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TIME SERIES ANALYSIS – A COMPARATIVE ANALYSIS BETWEEN ANN AND RNN

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Abstract: **Time series analysis is a significant undertaking in time series data mining and has pulled in extraordinary interests and huge endeavours during the most recent decades. However, data handling is a prior task in time series data. The main objective of time series analysis is to get intuition of the data. In recent years, AI models come with some enormous results in time series analysis. The motivation of this study is to determine a suitable artificial intelligence-based model for time-series related analysis. In this comparative analysis, authors utilize a publically accessible dataset to conduct the research. Author utilizes Long Short Term Memory (LSTM) model along with Feed Forward Neural Network (FNN), Time lagged Neural Network (TLNN) and Seasonal Artificial Neural Network (SANN) to compare the performance. However, some extensively used performance matrices such as Mean Squared Error (MSE), Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) utilize for the evaluate all the models.**

Keywords: *Time Series; Long short term memory; Recurrent neural network; Artificial neural network.*

1. INTRODUCTION

Time series is a significant class of transient information object and can be handily acquired by recording a progression of perceptions sequentially [1]. Weather forecasting, stock price or electrocardiogram (ECG) [1] can be the ideal example of time series analysis. There are more example can be added. Time series as an acknowledgement of a stochastic time series procedure or model, and the principal reason for breaking down time series in this methodology is to build a potential basic procedure and use it for estimating, deduction, and control [2]. There are various time-series analysis such as discrete-time series, continuous-time series, discrete-valued time series etc [3].

An efficient prediction system is important for time-series analysis. However, there are several statistical prediction models to predict further outcome of the data. But sometimes these are not sufficient to predict the desired result.

Time-series analysis can be separated as univariate time-series analysis and multivariate time-series analysis [2]. The Crucial investigation of time-series analysis is a sort of venture experiment where the offer estimation of an organization is evaluated by breaking down its business, income, benefits and other financial elements. This strategy is generally appropriate for long haul determining. Specialized investigation utilizes the authentic cost of stocks for distinguishing the future cost. Moving normally is a regularly utilized calculation for specialized examination [4].

In this paper, authors attempt to locate the best model for time-series analysis. Authors utilizes a publically accessible time-series dataset, 'Precipitation Data of Pune from 1965 to 2002', which contains rainfall data of 37 years of Pune, India. Various kinds of Artificial Neural Network models as well as Recurrent Neural Network models are applied to determine the better model for time series analysis. Feed Forward Neural Network (FNN), Time Lagged Neural Network (TLNN) and Seasonal Artificial Neural Network (SANN). Alongside the Artificial Neural Network algorithms, additionally applied one of the finest recurrent neural network model, called Long Short Term Memory (LSTM).

At last, the authors come to summarize that Long short term memory (LSTM) has performed amazingly well than different models in this comparative analysis.

2. RELATED WORKS

In recent years, time-series analysis has become a day by day part of our regular daily existence. Time-series can be utilized such huge numbers of area, for example, banking, climate estimating, clinical patient recuperation, etc. So there are such a large number of tremendous techniques has been acquainted by analysts with investigating more adequately.

Zhao et al. 2017 [1] have executed a convolutional neural system for contributing to proficient execution on time-series analysis. They achieved around 88% accuracy in various time-series dataset on average. S. Selvin et al. [4] have worked in a stock prediction analysis. Where they actualized a

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convolutional neural network, and long short term memory (LSTM) model to anticipate different securities exchange dataset. The convolutional neural model has predicted marginally better than other ones. Zheng et al. [6] have performed a chaotic time series prediction analysis by a modified version of the recurrent neural network. They assessed the best possible boundaries of stage space reproduction and streamlines the structure of recurrent neural networks and optimized as evolving recurrent neural network (ERNN). R. Adhikari et al [7] have worked with six true-time series dataset having prevailing occasional changes. They executed an artificial neural network and traditional support vector machine model to legitimize better outcome in their analysis. In that analysis, they have accomplished, the seasonal artificial neural network has performed better than the traditional machine learning model. A. Gers et al. [8] have implemented long short term memory (LSTM) model in several datasets. They also made a comparison between traditional multi-layer perception (MLP) models with LSTM. Where LSTM has performed better than MLP as a prediction model. Jerome T. et al. [9] have actualized recurrent neural network in their Puget Power Electric Demand time-series dataset. They changed the autoregressive moving normal (ARMA) model into the NARMA recurrent unit model to ensure better result in terms of foreacsting. S.M. Karthik et al. [10] have implemented seasonal artificial neural network in rainfall prediction of India. They evaluated their model by MSE, RMSE, MAD, MAPE. They also changed model parameters to 1-9 and got the best outcome in 8. P. Gupta et al. [12] have implemented a pre-trained recurrent neural network model in their medical time-series dataset. J. Gamboa et al. [13] have utilized the Muse and Nottingham datasets in their time series analysis. They implemented RNN, LSTM in their experiment.

