



USING DEEP LEARNING TO PREDICT PLANT GROWTH AND YIELD IN GREEN HOUSE ENVIRONMENT

Dr. Y. Jeevan Nagendra Kumar¹, M A Sajeed Hussain²

¹Professor and Dean, Department of Information Technology,
Gokaraju Rangaraju Institute of Engineering and Technology, JNTUH, Hyderabad, India

² Department of Information Technology,
Gokaraju Rangaraju Institute of Engineering and Technology, JNTUH, Hyderabad, India

1.ABSTRACT

Growing plants in greenhouses and on farms in general requires accurate forecasting of plant growth and output. Growers may enhance environmental management to increase productivity, match supply and demand on the market, and save costs by developing models that can accurately estimate growth and yield. Deep learning (DL), can deliver powerful new analytical tools. In the proposed study, tomato yield prediction and Ficus benjamina stem growth are two separate instances where crop variance and plant development are forecasted using a controlled greenhouse environment (DL). We use the neural model of long-term memory to build (RNN) based on the prediction equations (LSTM). Based on historical data on yield, growth, stem diameter, and microclimatic conditions, the RNN project simulates the necessary growth characteristics. The (MSE) criterion is used to compare the effectiveness of the various tactics employing ML techniques like support vector regression and random forest regression.

2. INTRODUCTION

Many producers increasingly favor greenhouse cultivation over field cultivation. Crops grown in greenhouses can extend their growing season, are shielded from temperature variations and environmental hazards, and thus enjoy a secure environment. Additionally, it is now feasible to regulate environmental factors in a contemporary greenhouse, such as humidity, heat radiation, carbon dioxide, etc., to guarantee that crops are produced in the ideal climate [1]. Crop yield predictions in greenhouses are crucial to the administration and planning of agriculture. Maximum crop yields are assured by the ideal regulation of environmental factors in the greenhouse. The greenhouse yield forecast can help farmers and producers make wise financial and operational choices [2]. It is, however, a very difficult task. Crops are impacted by

a variety of things. It is difficult to create an explicit model that captures the interaction between several elements and the crop, such as greenhouse performance, radiation, carbon dioxide concentrations, temperature, crop seed quality, soil quality and fertilizer, and disease outbreaks [3].

3. LITERATURE SURVEY

A Survey on Diseases Detection and Classification of Agriculture Products using Image Processing and Machine Learning: The magnitude of a nation's agricultural output is essential to that nation's economic development. Therefore, locating locations with hazardous plants might be considered as a means of reducing harvest losses and production. The traditional approach to diagnosing and categorising diseases in the past took a tremendous amount of time, a tremendous lot of work, and regular business monitoring. In recent years, this has been achievable because to the advancement of technology and the focus of researchers in the field. Several techniques used across fields. This article discusses a number of methods that are now in use to identify illnesses in agricultural goods. This article also looks at the misconceptions surrounding disease classification, stakeholder segmentation, and disease screening. It also provides an overview of various feature extraction methods, segmentation methods, and classifiers, along with a discussion of their advantages and disadvantages. (10) (PDF) study on the use of machine learning and image processing in the identification and categorization of illnesses in agricultural products [4]

Towards Detecting Crop Diseases and Pest by Supervised Learning: Extremes in temperature and humidity, together with other abiotic factors, endanger agricultural productivity and contribute to the aetiology of crop disease and insect issues. The application of computer techniques, such supervised learning algorithms, to foretell the presence of diseases and pests in crops has been the focus of recent research efforts on the topic. In this article, we provide an overview of the supervised learning algorithms that are frequently used in agriculture for the detection of pests and diseases in crops like corn, rice, coffee, mango, peanut, and tomato, among others, in order to choose the algorithms that work best for the agricultural sector [5].

