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Use of Appropriate Loss Function in Rainfall Prediction using Deep Learning

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Abstract: ***India is an agricultural country, and rainfall is the main source of irrigation for agriculture. Prediction of rainfall is very crucial for farmers to make decisions. In this research paper, the prediction model has been developed through deep learning using historical data of 10 years of rainfall. A deep learning approach used Keras API with an artificial neural network technique to predict the daily rainfall. The prediction model has been assessed by four-loss function, i.e., MSE, MAE, Hinge, and Binary Cross-Entropy.***

Keywords: ***ANN, deep learning, loss function, rainfall prediction.***

I. INTRODUCTION

Rainfall: - In India, more than 65% of the population resides in rural areas, out of which most of the people are farmers and mainly rely on agriculture. In India, a state like Gujarat has different topographic features, having average rainfall between250 mm to 1500 mm across various zones [14]. In Gujarat, rain is the primary source of irrigation for agriculture, so rainfall prediction is crucial for farmers to make many decisions. Therefore, rainfall prediction required an appropriate approach [12]. Weather Prediction used different statistical methods, but these methods will not accurately predict the rainfall because rainfall data are mostly non-linear, and statistical methods are best suited for linear data [7].

Artificial Neural Network: - An artificial neural network (ANN) is a set of connected artificial neurons capable of storing experiential knowledge and sharing among researchers and practitioners as an alternative tool [15]. Artificial Neural Network (ANN) is capable of predicting real-world problems and resulting in nearly the perfect solution for the given problems with the help of proper training and testing mechanism [9].

Deep Learning: - In artificial intelligence (AI), Deep Learning (DL) is a subset of machine learning based on Neural Network (NN) having a capability of learning (supervised or unsupervised) from data. DL has various architectures like recurrent neural networks, deep neural networks, etc. [8]. Based on Neural Network, a reliable machine learning technique i.e., DL has been applied to different fields, including forecasting systems, computer vision, automatic speech recognition, many more. It has achieved success in improving the results for the given tasks [16].

The Keras Framework: - Keras is an excellent high-level open-source neural network API framework, written in Python. It can train and execute deep learning models using Theano, Tensor Flow, and CNTK backend [17]. The models will quickly turn into products with the combined effort of Keras API and Tensor Flow framework, then after it will deploy across various platforms, i.e., Google cloud, Python, iOS, Android, etc. [11]. Francois Chollet used four guiding principles to developed and maintained Keras i.e., Modularity, User-friendliness and minimalism, Easy extensibility and Work with Python Model [6].

Loss Function: - In Keras framework, the loss function is an objective function required to compile a deep learning model. The loss function is necessary to calculate the model error. The loss function measures the amount by which the predicted value deviates from the actual value. For the right prediction, loss value is lower and vice versa. Different types of loss functions are available in Keras, such as Mean Squared Error (MSE), Binary Cross-Entropy, Mean Absolute Error (MAE), Hinge, Mean Squared Logarithmic Error (MSLE) and many more [18].

II. RELATED WORK

S. Renuga Devi and her team have published a survey that compared the forecasting capabilities of different Artificial Neural Network models to predict the daily rainfall. ANN models includes distributed time-delay (DTD), feed-forward (FF), and cascade-forward (CF) back-propagation, non-linear autoregressive exogenous network. In this study, rainfall data sets of Nilgiris were divided into two parts, the first part contained temperature, humidity, and daily rainfall data and the second part contained only daily rainfall data. The result shows that a non-linear autoregressive exogenous network is best suited as compared to other networks on performance analysis based. From the prediction capabilities point of view, FF back-propagation neural network outperformed DTD neural network and CF back propagation neural network. However, there is a minor difference in their performances [15]. The principle of decomposition and ensemble are used by Beltr' an-Castro and his team to forecast the rainfall. In their work, the original data are divided into a set of simple components by employing decomposition technique i.e., Ensemble Empirical Mode Decomposition (EEMD). Moreover,

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a Feed-Forward Neural Network (FNN) used as a forecasting tool to model each component. Results obtained from an experiment performed on a real-observed rainfall data of Manizales city, Colombia, were compared with a single FNN model, which improved the system [3].

