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Real time satellite image based CCF approximation model for efficient sugarcane growth and yield estimation using artificial neural networks

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Abstract

Objective: To improve the performance of an efficient satellite image based CCF (Color, Climate, Flow) approximation model is presented in this article. **Method:** We attempted for plant growth estimation and yield estimation using artificial neural networks. The model receives the satellite images and preprocesses to improve the quality of the image. From the quality improved image, the method extracts the color values. Further, the features like climate and flow features from the data set of the region have been extracted. Using these features, for different time window, the method generates number of neurons and initializes them with the set of features. The set of images from the data set are used to extract several features and used to train the network. The classification is performed according to the same set of features obtained from input satellite image and the other features of the region at current window. The method estimates CCF plant growth and yield support measures as result. Based on these values, the yield estimation is performed. **Result:** The proposed method improves the performance of plant growth up to 97.25 and the yield estimation performance is increased up to 985 which is higher than previous approaches. Provide comparative estimation. **Novelty:** The proposed CCF model consider color, climate and features in plant growth estimation which differ from other approaches by considering maximum features obtained from satellite images as well as features collected from ground truth in different time stamp.

Keywords: Sugarcane yield; plant growth; ANN; CCF model; feature approximation; satellite images; CCF support

1 Introduction

This research is focused on increasing the yield of sugarcane plant, by estimating the plant growth in different time span of plant cultivation. In most times, the yield becomes less due to the improper planning of the plant cultivations. First of all, the rain fall is getting reduced every year due to the environment changes and global warming. This affects the yield and growth of sugarcane plants. So, there exists water scarcity throughout the country in different time. Due to this, the farmers cannot supply enough water to the plants to achieve higher plant growth and yield. By analyzing the various factors, the performance of plant growth and yield can be improved.

The satellite images are used in several problems like predicting climate changes and rainfall. Such satellite images of different agricultural lands can be used in estimating and predicting the plant growth of sugarcane. By predicting the growth of the plant, the yield obtained can be measured[1]. This would support the development of agricultural sector and a number of decisions can be taken by the cultivators. The satellite images contain different features and by extracting the features from the image, predictions on the plant growth can be made. When the plant growth is higher, the empty lands will be less and by applying the image processing techniques, the plant growth can be measured[2].

Towards the scope, there are number of methods have been discussed by various researchers. In general, the plant growth is measured according to the value of rainfall, water poured, temperature and so on. However, they suffer to achieve higher performance in sugarcane yield estimation. This article considers this problem and defines an efficient satellite image based CCF approximation model. The image processing techniques are more useful in variety of problems. The plant growth and yield estimation also can be performed using such images. The satellite images are used for several problems like wind monitoring, cyclone prediction and so on. According to this, the satellite images of agricultural lands can be used in estimating the plant growth and yield estimation. The satellite images would be color full and from the color images, the area of cultivation, the plant region, soil type, and volume of fluid available can be extracted. By extracting such features, the plant growth can be measured. Similarly, the yield estimation can be performed using them.

Apart from satellite images, the details of previous records on the plant at the same land can be used in measuring the plant growth. Different regions of any country would be having different climate conditions and rainfall ratio. By considering various factors of climate, fluid and soil conditions the performance of plant growth can be improved. Similarly, the artificial neural networks have been used in several problems where there is an issue of missing features and high dimension. The neurons are capable of measuring weight which has been feed to the next layer neurons to perform plant growth estimation. Such an approach is presented in this paper, and the proposed CCF approximation model uses color, climate and fluid approximation model consider temperature, humidity, water poured rainfall, and other features in estimating the plant growth and yield estimation. The detailed approach is discussed in detail in the next section.

Number of approaches are available in estimating the plant growth and yield produced by sugarcane plants. Still the methods suffer to achieve higher performance in the performance of estimating the growth and yield. With the motivation to improve the performance of plant growth estimation and yield, a CCF approximation model is presented in this article. The method is focused in estimating the plant growth of sugarcane according to satellite images and the data set of different region.

The methods on sugarcane plant growth and yield estimation has been analyzed in this part. A satellite image based sugarcane crop yield estimation is presented in[3], 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[4], 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 depends 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[1], which extracts texture, color features in classifying the plants towards yield estimation. In[15], 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[16] 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[17] , 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[18]. In[19], 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[20], 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[21], 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[22], 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[23], 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.

