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Sunspot Prediction Using Svm Classifiers and Adaptive Machine Learning Algorithms

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ABSTRACT

Sun spot is a natural phenomenon which impact on various changes in the earth especially in weather, climatic conditions, disasters and diseases etc. The existing methods on prediction of sun spots are majorly focused on mathematical and statistical implications. In order to make more productivity, in this research, we applied Artificial Neural network and Machine Learning Methods on sun spots data set to prediction accuracy of various sunspot data. The results and accuracy are based in the training of dataset with SVM classifiers and Machine Learning Methods. The merits of this research prove the prediction accuracy of sun spot numbers and LSTM models are to be applied for the sunspot predictions which performs better in accuracy. SVM classifiers hold various advanced algorithms to make training on data to achieve better accuracy and performance. Among the various kinds of SVM classifiers in the area of prediction Linear SVM, Quadratic SVM and Cubic SVM are been considered for this performance evaluation especially in Prediction accuracy. The main parameter applied for prediction is Rooted Mean Square Error (RMSE). The experimentation part take place using the MATAB tool. An improved Vanilla LSTM model is proposed to overcome the various challenges in the existing models. The main objective of this model is to make predictions using sun spots. This Vanilla Long-Short Term Memory (LSTM) model is applied with optimized hyper parameters with fine tuning i.e. batch size, epoch, and optimizer etc., Adam optimizer is applied for the optimization during the process. Single layer is used and the optimized hyper parameters provide better results. The prediction process is accomplished by data set and is pre-processed with normalization then the sequence is created and the LSTM architecture is established. Based the training and testing data the prediction process is done. The model evaluates the similarity measures such as Absolute Error, Relative Error and Related Mean Square Error (RMSE). The performance of the model is estimated by comparing with the existing Stacked LSTM and Vanilla LSTM model.

1. INTRODUCTION

The Sun is the star which is located at the centre of the solar family. It is a gigantic, hot ball of plasma, overblown and heated by nuclear fusion reactions at its core. Sunspots are areas with strong magnetic field, due to which the magnetic pressure increases, while the surrounding atmospheric pressure decreases. This in turn lowers the temperature relative to its surroundings because the concentrated magnetic field inhibits the flow of heat, new gases from the Sun's interior to the surface. Sunspots appear dark since they are cooler than other parts of the Sun's surface. Sunspots increase and decrease through an average cycle of 11 years, which is known as Solar Cycle. Dating back to 1749, we have experienced 24 full solar cycles. We are currently in Solar Cycle 25, which began in December 2019 and is expected to continue until around 2030.During this eleven-year cycle of sunspots, the sunspot number increases-solar maximum and decreases-solar minimum. Based on the change in sunspot numbers, extreme weather events such as wildfires, rainfall, and sea level rise, global warming level can be predicted

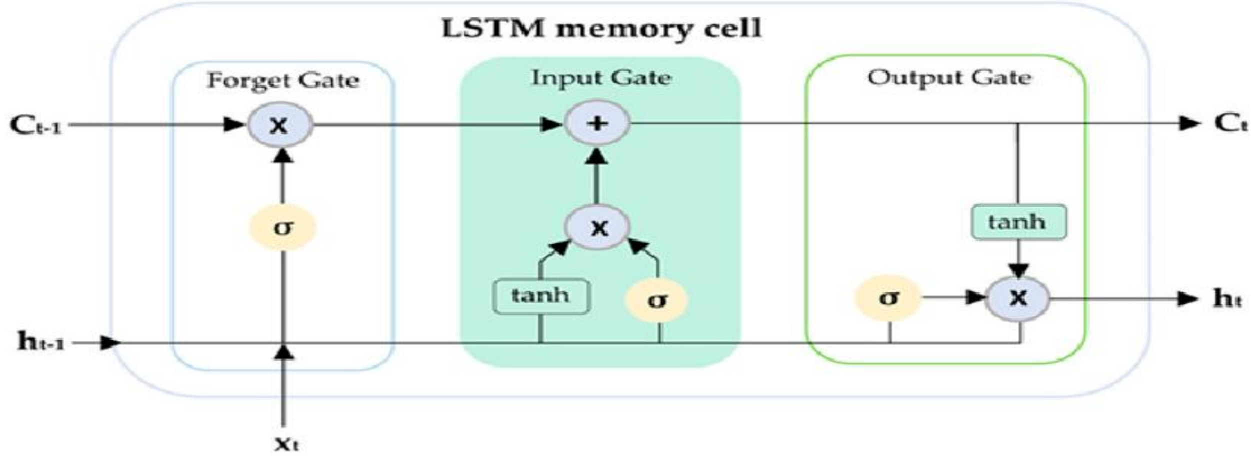
2. METHODOLOGY

An Adaptive Machine Learning Model for Sun Spot Prediction with Improved Vanilla LSTM Model

