IJARSCT

ISSN (Online) 2581-9429

International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)

Impact Factor: 7.301

Volume 3, Issue 3, April 2023

Deep Learning to Predict Plant Growth and Yield in Green House Environment

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Abstract: *Effective plant growth and yield prediction is an essential task for greenhouse growers and for agriculture in general. Developing models which can effectively model growth and yield can help growers improve the environmental control for better production, match supply and market demand and lower costs. Recent developments in Machine Learning (ML) and, in particular, Deep Learning (DL) can provide powerful new analytical tools. The proposed study utilities ML and DL techniques to predict yield and plant growth on Ficus Benjamin stem growth, in controlled greenhouse environments. We deploy a new deep recurrent neural network (RNN), using the Long Short-Term Memory (LSTM) neuron model, in the prediction formulations. Both the former yield, growth and stem diameter values, as well as the microclimate conditions, are used by the RNN architecture to model the targeted growth parameters. A comparative study is presented, using ML methods, such as support vector regression and random forest regression, utilizing the mean square error criterion, in order to evaluate the performance achieved by the different methods.*

Keywords: Machine learning, data set, web scraping, stem diameter, prediction, deep learning, recurrent LSTM neural networks

I. INTRODUCTION

This method has many advantages such as fewer limitations or predictions, ability to predict poor performance, high predictive power, and transferability to different products (Buchmann, 2003). According to Singh et al. Reviewed by Liacos et al, 2016. 2018 Machine learning (ML), linear polarization, wavelet-based filtering, visibility index (NDVI), and regression analysis are the most popular methods for data analytics farm. However, in addition to the above methods, a new method that has emerged recently is deep learning (DL) (Friends ET AL., 2016).

Dynamic Application Security Test (DAST) is a technique that can check for vulnerabilities by entering a list of URLs for web applications into a software browser. There are many crawlers that scan URLs and report bad ones. There are many crawlers that scan URLs and report bad ones.

Crop quality and yield forecasting is an important task for growers and farmers.

Models that can simulate growth and yield can help growers improve environmental stewardship to produce better crops and match product and business printing needs with yes and discount. Recent advances in machine learning (ML) and particularly deep learning (DL) can provide new AI analytics tools

1.1 Machine Learning

Automated analytical modeling using machine learning. It is a way of analyzing data. It is one of the artificial intelligen ce applications that reduces its dependence on human interaction when machines learn, make decisions and recognize p atterns. The two most popular machine learning methods are supervised learning and unsupervised learning. The two m ain goals of unsupervised learning are to find patterns in data and search for data.

Classification, regression and predictive modeling are used here. The three main elements of education are education, e nvironment and action. The goal is for the agent to select activities that use the payment.

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II. RELATED WORK

By evaluating the performance of various machine learning algorithms such as plant yield/growth, SVR(Support Vector Regression), Random Forest Regression (RF) algorithms in a previous project. SVR and RF are old methods because without deep learning the prediction performance will be very poor.

Support vector Regression

(SVR) Support Vector Regression (SVR) is derived from the inequality of the general graph model developed by Vapni k (Cortes and Vapnik, 1995). It uses a kernel function to organize the input data in higher space and uses a hyperplane t o separate the different classes of data. The trade-off between margin and error is controlled by the constant c. SVR with Radial Based Core (SVRrbf) using $K(xi, xj)$ = e xp $(-y\|xi - xj\| 2)$. Here y is the constant used in the radial basis function.

Random Forest

(RF)RF belongs to the category of group learning algorithms proposed by Ho in (Ho, 1998). As root learner for clusteri ng, RF uses decision trees. The idea of ensemble learning is that a single estimator is not enough to estimate the value o f test data. This is because, based on sample data, a person cannot distinguish between noise and structure. RF generates several independent regression trees from each of whichbootstrapping samples of the training data are selected**.**

Deep Learning

(DL) Deep learning connects to classical machine learning by adding "depth" (complexity) to the model and transformin g data using various functions that create a hierarchical representation of data from different levels of abstraction. One o f the advantages of DL is custom learning, i.e. automatic extraction of features from raw data, where lower quality featu res are combined to create higher features in the hierarchy. DL solves particularly difficult problems quickly due to the use of more models, which allows for a great deal of parallelism.

