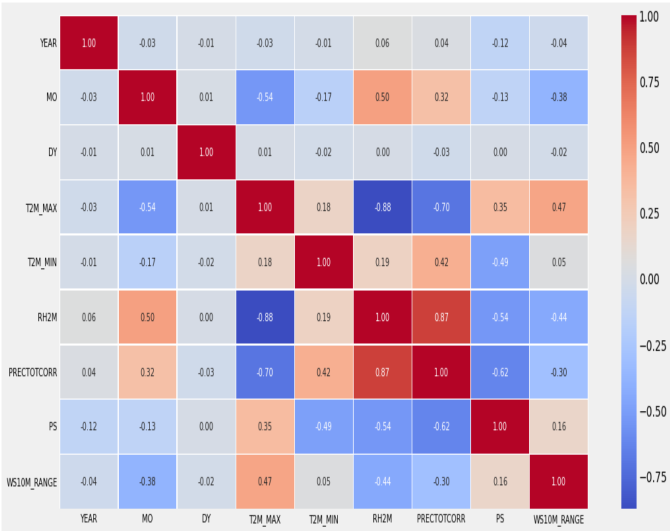

Fig. 4. Visualization of the correlation between the parameters

Here Fig 4. shows the correlation between the parameters. Each point in the matrix shows whether the relationship between two parameters is positive or negative. So from here, we can conclude that all the parameters that we are taking are responsible for rainfall.

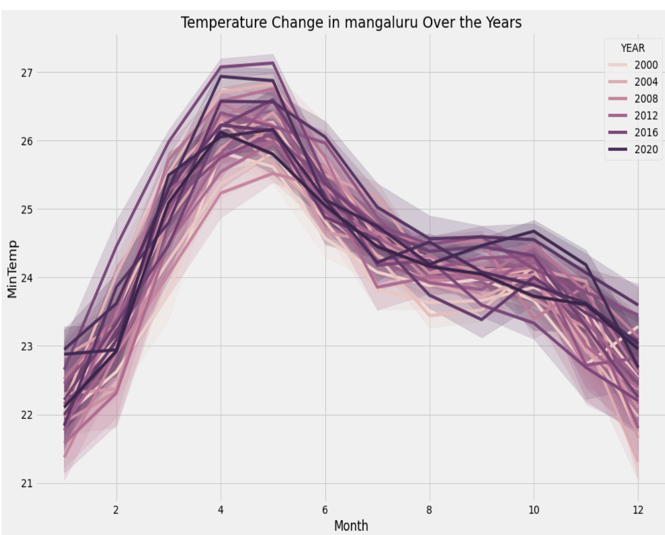

Fig. 5. Visualization of Monthly Minimum_temperature over the years

Here in Fig 5, we can see that the minimum temperature is depending on the month of the particular year.
We can say that the temperature is varying based on the month and the every year, trend in temperature reamins same.Like temperature is minimum in the month of December and maximum in the month of may.So from here we can interpret that one of the parameters is minimum in December and can affect the rainfall.

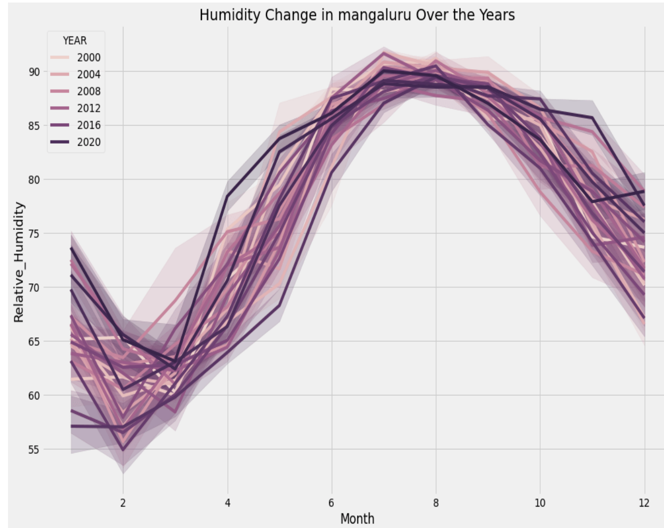

Fig. 6. Visualization of Relative Humidity

Here in Fig 6. relative humidity is highest in August and lowest in February. And we know that relative humidity is one of the most affecting factors of rainfall ,so we can conclude that rainfall will be maximum in august and can be minimum in february.