Plant Disease Detection Using Image Processing: The identification of plant diseases is the key to preventing a reduction in agricultural output and quantity. Studies on plant diseases use visual models that are visible on the plant. Disease identification and plant health management are crucial for agriculture to remain sustainable. Plant disease monitoring manually is fairly difficult. It requires a lot of work, understanding of plant diseases, and processing time. Image processing is therefore used for plant disease detection. The processes involved in disease detection include image acquisition, image preprocessing, image segmentation, feature extraction, and classification. The methods for diagnosing plant illnesses using images of their leaves have been discussed in this article. Methods for segmenting data and extracting features are used to find plant diseases [6]

4. EXISTING SYSTEM

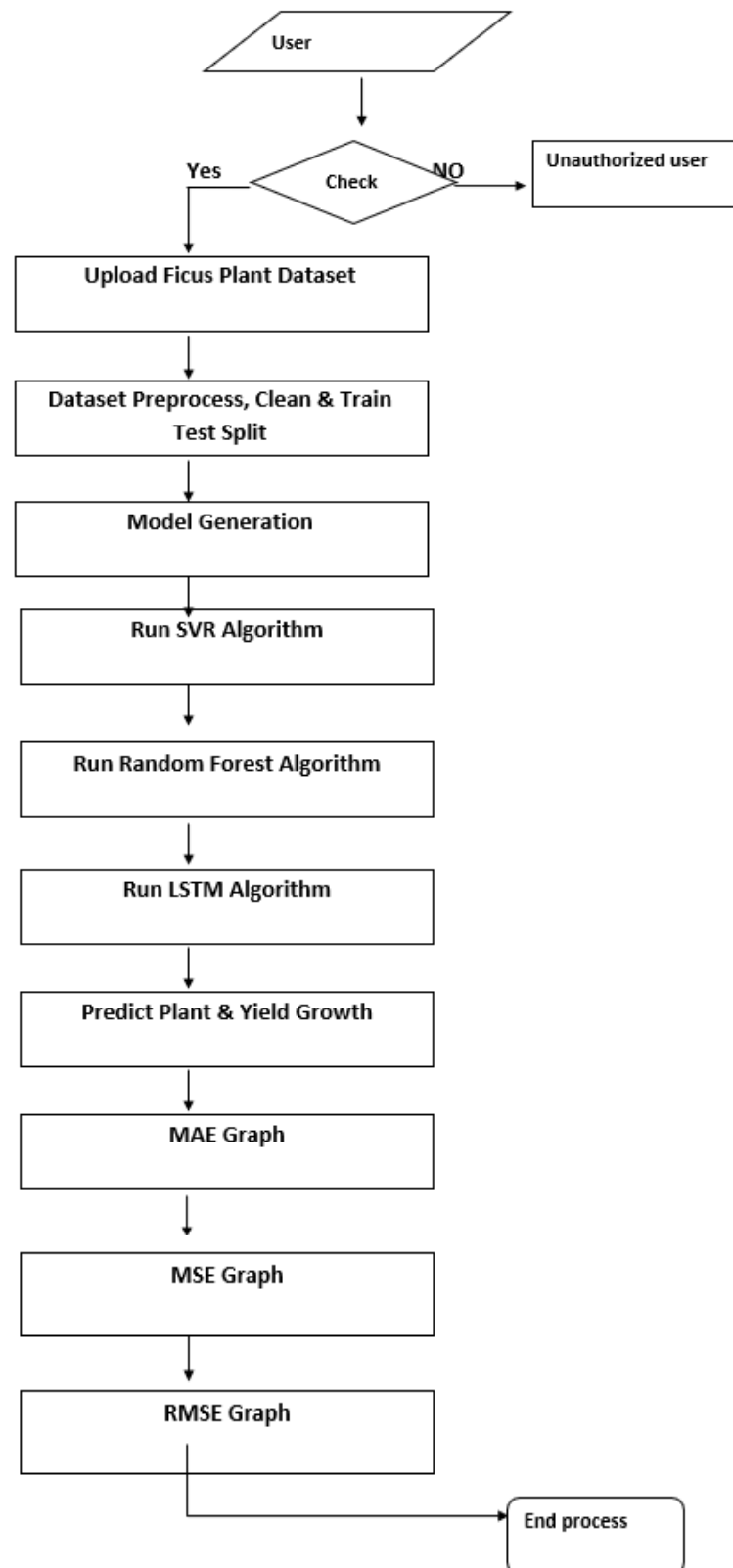
On ten crop datasets, González-Sánchez et al. (2019) compared agricultural yield prediction methods using ANN, SVR, M5-prime, KNN ML, and multiple linear regression [7]. To evaluate the accuracy of the models in their research, the following metrics were used: correlation factor, normalized mean absolute error, relative root square error (RRSE), root mean square (RMS), and (R). The results showed that M5-Prime had the fewest errors in agricultural yield patterns of RMSE, RRSE, R, and of this study, the approaches were ranked M5-Prime, kNN, SVR, ANN, and MLR in that order, from best to worst. SVM, random forests, very random trees, and deep learning were the four machine learning approaches used by Nair and Yang-Won (2016) [8]

