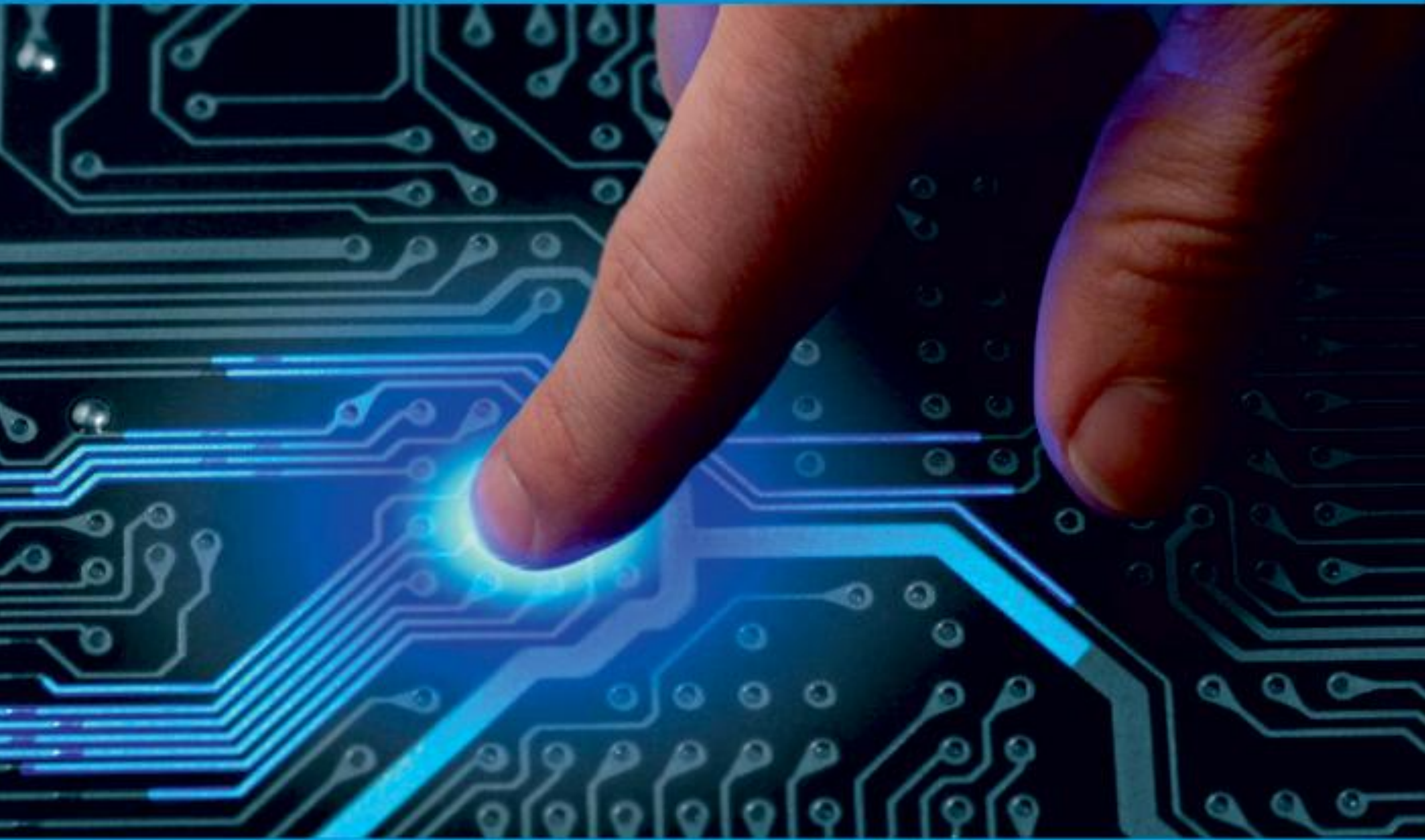
IJIRCCE

e-ISSN: 2320-9801 | p-ISSN: 2320-9798



INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN COMPUTER & COMMUNICATION ENGINEERING