2 Satellite image based CCF approximation model using ANN

The proposed satellite image based CCF approximation model uses both numerical and image data set of agricultural sector. From the data set, the satellite images are preprocessed to remove the noise and enhance the quality of the image. The features like color have been extracted to approximate the plant growth, as well as from the data set given, the features like temperature, area of cultivation, humidity, soil type, rainfall, plant growth and yield. The same sets of features are obtained from the test sample to perform yield estimation and plant growth. The detailed approach is discussed in this section.

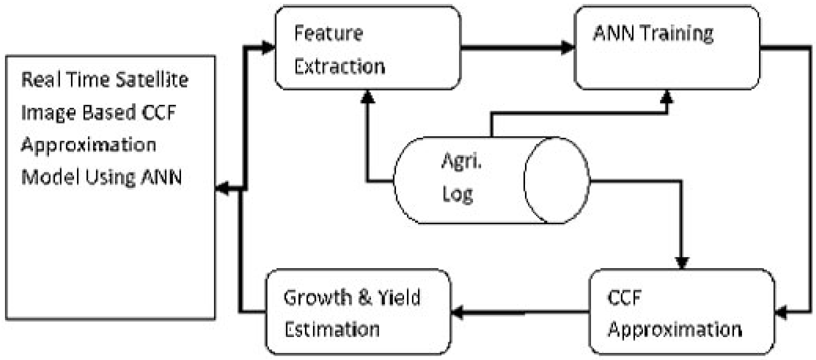

Fig 1. Architecture of CCF approximation model

The working of proposed CCF Approximation model has been presented in Figure 1. This section details each stages clearly.

2.1 Feature extraction

The preprocessing is performed in satellite images to eliminate the noise initially. First, the Gabor filter has been applied to eliminate the noise introduced by the capturing device. Then, the histogram equalization is performed to improve the noise. From the noise removed image, the methods perform segmentation according to the color values. The result of segmentation is used to extract the number of pixels at each group like fluid, soil, plant. Similarly, the features from the agricultural data are extracted by preprocessing them to eliminate the noise data points with missing values. The features like area, water poured, rainfall, temperature, humidity, and yield are extracted. Extracted features are converted into feature vector to perform ANN training in the next stage.

Algorithm

Input: Agriculture Data Set Ads, Satellite Image Data set Sis

Output: Feature Vector Set Fvs

Start

Read Ads, Sis

For each satellite image Si

Noise removed image Nri = $\int GaF(Si)$ – (1)

Segmented Image Si = Segmentation (Nri, Color Threshold)

Compute No of Fluid pixels Fp = $\int_{i=1}^{size(Segi)} \sum Segi(i).value \rightarrow G1$ – (2)

Compute No of Soil pixels Sp = $\int_{i=1}^{size(Segi)} \sum Segi(i).value \rightarrow G2$ – (3)

Compute No of Plant pixels Pp = $\int_{i=1}^{size(Segi)} \sum Segi(i).value \rightarrow G3$ – (4)

Compute fluid volume Flv = $\frac{Fp}{size(Sei)}$ – (5)

Compute area of cultivation Ac = $\frac{Sp}{size(Sei)}$ – (6)

Compute plant area Pa = $\frac{Pp}{size(Sei)}$ – (7)

End

For each agriculture data Ad

Extract cultivation area Ca = $\int Ad.Area$

Extract temperature Temp = $\int Ad.Temp$

Extract Humidity Hum = $\int Ad.Humidity$

Extract Rainfall Rf = $\int Ad.Rainfall$

Extract water poured wp = $\int Ad.Water\ poured$
Extract Yield Yi = $\int Ad.yield$
End
Generate feature vector fv = {Flv, Ac, Pa,Ca, Temp, Hum, Rf, Wp, Yi}
Add to feature vector set
Stop

The feature extraction algorithm extract the different features from the satellite image of the region on specific time and extract different features according to the region on the same period from the agriculture log. Extracted feature vectors are added to the feature vector set. The features extracted are used to perform plant growth estimation and yield estimation.

