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Research Article

Satellite Image Based Dual Level Feature Approximation Technique for Efficient Sugarcane Monitoring Using ANN

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Abstract

The problem of plant growth and yield estimation on sugarcane has been well studied. There exist numerous approaches towards the problem which consider only limited features like temperature, rainfall and so on. The methods suffer with poor accuracy in estimating growth and yield of sugarcane plants. To solve this issue, a dual level feature approximation model (DLFAM) has been presented in this article. The method uses both satellite and field images with other environmental features like temperature, humidity and hydrology features like water poured and rain fall. Also, the features of ground like soil type, area of cultivation are considered. Using all these features, the method estimates support on low level features towards plant growth and yield according to color, contrast features. Also, the method computes the support on high level features according to different hydrology, environmental and other features. Using all these support values, the method computes the value of plant growth and yield towards efficient monitoring. Such features are trained with artificial neural network which classify the test features and returns the weight towards different class of sugarcane plants. The method introduces higher performance in plant growth and yield estimation.

Index Terms: ANN, Sugarcane Plant, Yield, Plant Growth, Dual Level Feature Approximation, Satellite Image.

1. Introduction

The increase in population claims higher rate agriculture now a day. But the increase in population decreases and occupies the agriculture lands and it is occupied by the industries and residential sectors. This decreases the overall production of agriculture sector. However, to meet the food requirements and other agriculture requirements, it is necessary to improve the production of agriculture sector. On the other side, the production of agriculture sector is affected by several ways. First, the change in environment conditions affects the yield of agriculture products as the temperature of any country getting increases every year. Also, the rainfall becomes decreasing every year and it affect the overall growth and yield of any agriculture products. Similarly, there are number of factors can be named which affect the growth and yield of agriculture plants.

The sugarcane plants are the one which are cultivated in different countries. In India it has been cultivated in different states to meet the requirement of sugar products. The plant growth has been monitored and estimated according to different factors. There are number of approaches available to measure the plant growth. In simple case, it has been measured according to the temperature and water poured. Similarly, there are number of approaches available which uses various features and measures. However, the growth of any plant is not just depend on the temperature but also depend on humidity, rainfall, soil, area and so on. Similarly, the yield of any plant is depending on the timely regulation of water and fertilizers as well as environmental conditions. Towards this various approaches are discussed in literature.

Image processing techniques are greatly used in several problems. The same can be used in the plant growth estimation of sugarcane. The article focused on using the satellite images in sugarcane monitoring. The images of agriculture sector captured through satellite can be used in the problem. From the agriculture satellite image, the features of color can be used in extracting set of features related to plant as well as soil and hydrology features. Similarly, by applying the image processing techniques, the features of plant at the field can be extracted to perform yield estimation. Similarly, the neural network has been adapted in several problems where the dimensionality becomes an issue and where there exists a missing feature. By extracting the features of sugarcane fields from the satellite and localized images, the problem of growth and yield estimation can be handled effectively.

By considering all these, a dual level feature approximation model (DLFAM) is presented in this article. The model considers both high and low level features towards the monitoring of sugarcane plants. The features extracted has been trained with neural network to support plant growth and yield estimation. The detailed approach is discussed in detail in next sections.

2. Related Works

Various approaches are discussed towards growth and yield estimation of sugarcane plants. This section details set of methods related to the problem.

A satellite image based sugarcane crop yield estimation is presented in [1], which consider different features and applies image processing methods towards crop yield estimation. A mathematical model is presented towards crop yield estimation which consider different features being extracted from satellite images and uses remote sensing approaches.

An android through yield estimation on Kiwi fruit is presented in [3], which consider features like cultivation area and the total number of fruit. A wheat plant crop yield estimation technique based on image processing is presented which subtracts the background and extract the features to estimate the crop yield. Similarly, a vision based infection detection scheme for plants are presented in [5], where the color features are extracted to measure the rate of infection. In this approach, the input image has been segmented using k means to generate gray level covariance matrix to measure the similarity.