3. METHODS

In this comparative analysis, Authors have attempted to show the best-fitted model for time-series analysis. Regarding this, author also executed several artificial neural network algorithms and recurrent neural network algorithm to enable the best possible outcome from these algorithms. Authors also used extensively used models such as feed-forward neural network (FNN), time-lagged neural network (TLNN), seasonal artificial neural network (SANN) and Long short term memory (LSTM). Then we evaluated our models in terms of MSE, MAE and RMSE.

A. Reference Dataset

In this time-series analysis, we utilized a publically accessible dataset from kaggle, 'Precipitation Data of Pune from 1965 to 2002' [16]. It consists of 37 years rainfall data. Later on, authors have changed over the XML data into comma separated value (CSV) format for analysis convenience. The dataset breaks rainfall data into consistent months and years (1965-2002).

B. Feed forward neural network (FFNN)

Feed forward neural network (FFNN) has a significant numbers of nodes as a computational model. The nodes are connected to each other using weights in layer-by-layer. It has a very specific architecture in which the nodes have a forward connection from past layers. A node which can proceed information coming from the weights (Fig. 1). Output of a node y_i can be expressed mathematically [5],

$$y_i = \varphi\left(\sum_{j=1}^{n^i} w_j^i z_j^i + b^i\right)$$

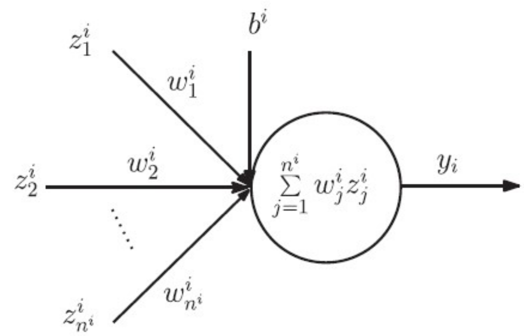

Fig. 1: Node of the network [5].

Where, z^i is the input of the node, b^i is the bias, w^i denotes as the weight and ɸ is the activation function at the ith node in the FFNN and n^i denotes the total connections.

C. Time lagged neural network (TLNN)

Time-lagged neural network of action empowers the system to find acoustic-phonetic highlights and the temporal connections between them autonomous of position in time and henceforth not obscured by fleeting movements in the input. The time-delay neural network architecture is designed for undermining speech sequences in an efficient manner. It is usually used for time-shift arrangement. It generates output regarding on input sequences. There are two extensive features for time-delay neural network.

1. The TDNN needs to perceive aftereffects that may happen at non-fixed situations in the input window. Subsequently the system needs to discover

that the aftereffect is a component free of movements in its position.

2. The TDNN needs to perceive includes in any event, when those highlights show up at various relative positions. This circumstance emerges in situations where various aftereffects happen in the information window with various relative separations. This happens much of the time in genomic arrangements when at least one components are embedded or erased in a given advertiser in a given network [14].

D. Seasonal artificial neural network (SANN)

Seasonal artificial neural network (SANN) mainly used for time series forecasting in non-linear depended data. Like ARIMA model, it does not require to eliminate the seasonal variational data. However, SANN is capable of modelling non-linear dependencies. Input of seasonal neural network has s nodes, and a hidden layer with fixed numbers neurons. The neurons of the hidden layers are responsible to indicate the complexity of SANN model. If the number of neurons have increased, then the training data might be not enough to train the model [10].