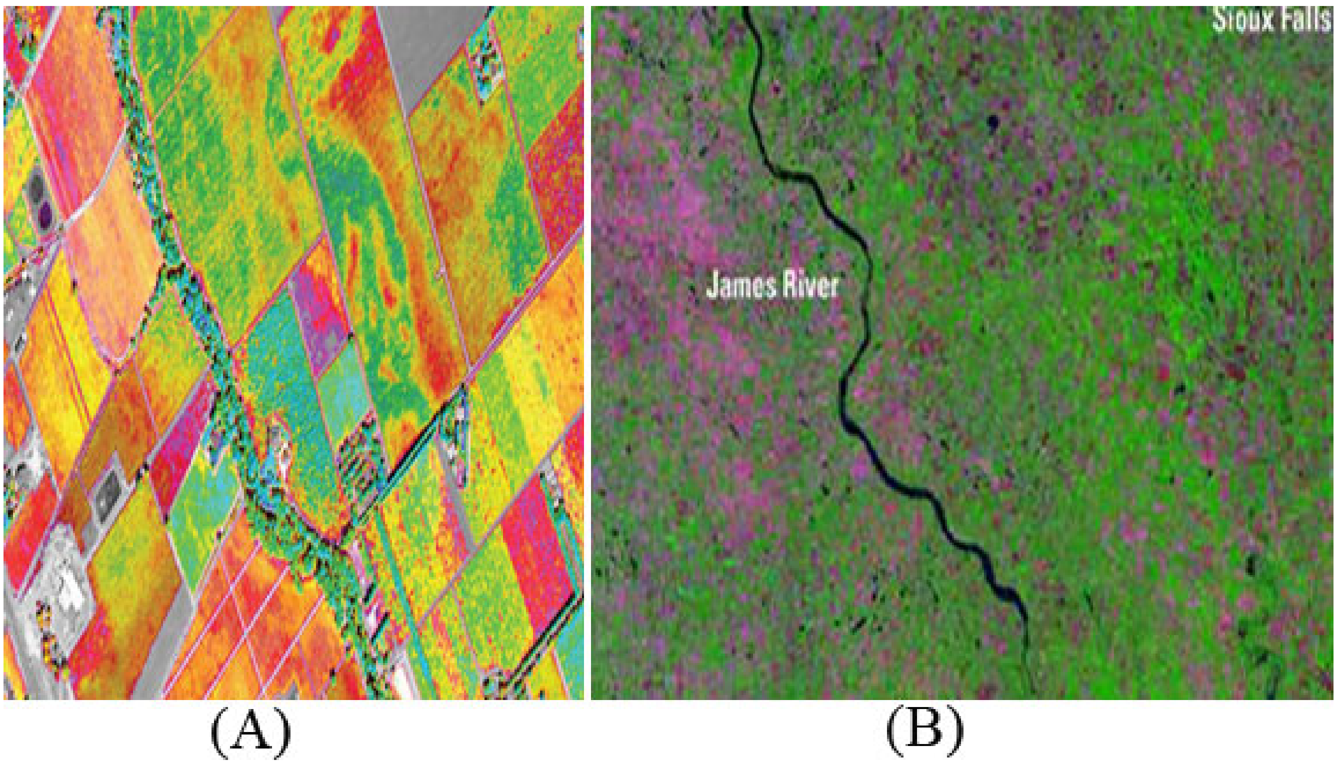

Fig 2. (A) Healthy Crop Image. (B) Vacant and Cultivated Area

The health crops identified from USA has been captured and presented in Figure 2 (A) and the vacant and cultivated area captured from satellite is presented in Figure 2(B). The images represent the result of segmentation performed according to the color values. By segmenting the satellite images, the area of cultivation, the water source present, type of soil can be extracted by applying image processing techniques to support plant growth and yield estimation.

2.2 ANN training

The neural network is generated according to the features extracted. The method generates the neural network according to the time window considered. At each time window, a separate layer of neurons are generated. Each layer neuron is initialized with set of features extracted in the feature extraction stage. First, the method identifies the list of time stamp and split the logs accordingly. Using them, the method generates number of layers and number of neurons at different layer. Each layer neuron is initialized with the feature values extracted by the feature extraction algorithm. Generated ANN has been used to perform plant growth estimation and yield estimation.

Algorithm:
Input: Agriculture data set Ads, Satellite Image Set SIS
Output: Neural Network Nn
Start
Read Ads, SIS
Identify time stamp Ns = $\int_{i=1}^{size(Ads)} \sum Ads\,(i)\,.Timestamp \ni Ns$ – (8)
Initialize Neural network NN = $\int_{i=1}^{size(Ns)} Generate\ Neural\ layers\ NN(i)$ – (9)
For each time stamp Ts
Feature vectors set Fvs = Feature Extraction (Ads, SIS)
For each feature vector fv
Generate Neuron N.
Initialize N = {Fvs(Fv)}
Add neuron N to layer l.
NN (l) = Fv
End
Perform polling.
End
Stop

The ANN training algorithm identifies the list of time stamp available. According to the time stamp available, the method generates neural network with number of layers. The time stamp logs are split and features are extracted. According to the features extracted, the method generates neurons and initializes them to add to the layer. Generate neural network is used to perform yield estimation. The number of layers of ANN decided according to the data size which represent the number of time window. For example, if the data has tuples for one year, then it can be decided as 12 layers; similarly, if the tuples are generated in 2 years then the number of layers considered are 24. Further, it can be considered as quarterly, half yearly and yearly time stamp as single time window when the number of records increases or number of years covered.

