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PREDICTING PLANT GROWTH IN GREENHOUSE ENVIRONMENTS USING DEEP LEARNING

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ABSTRACT

Plant development and production forecasting are crucial tasks for greenhouse farmers and farmers in general. Creating designs that closely replicate growth and yield may assist growers in improving environmental management for higher output, healthy grant and market demand, and cheaper costs.Deep Learning (DL) and Machine Learning (ML) are developing as powerful new analytical tools. In controlled greenhouse circumstances, the proposed research combines machine learning and deep learning approaches to estimate production and plant development in two separate situations: tomato yield forecasting and Ficusbenjamina stem growth. In the prediction formulae, we use the LSTM neuron model to construct a new deep RNN. The RNN structure is utilised to change the intended increase parameters based on prior yield, growth, and stem diameter data, as well as microclimate circumstances. A comparative investigation is presented to evaluate the overall performance of the various solutions, which includes machine learning methods such as assist vector regression and random woody area regression, as well as the propose rectangle error criterion.

1.INTRODUCTION

Plant development, like many biosystems, is a complex and dynamically coupled system that is controlled by the environment. As a result, boom and yield modelling is a serious scientific endeavour. A lot of factors influence modelling processes.According to two main modelling approaches are possible: "knowledge-driven" modelling and "data-driven" modelling. The understanding pushed method is strongly dependant on current field knowledge. A data-driven modelling technique, on the other hand, may create a mannequin entirely from acquired data without the requirement for prior knowledge of the region.Data pushed techniques include classic Machine Learning methodologies, artificial neural networks (Daniel et al., 2008), assist vector machines (Pouteau et al., 2012), and generalised linear models (DDM).

These techniques have a number of desirable properties, such as the capacity to approximate nonlinear functions, high prediction abilities, and adaptability to multimodal machine inputs (Buhmann, 2003). Machine learning (ML), linear polarizations, wavelet-based filtering, vegetation indices (NDVI), and regression analysis are among the most well-known approaches for assessing agricultural data, according to Singh et al., 2016, and reviewed by Liakos et al., 2018. Deep studying (DL) is an innovative method that is gaining traction in the absence of the previously mentioned strategies (Goodfellow et al., 2016).DL is a computer device mastering computational discipline that is comparable to ANN. DL, on the other hand, is about "deeper" neural networks that can execute a variety of operations and give a hierarchical representation of data. This enables greater mastery and, as a result, enhanced overall performance and precision.

The results revealed that M5-Prime produced the fewest errors of any crop yield model examined. M5-Prime, kNN, SVR, ANN, and MLR were graded best to worst in terms of RMSE, RRSE, R, and MAE, in the following order: M5-Prime, kNN, SVR, ANN, and MLR. Another study (Nair and Yang-Won, 2016) estimated corn yield in Iowa State using four machine learning algorithms: SVM, RF, ERT, and DL. Validation data comparisons demonstrated that DL produced more secure results, hence resolving the overfitting problem.

2.LITERATUREREVIEW

Agriculture is crucial in densely populated nations such as India. The weather has a significant influence on agricultural yield. This connection is being modelled in order to increase the component's massive environmental impact repercussions. We provide a method for calculating millet crop yields using high-dimensional data.

Utilizing the Random Forest Classifier, we were able to compute the millet crop production estimate with 99.74 percent accuracy using a variety of input fields such as soil, lowest temperature, highest temperature, humidity, rainfall, and so on.As a result, Millet Crop Yield Prediction is a critical agricultural issue, and our research will assist farmers in identifying crop losses and preventing them in the future. We would want to expand on this study by calculating millet crop production and comparing the accuracy of Support Vector Machine (SVM) and Linear Regression models (LR).

Agroecological systems are challenging to model due to their great complexity and nonlinear dynamic reactivity. Such systems evolve through a plethora of ill-defined mechanisms that span time and whose interactions are typically non-linear and unpredictable. According to Schultz et al. (2000), there are two primary problems to consider when modelling agroecological systems. On the one hand, there are no tools capable of accurately gathering data, and on the other hand, such systems are poorly understood. As a result, researchers must build styles in both rich and low data circumstances by merging many sources of data, even if the data is noisy, fragmented, and erroneous.