The application of IoT devices are grown to different level and has been adapted to the agriculture industries. The method extracts the color, texture and shape features to generate the pattern and based on that yield estimation is performed [6]. Similarly, in [7], an image based yield estimation algorithm is presented which groups the area of cultivation in to number of clusters and estimates set of weights towards estimation. Different articles on crop yield estimation is presented in [8], which consider different image processing techniques and in [9], an efficient plant disease recognition approach and applies region growing techniques towards yield estimation. The deep learning pipeline techniques are adapted to the problem which uses threshold, and the size of output [10].

The yield estimation of red macroalga from satellite image is presented in [11], where the images obtained from Indonesia. The method identified that the plant yields higher value when the temperature is moderate and the growth is depending on mass value. A remote sensing based evapotranspiration technique is presented in [12], where the remote sensed data is used to measure the ratio of evapotranspiration from satellite images.

The artificial intelligence with satellite image based crop yield estimation algorithm is presented in [13], which extracts temporal features like humidity, temperature, cultivation area and water sources in estimating the yield and growth of plants. Similarly, in [14], the random forest algorithm is clubbed with decision tree approach in measuring the plant growth. The crop classification problem is handled with images obtained from satellite in [15], which extracts texture, color features in classifying the plants towards yield estimation. In [16], the yield estimation is performed by considering contextual and temporal features obtained from satellite images. The Maize plant cultivated in Zimbabwe has been estimated for its yield in [17] which performs inference on yield according to the yield model maintained by the country. The corn plant is cultivated in many countries and the height of the plant support the yield to be calculated in [18], which extracts RGB features extracted from satellite images to estimate the yield. Similarly, for the application of fertilizer support for the corn plants a satellite image based approach is presented [19]. In [20], a chlorophyll estimation approach with sat. Image is presented where the SMLR-PSO model extracts different features from spectral images to estimate the yield. The prediction is performed with PSO technique.

In [21], the author presents set of route map towards crop farming. The article studies set of methods towards fruit grading, counting, estimating the yield, and so on, Also, the article focused on monitoring the health of plants towards weed, disease and insects. In [22], the author discusses the importance of NDVI (Normalized Difference Vegetation Index) of leaf tissues of plants in yield of sugarcane plants. The method has been adapted for the removal of straw from the plants. The evaluation is performed in Brazil and straw removal rate are recorded and monitored. According to the data recorded, a prediction model is designed towards sugarcane yield estimation.

In [23], the author investigates the vegetation indices power in estimating the sugarcane yield and growth pattern. The indices extracted from different satellite images are applied with time series analysis. According to the result of time series analysis, the sugarcane yield estimation is performed. In [24], the author presented detailed application of deep learning model in fruit tree crop load estimation. Also various extrapolation of tree images counts to orchard yield estimation are reviewed in detail.

The methods analyzed are subject to introduce poor performance in yield and growth estimation.

3. Dual Level Feature Approximation Model (DLFAM)

The proposed dual level feature approximation model reads the images of satellite and filed with the agriculture data set. From the satellite image and field image, the method applies gabor filter to remove noise and extracts high level features like color, contrast where from the agriculture data set, the method extracts the low level features like temperature, humidity, rainfall, water poured, fertilizer and so on. Using all these features, the method train the network and the neurons estimates the value of plant growth support on each of them and yield support. Using all these support values the method estimates the value of plant growth and yield. The detailed approach is discussed in this section.