2.3 CCF Approximation

The color climate fluid approximation algorithm estimates the plant growth and yield according to the different features of satellite color image, climate features and fluid features of the region identified. Each neuron of the network generated is capable of performing this approximation which forwards the result of approximation to the next layer neurons. The neuron reads the features initialized and estimates climate growth induction rate (CGIR), Color Growth Induction Rate (COGIR), Fluid Growth Induction Rate (FGIR), and Soil Growth Induction Rate (SGIR). All these measures estimated are given to the next layer towards approximation.

Algorithm:
Input: Feature Vector Fv, Feature vector set Fvs
Output: CGIR, COGIR, FGIR, SGIR.
Start
Read feature vector Fv, Fvs
Compute Climate Growth Induction Rate

$$CGIR = \left(\frac{Fv(Temp)}{\sum_{i=1}^{size(Fvs)} \mathrm{Fvs}(i)\cdot temp/\,\mathrm{size}(Fvs)} \times \frac{Fv(Hum)}{\sum_{i=1}^{size(Fvs)} \mathrm{Fvs}(i)\cdot Hum/\,\mathrm{size}(Fvs)} \right) \times \sum_{i=1}^{size(Fvs)} \mathrm{Fvs}(i)\cdot Yield/\,\mathrm{size}(Fvs) \quad (10)$$

Compute Color Growth Induction Rate COGIR.

$$COGIR = \left(\frac{Fv(Flv)}{\sum_{i=1}^{size(Fvs)} \mathrm{Fvs}(i)\cdot Flv/\mathrm{size}(Fvs)} \times \frac{Fv(Ac)}{\sum_{i=1}^{size(Fvs)} \mathrm{Fvs}(i)\cdot Ac/\mathrm{size}(Fvs)} \times \frac{\mathrm{Fv}(Pa)}{\sum_{i=1}^{size(Fvs)} \mathrm{Fvs}(i)\cdot Pa/\mathrm{size}(Fvs)}\right) \times \sum_{i=1}^{size(Fvs)} \mathrm{Fvs}(i)\cdot Yield/\mathrm{size}(Fvs) \quad (11)$$

Compute Fluid growth induction rate

$$FGIR = \left(\frac{Fv(Rf)}{\sum_{i=1}^{size(Fvs)} \mathrm{Fvs}(i)\cdot Rf/\mathrm{size}(Fvs)} \times \frac{Fv(Wp)}{\sum_{i=1}^{size(Fvs)} \mathrm{Fvs}(i)\cdot Wp/\mathrm{size}(Fvs)}\right) \times \sum_{i=1}^{size(Fvs)} \mathrm{Fvs}(i)\cdot Yield/\mathrm{size}(Fvs) \quad (12)$$

Compute Soil Growth Induction Rate SGIR.

$$\frac{Fv(Pa)}{\sum_{i=1}^{si\,ze(Fvs)} \mathrm{Fvs}(i)\cdot Pa/\mathrm{size}(Fvs)} \times \sum_{i=1}^{si\,ze(Fvs)} \mathrm{Fvs}(i)\cdot Yi\,eld/\mathrm{size}(Fvs) \quad (13)$$

Stop

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

2.4 Growth-Yield estimation

The proposed real time satellite image based CCF Model uses artificial neural network for growth and yield estimation of sugarcane plants. The input satellite image and agriculture features are used for estimation of different factors. First the method performs feature extraction from the input satellite image which is preprocessed to eliminate the noise and perform segmentation to group the similar pixels which represent the plants, soil and water fields. From the segmented image, the method extracts the features and estimate fluid volume, area cultivation and area of plant. Such features extracted with the field features like temperature, humidity, rainfall, water poured has been used to perform plant growth estimation and yield estimation. Obtained features are tested with the generated artificial neural network, which produces four different factors like climate growth induction rate (CGIR), color growth induction rate (COGIR), Soil growth induction rate (SGIR), and Fluid growth induction rate (FGIR). Based on the values obtained by the artificial neural network, the plant growth and yield estimation are computed.