In order to comprehend an agroecological system, we can approach the work as a regression or classification problem. When modelling herbal procedures such as crop production, local climatic and physiological parameters, vegetation dynamics, greenhouse conditions, severity of a certain pest and/or disease, and so on, we have a regression problem. In contrast, while dealing with a classification challenge, we choose to represent aspects such as environmental variability, yield quality and quantity, genetic variation, soil qualities, land cover, and so on.Given that the device's dependent variables are categories, and the core idea is assigning the same category to persons with comparable qualities (i.e., by means of forming groups).

3.PROPOSEDMETHOD

The author of this research evaluates the performance of various machine learning techniques in forecasting ficus plant growth/crop yield, including deep neural network algorithms SVR (Support Vector Regression), Random Forest Regression (RF), and LSTM (Long Short Term Memory). Due to a lack of deep learning techniques, SVR and RF are typical old algorithms with low prediction performance. To tackle this challenge, the author employs the LSTM deep neural network technique to forecast plant growth.

Deep Learning extends traditional machine learning by adding "depth" (complexity) to the model and remodelling the data with a variety of features that generate new representations in a hierarchical fashion via many degrees of abstraction. A key benefit of DL is feature learning, or the automatic extraction of functions from raw data, with facets at higher levels of the hierarchy affected by the composition of lower level features.

Because of the more advanced models utilised, DL can solve complex problems precisely and quickly. This allows for a lot of parallelization. If large datasets accurately characterising the problem are available, these sophisticated models used in DL can improve classification accuracy or reduce error in regression settings.Convolutions, pooling layers, completely related layers, gates, memory cells, activation functions, and encoding/decoding techniques are all distinct components of DL, depending on the community structure used, which includes Convolutional Neural Networks, Recurrent Neural Networks, and Unsupervised Networks.

The LSTM model is offered to characterise long-term temporal interdependence and to calculate the proper time lag for time collection challenges. An LSTM community is made up of three layers: an entrance layer, a recurrent hidden layer, and an output layer. The memory block is the essential unit of the buried layer, which contains recollection cells with self-connections that remember the temporal country and a pair of adaptive, multiplicative gating mechanisms that govern data contained in the block.

The memory phone is a commonly self-connected linear gadget known as the Constant Error Carousel (CEC), and turning on the CEC depicts the telephone country.The multiplicative gates investigate when to open and close them. By maintaining the community error constant constant, LSTM may handle the vanishing gradient problem. Furthermore, while conquering long time series, a bypass gate is provided to the memory mobile, preventing the gradient from bursting.

3.2 IMPLEMENTATION

Thisprojectconsists offollowing modules

1. Upload of the FICUS plant dataset: This module will be used to upload the FICUS plant dataset.

2. Dataset cleaning: This module will be used to find and replace empty values in the dataset with mean or 0 values.

3. Train and Test Split: We will divide the dataset into two sections in this module: training and testing. All machine learning techniques train the classifier with 80% of the dataset and measure prediction accuracy with 20% of the dataset. If the classifier prediction accuracy is high, the mean square error, root mean square error, and mean absolute error will be deleted. Classifier for SVR: We will use this module to train an SVR classifier on data that has been partitioned into 80 percent and 20% to calculate performance.

4. Run SVR Classifier: Using this module, we will train the SVR classifier using splitted data from 80 percent and calculate its performance with data from 20 percent.

5. Run Random Forest Classifier: Using this module, we will train a Random Forest classifier using an 80/20 data split to calculate its performance.

6. Run the LSTM Classifier: In this module, we will train the LSTM classifier with 80% split data and 20% data to determine its performance.

7. Forecasting Plant and Yield Growth: In this session, we will upload the test data and use LSTM classifiers to anticipate plant and yield growth.