The machine learning methods especially the deep learning methods are analyzed and experimented with the sunspot data to find the better prediction for various factors. Various methods are been analyzed and tested. Among them the proposed improve Vanilla model provides better accuracy in predictions. In order to obtain more accuracy, the existing Linear SVM, Quadratic, Cubic SVM models are been experimented with the sunspot data. To get more accuracy rather than these three models. This proposed improved Vanilla LSTM model has been designed with the improvement in the hyper parameters. The performance is evaluated in terms of Absolute Error, Relative Error and Root Mean Squared Error

3. MODELING AND ANALYSIS

A Long Short Term Memory (LSTM) network is a type of recurrent neural network (RNN) that is designed to capture historical information of time series data and is suitable for predicting long-term non-linear series. A traditional RNN has a single hidden state that is passed through time, which can make it difficult for the network to learn long-term dependencies. LSTM model addresses this problem by introducing a memory cell, which is a container that can hold information for an extended period. LSTM memory cells are equipped with the gating mechanism that allows the network to selectively retain or discard information, and to learn long-term relationships in data.



From the above figure 4.1 the architecture of the LSTM (Long Small Term Memory) with the input and output parameters in which it determined that Xt: input time step, ht: output, internal cell state, forget gate (ft), input gate (it), output gate (Ot), and cell state (Ct). Operations inside the light red circle are point wise, which data from the current input should be stored in the memory cell is determined by the input gate.

During the initial process the initial requirements are been initiated in the proposed model the tensor flow, keras and the optimizer and optimized hyper parameters. During training, LSTMs learn to adjust the parameters of the gates and memory cell based on the input data and the desired output. This is typically done using gradient descent and back propagation through time.

Hyper Parameter Tuning:

The effectiveness of an LSTM model can be influenced by various hyper parameters, including the number of LSTM units, the number of layers, the learning rate, and more. Experimentation and tuning are often necessary to achieve optimal performance.

The proposed improved Vanilla LSTM have proven to be highly effective in capturing patterns in sequential data and are widely used in various fields for tasks involving time series and sequential information.

Rectified Linear Unit:

One common modification is to add a ReLU (Rectified Linear Unit) activation layer after the LSTM layer. This additional non-linearity might help capture more complex patterns in the data. Below is an example of how you could modify the architecture to include a ReLU layer after the LSTM layer. In this work, the ReLU Layer is added immediately after the LSTM layer. The ReLU activation function introduces non-linearity and has been found to be effective in much deep learning architecture. However, the impact of adding a ReLU layer can vary depending on the specific characteristics of your data and the nature of your problem. It's important to note that model improvement is often an iterative process, and it may involve experimenting with various architectural changes, hyperparameters, and training strategies. Additionally, consider monitoring the training progress and evaluating the model's performance on validation or test data to ensure meaningful improvements.

The architecture of a Long Short-Term Memory (LSTM) network consists of several layers, each serving a specific purpose in capturing and learning patterns from sequential data. Here's a breakdown of the typical architecture of an LSTM network. The output layer produces the final prediction or classification. For regression tasks, it might consist of a single neuron with a linear activation function. For classification, it may use a soft max activation for multi-class problems. Experimenting with different activation functions and network architectures, including or excluding ReLU layers, is a part of the model tuning process to find the configuration that best suits your specific problem.

The Adam Optimizer

The Adam optimizer is an optimization algorithm applied that combines ideas from two other popular optimization methods: RMSprop (Root Mean Square Propagation) and Momentum. It is well-suited for training deep neural networks and is widely used in various machine learning tasks. The key features of the Adam optimizer include adaptive learning rates for each parameter and momentum-based updates. These features make Adam robust and efficient for optimizing complex and high-dimensional objective functions, as follows

Adaptive Learning Rates: Adam adapts the learning rate for each parameter individually based on the historical gradients for that parameter. It uses the moving average of both the gradients and their squared values.