Volume 9, Issue 7, July 2021

INTERNATIONAL STANDARD SERIAL NUMBER INDIA

Impact Factor: 7.542

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 7.542 |

|| Volume 9, Issue 7, July 2021 ||

| DOI: 10.15680/IJIRCCE.2021.0907180 |

Ameliorated Approach to Predict the Plant Growth in Greenhouse Environments Using Deep Learning

Dr.Hareesh K [1], Parinitha J [2], Poornima Haveri [3], Srilakshmi B P [4], Bandavya M [5]

[1] Professor& Head, Dept of CSE, Government Engineering College, KR Pet, Mandya, Karnataka, India

[2] UG Student, Dept of CSE, Government Engineering College, KR Pet, Mandya, Karnataka, India

[3] UG Student, Dept of CSE, Government Engineering College, KR Pet, Mandya, Karnataka, India

[4] UG Student, Dept of CSE, Government Engineering College, KR Pet, Mandya, Karnataka, India

[5] UG Student, Dept of CSE, Government Engineering College, KR Pet, Mandya, Karnataka, India

ABSTRACT: Agriculture is the backbone of Indian economy. Due to global warming and climate change traditional farming in the regular months have been distorted and crops have been ruined is the most common phrase seen today. This not only gives economic losses but also the main reason for farmer sucide. Now agriculture needs support, time has come for technology to take over change. For a crop to grow ,favourable soil conditions, ambient rainfall and temperature is necessary. So as now due to climate change temperature and rainfall cannot be well defined, example rains in December and January or irregular temperatures have made it difficult for farmers and common man to predict months of plantation and yield of the crop due to irregularities. So we have formulated an analysis by prediction of a favourable crop based on temperature and current rainfall with soil conditions.

I. INTRODUCTION

Compared to various other sectors of economy, agriculture is unique, whose output is largely dependent on weather conditions. The degree of success of agriculture production and its economics is determined to a significant extent by how well weather conditions corresponding to the optimal requirements of the crop are best exploited to raise the crops. Also, how effectively adverse weather conditions, which cause moisture, thermal, wind, radiation and biotic stress impeding growth and development of crop are managed to minimize their adversity. Further to this, it also depends on management aspects of preventing the crops from severe weather conditions.

Weather plays an important role in agriculture production. Thus there is no aspect of crop culture that is immune to impact of weather. Weather factor contribute to optimal crop growth, development and yield. For rainfall variability needs to be expressed in terms of percentage so that minimum assured rainfall amounts at a certain level of probability. For optimal productivity at a given location crops must be such that their weather requirements match the temporal match of relevant weather elements. A detailed knowledge of rainfall regime at a place is an important prerequisite for agriculture planning and management. Soil fertility refers to the inherent capacity of soil to supply nutrients in adequate amount and in suitable proportion for crop growth and crop yield.

Data science have proved that data which we have plays a vital role in predictions and iot based applications. Data science in agriculture is a growing field and has a wide scope in future.

II. RELATED WORK

Data driven models (DDM) include classical Machine Learning techniques, artificial neural networks (Daniel et al., 2008), support vector machines (Pouteau et al., 2012), and generalized linear models. Those methods have many desirable characteristics, such as imposing fewer restrictions, or assumptions, the ability to approximate nonlinear functions, strong predictive abilities, and the flexibility to adapt to inputs of a multivariate system (Buhmann, 2003).

According to Singh et al., 2016 and reviewed by Liakos et al., 2018 Machine Learning (ML), linear polarizations, wavelet-based filtering, vegetation indices (NDVI) and regression analysis are the most popular techniques used for analyzing agricultural data. However and besides the aforementioned techniques, a new methodology which is recently gaining momentum is deep learning (DL)(Goodfellow et al., 2016). DL belongs to the machine learning computational

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 7.542 |

|| Volume 9, Issue 7, July 2021 ||

| DOI: 10.15680/IJIRCCE.2021.0907180 |

field and is similar to ANN. However, DL is about “deeper” neural networks that provide a hierarchical representation of the data by means of various operations. This allows larger learning capabilities, and thus higher performance and precision. A strong advantage of DL is feature learning, i.e., automatic feature extraction from raw data, with features from higher levels of the hierarchy being formed by composition of lower level features (Goodfellow et al., 2016). DL can solve more complex problems particularly well, because of the more complex related models (Pan and Yang, 2010). These complex models employed in DL can increase classification accuracy and reduce error in regression problems, provided there are adequately large data-sets available describing the problem.

