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Using Deep Learning to Predict Plant Growth/Yield in Green House Environments

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ABSTRACT

In this project we are predicting Ficus plant growth/crop yield by evaluating performance of various machine learning algorithms such as SVR (Support Vector Regression), Random Forest Regression (RF) and LSTM (Long Short-Term Memory) deep neural network algorithm. SVR and RF are the traditional old algorithms whose performance of prediction will be low due to unavailable of deep learning technique. To overcome from this problemwe are using LSTM deep neural network algorithm to predict plant growth. These complex models employed in DL can increase classification accuracy, or reduce error in regression problems, provided there are adequately large datasets available describing the problem. These complex models employed in DL can increase classification accuracy, or reduce error in regression problems, provided there are adequately large datasets available describing the problem. The LSTM model is introducing with the objective of modelling long term dependencies and determining the optimal time lag for time series problems. A LSTM network is composed of one input layer, one recurrent hidden layer, and one output layer.The basic unit in the hidden layer is the memory block, containing memory cells with self-connections memorizing the temporal state and a pair of adaptive, multiplicative gating units controlling information flow in the block. The memory cell is primarily a recurrently self-connected linear unit, called Constant Error Carousel (CEC), and the cell state is represented by the activation of the CEC. The multiplicative gates learn when to open and close. By keeping the network error constant, the vanishing gradient problem can be solved in LSTM. Moreover, a forget gate is added to the memory cell preventing the gradient from exploding when learning long time series.

Keywords: Growth, yield rate, Prediction, deep learning, recurrent LSTM neural networks.

1. INTRODUCTION

When plants and crops are affected by pests it affects the agricultural production of the country. Usually, farmers or experts observe the plants with naked eye for detection and identification of disease. But this method can be time processing, expensive and inaccurate. Automatic detection using image processing techniques provide fast and accurate results. This paper is concerned with a new approach to the development of plant disease recognition model, based on leaf image classification, by the use of deep convolutional networks. As with many bio-systems, plant growth is a highly complex and dynamic environmentally linked system. Therefore, growth and yield modeling is a significant scientific challenge. Modeling approaches vary in a number of aspects (including, scale of interest, level of description, integration of environmental stress, etc.). According to (Todorov ski and Demoski, 2006; Atanas ova et al., 2008) two basic modeling approaches are possible,

namely, "knowledgedriven" or "data-driven" modeling. The knowledge driven approach relies mainly on existing domain knowledge. In contrast, a data-driven modeling approach is capable of formulating a model solely from gathered data without necessarily using domain knowledge.

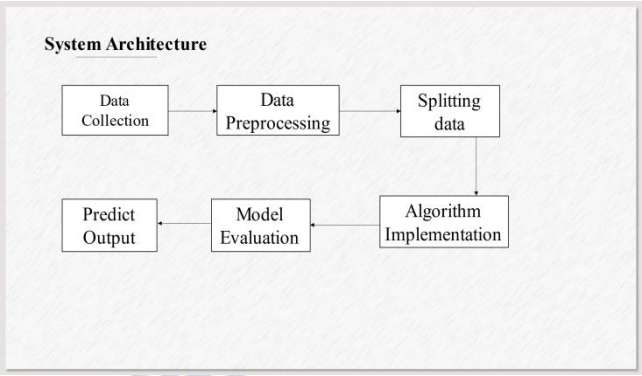
2. LITERATURE SURVEY:

A review is given of the state of knowledge in the field of assessing climate change impacts on agricultural crops and livestock. Starting from the basic processes controlling plant growth and development, the possible impacts and interactions of climatic and other biophysical variables in different agro-environments are highlighted. Qualitative and quantitative estimations of shifts in biomass production and water relations, inter-plant competition and crop species adaptability are discussed. Special attention is given to the problems encountered when scaling up physiological responses at the leaf- and plant level to yield estimates at regional to global levels by using crop simulation models in combination with geo-referenced, agro-ecological databases. Some non-linear crop responses to environmental changes and their relations to adaptability and vulnerability of agro-ecosystems are discussed.

