Block Level Optimization Based Mapping and Ensemble Classification Based Segmentation for Fruit Flower Detection

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***Abstract:** In the field of agricultural, the crop estimation task entirely depends on the process of detecting and counting the number of fruits on trees. The crop estimation task is mainly used in the agricultural field. Currently, counting the fruits and vegetables manually is performed at several locations. Manual counting has several disadvantages since it consumes too much time and needs an excessive amount of labor. The agriculture productivity can be improved by incorporating the automatic fruit counting technique with a crop management system to gather the information to predict the yield. This information may be used to schedule the harvesting. This research approach creates maps about flowers at the block level. This research work employed the Modified Bat Optimization technique for the generation of a direct map from blocks with no computationally intensive refinement phase. Once the block-level mapping is done, then the ensemble classification is introduced for flower identification, which is reliable against uncertain environments and suitable for various flower species. The proposed technique depends on the Support Vector Machine (SVM) classifier and an Enhanced Convolutional Neural Network (ECNN) for carrying out semantic segmentation. To improve its sensibility towards flowers, this Ensemble Classification Framework (ECF) is fine-tuned with the help of a weighted majority function of apple flower images. Also, a refinement technique is used for all the classifiers to better differentiate between different flower instances. The dataset with pixel-accurate labeling is used for the implementation of the proposed technique. The dataset has images with high resolution.*

***Keywords:** Counting, Enhanced Convolution Neural Network, Modified Bat Optimization, Optimization, Support Vector Machine, Weighted Majority function.*

I. INTRODUCTION

The crop management system should be incorporated with automated yield prediction technology to produce good results and get more productivity with less amount. The incorporation is a challenging task [1]. The prediction can be done by using yield estimates which gives important information. The yield estimates are also used to create prescription maps that can be utilized by tree intensive applications. The productivity and efficiency of the plant science can be enhanced with the help of technological developments in sensing, robotics and computing algorithms [2].

The detailed information about the yield prediction can be conveyed to the farmers via the mobile data collection system. This system may assist the farmers in decision making. More specific solutions can be given by the decision support software with the help of collected data. The mobile field robotic technology uses this method directly to make a decision. In the field of plant phonemics, the throughput is increased by the mobile data system. This process rectifies the problem of labor deficiency and increases the yield.

The analysis in industries and other fields are carried out using the technological development in the field of image processing. The fields like astronomy, crop industry medicinal uses, and soil research use image processing technology besides automated counting techniques. The results of automated counting are inexpensive, quick reliable and very easy when compared to manual counting [3].

Several times it is seen that professional advice may be expensive and cannot be afforded and also the presence of specialists and their services may lead to the consumption of both time and resources. These difficulties are resolved by the usage of image processing techniques with incorporated communication networks [4].

In a specific location, the cultivation methods and crop management are applied by mapping the yield. The mapping represents the quantity of crops that can be cultivated at a specific location at a specific time. This mapping is mainly used to generate the crop yield using the software. This mapping is also used to get the information to identify the variation between the crops in a specific location. In modern approaches, the estimate of yield of fruits is a procedure used for finding the overall number of fruits available in a tree automatically by generating the maps of flowers at the block level. To successfully apply these efficient control techniques, the yield information on every tree is a pre-condition in real-time.

The image can be segmented into the foreground region and background region using various segmentation algorithms. Background regions are eliminated for further processing [5]. The segmentation is done using the intensities of the pixels. The background color should be chosen in such a way to differentiate from the foreground. The user can select any background color for operations but it may produce less expected results. The automatic processing can be used to select the background color to improve efficiency. The images are captured with high-resolution devices nowadays and processing speed of image segmentation is another issue in modern segmentation algorithms.

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In this paper, the literature review is presented in section 2, section 3 describes the proposed work, and result comparison and conclusion are given in section 4.

II. LITERATURE REVIEW

Meena [1] used color and shape analysis to model an automatic detection, yield estimate, and counting algorithm. At the initial phase preprocessing of fruit, tree images done to enhance it. The RGB image is transformed into L*a*b color space. This transformation is used to detect the background. Segmentation is done using Otsu's approach. Noise is eliminated by the Morphological operation. Region labeling is used to extract the fruit regions. The edges of fruit regions are found by edge detection approaches. The fruit count is calculated from this edge detected image by a circular fitting algorithm.

Underwood et al [2] predicted the yield of various tress by using a mobile terrestrial scanning system. The mobile terrestrial scanning system is used for almond orchards. It is capable to map fruit and flower distribution. The 3D map of the orchard is produced by using an automated software pipeline in offline mode by processing the data. This map is used to detect the presence of trees. The flower and fruit images are classified using the measure called canopy which s measured from that 3D graph. The yield association is calculated by comparing this measure with harvest weights.