Emilcy Hernandez and his team have introduced Deep Learning architecture, to predict the daily precipitation for the next day by using neural networks and auto-encoders. The day-to-day accumulated rainfall forecasts using the data collected from the meteorological station of Manizales city (Colombia). Different methods like MLP, Naive 1, Naive 2, etc. have been compared with the proposed architecture. The results show that in terms of the Mean Square Error and Root Mean Square Error, the proposed architecture outperforms other methods [6].

To predict the trend of stock prices, Akira Yoshihara and her team adopt a deep learning approach that used a recurrent deep neural network by concentrating on long-term active new events. The study utilized ten years of published data of Nikkei newspaper articles. Data from 1999 to 2007 used to train the model, while 2008 data used to test the model. The uptrend and downtrend of the stock prices have been predicted by choosing the Nikkei Stock Average and popular top ten brands appearing in the newspaper. This prediction, when compared with Deep Belief Network (DBN) and support vector machines (SVM), the obtained result state that the proposed deep learning approach has statistically significant with the lowest error rate with SVM[2].

Daisuke Matsuoka and his team adopted a deep learning approach to identify tropical cyclones (TCs) and their precursors. Deep convolutional neural networks (CNNs) used to train the model by using outgoing long wave radiation (OLR) data of 10 years for detecting precursors and TCs. For the binary classification of data, there are 50,000 TCs with precursors and 500,000 non-TC data trained by CNN. Seasons, lead times, and basins used to investigate CNN's performance. In the western North Pacific, TCs and their precursors are successfully detected between July to November with the False Alarm Ratio (32.8-53.4%) and Probability of Detection (79.9-89.1%) using the CNN model. In the western North Pacific, detection results of precursors for days 2, 5, and 7 are 91.2%, 77.8%, and 74.8%, respectively [4]. E. T. Lau, L. Sun, and Q. Yang built a model to predict student's performance using a conventional statistical analysis combining with a neural network. Conventional statistical evaluations used to identify the factors that affect students' performance. The neural network with the Levenberg–Marquardt algorithm and back-propagation training rule is modeled with input layers (11), hidden layer (2), and output layer (1). The model performance is evaluated through the error performance, regression, error histogram, confusion matrix. Finally, the model will achieve 84.8% accuracy along with some limitations [5].

III. METHODOLOGY

A deep learning approach has used to build the proposed prediction model. The model aims to predict the daily rainfall using historical data of 10 years of rainfall by implementing a deep learning approach using Keras API with an artificial neural network technique. The prediction model has been assessed by four-loss functions i.e., MSE, MAE, Hinge, and Binary Cross-Entropy; out of them, the best loss function is derived with high prediction accuracy with minimal error loss. The proposed prediction model approach is to collect raw weather data, pre-process the raw data, process deep neural network for prediction, and compare the performance of the model using different loss functions.

A. Raw Data Collection

Raw data are collected from the Agri-meteorological Department of Navsari Agricultural University, Navsari for ten years. Data is separated into training data and testing data, which consists of 70% (2009 – 2015 i.e., 2555 records) from 2009-2015 and 30% (2016-2018 i.e., 1096 records) of total data (3651 records) respectively. Weather parameters used in this model are minimum temperature (Tmin), maximum temperature (Tmax), relative humidity (RH), wind speed (WS), and rainfall (Rf).