These nice models working in DL can improve the accuracy of classification or reduce the error in regression problems, given large enough data to explain the problem. Depending on the network architecture used, DL can be classified as c onvolutional neural networks, recurrent neural networks, Unsupervised networks (Kamilaris et al., 2018).

Long short-term memories (LSTM)

The LSTM model was initial introduced in (Hoch Reiter and Schmid Huber, 1997) 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.

III. EXISTED SYSTEM

In Previous Project Ficus Plant Growth/Crop Yield By Evaluating Performance Of Various Machine Learning Algorithms Such As SVR (Support Vector Regression), Random Forest Regression (RF) Algorithm. SVR And RF Are The Traditional Old Algorithms Whose Performance Of Prediction Will Be Low Due To Unavailable Of Deep Learning Technique .

IV. PROPOSED SYSTEM

In this project, the growth/yield of the Ficus plant is evaluated by evaluating the performance of machine learning and deep learning algorithms. Deep learning can solve complex problems particularly well and quickly due to the use of more common models that also allow for massive parallelism. The LSTM model is a long-term performance model and

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determines the best time to trade for a crisis period. An LSTM network consists of an input layer, a repetitive layer, and an output layer. To solve the above problems, all customers should be diligent in providing evaluation.

This article presents a method for a restaurant rating system that requires each customer to rate after one visit to improv e the rating. According to the purpose of the transaction, the restaurant can be used without visitors; scores are based on face detection using a retrained Convolutional Neural Network (CNN) model. It allows customers to rate food by snapp ing or snapping a criminal photo to share their opinion. It contains less information than the points collected and does n ot collect personal information. However, this simple, quick and detailed review requires customers to have a general u nderstanding of the restaurant concept.

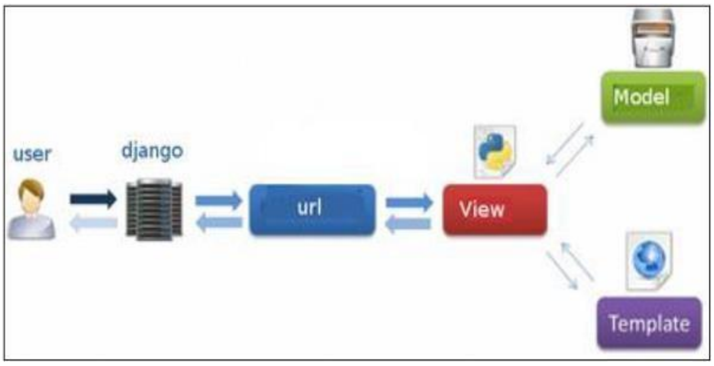
Django–Design Philosophies

Django comes with a lightweight web server to facilitate endtoend application development and testing. As you know D jango is a Python web application. Like most frameworks today, Django supports the MVC model. Before we look at w hat a Model-View-
Controller (MVC) pattern is, let's look at Django's custom ModelViewTemplate (MVT). The MVC pattern refers to app lications that provide a user interface.(web or desktop top) We usually talk about MVC architecture when programming

DjangoMVC- MVT Pattern:

Model View Template (MVT) is slightly different from MVC. In fact, the main difference between the two models is that Django itself takes care of the controller (software code that manages the interaction between the model and the view), leaving our model. Templates are HTML files integrated with the Django Template Language (DTL). The diagram below shows how each of the MVT models interact with each other to fulfill a user request. The developer model provides the view and the template. Then the template exposes it to the URL and Django works fine for the user.