Momentum: Adam includes a momentum term that helps the optimizer continue moving in the same direction (with a certain inertia) even when gradients become small. This helps the optimizer navigate flat regions and accelerates convergence.

Bias Correction: To address the issue of the moving averages being biased toward zero in the initial training steps, Adam applies a bias correction term to the estimates.

The update rule for a parameter w in Adam is given by the following equations:

$$m_t = \beta_1 . m_{t-1} + (1-\beta_1). \nabla J(w_t)$$

$$v_t = \beta_2 . v_{t-1} + (1-\beta_2). (\nabla J(\boldsymbol{w_t}))^{\mathbf{2}}$$

$$\widehat{m_t} = \frac{m_t}{1-\beta_1^t}$$

$$\widehat{v_t} = \frac{v_t}{1-\beta_1^t}$$

$$w_{t+1} = w_t - \boldsymbol{\alpha}. \frac{\widehat{\boldsymbol{m_t}}}{\sqrt{\widehat{\boldsymbol{v_t}}+\boldsymbol{\epsilon}}}$$

where

- m_i is moving average of the gradients
- v_t is the moving average of the squared gradients
- $\widehat{m_t}$ *and* $\widehat{v_t}$ are bias correlated estimates
- β_1 *and* β_2 are exponential decay rates
- $\boldsymbol{\alpha}$ is the Learning Rate
- $\boldsymbol{\epsilon}$ is the small constant to prevent division by zero

SIMILARITY MEASURES

For assessing the prediction performance of our proposed model, four measures of error such as absolute error (AE), mean absolute error (MAE), relative error (RE), and the root mean-square error (RMSE) have been employed in the prediction experiments.

$$AE = \left[SN_{obs} - SN_{pred}\right]$$

$$MAE = (\sum_{i=1}^{n} \left|SN_{obs}(i) - SN_{opred}(i)\right|)/N$$

$$RE = \frac{\left|SN_{obs-}\, SN_{pred}\right|}{SN_{obs}}$$

$$RMSE = \sqrt{\frac{1}{N}(\sum_{i=1}^{N}(SN_{obs} - SN_{pred})^2}$$

where , SN_{obs} is the observed sunspot-number value, SN_{pred} is the predicted value , and N is the number of $SN_{obs.}$

PROPOSED ALGORITHM-IMPROVED VANILLA LSTM MODEL :

Input ***:*** *Sunspot Number Dataset*

Output: *Sunspot Predicted*

Step 1: *Loading and Visualization:*

Step 2*:* *Normalization:*

Step 3*:* *Sequences generation of input-output pairs*

Step 4*:* *Model architecture and input hyper parameters*

Step 5*:* *Training and Testing*

Step 6*:* *Prediction and results*

Step 7*:* *Repeat Hyper parameters until best results are obtained*

Step 8*:* *Display the accurate results*

4. RESULTS AND DISCUSSION

DATASET PREPERATION

The sunspot activity is utilized for predicting the features of future solar cycles, which is categorized as univariate multi-step time-series prediction. Before employing the sunspot number (SSN) data for forecasting purpose, each of the observed SSN data series needs to be standardized. Data standardization leads to elimination or reduction of insignificant points or identical data as well as other redundancies and helps in effective upgrading of neural network parameters. Data standardization is done by

x_(n)= (x_(t)-μ)/σ

where, μ denotes the mean and σ denotes the standard deviation of the data under consideration. xt is the observed value.