E. Recurrent neural network (RNN)

Recurrent neural network (RNN) is a new state-of-art method for sequential data analysis. It is widely used in natural language processing, speech recognition, time-series analysis. It is a recent neural network that works by feeding output of previous step to the newer step input. Other neural networks have independent inputs and outputs but in recurrent neural network has connected input and output phase. It has a hidden layer in each network, where the hidden layer helps to work with the sequential data. It has a memory block which remembers the previous input data. The hidden layer dominates the input. It also has more than one hidden layers in complex networks. The hidden layers also have weights and bias as like other neural networks. In this analysis, we have utilized one of the most impressive RNN as LSTM. Which is a more confined RNN network for sequential time-series analysis.

F. Long short term memory (LSTM)

Long Short-Term Memory (LSTM) is an advanced recurrent neural network (RNN) design that had been appeared to overcome the conventional RNN limitations [8]. LSTM has been specifically designed for sequential tasks. It holds a memory blocks in the hidden recurrent layers. There are several memory cells in the memory blocks, which are self-connected to each other. One input gate and one output gate has been associated to each memory block. [11]. Input gates are responsible for to control the activation of the inputs which are inside in the memory cell. The output activation is controlled by the output gate in the whole remain network. However, a new gate called forget gate has been connected to the memory block in the later part. Before connecting to the input, the forget gate enhances the internal structure of the cell so that it can reset the memory in a convenient way. The latest architecture of LSTM has some peephole connections to incline the timing capability of outputs.

In the Fig. 2 we can see some parameters such as f_i, i_i, o_i, c_i. Which are representing forget gate, input gate, output gate and cell activation respectively. Fig. 2 shows the long-shot term memory architecture.

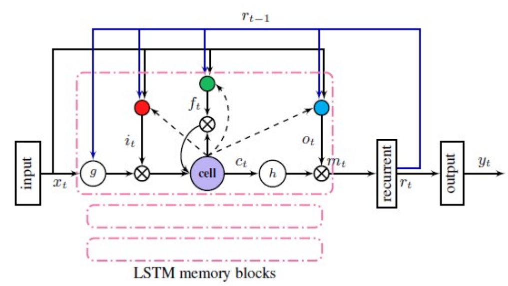

Fig. 2: Long Short term Memory (LSTM)-RNN Architecture [11].

4. PERFORMANCE METRICS

In this analysis, authors have evaluated each model performance with some extensively used metrics such as mean squared error (MSE), mean absolute error (MAE) and root mean squared error (RMSE). These are very widely used in forecasting time-series analysis evaluation.

Mean Square Error (MSE): Mean square error is the average of squared errors of forecasted values. It can eliminate the extreme errors of forecasted value [15].

$$\mathbf{MSE} = \frac{1}{n}\sum_{i-1}^{n}(x_i - k_i)^2$$

where, x_i stands for actual value and k_i stands for forecasted value.

Mean Absolute Error (MAE): Mean absolute error is the measure of absolute errors of forecasted value. It also defines the magnitude of the forecasted error [15].

$$\mathbf{MAE} = \frac{1}{n}\sum_{i=1}^{n}|x_i - y_i|$$

where, x_i stands for actual value and k_i stands for forecasted value.

Root Mean Squared Error (RMSE): Root mean squared error is the square root of mean square error. It has the all properties of MSE and most effective in evaluation purpose [15].

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\boldsymbol{x_i} \quad \boldsymbol{k_i})^2}$$

where, x_i stands for actual value and k_i stands for forecasted value.

5. EXPERIMENTAL RESULTS

In this analysis, authors have utilized feed-forward neural network, time-lagged neural network, seasonal neural network and long short term memory. However, for SANN, s nodes is taken to 12 as the dataset consists of monthly data and the neurons are set to 6 to avoid insufficient training data problem. To the LSTM model, the dataset split into 80% and 20% with 60 epochs. And the batch size is 24 with 25% dropout. After the experiment, authors have actualized that RNN-based Long Short Term Memory (LSTM) has performed drastically well than other models. LSTM has the lowest root mean square error of 94.24. On the other hand, feed forward neural network (FNN) has 118.39 RMSE, time-lagged neural network (TLNN) has 126.36 RMSE and seasonal artificial neural network (SANN) has 138.59 RMSE. Table 1 shows the performance evaluation of every model.