5. PROPOSED SYSTEM

By comparing the effectiveness of several machine learning algorithms, including SVR (Support Vector Regression), Deep Neural Network method, Random Forest Regression (RF), and LSTM (long-term memory), the author in this paper predicts the growth/yield of ficus plant harvests [9]. Due to the lack of deep learning technology, the prediction performance of SVR and RF, two dated classical algorithms, would be poor. The use of LSTM deep neural network technique to predict plant development in order to get past this problem [10]

6. METHODOLOGY

Long short-term memory (LSTM) is known as LSTM. Recurrent neural networks' memory is increased by this paradigm or architecture. Recurrent neural networks typically have "short term memory" in that they make use of durable prior knowledge in the present neural network. In essence, the current work makes use of the prior knowledge. Therefore, we are not in possession of a complete list of all the prior data that was made available for the neural node [11]



Recurrent neural networks are given long-term memory thanks to LSTM. It reduces the vanishing gradient problem, which occurs when a neural network stop learning because the updates to its various weights get progressively smaller. It accomplishes this by using a number of "gates." [12]

Dataset:

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S
1	CO2	Radiation	diameter	humidity	outside_t	inside_t	sensor measurement	Yield											
2	35.7	20.85	29.53	0.91	35.7	27.48	2.46	35.7											
3	35.1	26.92	29.77	0.93	35.1	26.92	2.83	35.7											
4	33.38	26.95	29.36	0.94	33.38	26.95	2.95	35.7											
5	28.05	25.93	29.47	0.94	33.19	27.17	2.89	35.7											
6	28.83	25.98	29.86	0.94	33.85	27.07	2.97	35.7											
7	30.32	22.4	28.91	0.91	33.19	28.79	2.85	35.7											
8	61.87	24.98	33.35	0.72	61.87	29.61	9.7	14.4											
9	61.94	24.74	33.2	0.72	61.94	29.57	9.72	14.4											
10	61.19	26.95	35.18	0.75	61.19	31.49	9.58	14.4											
11	61.35	26.87	35.15	0.73	61.35	32.62	9.76	14.4											
12	61.17	27.18	35.47	0.74	61.17	32.67	9.72	14.4											
13	60.71	28.19	36.32	0.76	60.71	33.33	9.68	14.4											
14	57.6	31.2	34.54	0.69	57.6	36.15	9.91	46.5											
15	57.36	30.05	34.05	0.69	57.36	36.14	9.93	46.5											
16	57.51	30.79	34.5	0.69	57.51	36.27	9.92	46.5											
17	57.4	30.3	34	0.68	57.4	36.95	9.93	46.5											
18	57.25	30.99	33.59	0.67	57.25	35.97	9.96	46.5											
19	57.23	31.33	33.55	0.67	57.23	35.9	9.96	46.5											
20	54.83	25.6	30.61	0.66	54.83	31.49	9.94	45.6											
21	56.56	29.7	33.18	0.67	56.56	35.38	9.95	45.6											
22	56.86	29.41	32.8	0.67	56.86	35.64	9.96	45.6											
23	55.43	26.39	31.3	0.67	55.43	32.2	9.94	45.6											
24	55.15	25.42	31.27	0.67	55.15	31.8	9.98	45.6											
25	54.87	28.86	32.39	0.67	54.87	35.73	9.97	45.6											
26	66.45	34.7	43.11	0.75	66.45	39.12	9.75	13.1											
27	66.4	34.74	42.24	0.73	66.4	39.81	9.84	13.1											
28	67.2	38.17	44.86	0.75	67.2	41.61	9.79	13.1											
29	62.32	38.45	45	0.75	62.32	41.75	9.8	13.1											