Algorithm

Input: ANN, Satellite Image Simg, Current Agri. Feature CAF

Output: Yield Y, Growth G

Start

Read ANN, Simg, CAF.

Noise removed image Nri = $\int GaF(Simg)$

Segmented Image Si = Segmentation (Nri, Color Threshold)

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

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

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

Compute fluid volume Flv = $\frac{Fp}{size(Sei)}$

Compute area of cultivation Ac = $\frac{Sp}{size(Sei)}$

Compute plant area Pa = $\frac{Pp}{size(Sei)}$

[CGIR, COGIR, FGIR, SGIR] = ANN-Test (Flv, Ac, Pa, CAF)

Compute Plant Growth G = $\frac{CGIR}{SGIR} \times FGIR$ – (14)

Compute Yield value Y = $\frac{CGIR \times CGIR}{SGIR} \times FGIR$ – (15)

Stop

The above discussed algorithm represents how the plant growth is measured. The method extracts the features from satellite image and agricultural trace. Using them, the features are tested with ANN which returns the different induction rate on various features. Obtained induction rate are used to measure the plant growth and yield value.

3 Results and Discussion

The CCF model proposed uses the satellite images and the model has been hard coded with mat lab. The performance of the method is evaluated using various data set which are collected from 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.

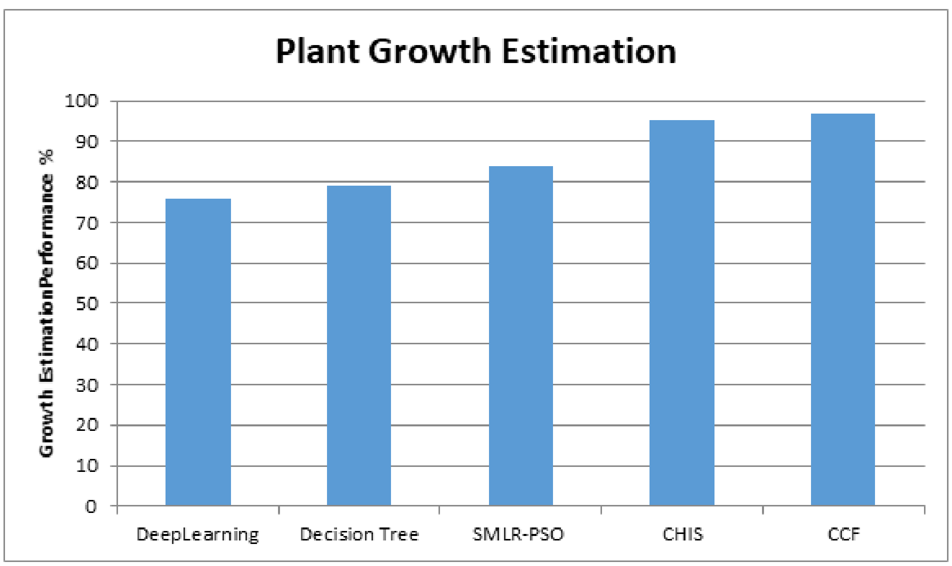

Fig 3. Analysis on plant growth estimation

The efficiency of estimating the plant growth is measured for different techniques and populated in Figure 3 , which debit that the CCF model introduced higher efficiency in plant growth estimation. The inclusion of CCF model encourages the plant growth estimation to be performed by considering color, climate and flow features increases the estimation to be performed in most efficient manner. The proposed CCF model introduces the plant growth estimation performance up to 97% which is higher than Deep learning, DecisioniTree, SMLR-PSO and CHIS models.