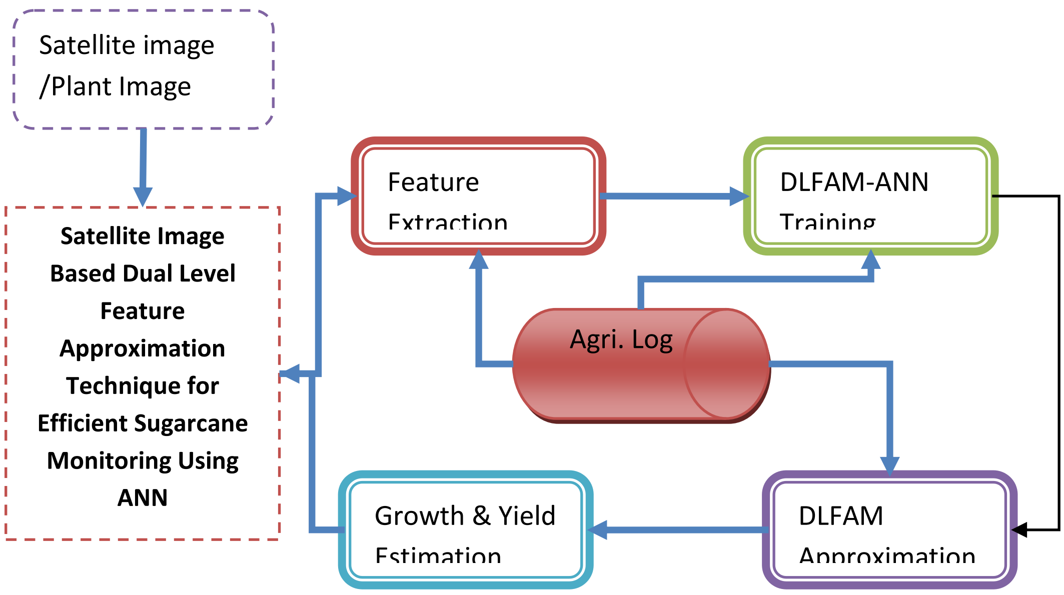

Figure 1: Architecture of Proposed DLFAM Model

The working architecture of proposed DLFAM model has been presented in Figure 1, and the components of the model has been discussed in detail in this section.

3.1 Feature Extraction:

The method read the satellite and field images with agricultural data set. From the satellite and field image, the method applies the gabor filter in multiple level. This eliminates the noise from the images. Further, the method applies the histogram equalization technique to improve the image quality. Second, the method extracts the color features, contrast features belong to various segments. According to the color, contrast features, the features of different properties are identified. From the agriculture data set, the method extracts different features belongs to environment, hydrology and soil features. Such features extracted are framed as feature vector towards train with the neural network.

Algorithm:

Given: Agriculture Data Set Agds, Satellite Image Data set Sids, Field Image Fimg

Obrain: Feature Vector Set Fvs

Begin

Read Agds, Sids

Initialize Gabor Filter GF = $\int_{\mathrm{i=1}}^{\mathrm{No\ of\ level}} \mathrm{Initialize(coeficient, level)}$

From each satellite image Sai

Noise removed image Ni = $\int \mathrm{GF(Sai)}$

Segmented Image Sei = Segmentation (Ni, Color Threshold)

Compute No of Fluid pixels Flp = $\int_{\mathrm{i=1}}^{\mathrm{size(Segi)}} \sum \mathrm{Sei(i).value} \rightarrow \mathrm{G1}$

Compute No of Soil pixels Sp = $\int_{\mathrm{i=1}}^{\mathrm{size(Segi)}} \sum \mathrm{Sei(i).value} \rightarrow \mathrm{G2}$

Compute No of Plant pixels Pp = $\int_{\mathrm{i=1}}^{\mathrm{size(Segi)}} \sum \mathrm{Sei(i).value} \rightarrow \mathrm{G3}$

End

From each field image Fimg

Noise removed image Ni = $\int \mathrm{GF(Fimg)}$

Segmented Image Sei = Segmentation (Ni, Color Threshold)

Compute No of Fluid pixels FFlp = $\int_{\mathrm{i=1}}^{\mathrm{size(Segi)}} \sum \mathrm{Sei(i).value} \rightarrow \mathrm{G1}$

Compute No of Soil pixels FSp = $\int_{\mathrm{i=1}}^{\mathrm{size(Segi)}} \sum \mathrm{Sei(i).value} \rightarrow \mathrm{G2}$

Compute No of Plant pixels FPp = $\int_{\mathrm{i=1}}^{\mathrm{size(Segi)}} \sum \mathrm{Sei(i).value} \rightarrow \mathrm{G3}$