S.No	Year	Month	Day	Date In Fraction Of Year	Number of Sunspots	Standard Deviation	Observations	Indicator
0	1818	1	1	1818.001	-1	-1	0	1
1	1818	1	2	1818.004	-1	-1	0	1
2	1818	1	3	1818.007	-1	-1	0	1
3	1818	1	4	1818.01	-1	-1	0	1
4	1818	1	5	1818.012	-1	-1	0	1
5	1818	1	6	1818.015	-1	-1	0	1
6	1818	1	7	1818.018	-1	-1	0	1
7	1818	1	8	1818.021	65	10.2	1	1
8	1818	1	9	1818.023	-1	-1	0	1
9	1818	1	10	1818.026	-1	-1	0	1
10	1818	1	11	1818.029	-1	-1	0	1

Table 1: Sample dataset of the standard sunspot database

RESULTS OF EXISTING SVM MODELS

The above table shows the sample data obtained from the standard sunspot database and the required data for experimentation is considered. The considered data set is established based on cycle-wise sunspot data for the cycle 21, 21,. The following Table illustrate the overall sunspot prediction is as follows:

Cycle21

S.No	Model	RMSE	R-Squared	MSE	MAE	Speed Obs	Training Time Sec
1	Linear SVM	100.63	0.28	10126	85	16000	0.3585
2	Quadratic SVM	45.47	0.74	2067.3	38.48	15000	0.3319

3	Cubic SVM	39	0.81	1493.7	32.06	14000	1.1159

Table 2 : Results of Cycle 21

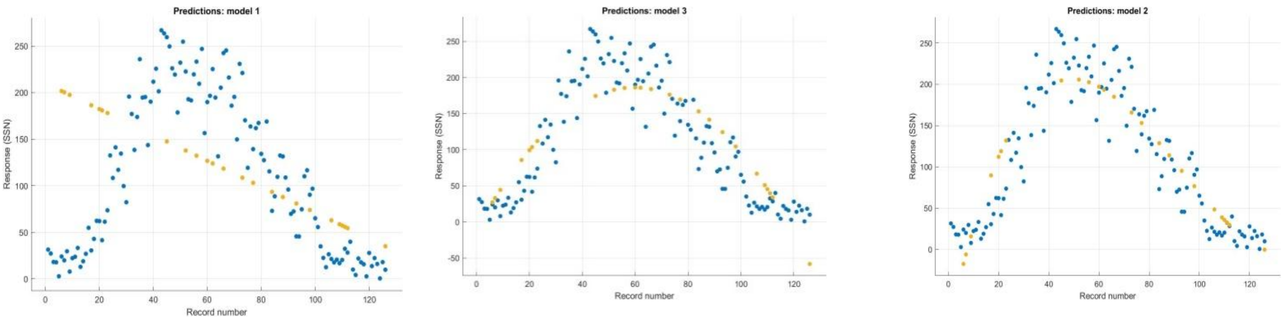


Figure 1: Results of Cycle 21

RESULTS OF EXISTING VANILLA LSTM MODEL:

The sunspot data set is experimented with various model viz., Bi-LSTM, peephole LSTM and other supervised models. Here the Vanila LSTM model is considered for the final experimentation which is compared with the proposed Improved Vanilla LSTM model.

The dataset of sunspot cycle 21, 22, 23, 24 and cycle 25 is experimented along with this cycle the combined Cycle 21-22,22-23,23-24,24-25 and 21 to 25 are experimented with the existing Vanilla LSTM model as per the algorithm. The obtained result from the Vanilla LSTM model is represented in the following table 3.

VANILLA LSTM Model						
S.No	**Solar Cycle**	**Observed Peak Value**	**Predicted Peak Value**	**AE**	**RE**	**RMSE**
1	21	266.90	266.6515	0.2484	0.0930	0.2929
2	22	284.50	284.209	0.2907	0.1021	0.3272
3	23	244.30	244.0721	0.2278	0.0932	0.2660
4	24	146.10	145.81	0.2922	0.2000	0.3269
5	25	34.00	33.7315	0.2684	0.7894	0.3067
6	21-22	284.50	284.284	0.2159	0.0758	0.2543
7	22-23	284.50	284.2552	0.2447	0.0860	0.2877
8	23-24	244.30	244.0049	0.2950	0.1207	0.3404
9	24-25	146.10	145.81	0.2909	0.1991	0.3357
10	21-25	284.5	284.3103	0.1896	0.0666	0.2277

Table 3: Experimental Results of Vanilla LSTM model

From the above table 3, the experimentation results of the existing Vanilla LSTM model is represented. The Vanilla LSTM model performance is evaluated in terms of Absolute Error, Relative Error and Relative Mean Square Error. From for the solar cycle 21 the model provides the absolute error 0.2484 , Relative error 0.0930 and RMSE is 0.2929. During this cycle the present observing timing September 1979 and the next peak prediction time October 1979 i.e the next year. Similarly, the cycle 22,23,24,and 25 along with the combined cycles are shown and the output of the represented in the following figures as follows.