Table- I: Weather Parameters Details

Sr. no.	Name	Description	Measurement Unit
1	TMax	Maximum Temperature	◦C
2	RH	Relative Humidity	%
3	WS	Wind Speed	Km/h
4	TMin	Minimum Temperature	◦C
5	Rf	Rainfall	Mm

1	Days	DATE	Tmax	Tmin	RH	Ws	Rf
1616	1615	04-Jun-13	35.2	27	83.67	5.03	0
1617	1616	05-Jun-13	34.5	27	87.51	5.18	0
1618	1617	06-Jun-13	34	29.2	86.54	5.48	0
1619	1618	07-Jun-13	34.5	27.8	98.79	5.91	0
1620	1619	08-Jun-13	32.5	24.5	86.77	0.99	63
1621	1620	09-Jun-13	32.5	26.5	88.66	3.73	0
1622	1621	10-Jun-13	31.5	24	94.56	5.78	164
1623	1622	11-Jun-13	30	22.5	93.73	3.63	26.4
1624	1623	12-Jun-13	29	25.5	81.14	3.2	30
1625	1624	13-Jun-13	31	24.9	95.11	4.45	16
1626	1625	14-Jun-13	30	24.5	83.79	2.88	14
1627	1626	15-Jun-13	31.5	25.5	94.48	3.82	9
1628	1627	16-Jun-13	30	26.2	88.18	2.71	2
1629	1628	17-Jun-13	30	24.2	97.54	3.4	36
1630	1629	18-Jun-13	27	25	91.84	1.65	40
1631	1630	19-Jun-13	30	24.5	88.7	4.08	37
1632	1631	20-Jun-13	30.5	25.5	82.95	1.65	3
1633	1632	21-Jun-13	31.5	25.5	89.71	3.17	15

Fig. 1.Raw Data

B. Pre-Processing Data

In data pre-processing, the data cleaning operation is performed where missing value is replaced by central measurement value like a mean of giving parameters. Further, the binning process is applied to set the value of the given parameters and partitions them into bins. After cleaning the data, rainfall data will be normalized [13] and rescaling into the range (0 – 1) [1], which minimizes the error.

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1	Days	DATE	Tmax	Tmin	RH	Ws	Rf
3443	3442	June 5, 2018	0.83	0.92	0.76	0.29	0.00
3444	3443	June 6, 2018	0.84	0.75	0.86	0.27	0.04
3445	3444	June 7, 2018	0.83	0.92	0.83	0.29	0.00
3446	3445	June 8, 2018	0.83	0.93	0.80	0.32	0.00
3447	3446	June 9, 2018	0.82	0.96	0.85	0.37	0.00
3448	3447	June 10, 2018	0.81	0.95	0.86	0.43	0.00
3449	3448	June 11, 2018	0.81	0.87	0.91	0.44	0.02
3450	3449	June 12, 2018	0.80	0.92	0.84	0.44	0.00
3451	3450	June 13, 2018	0.80	0.93	0.78	0.47	0.00
3452	3451	June 14, 2018	0.79	0.93	0.76	0.47	0.00
3453	3452	June 15, 2018	0.79	0.96	0.78	0.41	0.00
3454	3453	June 16, 2018	0.80	0.87	0.97	0.43	0.00
3455	3454	June 17, 2018	0.75	0.74	0.86	0.32	0.16
3456	3455	June 18, 2018	0.76	0.79	0.74	0.34	0.00
3457	3456	June 19, 2018	0.81	0.83	0.77	0.29	0.00
3458	3457	June 20, 2018	0.82	0.89	0.74	0.22	0.00
3459	3458	June 21, 2018	0.82	0.89	0.73	0.25	0.00
3460	3459	June 22, 2018	0.80	0.92	0.83	0.30	0.00
3461	3460	June 23, 2018	0.75	0.84	0.83	0.24	0.00

Fig. 2.Data after preprocessing

C. Building Deep Neural Network Predictive Model

Keras API framework used to develop deep learning-based fully connected Neural Network predictive model. Three layers of an artificial neural network i.e., input, hidden, and output layer, where nodes get interconnected between two layers to build a fully-connected neural network. No links established between the nodes of the same layers [10]. In this prediction model, a deep neural network used two hidden layers and one input & output layer. 'Relu' activation function has been applied at the input and hidden layer, while 'sigmoid' activation functions has applied at the output layer. The Loss function, namely MSE, MAE, Hinge, and Binary Cross-Entropy, evaluates the model's performance with minimal loss and high accuracy. Parameters that applied to the model are given in the below table.