End

Compute fluid volume Flv = $((Flp + FFlp)/2) \big/ size(Sei)$

Compute area of cultivation Ac = $((Sp + Fsp)/2) \big/ size(Sei)$

Compute plant area Pa = $((Fpp + Pp) + 2) \big/ size(Sei)$

For each agriculture data Ad

Extract cultivation area Ca = $AreainSquareMeter \in Ad$

Extract temperature Temp = $Temperature \ \in Ad$

Extract Humidity Hum = $Humidity \ \in Ad$

Extract Rainfall Rf = $Rainfall \in Ad$

Extract water poured wp = $\mathrm{Water}_{\mathrm{Poured}} \in \mathrm{Ad}$

Extract fertilizer supplied Fsup = $Fertilizer\_volume \in \quad Ad$

Extract Yield Yi = Yield ∈ Ad

End

Generate feature vector fv = {Flv, Ac, Pa,Ca, Temp, Hum, Rf, Wp, Fsup, Yi}

Add to feature vector set

Stop

The above discussed algorithm represent how the method extract the features from both satellite and field images. The feature extracted are converted into feature vector to perform plant growth and yield estimation towards sugarcane monitoring.

3.2 DLFAM-ANN Training:

The growth of sugarcane plants is varying on each time stamp of the entire cultivation. To perform training and test with neural network, the features of the data set is extracted at each time stamp traces. Such feature extracted at each time stamp or window are organized at each level or layer neuron. The features extracted are initialized with the neurons of specific time stamp or layer. To perform this, first, the number of time window or layer present in the data set according to the agriculture data set is identified. According to the number of time stamp, the method generates number of layers in the neural network and generates dedicated neuron for each log available. The feature extracted from the log is initialized with the neuron. Generated neural network and the value of neuron are applied in estimating the plant growth and yield value.

Algorithm:

Given: Field Image Set FIs, Agriculture data set Ads, Satellite Image Set SIS

Obtain: Neural Network Nn

Begin

Fetch FIS, Ads, SIS

Find the list of time stamp Tsl = $\int_{\mathrm{i}=1}^{\mathrm{size(Ads)}} \sum \mathrm{Ads(i).Timestamp} \ni \mathrm{Ns}$

Initialize Neural network NN = $\int_{\mathrm{i}=1}^{\mathrm{size(Tsl)}} \mathrm{Generate\ Neural\ layers\ NN(i)}$

At each time stamp Ti

Feature vectors set Fvs = Feature Extraction (FIS,Ads, SIS)

At each feature vector fv

Generate a Neuron N.

Initialize N = {Fvs(Fv)}

Add neuron N to layer l.

NN (l) = Fv

End

Perform polling.

End

Stop

The above discussed algorithm represents how the neural network is generated and trained. To perform this, the method first identifies the set of all time windows available according to the traces of agriculture generated. Further, the method identifies the logs generated and generates number of neurons to be initialized with the features extracted from the logs. The neurons are generated for number of layers according to number of time stamp and generated neurons are used to perform plant growth and yield estimation.

3.3 DLF Approximation:

The dual level feature approximation scheme reads the feature vectors of specific layer and input feature vector given. Using them, the method finds the features belongs to specific region and according to the features, the neurons of the layer would estimate different support for various features like environmental, filed, fluid, fertilizer, and high level features. The neuron estimates the high level support according to the color and contrast features available and obtained from the satellite and field images. Similarly, the environmental growth support is measured according to the temperature and humidity values. The value of field support is measured according to the value of cultivation area and the industrial sectors. The fluid growth support is measured according to the rainfall, and water poured. Finally, the color values are used in measuring the high level feature support. Using all these features, the next level neuron would estimate the support towards various factors to perform growth and yield estimation.

Algorithm:

Given: Feature Vector Fv, Feature vector set Fvs

Obtain: CGIR, COGIR, FGIR, SGIR.