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4.RESULTSANDDISCUSSION

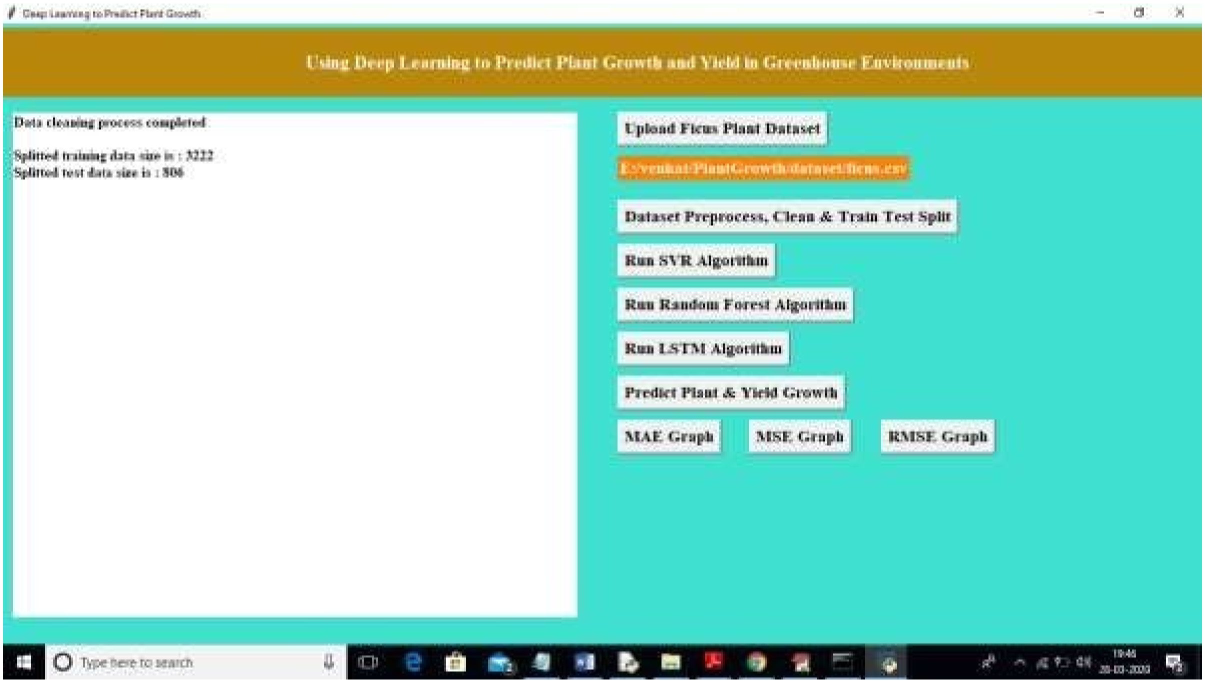

Fig 1:On the screen above, we can see that the programme has split the dataset into 80 and 20 percent, with 3222 records used for training and 806 records used for testing. Now that the dataset has been divided and loaded, click the 'Run SVR Algorithm' button to train the SVR algorithm.