Dias et al [6] performed the segmentation of the fruit image by using the end-to-end residual Convolutional Neural Network (CNN). This network uses the apple flower dataset to enhance the sensitivity of the system to flowers. A refinement technique is used to make the difference between various flowers, as the result of CNN is coarse. The proposed method produced better results for the peach and pear flowers and apple dataset without any preprocessing or training which shows the reliability and suitability of the proposed technique.

Aggelopoulou et al [7] made the site-oriented management decisions based on the distribution of apple flower. The major work of this research includes the image analysis to find the density variability in an apple orchard and correlate the fruit yield and flower densities. This work utilizes central Greece's commercial apple orchard. Tree yield is evaluated by designing the image processing-based algorithm. This algorithm uses the image with the full bloom of it. The experimental result using the case study produces the 18% error with respect to the yield prediction.

Dias et al [8] introduced a technique in which a pre-trained CNN is refined to exhibit special sensitivity to flowers. The results obtained from experiments carried out on a massive dataset show that this technique performs considerably better than the three techniques. It has more than 90% of precision and recall value for flower detection. Three more datasets with different flower species are used by the network to evaluate the performance. The experimental results show that the performance of the proposed technique is extremely better than the baseline schemes concerning generalization capability.

Nisar et al [9] presented a system to make the counting of fruits in the interesting region automatically. The system uses, shape analysis, image segmentation, noise elimination, and size thresholding algorithms to predict the yield. The experimental results show that the better yield prediction can be done using Cr channel of YCbCr color model.

Durand et al [10] incorporated the effect of site and time in yield prediction by using linear and Markovian mixed models. The periodicity, synchronicity and flowering unevenness are measured using tree and axis scale. The fusion of a Biennial Bearing Index (BBI) is predicted. It has an autoregressive coefficient (γg). Using these coefficients, genotype behaviors are classified with few misclassifications. The tree breeding values to measure the regularity of flowering is evaluated by using posteriori sampling of axes and statistical indices based time-saving technique.

Bairwa et al [11] implemented a counting algorithm to count the products of agriculture by using various existing techniques. The yield estimates are evaluated and analyzed the drawbacks of it. Hue Saturation and Value (HSV) color space is used to evaluate the performance of the system. Gerbera flowers are used in this space. The overlapping problem is minimized using the erosion process. The experimental results produce 89.86%.

Syal et al [12] utilized computer vision approach to make an effective and automated counting system. The fruit regions are segmented from the input image by using the segmentation approach based on minimum Euclidean distance. The apples in the test image are detected and counted effectively using this approach.

Jadeja and Tenhumberg [13] examined if the inherent process of competition for less resource between fruits and flowers because of resource appropriation or sink potential of basal fruits, or architectural impacts owing to positional changes in the possibility of retention of flowers, gives the reasons for a lesser probability of having distal flowers retained in Yucca glauca. A field study is also carried out for the comparison of flower retention among nine combinations of three inflorescence treatments and three ovule damage treatments which act as a stimulant for strong future seed herbivory.

III. PROPOSED METHODOLOGY

This research work introduced a technique for automated fruit prediction based on the intensity of flower that is detected employing Support Vector Machine (SVM) classifier and Enhanced Convolutional Neural Network (ECNN) for semantic segmentation once the maps of flowers are created at the block level employing modified Bat optimization algorithm. Base counting and yield prediction may prove to be very useful in the agricultural automation field. The deep learning architecture makes use of a multilayer stack comprising of simple modules, and many of them are targeted at learning, and also few mappings for computing the nonlinear input and output. Every module in the stack transforms its input to maximize the selectivity and immutability of the expression. Enhanced Convolution Neural Network (ECNN) is a generic depth learning model that comprises of a sequence of modules.

SVM is one of the popular techniques in pattern classification and image classification. Figure 1 illustrates an overview of the proposed technique.