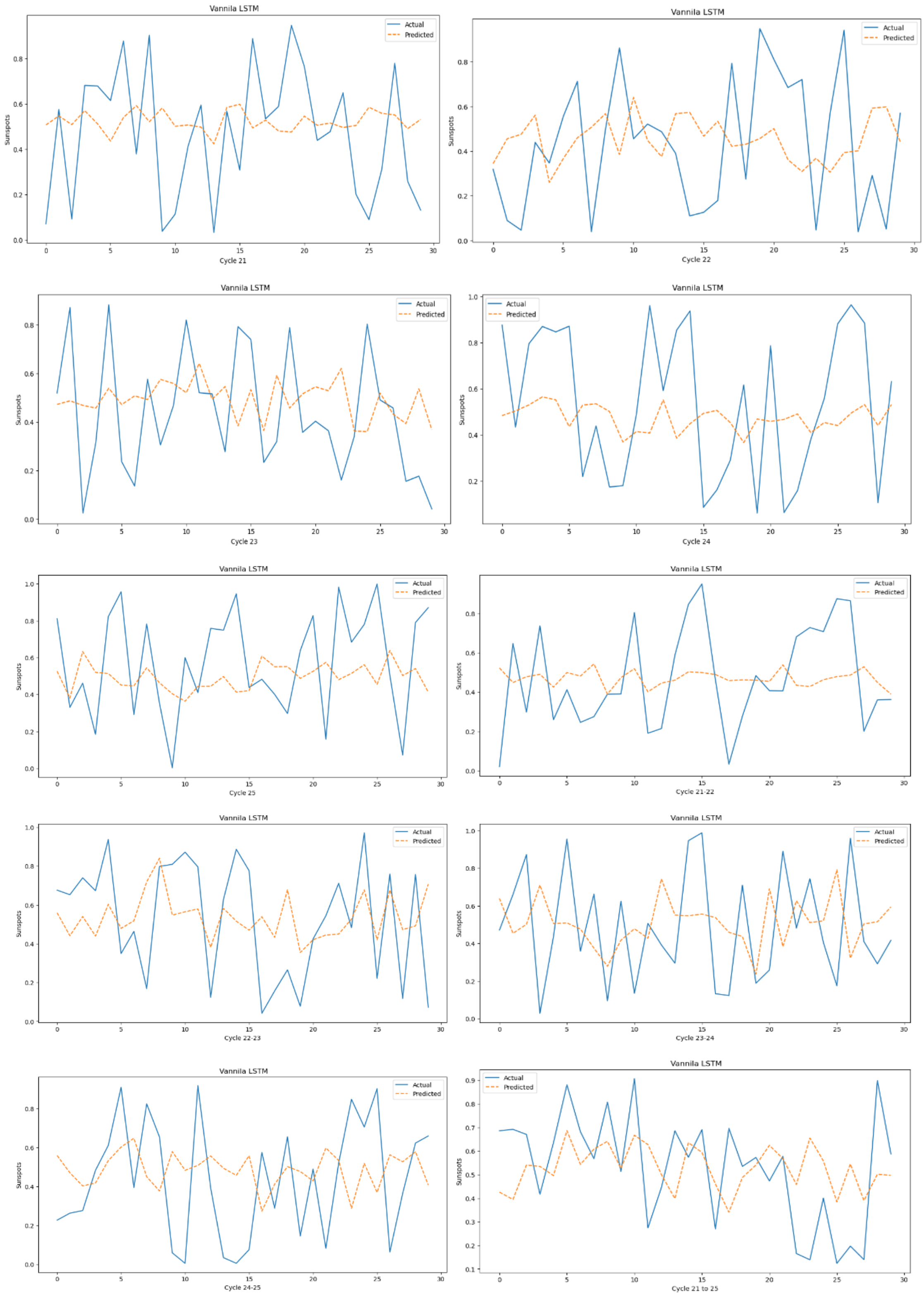


Figure 2: Resultant images for Existing Vanilla LSTM model

RESULTS OF PROPOSED IMPROVED VANILLA LSTM MODEL

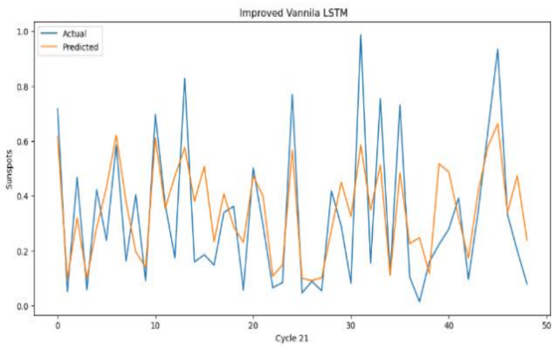
In order to obtain better and accurate results compared to the existing vanilla LSTM architecture, this proposed improved Vanilla LSTM model has been designed with the improvement in the hyper parameter. During the experimentation, the optimal result with minimum error and maximum predictions are obtained by using the proposed model.

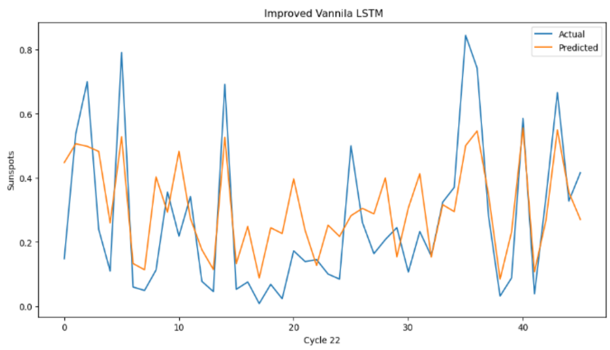
The dataset of sunspot cycle 21, 22, 23, 24 and cycle 25 is experimented along with this cycle the combined Cycle 21-22,22-23,23-24,24-25 and 21 to 25 are experimented with the proposed Improved Vanilla LSTM model and the obtained results are represented in the following Table 4.

Improved VANILLA LSTM						
S.No	**Solar Cycle**	**Observed Peak Value**	**Predicted Peak Value**	**AE**	**RE**	**RMSE**
1	21	266.90	266.75	0.1470	0.0552	0.1707
2	22	284.50	284.36	0.1320	0.0480	0.1567
3	23	244.30	244.15	0.1327	0.0543	0.1594
4	24	146.10	145.90	0.1437	0.0983	0.1863
5	25	34.00	33.82	0.0584	0.1717	0.1332
6	21-22	284.50	284.36	0.1362	0.0478	0.1628
7	22-23	284.50	284.41	0.0825	0.0825	0.1026
8	23-24	244.30	244.24	0.0526	0.0215	0.0716
9	24-25	146.10	145.98	0.1163	0.0796	0.1494
10	21-25	284.5	284.47	0.025	0.0088	0.0332

Table 4: Experimental Results of Improved Vanilla LSTM model

From the above table 4, the experimentation results of the existing Vanilla LSTM model is represented. The Vanilla LSTM model performance is evaluated in terms of Absolute Error, Relative Error and Relative Mean Square Error. From for the solar cycle 21 the model provides the absolute error 0.1470, Relative error 0.0552 and RMSE is 0.1707. During this cycle the present observing timing September 1979 and the next peak prediction time October 1979 i.e the next year. Similarly, the cycle 22,23,24 and 25 along with the combined cycles are shown and the output of the represented in the following figures as follows.