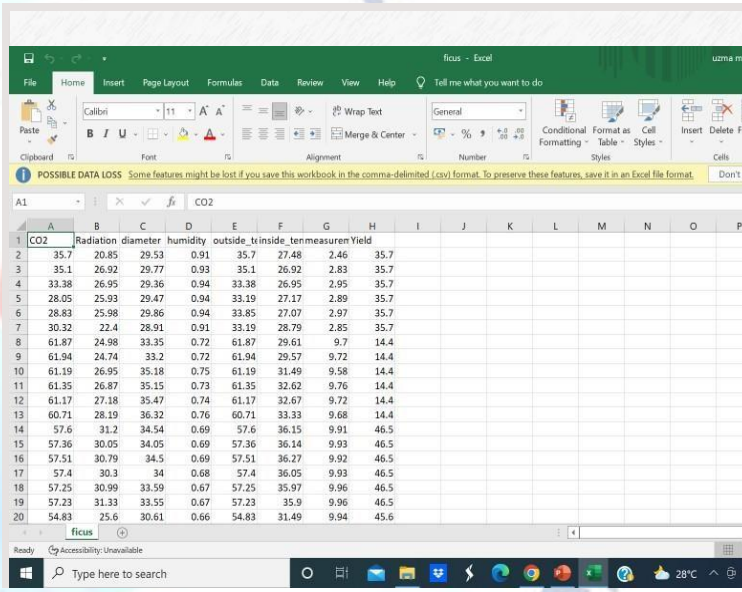
3. PROPOSED METHOD:

In this project we are predicting Ficus plant growth/crop yield by evaluating performance of various machine learning algorithms such as SVR (Support Vector Regression), Random Forest Regression (RF) and LSTM (Long Short Term Memory) deep neural network algorithm. SVR and RF are the traditional old algorithms whose performance of prediction will be low due to unavailable of deep learning technique. To overcome from this problem author is using LSTM deep neural network algorithm to predict plant growth.

ARCHIRECTURE:



DATASET:



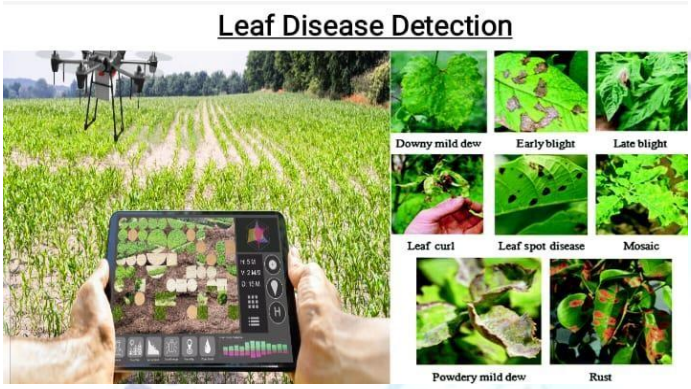
CO2	Radiation	diameter	humidity	outside_te	inside_ten	measuren	Yield
35.7	20.85	29.53	0.91	35.7	27.48	2.46	35.7
35.1	26.92	29.77	0.93	35.1	26.92	2.83	35.7
33.38	26.95	29.36	0.94	33.38	26.95	2.95	35.7
28.05	25.93	29.47	0.94	33.19	27.17	2.89	35.7
28.83	25.98	29.86	0.94	33.85	27.07	2.97	35.7
30.32	22.4	28.91	0.91	33.19	28.79	2.85	35.7
61.87	24.98	33.35	0.72	61.87	29.61	9.7	14.4
61.94	24.74	33.2	0.72	61.94	29.57	9.72	14.4
61.19	26.95	35.18	0.75	61.19	31.49	9.58	14.4
61.35	26.87	35.15	0.73	61.35	32.62	9.76	14.4
61.17	27.18	35.47	0.74	61.17	32.67	9.72	14.4
60.71	28.19	36.32	0.76	60.71	33.33	9.68	14.4
57.6	31.2	34.54	0.69	57.6	36.15	9.91	46.5
57.36	30.05	34.05	0.69	57.36	36.14	9.93	46.5
57.51	30.79	34.5	0.69	57.51	36.27	9.92	46.5
57.4	30.3	34	0.68	57.4	36.05	9.93	46.5
57.25	30.99	33.59	0.67	57.25	35.97	9.96	46.5
57.23	31.33	33.55	0.67	57.23	35.9	9.96	46.5
54.83	25.6	30.61	0.66	54.83	31.49	9.94	45.6