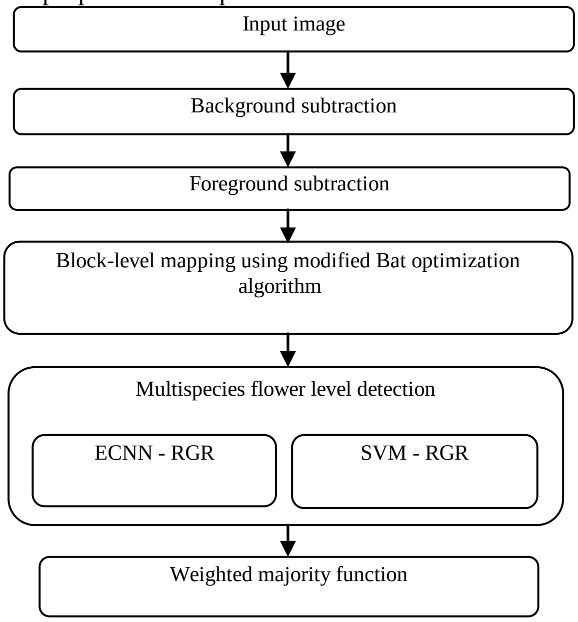

Figure 1 Overview of the proposed methodology

A. Background subtraction

The foreground components in an image are separated from the background by using the background subtraction approach. It is done using mask creation. The dynamically moving objects can be detected by using this method and this is an important task in object tracking. Various visual monitoring applications use the background subtraction as a pre-processing tool [5]. The objects in the region of interest can be detected using background subtraction. Variation of illumination and movement in the image may produce the wrong prediction while using simple background modeling and subtraction that leads to a large amount of count mismatch. The images captured in forest areas may have the foreground mixed with the background. There will be a quick transition between shadow and light.

The information required for segmentation of an image can be extracted from a single image but this will not produce good results of segmentation [14]. Truly, there are chances that the objects convey different information in them, which, in turn, makes it hard for segmentation even when the background can be selected independently. New information can be acquired by adding one more image with the same foreground but another background in comparison with the actual one to the process of segmentation. As per the literature, it is uncommon to perform this process employing two images, which distinguish themselves only for background. Due to limitations of storage and time, only one image is analyzed. In spite of that, in recent days, memory storage capacity is seeing an exponential increase daily, while the time analysis problem is relative since it is based on the current scenario.

B. Foreground subtraction

The pixels corresponding to background and foreground are calculated by comparing the grayscale of the color video frame with the background model. This process is done by the foreground detector. The foreground mask is calculated using this. The foreground objects of an image are detected by using background subtraction.

C. Block-level mapping using a Modified bat optimization algorithm

The real-life and academic optimization challenges can be easily solved by using Bat Algorithm (BA) [15]. But BA fails to calculate the global optimum value and it is not having a proper balance between exploration and exploitation. Mostly it uses a local optimum function. The problems in the bat algorithms are solved by using a modified bat optimization algorithm.

The required features are selected from the dataset using the proposed modified Bat optimization algorithm. As with the modified bat algorithm, the temperature dataset is regarded to be the initial Bat population and every data exhibits a particular frequency gr_i and velocity ve_i. The estimation of the frequency and velocity is done and updated once each iteration finishes. In this, the modified bat algorithm is utilizing for blocking the level of flower in the detection stage and the algorithm given below will be executed.

Modified BAT Algorithm

1. Initialization of ds_i , we, Where ds=Dataset, 1<=i<=n
2. Initialization of gri, vei, where frequency gri, velocity vei.
3. While (t<ds_i) do
4. Update gr_i,ve_i
5. Generate the first set of solution
6. Update ds_i
7. Generate random number r
8. Choose random instance from ds_i
9. Compute similarity
10. Choose the location among the current best solution
11. If (a better solution is found)
12. Update the current best
13. Generate a new solution
14. If (rand<ds_i&($g(x_i)<g(g_{best})$))
15. Keep the new solution
16. Sketch the global best solution
17. Sort the feature based on g_{best}
18. Terminate iteration once target is attained.

Next, this research work will focus on ensemble classification used for semantic segmentation of flowers and Region Growing Refinement (RGR) for fine-tuning the networks to boost the performance of the classifier as well as its accuracy.

D. Ensemble classification framework

This research work introduces the Ensemble Classification Framework (ECF) that demonstrates the benefits of both ECNN and SVM and these classifier results are fine-tuned with the help of RGR algorithm and at last, the results of two classifiers are combined with weighted majority algorithm.

ECNN-RGR

The combined ensemble of Convolutional Neural Networks (ME-CNN) is used to classify the ROI of an image as benign or malignant [15]. Figure 2 shows the mixture ensemble model. The input is shared between the gating network and L experts. In high-dimensional input space, an expert will be a specialist in one area. Input adaptive weights are generated by the gating network by the training process. The adaptive weights are used to combine the expert's result. The experts and gating are modelled as CNN in the proposed model. The end-to-end optimization process is used to train the components of the network at the same time.