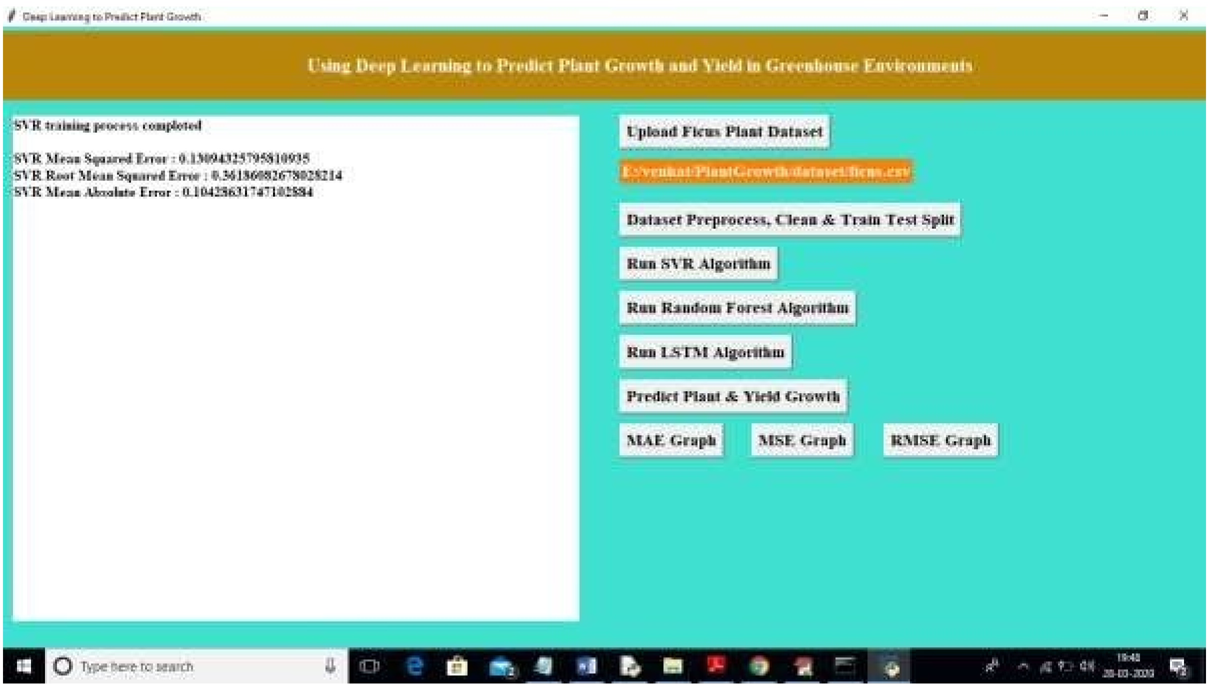

Fig 2: On the previous page, we saw the RMSE, MAE, and MSE errors for the SVR algorithm, and now we'll train the random forest algorithm by clicking the 'Run Random Forest Algorithm' button.

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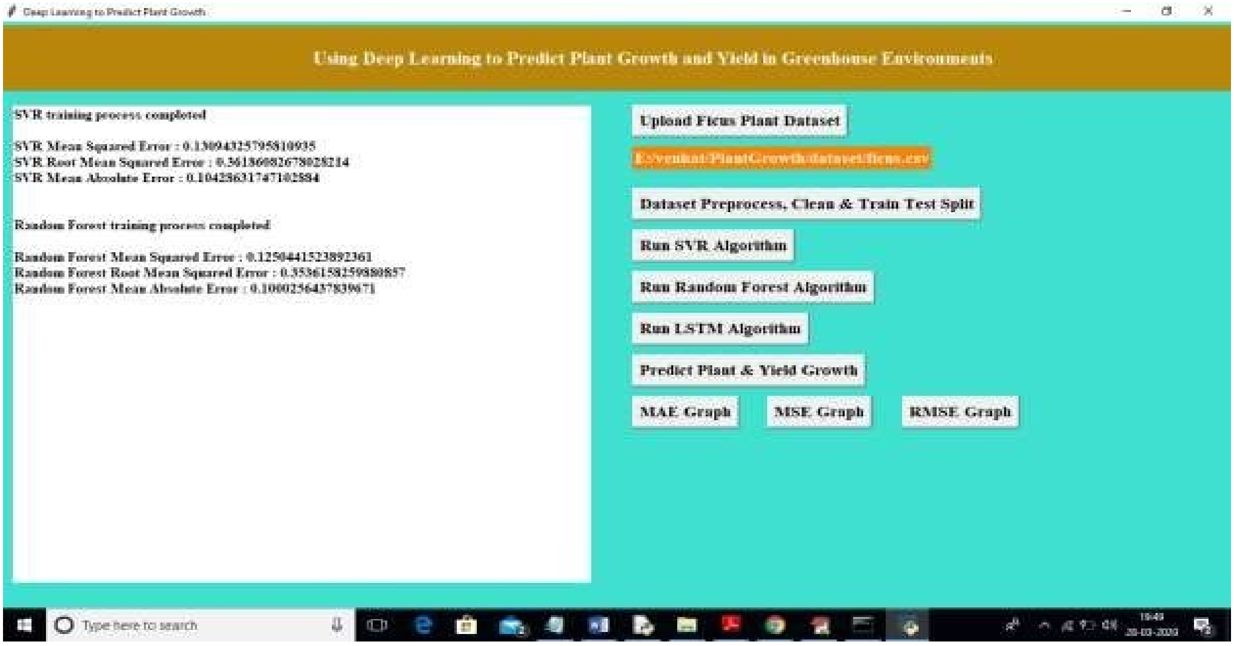