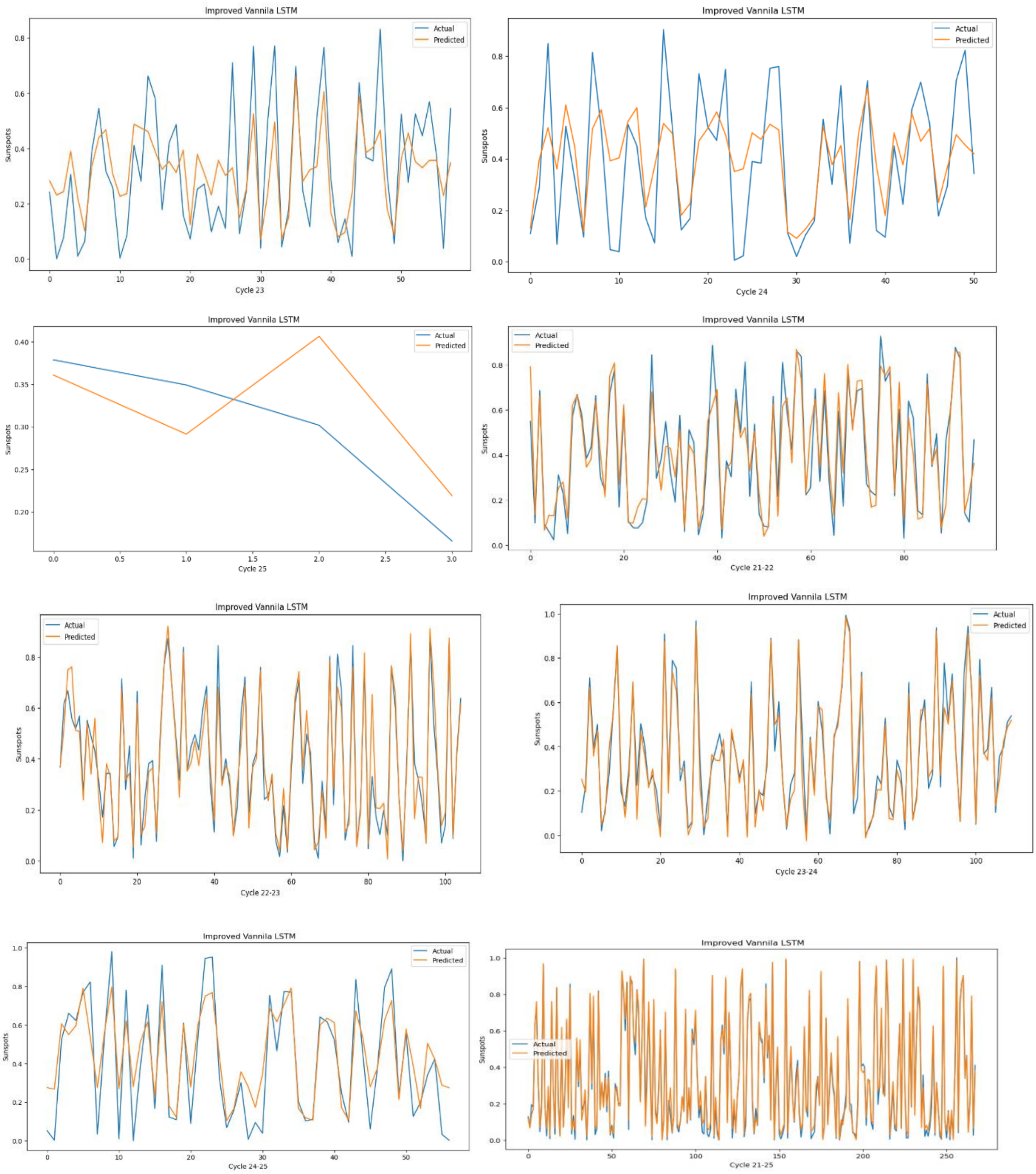


Figure 5.7 Resultant images for Proposed Improved Vanilla LSTM model

5. CONCLUSION

Many machine learning methods especially the deep learning methods are analyzed and experimented with the sunspot data to find the better prediction for various factors. More than five methods are been analyzed and tested. Among them the LSTM model provides better accuracy in predictions. In order to obtain more accuracy the existing Stacked LSTM and Vanilla LSTM model are been experimented with the sunspot data. Based on the results obtained the Stacked LSTM model provided minimum among the Vanilla LSTM. The stacked LSTM works on multilayer technique. Next the Vanilla LSTM seems to be better than Stacked LSTM model. To get more accuracy rather than these two models. This proposed improved Optimized LSTM model has been designed with the improved in the hyper parameter also by incorporation of advanced deep learning framework Tensor flow architecture also turning the parameter, optimizers and size of the LSTM during the experimentation the optimal result with minimum error and maximum predictions are obtained by using the proposed model. Based on the results the proposed model performs well and good in accuracy and predictions when compared with the existing Stacked LSTM and Vanilla LSTM models and is evaluated in terms of absolute error, Relative error and RMSE. Compared to this the proposed model predicts better next level prediction timings

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