Begin

Read feature vector Fv, Fvs

Compute Environmental Growth Support EGS =

$$\left(\frac{Dist(Fv(Temp) - (\sum_{i=1}^{size(Fvs)} Fvs(i).temp \big/ size(Fvs))}{\sum_{i=1}^{size(Fvs)} Fvs(i).temp \big/ size(Fvs)} \times \frac{Dist(Fv(Hum) - (\sum_{i=1}^{size(Fvs)} Fvs(i).Hum \big/ size(Fvs))}{\sum_{i=1}^{size(Fvs)} Fvs(i).Hum \big/ size(Fvs)}\right) \times \sum_{i=1}^{size(Fvs)} Fvs(i).Yield \big/ size(Fvs) \quad \text{-- (10)}$$

Compute High level growth support HLGS.

$$HLGS = \left(\frac{Dist(Fv(Flv) - (\sum_{i=1}^{size(Fvs)} Fvs(i).Flv \big/ size(Fvs))}{\sum_{i=1}^{size(Fvs)} Fvs(i)Flv \big/ size(Fvs)} \times \frac{Dist(Fv(Ac) - (\sum_{i=1}^{size(Fvs)} Fvs(i).Ac \big/ size(Fvs))}{\sum_{i=1}^{size(Fvs)} Fvs(i)Ac \big/ size(Fvs)} \times \frac{Dist(Fv(Pa) - (\sum_{i=1}^{size(Fvs)} Fvs(i).Pa \big/ size(Fvs))}{\sum_{i=1}^{size(Fvs)} Fvs(i)Pa \big/ size(Fvs)}\right) \times \sum_{i=1}^{size(Fvs)} Fvs(i).Yield \big/ size(Fvs)$$

Compute Fluid Growth Support FlGS =

$$\left(\frac{Dist(Fv(Rf) - (\sum_{i=1}^{size(Fvs)} Fvs(i).Rf \big/ size(Fvs))}{\sum_{i=1}^{size(Fvs)} Fvs(i)Rf \big/ size(Fvs)} \times \frac{Dist(Fv(Hum) - (\sum_{i=1}^{size(Fvs)} Fvs(i).Wp \big/ size(Fvs))}{\sum_{i=1}^{size(Fvs)} Fvs(i).Wp \big/ size(Fvs)}\right) \times \sum_{i=1}^{size(Fvs)} Fvs(i).Yield \big/ size(Fvs)$$

Compute Field Growth Support FGS.

$$\frac{Dist(Fv(CA) - (\sum_{i=1}^{size(Fvs)} Fvs(i).CA \big/ size(Fvs))}{\sum_{i=1}^{size(Fvs)} Fvs(i).CA \big/ size(Fvs)} \times \frac{Dist(Fv(Fsup) - (\sum_{i=1}^{size(Fvs)} Fvs(i).Fsup \big/ size(Fvs))}{\sum_{i=1}^{size(Fvs)} Fvs(i).Fsup \big/ size(Fvs)} \times \sum_{i=1}^{size(Fvs)} Fvs(i).Yield \big/ size(Fvs) \quad \text{-- (13)}$$

Stop

The above discussed algorithm represents how the DLF approximation is performed by each neuron towards yield and plant growth estimation.

3.4. Growth-Yield Estimation:

The proposed dual level feature approximation algorithm reads the satellite images as well as field images of any agricultural sector. With these images, the method reads the agriculture data set. Using the images, the method applies preprocessing to eliminate the noisy features and enhances the images. Further, the preprocessed images are segmented to group the pixels under their similarity. Now, from the images and the data sets, the method extracts various feature related to environmental, high level as color, contrast, fluid, and cultivation field features. The features extracted are combined with the features like rainfall, water poured, temperature, humidity, area of cultivation, fertilizer supplied and other features from the data set. Using all these features, the method computes the different values of support on Environmental growth support (EGS), High level growth support

(HLGS), Field Growth Support (FGS), Fluid Growth support (FLGS). Such support values are obtained by test with the input feature over the artificial neural network trained. Using these support values, the method computes the value of Plant Growth Factor and Yield Factor.

Algorithm:

Given: ANN, Satellite Image Simg, Current Agri. Feature CAF, Field Image Fimg

Obtain: Yield Factor YF, Growth Factor GF

Begin

Read ANN, Simg, CAF, Fimg.