III. PROPOSED METHODOLOGY

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.

Deep Learning extends classical ML by adding more "depth" (complexity) into the model, as well as transforming the data using various functions that create data representations in a hierarchical way, through several levels of abstraction. A strong advantage of DL is feature learning, i.e., automatic feature extraction from raw data, with features in higher levels of the hierarchy being formed through composition of lower level features. DL can solve complex problems particularly well and fast, due to the more complex models used, which also allow massive parallelization. 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. DL includes different components, such as convolutions, pooling layers, fully connected layers, gates, memory cells, activation functions, encoding/decoding schemes, depending on the network architecture used, e.g., Convolutional Neural Networks, Recurrent Neural Networks and Unsupervised Networks.

The LSTM model is introduce 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.

Proposed methodology is implemented with below following modules

1) upload dataset: using this module we will upload FICUS plant dataset
2) Dataset cleaning: using this module we will find out empty values in the dataset and replace with mean or 0 values.
3) Train & Test Split: Using this module we will split dataset into two parts called and training and testing. All machine learning algorithms take 80% dataset to train classifier and 20% dataset is used to test classifier prediction accuracy. If classifier prediction accuracy high then Mean Square Error, Root Mean Square Error and Mean Absolute Error will be dropped.
4) Run SVR Classifier: Using this module we will train SVR classifier with splitted 80% data and used 20% data to calculate it performance
5) Run Random Forest Classifier: Using this module we will train Random Forest classifier with splitted 80% data and used 20% data to calculate it performance
6) Run LSTM Classifier: Using this module we will train LSTM classifier with splitted 80% data and used 20% data to calculate it performance
7) Predict Plant & Yield Growth: Using this module we will upload test data and then apply LSTM classifier to predict it growth value

IV. SIMULATION RESULTS

We have developed and tested DL (LSTM), SVR and RFR prediction models to predict plant yield and growth in greenhouse environments for: a) ficus growth prediction based on the SDV indicator, b) tomato yield prediction. A

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 7.542 |

|| Volume 9, Issue 7, July 2021 ||

| DOI: 10.15680/IJIRCCE.2021.0907180 |

commonly used method, grid search, was utilized to determine the parameters of each model. The parameters gamma and C were of importance for the SVR model design. The number of trees in addition to max depth of the tree was of importance in the RF model design. The number and size of hidden layers were of importance for the DL LSTM model design. The implemented approach involved three steps:

Data preprocessing and data cleaning.

• Data splitting into training, validation and test datasets.

• DL/LSTM, SVR, and RF model design and use to generate one step ahead prediction.

The obtained results clearly show that the DL/LSTM model outperforms the SVR and RF ones, in both experiments.

Table 1 shows the obtained accuracy, in terms of MSE, RMSE and MAE, when each of the (trained) three models is applied to the test datasets, in both experiments.

Datasets	Ficus Growth(SDV)		
Models	SVR	RF	LSTM
MSE	0.006	0.006	0.001
RMSE	0.07	0.062	0.042
MAE	0.070	0.063	0.030