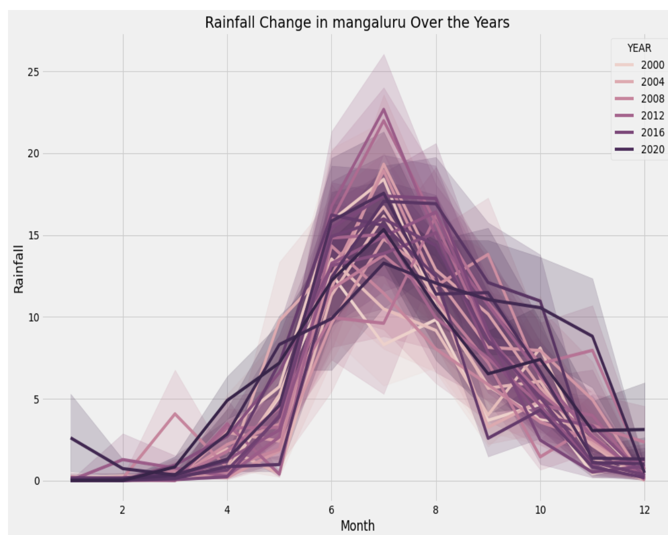

Fig. 7. Visualization of Monthly Rainfall(mm)

From Figure 7 we can easily see that in the month of December Rainfall is minimum and it is maximum in the month of August.So here we can make a conclusion that month also plays a major role in deciding the rainfall. And since Monsoon in Mangalore starts in June so we can see that the rainfall starts increasing from June and became highest in august and lasts upto September.

J. Training of Models

Various Models have been trained, and we have used two hidden layers for training ,we have split the data into two parts one is training and the other is testing data.We have used 80% of the data for training the model and 20% for data for testing the models. We have used Adam optimizer and ReLu function in hidden layers .In each model we have used Mean Squared Error (MSE) and Mean Absolute Error (MAE)[10] for loss values. We trained each model for 250 epochs with batch size 15 and recorded the Mean Squared Error (MSE) and Mean Absolute Error (MAE).