Noise removed image Nri = $\overset{Level}{\underset{i=1}{Apply}}\, GAF(Simg)$

Segmented Image Si = Segmentation (Nri, Color Threshold)

Compute No of Fluid pixels Fp = $\sum_{i=1}^{size(Segi)} Segi(i).value > 200$

Compute No of Soil pixels Sp = $\sum_{i=1}^{size(Segi)} Segi(i).value < 150$

Compute No of Plant pixels Pp = $\sum_{i=1}^{size(Segi)} Segi(i).value > 150 \,\&\&\, < 200$

Compute fluid volume Flv = ${}^{Fp}/_{size(Sei)}$

Compute area of cultivation Ac = ${}^{Sp}/_{size(Sei)}$

Compute plant area Pa = ${}^{Pp}/_{size(Sei)}$

Noise removed image Nri = $\overset{Level}{\underset{i=1}{Apply}}\, GAF(Fimg)$

Segmented Image Segi = Segmentation (Nri, Color Threshold)

Compute No of Fluid pixels FFp = $\sum_{i=1}^{size(Segi)} Segi(i).value > 200$

Compute No of Soil pixels FSp = $\sum_{i=1}^{size(Segi)} Segi(i).value < 150$

Compute No of Plant pixels FPp = $\sum_{i=1}^{size(Segi)} Segi(i).value > 150 \ \&\& < 200$

Compute fluid volume FFlv = $^{FFp}/_{size(Sei)}$

Compute area of cultivation FAc = $^{FSp}/_{size(Sei)}$

Compute plant area FPa= $^{FPp}/_{size(Sei)}$

[EGS, FGS, FLGS, HLGS] = ANN-Test((FFlv+Flv)/2),(FAc+AC)/2),(FPa+Pa)/2),CAF)

Compute Plant Growth Factor PGF = $\frac{FLGS}{FGS} \times EGS$

Compute Yield factor YF = $\frac{HLGS \times FLGS}{FGS} \times EGS$

Stop

The process of estimating yield and growth of sugarcane plant has been presented in the above discussed algorithm. The method computes extract the features of different fields from the satellite and field images with the agriculture data set. Using the features, the method test with the ANN and obtains different support on environmental growth, field growth, fluid growth and high level growth support values. Using these support values, the method estimates the plant growth factor and yield factor.

4. Results and Discussion

The proposed DLFAM model utilizes both satellite image of agriculture land as well as the field image. Further, the analysis is performed on the performance of the proposed model with the use of agriculture data set obtained from the agricultural sectors of India. The satellite images are collected from ARI (Agricultural Research India).

Table 1: Evaluation Detail

Key	Value
Implemented Using	Matlab
Period of Data	5 years
Source Of Data	ARI
Type of Data	Image and Numeric

The parameters and values used for the performance evaluation is presented in Table 1. The performance of the method is measure on different parameters and presented. The ARI provides the data set towards the cultivation of different plants in different regions of the country. Such data set can be obtained from each regional agricultural center. The data set contains both image and numeric features related to various properties considered.