Table- II: Model Parameters

Name	Description	Value
Input parameters	An input value used in the model.	4
Output parameter	An output values used in the model.	1
Epochs	An iteration used by the model to update the weight of the entire training dataset.	100
Initial Learning rate	An estimated error that controls the change in the model when the weight is updated.	0.001
Optimizer	An algorithm used to minimize the loss function while updating the weight.	'adam'
Batch size	The number of sets used to divide model dataset.	10

IV. RESULT & DISCUSSION

In this section, we will discuss the performance of the model. The model obtained the result in the form of accuracy and loss value of both training and testing dataset by using loss functions i.e., MSE, MAE, Hinge, and Binary Cross-Entropy. The below figure shows the result of an individual loss function.

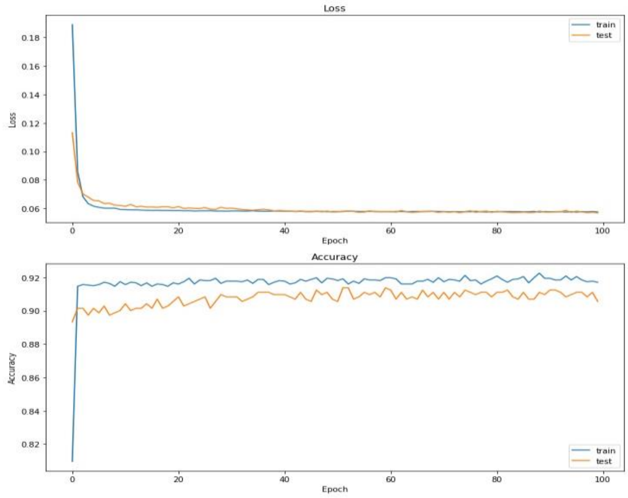

Fig. 3.Data Result obtained using MSE Loss function

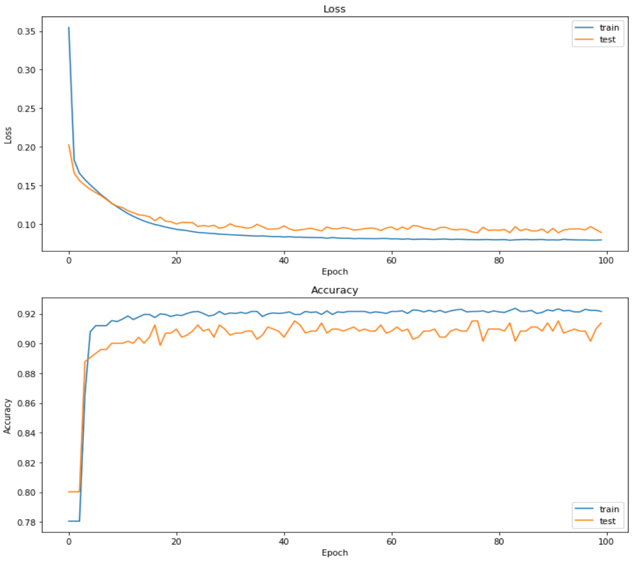

Fig. 4.Data Result obtained using MAE Loss function

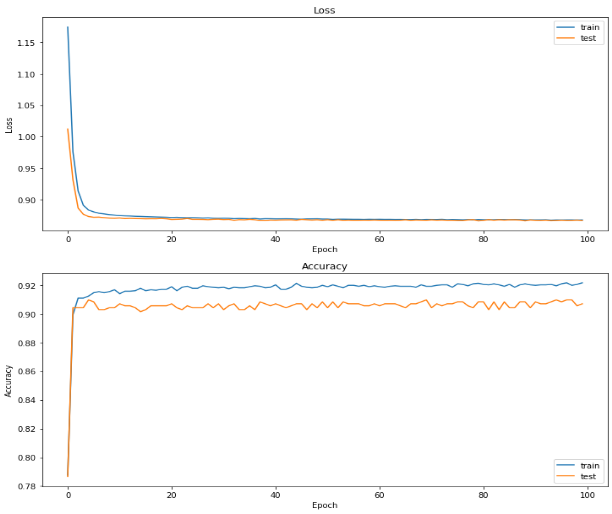

Fig. 5.Data Result obtained using Hinge Loss function

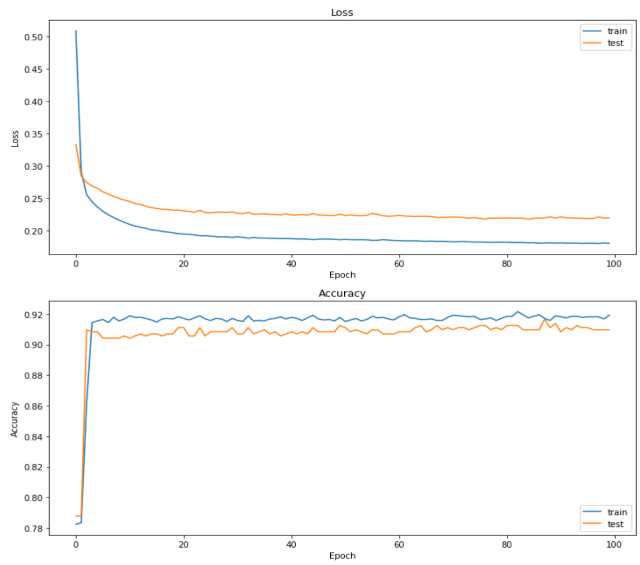

Fig. 6.Data Result obtained using Binary Cross-Entropy Loss function

In the above Figures 3, 4, 5, and 6, the first graph shows the minimization of loss value, and the second graph shows the maximization of accuracy at each epoch for both the train (blue) and test (orange) dataset. To evaluate the daily rainfall prediction model performance, we have compared the loss error value of all the loss functions using the same train and test dataset, activation function, and model parameter given in table II.