Fig 3: On the previous page, we saw the random forest MSE, RMSE, and MAE errors. Now, select the 'Run LSTM Method' button to train the dataset using the LSTM algorithm.

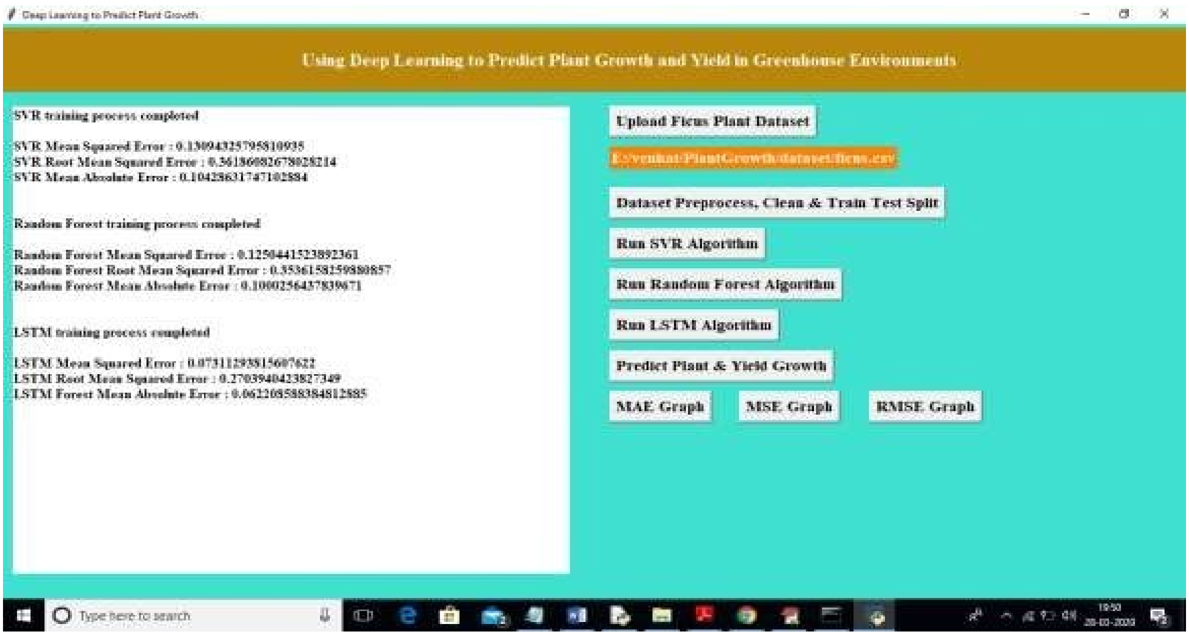

Fig 4: As can be seen in the image above, LSTM has lower MSE, RMSE, and MAE error than classical algorithms. Now that all of the algorithms have been trained, we can upload the test file and forecast its growth.