Table 1: prediction accuracy

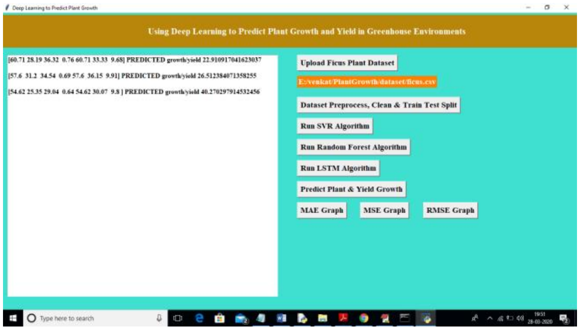
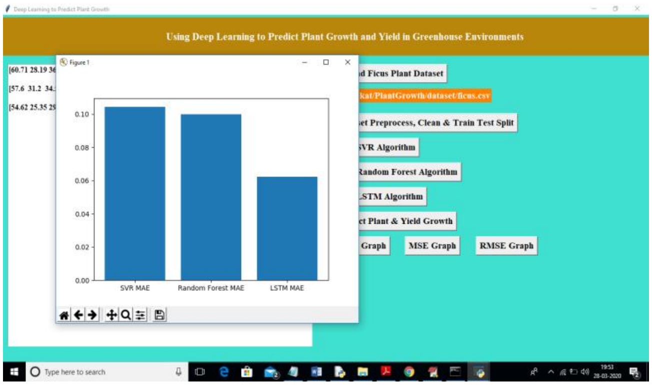
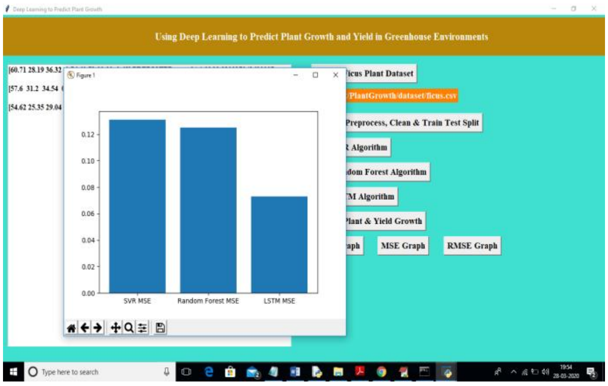


Figure 1: plant growth prediction

In above screen for first record growth prediction is 22% and second record 26% and third record having 40% growth prediction. Similarly u can add new records to test data and can predict its growth. Now click on ‘MAE Graph’ button to see MAE comparison graph between all algorithms





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 best compare to other two.

V. CONCLUSION AND FUTURE WORK

The simulation results showed that the proposed algorithm performs better with the total transmission energy metric than the maximum number of hops metric. The proposed algorithm provides energy efficient path for data transmission and maximizes the lifetime of entire network. As the performance of the proposed algorithm is analyzed between two metrics in future with some modifications in design considerations the performance of the proposed algorithm can be compared with other energy efficient algorithm. We have used very small network of 5 nodes, as number of nodes increases the complexity will increase. We can increase the number of nodes and analyze the performance.

REFERENCES

1. Abreu, P., Meneses, J. & Gary, C. 1998, "Tompousse, a model of yield prediction for tomato crops: calibration study for unheated plastic greenhouses", XXV International Horticultural Congress, Part 9: Computers and Automation, Electronic Information in Horticulture 519, pp. 141.

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 7.542 |

|| Volume 9, Issue 7, July 2021 ||

| DOI: 10.15680/IJIRCCE.2021.0907180 |

2. Adams, S. 2001, "Predicting the weekly fluctuations in glasshouse tomato yields", IV International Symposium on Models for Plant Growth and Control in Greenhouses: Modeling for the 21st Century-Agronomic and 593, pp. 19.
3. Atanasova, N., Todorovski, L., Džeroski, S. & Kompare, B. 2008, "Application of automated model discovery from data and expert knowledge to a real-world domain: Lake Glumsø", Ecological Modelling, vol. 212, no. 1-2, pp. 92- 98.
4. Barandiaran, I. 1998, "The random subspace method for constructing decision forests", IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 20, no. 8.
5. Breiman, L. 2001, "Random forests", Machine Learning, vol. 45, no. 1, pp. 5-32
6. Buhmann, M.D. 2003, Radial basis functions: theory and implementations, Cambridge university press.
7. Chlingaryan, A., Sukkarieh, S. & Whelan, B. 2018, "Machine learning approaches for crop yield prediction and nitrogen status estimation in precision agriculture: A review", Computers and Electronics in Agriculture, vol. 151, pp. 61-69.
8. Cortes, C. & Vapnik, V. 1995, "Support-vector networks", Machine Learning, vol. 20, no. 3, pp. 273-297.
9. Daniel, J., Andrés, P., Héctor, S., Miguel, B. & Marco, T. 2008, "A survey of artificial neural network-based modeling in agroecology" in Soft Computing applications in industry Springer, , pp. 247-269.
10. Duchesne, L. & Houle, D. 2011, "Modelling day-to-day stem diameter variation and annual growth of balsam fir (Abies balsamea (L.) Mill.) from daily climate", Forest Ecology and Management, vol. 262, no. 5, pp. 863-872.