7. RESULTS

Deep Learning to Predict Plant Growth

Using Deep Learning to Predict Plant Growth and Yield in Greenhouse Environments

- Upload Ficus Plant Dataset
- Dataset Preprocess, Clean & Train Test Split
- Run SVR Algorithm
- Run Random Forest Algorithm
- Run LSTM Algorithm
- Predict Plant & Yield Growth
- MAE Graph
- MSE Graph
- RMSE Graph

Deep Learning to Predict Plant Growth

Using Deep Learning to Predict Plant Growth and Yield in Greenhouse Environments

SVR training process completed

SVR Mean Squared Error : 0.13094325795810935
 SVR Root Mean Squared Error : 0.36186082678028214
 SVR Mean Absolute Error : 0.10428631747102884

Random Forest training process completed

Random Forest Mean Squared Error : 0.1250441523892361
 Random Forest Root Mean Squared Error : 0.3536158259880857
 Random Forest Mean Absolute Error : 0.1000256437839671

LSTM training process completed

LSTM Mean Squared Error : 0.07311293815607622
 LSTM Root Mean Squared Error : 0.2703940423827349
 LSTM Forest Mean Absolute Error : 0.06220858384812885

Upload Ficus Plant Dataset

[E:/venkat/PlantGrowth/dataset/ficus.csv](#)