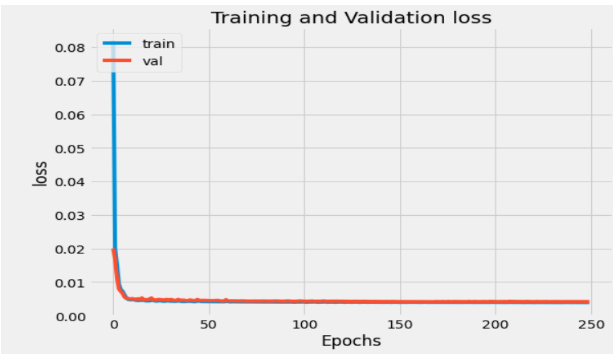

Fig. 8. Loss curve of MLP

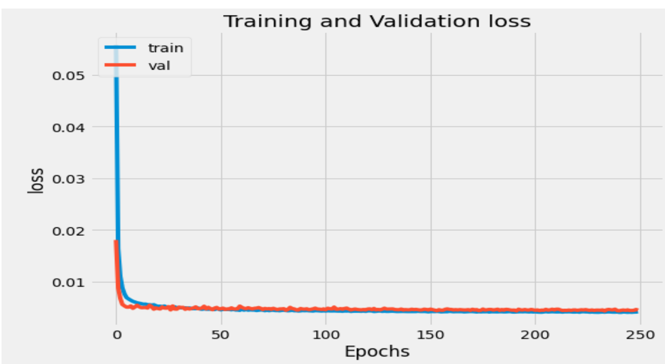

Fig. 9. Loss curve of LSTM

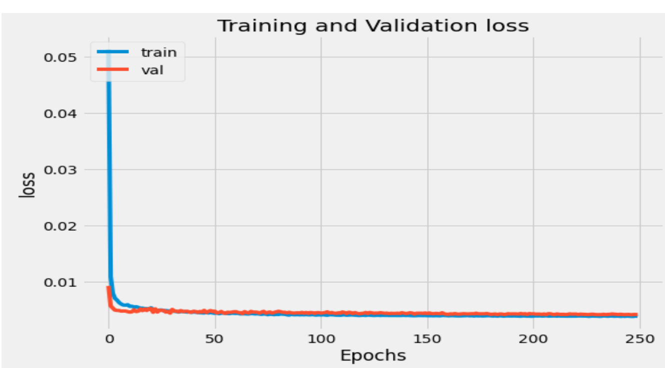

Fig. 10. Loss curve of BiLstm

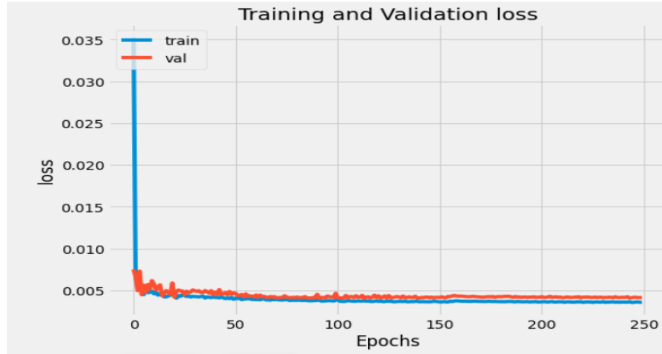

Fig. 11. Loss curve of CNN

In loss curve of each model(Fig.8,9,10,11) it can be seen training and validation loss that we have used. We can see that in the training and validation loss curve of every model, both the validation and training losses are continuously decreasing and converging to a value so we can say that none of our models are overfitting and every model is a good fit model.

TABLE I
RAINFALL REGRESSION RESULT FOR DEEP LEARNING MODELS

Model	MSE	MAE
MLP	0.0042	0.0464
LSTM	0.0042	0.0462
BI-LSTM	0.0041	0.0463
CNN	0.0041	0.0456

In Table 1, we can see MSE(Mean Squared Error), MAE(Mean Absolute Error) of all four models that we have used in our research. Among all the models Convolutional Neural Network (CNN) is best because its MSE(Mean Squared Error) & MAE(Mean Absolute Error) is less than all of the models. And Finally, all the models are evaluated on the testing data using K-fold cross-validation with 10 folds to check for overfitting for that we take a threshold of 0.005 to check for overfitting and we got that models are not overfitting because the difference is much less than 0.005 for all the models. By using the model user can predict the next day's rainfall by providing the previous day's data like all the parameters that are used in the prediction of rainfall. Users can easily predict the next day's rainfall and can plan their activities according to the intensity of rainfall.

IV. CONCLUSION AND FUTURE WORK

The prediction of rainfall is a very crucial task and important for the management of both the quality and quantity of water. Rainfall forecasting can be used in flood warning systems. Apart from this rainfall forecasting can be used for analyzing the water quality problem beforehand. Precipitation gives life on earth with salt- free water. So an accurate rainfall prediction is important for the living being and our day-to-day life activities and helps farmers in crop-related works. So This study for rainfall prediction for Mangaluru city focuses on creating a better model and it takes daily temperature(minimum), daily temperature (maximum), daily average rainfall,relative humidity,surface pressure and wind speed as input. In this study, all the daily parameters are used to predict the precipitation and for that, we have used multilayer perceptron (MLP), Convolutional Neural Network (CNN), Long Short-Term Memory (LSTM), and Bidirectional Long Short-Term Memory(Bi-LSTM) models and for evaluation, metrics used are Mean Absolute Error (MAE), and Mean Squared Error (MSE) and better result is given by the CNN model . we used K-Fold cross-validation also to evaluate our models and to check for the best fit. All models are giving similar results with Convolutional Neural Network (CNN) giving slightly lesser MSE & MAE.So Convolutional Neural Network (CNN) can be used for further predictions.

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