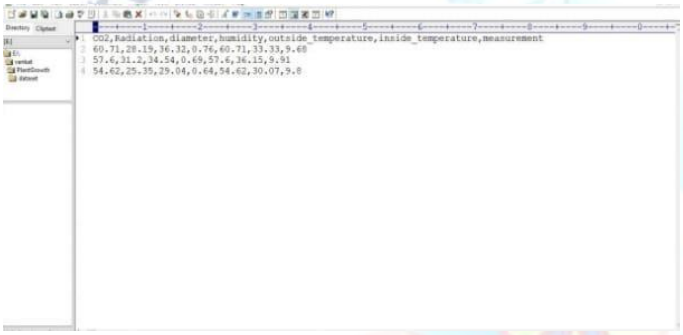
IMPLEMENTATION:

Steps:

1. We are first loading all the images in their respective categories from their directories.
2. Then we are splitting the images into train and test splits in the ratio of 80:20 from this we will be getting train data and test data separated.
3. After separation, we will be giving train images to the image generator which flips the images, shares the images and zoom the images so that all the features of the leaf can be feed for training so that we will be able to increase the robustness of the model.
4. Once the train set is ready we will be building the CNN layers. So in our CNN network, we have added 12 layers which include CNN layers, max pool layers, dropout layers.

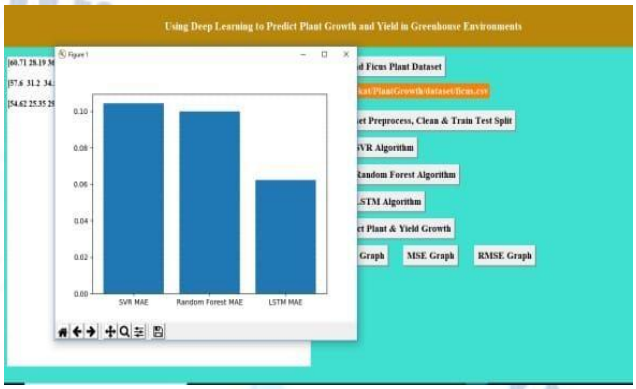
5. We have used different activation functions such as Relu, Softmax.
6. In our model, we have implemented 25 epochs.
7. After that, we have saved our model and loaded the model for prediction, using the Tkinter UI, in the UI we have used open CV to load the images.





IMPLEMENTATION RESULTS:

In the above screen we can see LSTM got less MSE, RMSE and MAE error compare to traditional algorithm. Now all algorithms training process completed and now we can upload test file and predict its growth.



In above graph x-axis represents algorithm name and y-axis represents MAE error. From above graph we can conclude that LSTM got less error and its prediction performance will be least compare to other two.

CONCLUSION:

The paper developed a DL approach using LSTM for Ficus growth (represented by the SDV) and tomato yield prediction, achieving high prediction accuracy in both problems. Experimental results were presented that show that the DL technique (using a LSTM model) outperformed other traditional ML techniques, such as SVR and RF, in terms of MSE, RMSE and MAE error criteria. Hence, the main aim of our project is to develop DL methodologies to predict plants growth and yield in greenhouse environment. Future studies looking at the continuity of : a) greatly increase the number of collected data that are used for training the proposed DL methods; b) extending the DL method so as to perform multi-step (at a weekly, or a multiple of weeks basis) prediction of growth and yield in a large variety of greenhouse, in the UK and Europe.

Conflict of interest statement

Authors declare that they do not have any conflict of interest.

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