TABLE I: Performance Evaluation of Every Model

Models	MSE	MAE	RMSE
FNN	14123.44	84.66	118.39
TLNN	15829.27	86.29	126.36
SANN	19801.56	104.32	138.59
(LSTM)	**8905.18**	**55.35**	**94.24**

In the later part, authors have investigated the forecasted result with the actual result. From the charts, we can separate that LSTM's result is further better than different models. Where seasonal artificial neural network (SANN) the most poor forecasting performance than other models. It can be seen that time-lagged neural network and feed forward neural network has very similar output. So it can be easily said that, LSTM has the overall better performance in time-series analysis. In Fig. 3, 4, 5, 6 have the forecasted prediction and actual prediction comparison. Where Fig.7 has the RMSE score based performances of each model.

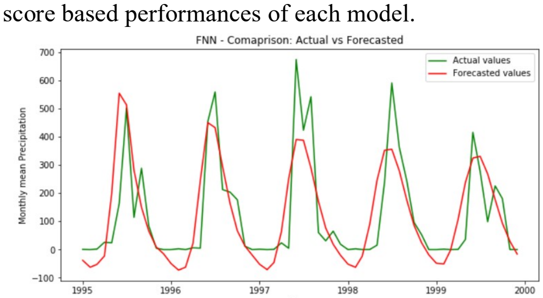

Fig. 3: Feed Forward Neural Network Comparison: Actual vs Forecasted.

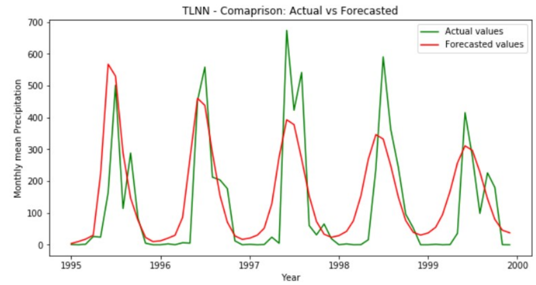

Fig. 4: Time Lagged Neural Network Comparison: Actual vs Forecasted.

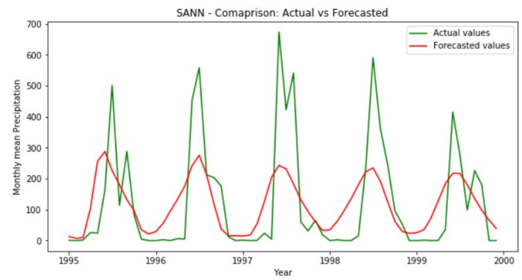

Fig. 5: Seasonal Artificial Neural Network Comparison: Actual vs Forecasted.

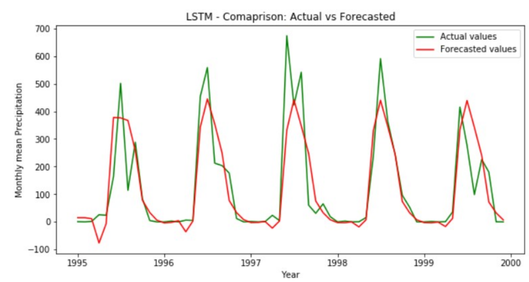

Fig. 6: Long Short Term Memory Comparison: Actual vs Forecasted.

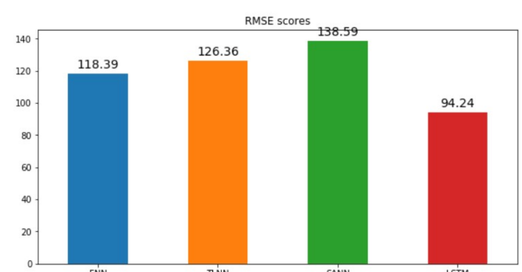

Fig. 7: Performance Analysis Based on RMSE.

7. CONCLUSION

Time-series analysis is one of the significant parts of statistical analysis. In recent years using different traditional machine learning models as well as deep learning models are making the time-series analysis more efficient. In this paper, authors tried to justify an efficient time-series analysis model between different Artificial Neural Network (ANN) models and Recurrent Neural Network model. In this analysis, we used a feed-forward neural network, time-lagged neural network, seasonal artificial neural network and long short term memory for justifying the best model. Authors evaluated and made recommendation for the best performing model based on some extensively used performance matrices such as mean squared error, mean absolute error and root mean squared error. In this way, Long-short term memory (LSTM) has the best result as well as the closest prediction value on respect to the actual value. It has 92.23 RMSE value which is far lower than other models. On the other hand, FNN, TLNN and SANN have 117.82, 123.56 and 135.52 RMSE value respectively. So authors have recommended and analyzed that LSTM has better output time-series related analysis.

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