Django MVC–MVT Pattern



V. SYSTEM ACHITECTURE

1. Cleaning datasets: Using this method we will find the null values in the dataset and replace them with defined or 0 values.
2. Train & Test Split: Using this model, we split the data into two parts called training and testing. All machine learning algorithms use 80% of the data to train the class and 20% of the data to evaluate the accuracy of the classification. If the classifier estimates with high accuracy, mean squared error, root mean square error, and mean absolute error will be discarded..
3. Run the SVR classifier: Using this module, we will use 80% of the data to train the SVR classifier and 20% of the data to calculate its performance.
4. Run Random Forest Classifier: Using this module we will train Random Forestclassifier withspitted 80%dataandused 20%data tocalculateit performance
5. Run Random Forest Classifier: Using this module, we will use 80% of the data to train a random forest classifier and 20% of the data to calculate its performance.
6. Predict Crop and Yield Growth: Using this module, we will load test data and then use the LSTM classifier to predict its growth

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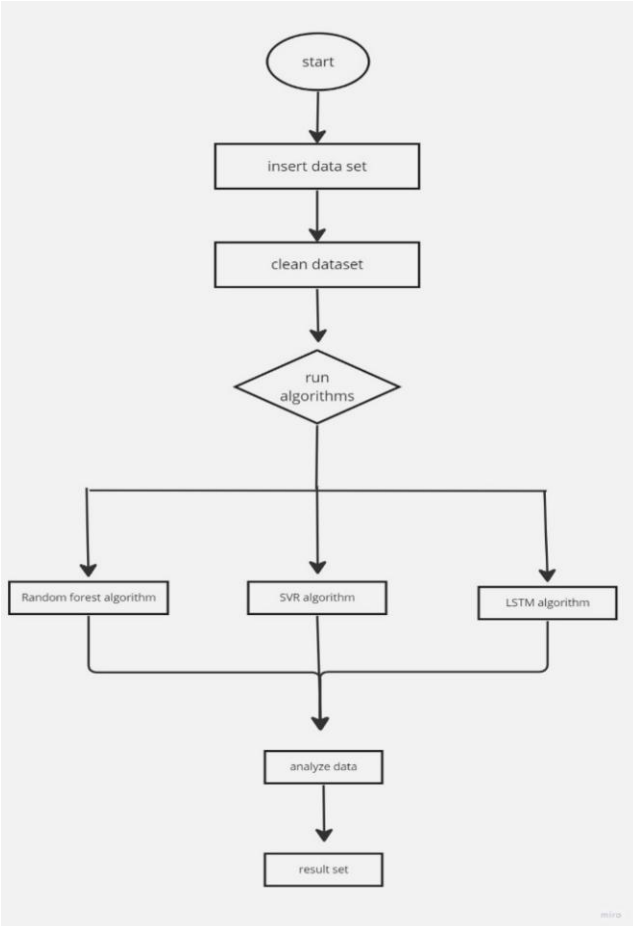


VI. ADVANTAGES

- The proposed system is much easier to handle and predicts very accurate plant growth than the precious models

VII. RESULT ANALYSIS

We developed and tested the DL (LSTM), SVR and RFR prediction models to predict plant yield and growth in a green house area:

a) SDV metric-based growth prediction of banyan trees

b) Tomato yield prediction

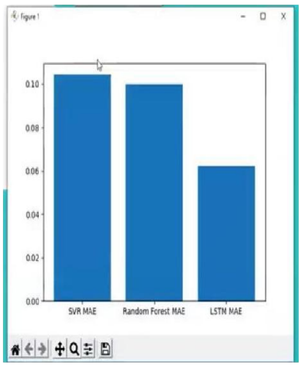
c) Commonly used approach, grid search is used to determine the parameters of each sample

The Gamma and C parameters are important for SVR models. In addition to the maximum tree height, tree composition is also important in RF design. The number and size of layers are important for DL LSTM model design. The implementation process consisted of three steps:

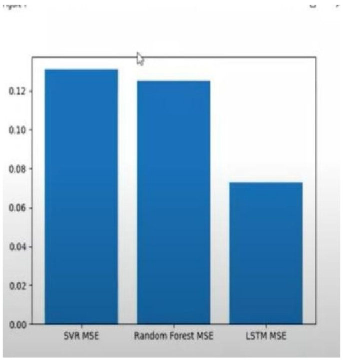
- Data preprocessing and data cleaning.
- Data is divided into training, validation, and test data.
- DL/LSTM, SVR and RF models were developed and used to generate onestep forward forecasts. The results cl early show that the DL/LSTM model outperformed the SVR and RF models in both experiments.

Data sets	Ficus growth		
Models	SVR	RF	LSTM
MSE	0.006	0.006	0.001
RMSE	0.073	0.062	0.042
MAE	0.070	0.063	0.030

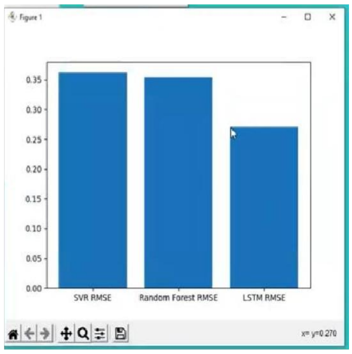
Table 1. Performance of the DL/LSTM model compared to those of SVR and RF models for plant yield and growth prediction



Mean Absolute Error

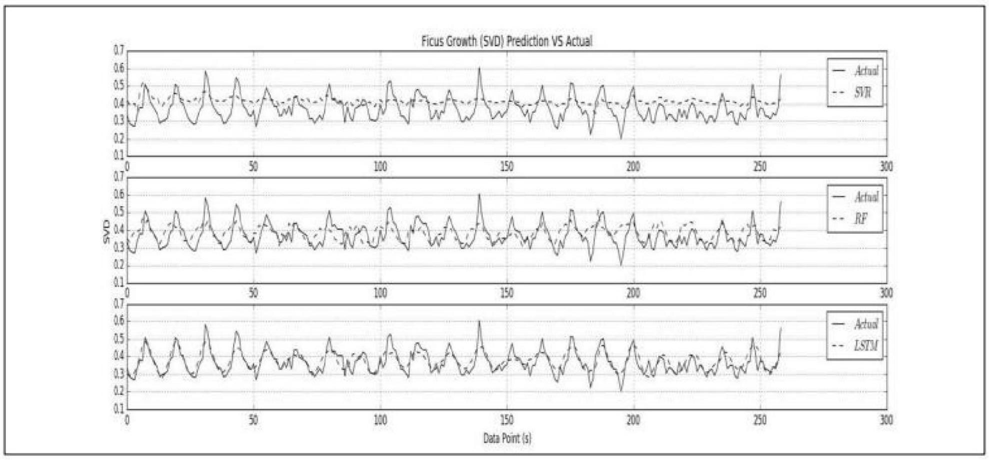


Mean Square Error



Rooted Mean Square Error

Testing results & comparison of Ficus growth (SVD) predictions



After measuring the performance of DL,SVR,RFR feature wise opinion summary and ranked features are processed. Figure 5 depicts the comparative analysis of the proposed framework.

VIII. CONCLUSION

This paper developed a DL method that uses LSTMs to predict the growth of peach (using SDV) and tomato and obtain s high estimates for both problems. Experimental results show that the DL method (using the LSTM model) outperform s other machine learning methods such as SVR and RF based on MSE, RMSE and MAE error criteria. Therefore, the m ain aim of our research is to develop a deep learning method to predict plant growth and yield in the greenhouse environ ment. Future research looks at the following extensions:

1. The increasing importance of data collection used to train the DL plan
2. Extended DL Methos for Multi Step (One week or Multi Weekly) estimation of growth and yield in several green houses with in the UK and Europe

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