Dataset Preprocess, Clean & Train Test Split

Run SVR Algorithm

Run Random Forest Algorithm

Run LSTM Algorithm

Predict Plant & Yield Growth

MAE Graph **MSE Graph** **RMSE Graph**

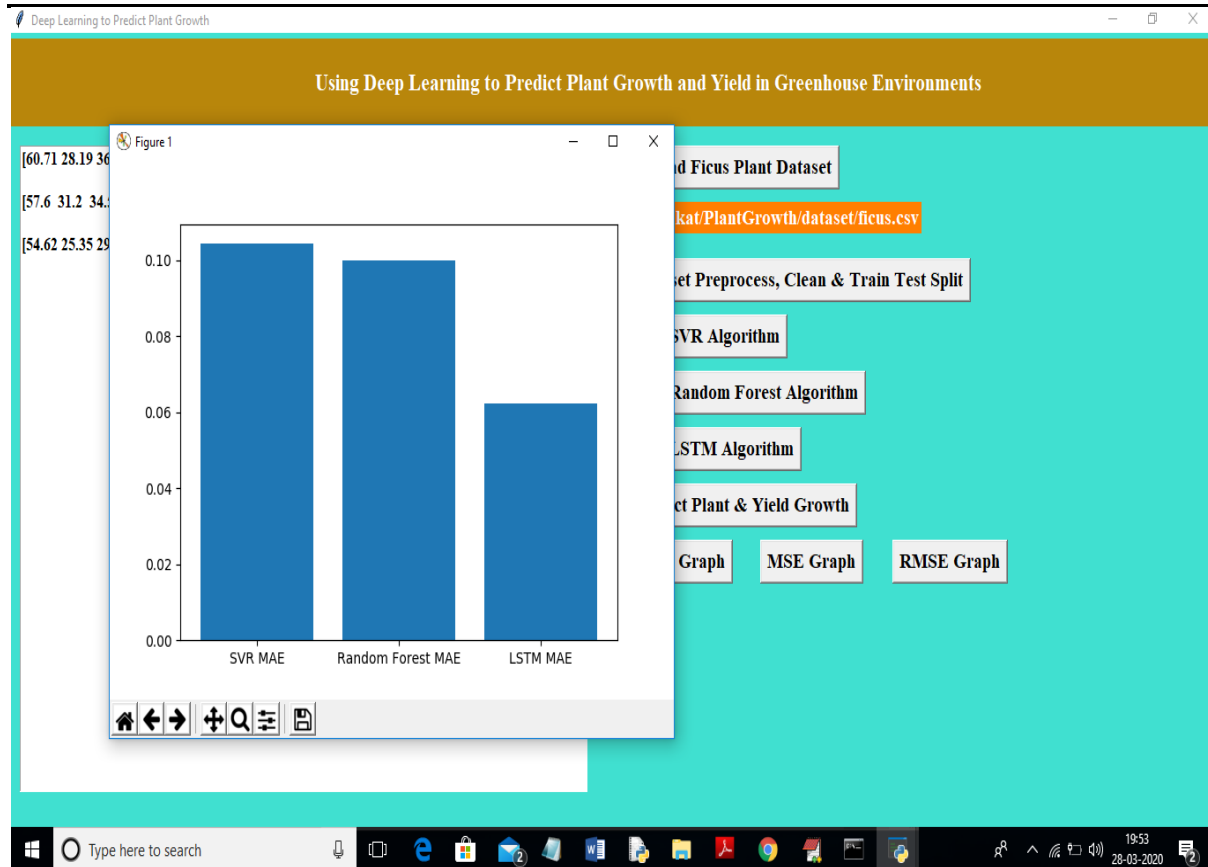
```

C:\Windows\system32\cmd.exe
E:\venkat\PlantGrowth>python PlantGrowth.py
Using TensorFlow backend.
Model: "sequential_1"

Layer (type)                 Output Shape                 Param #
-----
lstm_1 (LSTM)                 (None, 7, 5)                140
lstm_2 (LSTM)                 (None, 10)                  640
dense_1 (Dense)               (None, 1)                   11
-----
Total params: 791
Trainable params: 791
Non-trainable params: 0

None
WARNING:tensorflow:From C:\Users\Admin\AppData\Local\Programs\Python\Python37\lib\site-packages\keras\backend\tensorflow_backend.py:422: The name tf.global_variables is deprecated. Please use tf.compat.v1.global_variables instead.

Epoch 1/10
3222/3222 [=====] - 2s 587us/step - loss: 347.6852
Epoch 2/10
3222/3222 [=====] - 1s 353us/step - loss: 230.6849
Epoch 3/10
3222/3222 [=====] - 1s 349us/step - loss: 230.7072
Epoch 4/10
3222/3222 [=====] - 1s 352us/step - loss: 230.6181
Epoch 5/10
3222/3222 [=====] - 1s 366us/step - loss: 230.6064
Epoch 6/10
3222/3222 [=====] - 1s 422us/step - loss: 230.5403
Epoch 7/10
3222/3222 [=====] - 1s 365us/step - loss: 230.6282
Epoch 8/10
3222/3222 [=====] - 1s 352us/step - loss: 230.6031
Epoch 9/10
2640/3222 [=====>.....] - ETA: 0s - loss: 233.5647
    
```



8. CONCLUSION AND FUTURE ENHANCEMENTS

To evaluate tomato production and Ficus development (represented by SDV), the study devised a DL technique utilizing LSTM, attaining good prediction accuracy in both tasks. In terms of MSE, RMSE, and MAE error criterion, experimental results show that the DL technique using an LSTM model outperforms other conventional ML techniques like SVR and RF [19]. Our project's major goal is to create DL techniques that can forecast plant development and productivity in a greenhouse setting. Future research is expected to:

- significantly increase the amount of data collected for training the proposed ODL methods; and
- broaden the DL approach to develop multi-step (weekly or multiweekly) growth and yield estimates in a variety of greenhouses.

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