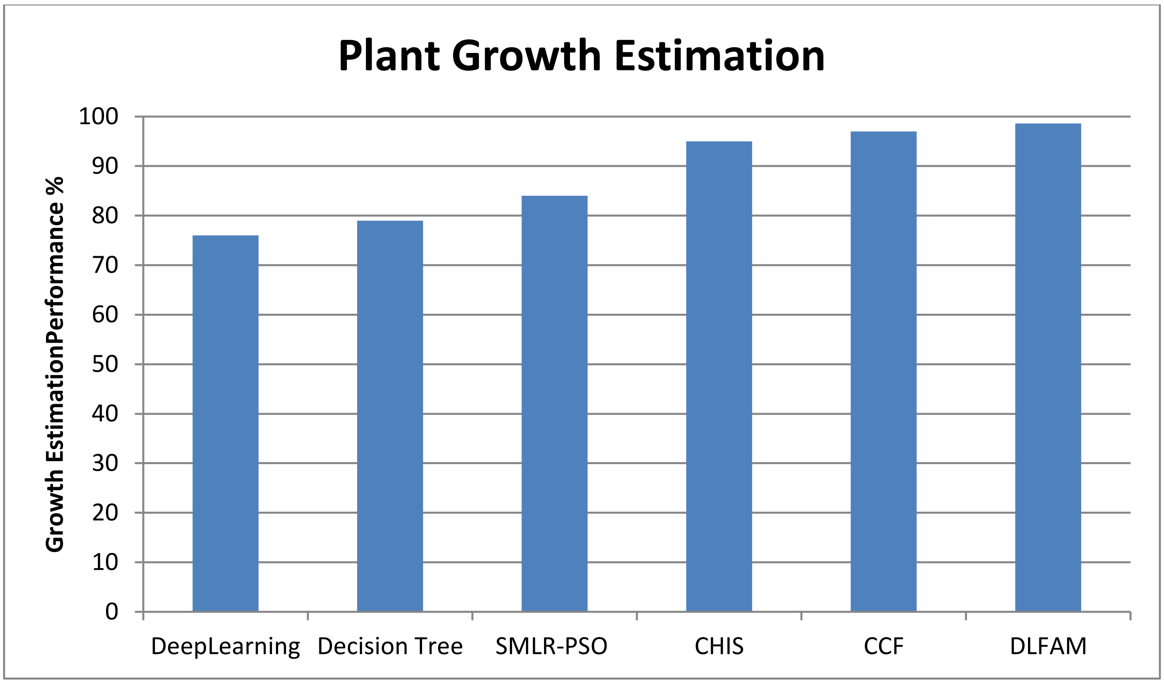

Figure 2: Analysis on plant growth estimation

The performance of the proposed DLFAM model has been measured on the value of plant growth estimation. The method considered both satellite image as well as field image and the features from both the images are obtained towards evaluation. The proposed method produced the plant growth estimation performance up to 98.6% which is higher than Deep learning, Decision Tree, SMLR-PSO, CHIS and CCF models.

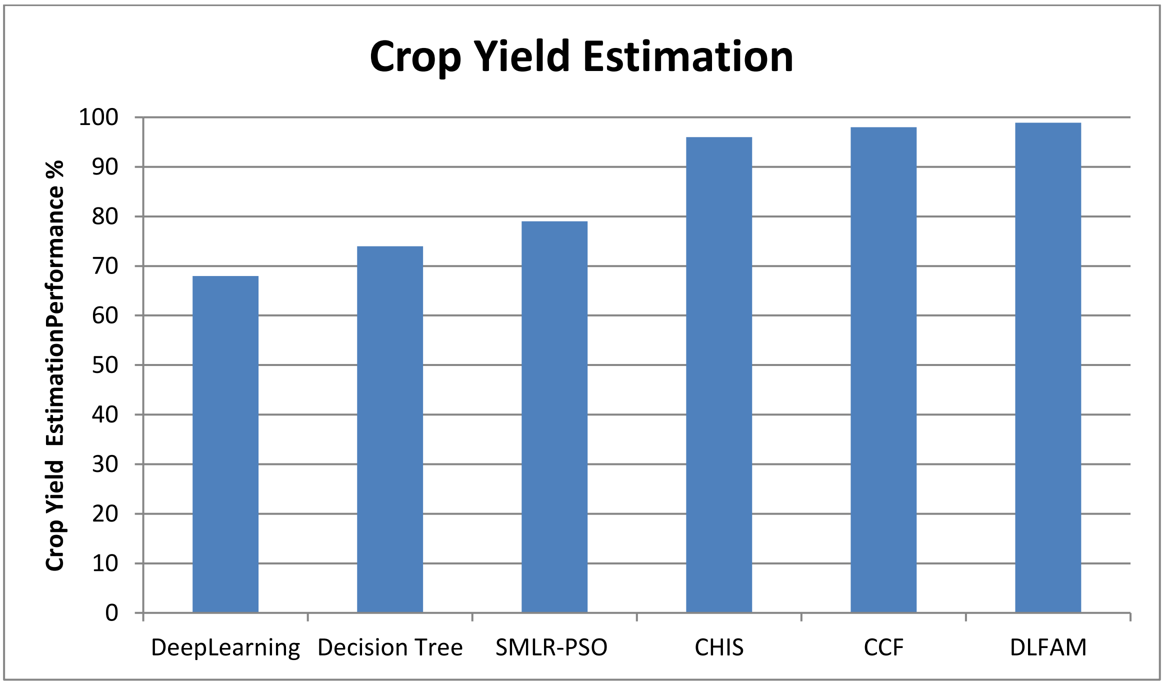

Figure 3: Analysis crop yield estimation

The proposed DLFAM approach has been measured for its performance in crop yield estimation. It has produced the performance up to 98.9% which is higher than existing Deep learning, Decision Tree, SMLR-PSO, CHIS and CCF model.