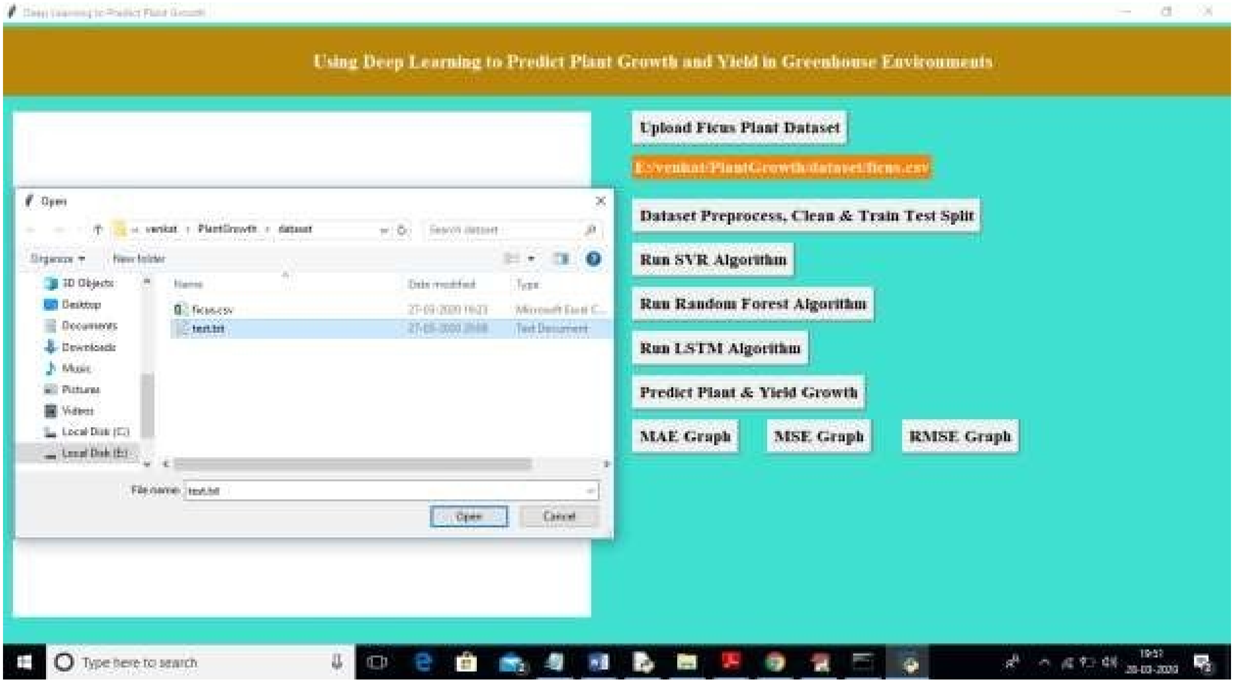

Fig5:I'm uploading the 'test.txt' file on the above page and then clicking the 'Open' button to anticipate test data increase**.**