Table III shows the loss value and accuracy obtained by evaluating the model for each loss function.

Table- III: Loss value comparison of different loss functions

**DS means Data Set, LV means Lost Value, Acc means Accuracy*

DS	MSE		MAE		Hinge		Binary Cross-Entropy	
	LV	***Acc***	***LV***	***Acc***	***LV***	***Acc***	***LV***	***Acc***
Train	0.06	92%	0.09	92%	0.89	92%	0.19	92%
Test	0.06	91%	0.09	91%	0.89	91%	0.22	91%

As seen from Table III, the training and testing dataset obtained the same accuracy with all four-loss functions i.e. 92% and 91%, respectively. But when compared with Loss value, MSE outperformed amongst all, with minimum loss error value of 0.06, while the Hinge results in maximum loss error value i.e., 0.89. The prediction model accuracy is 91%, which indicates that it is excellent to predict daily rainfall.

V. CONCLUSION

In this research, the prediction model has developed using Keras API using a deep learning approach to predict the daily rainfall based on historical data of 10 years of rainfall. This prediction is very crucial for farmers to make decisions. The model has evaluated using four-loss functions i.e., MSE, MAE, Hinge and Binary Cross-Entropy. All the loss functions have compared using the same training and testing dataset. MSE outperformed with a minimal loss error value of 0.06, while the Hinge resulted in maximum loss error value i.e., 0.89 with accuracy 92% (train) and 91% (test). The prediction model has an excellent overall 91% accuracy in predicting daily rainfall.

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