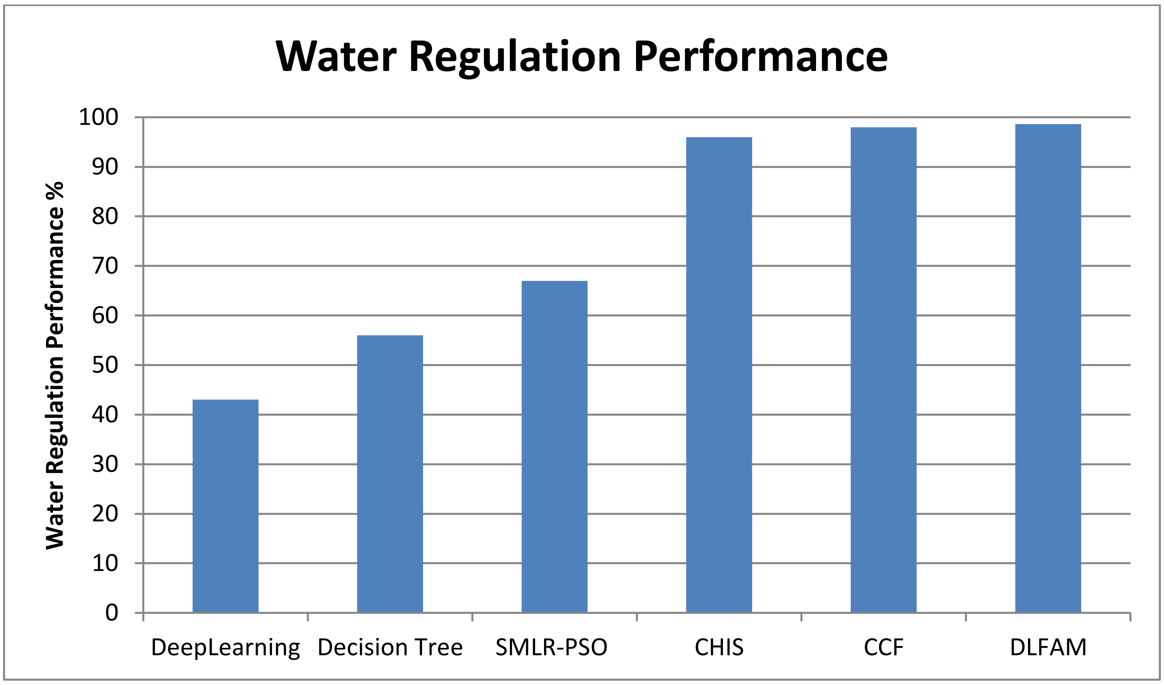

Figure 4: Analysis on water regulation

The performance of the DLFAM approach has been measured for water regulation performance. The proposed DLFAM algorithm has produced higher performance in water regulation which produced the water regulation performance up to 98.6% which is higher than existing Deep learning, Decision Tree, SMLR-PSO, CHIS and CCF model.

5. Conclusion

This article presented a novel DLFAM (Dual Level Feature Approximation Model) with ANN towards efficient plant growth and yield estimation on sugarcane plants. The method uses both satellite images as well as field images with agriculture data set. The images obtained are preprocessed and quality improved to extract various features of environmental, hydrology, field features. Also from the agriculture data set, the method extracts different features like temperature, humidity, rainfall, water poured, fertilizer and so on. Using these features the method generates a neural network which estimates different support values on various factors. Using these factors, the method computes the value of plant growth factor and yield factor. The proposed method improves the performance in growth estimation and yield estimation than other methods.

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