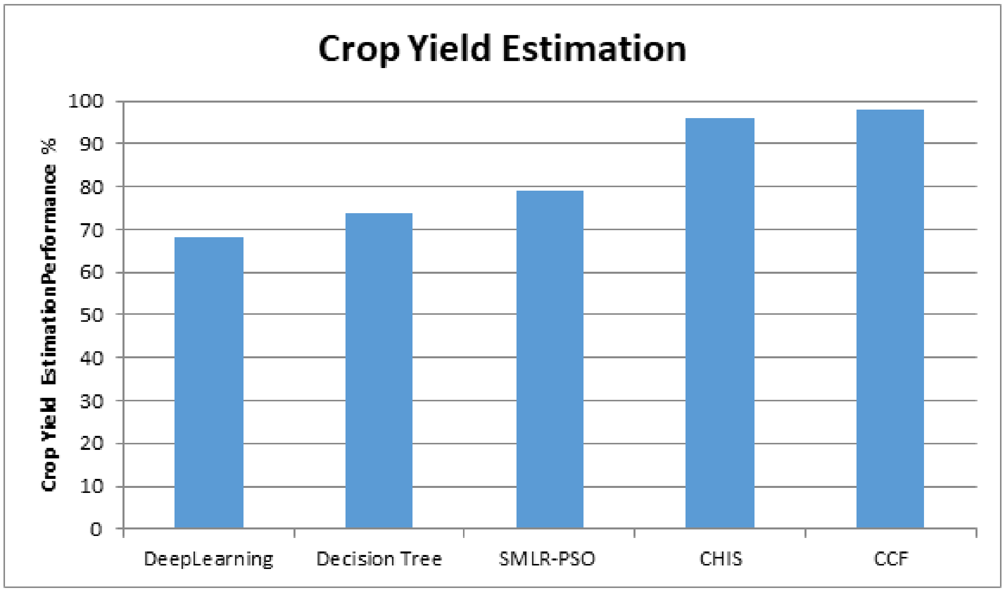

Fig 4. Analysis crop yield estimation

The performance on estimating the yield is measured for various approaches and presented in Figure 4 . The CCF model has achieved higher yield estimation performance compare to other techniques. The proposed CCF model consider the color, climate and flow features in estimating the crop yield. This supports the improvement of performance in crop yield estimation up to the ratio 98% which is higher than existing Deep learning, Decision Tree, SMLR-PSO and CHIS model.

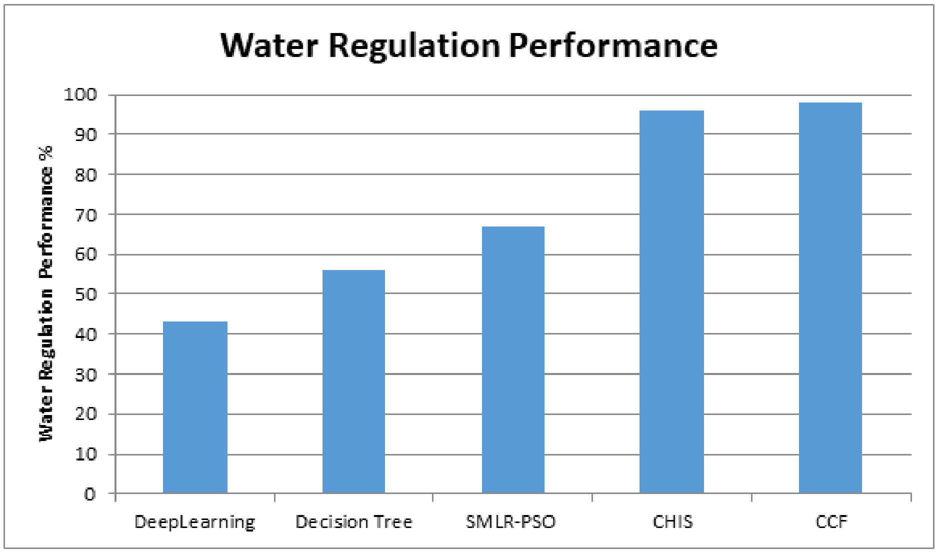

Fig 5. Analysis on water regulation

The analysis in water regulation is performed to measure the efficiency of the methods in regulating the water required. The CCF model is achieved great performance compare to other techniques. The proposed CCF model consider the color, climate and flow features in estimating the water required and water regulation performance. This supports the improvement of performance in water regulation performance up to the ratio 98% which is higher than existing Deep learning, Decision Tree, SMLR-PSO and CHIS model.

4 Conclusion

We presented an efficient satellite image based CCF (climate color fluid) approximation model. The method extracts features from satellite image set and features from the agricultural data set. Using the extracted features of different time stamp, the method generates number of layers and each layer has been generated with number of neurons according to the number of trace available at each time stamp. Similarly, at the test phase, the method extract the features and test on the ANN generated where each neuron performs approximation and produces different induction rate on color, climate, fluid and soil features. Based on the induction rate of different features, the method estimates the plant growth and yield value. The proposed method improves the performance in growth estimation and yield estimation than other methods.

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