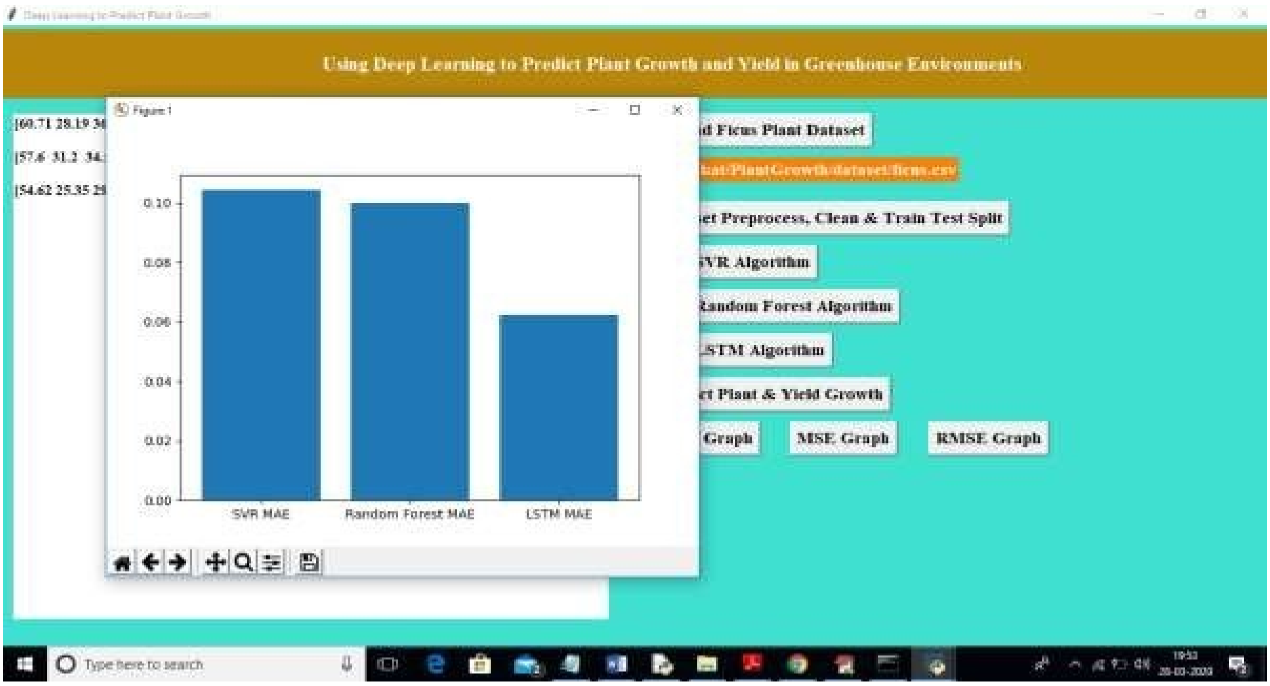

Fig 6 :The x-axis in the graph above reflects the algorithm name, while the y-axis is representing the MAE error. We can deduce by the above mentioned graph that LSTM has fewer error and will have the greatest prediction performance when compared to the other two.

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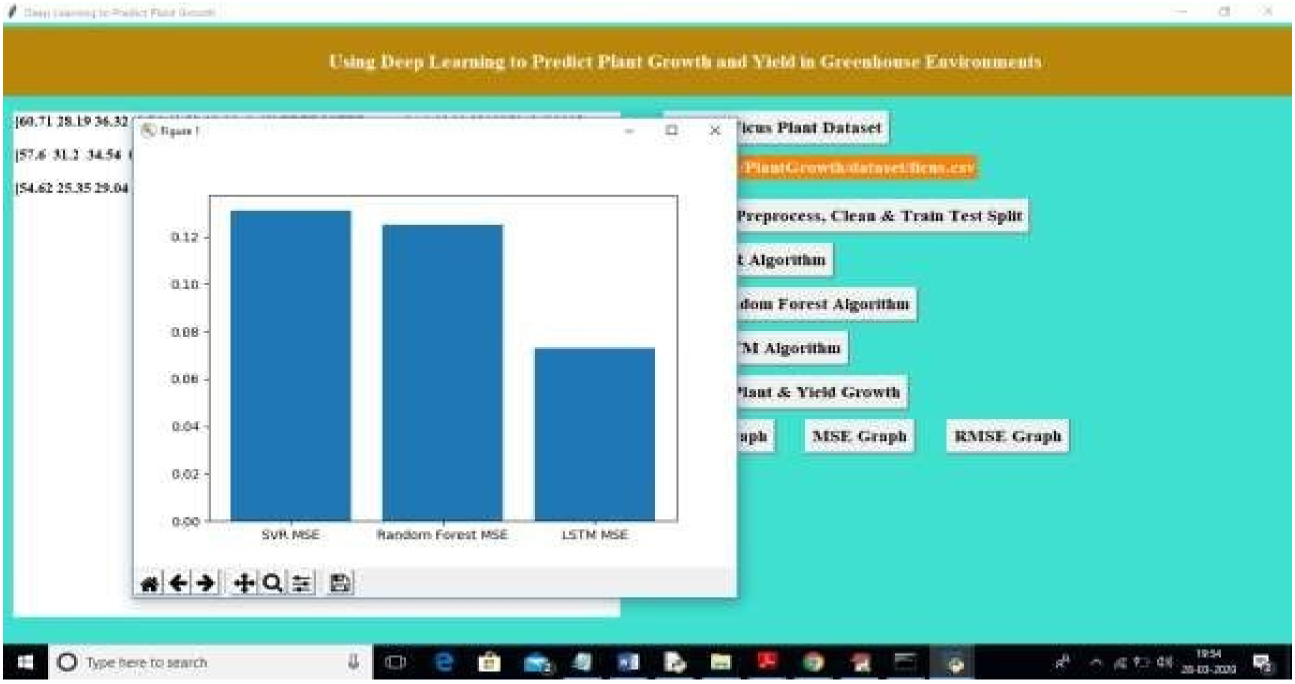

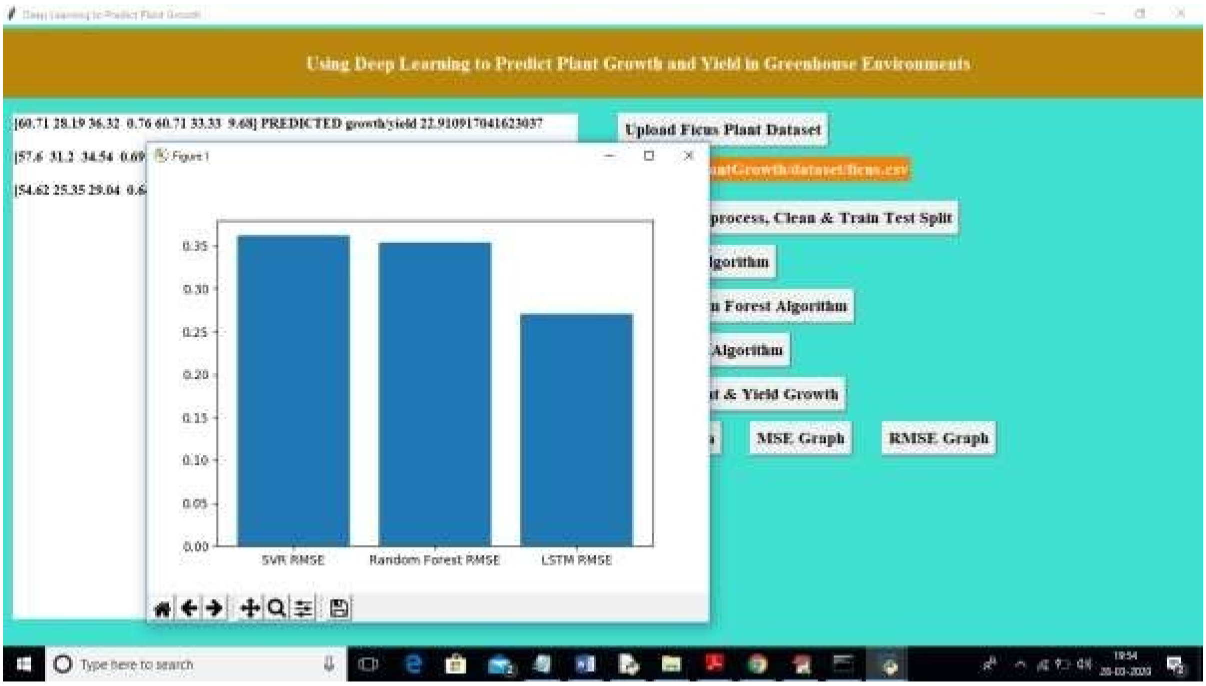

Fig8:RMSEgraph

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5.CONCLUSION

In this paper we developer DL for predictingFicus boom (expressed as SDV) and tomato field yields using LSTM, which performed well in both tests in terms of prediction accuracy. In terms of MSE, RMSE, and MAE error of criterion, the DL method (using an LSTM model) beat other common MachineLearning techniques, such as SVR and RF, according to experimental data. As a result, our project's primary purpose is to enhance DL approaches for predicting plant life cycle and yield in a greenhouse context.

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