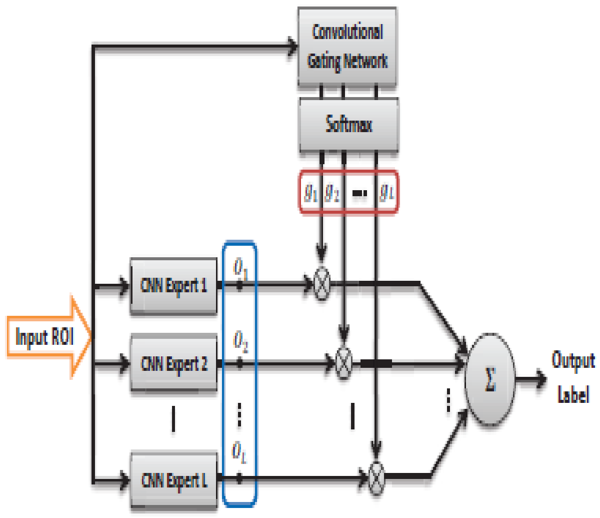

Figure 2. Schematic diagram of the proposed mixture ensemble of convolutional experts [16]

Mathematical expression: The output of L convolutional experts on the input sample is represented as O_1, O_2, ..., O_L. The input sample, activation function, and network adjustable parameters define the output. For all expert output O_i, weights gi are generated by training Convolutional Gating Network (CGN). The non-probabilistic outputs of the final layer of the CGN is given by $G_1, G_2, \ldots, G_L$. Fusion weights $\{g_i\}$ are generated by using the softmax function on non-probabilistic outputs $\{G_i\}$.

$$g_i = \frac{\exp(G_i)}{\sum_{j=1}^{L} \exp(G_j)} \qquad (1)$$

The fusion weights meet the condition:

$$\sum_{j=1}^{L} g_i = 1 \qquad (2)$$

The ultimate result of convolutional expert's mixture ensemble is provided as

$$O = \sum_{i=1}^{L} g_i O_i \qquad (3)$$

ME-CNN training: The training algorithm has to be changed for using a mixture ensemble on CNN. The convolutional gating and CNN experts are trained in the meantime. a training set of K samples, where $\mathbf{x}_k$ refers to the k^{th} input sample and $\mathbf{d}^k$ stands for the desired output vector

For the CNN experts, the sample is represented as

$$E_{expert}^{k} = -\ln\left(\sum_{i=1}^{L} g_i^k \exp\left(-\frac{1}{2}\left\|d^k - O_i^k\right\|^2\right)\right) \qquad (4)$$

Where the output vector of CNN expert is represented by O_k^i. The effective error signal for every training sample for CNN expert i, (a component in the derivative of E_{expert}^{k}) is computed as

$$e_i = \sum_{k=1}^{K} h_i^k (d^k - O_i^k) \qquad (5)$$

Where

$$h_i^k = \frac{g_i^k \exp\left(-\frac{1}{2}\left\|d^k - o_i^k\right\|^2\right)}{\sum_{j=1}^{L} g_j^k \exp\left(-\frac{1}{2}\left\|d^k - o_i^k\right\|^2\right)} \qquad (6)$$

Here, h_i^k is a posterior-probability estimate which is generated for input sample $\mathbf{x}_k$ of expert i. This value is high when: 1) output O_i^k of expert I for input sample $\mathbf{x}_k$ is near to the preferred output $\mathbf{d}^k$; and 2) weight g_i^k provided by the CGN to expert i is high. The total error function of a convolutional gating network is given by,

$$E_{gate} = \frac{1}{2}\sum_{k=1}^{K}\left\|h^k - g^k\right\|^2 \qquad (7)$$

Where $h^k \Delta \left[h_1^k, h_2^k, \ldots, h_L^k\right]^T$ is posterior probability estimates vector and CGN output vector is given by $g^k \Delta \left[g_1^k, g_2^k, \ldots, g_L^k\right]^T$.

The error backpropagation algorithm is used to calculate the gradient based on the computed error signal and function. The free parameters of the networks are utilized to compute the gradient. These free parameters of the CNNs and CGN are computed by the resilient back-propagation (RPROP) algorithm [17]. This method is used to make an expert specialized in one region of the high-dimensional input space. Optimized fusion weights are computed by training the Convolutional Gating Network.

At last, the final output of the novel ECNN sends to fine-tune the segmentation without requiring the specific datasets employing RGR algorithm.

SVM-RGR

The most popularly-employed and reliable classifier is the Support vector machine. It can not only perform the efficient classification of linear decision boundaries but can also carry out the classification of non-linear boundaries and resolve linearly inseparable problems. In this research work, the SVM classification is utilized for segmenting the flower and it is realized and then validated with:

1) Classical SVM employing various types of kernel

2) WFSVM employing pre-computed Linear Kernel.

It is employed with relevant weights in the diagonal of the kernel matrix.

The selection of kernel function and construction of kernel function makes the difference between these schemes. The SVM classification algorithm follows the same step [18]. The classification is done using the training step and testing step.

In the training step, low-level features are extracted from the training image. Clinical features are combined with this low level extracted features. In WFSVM model file of the constructed linear kernel matrix is generated. The linear kernel matrix is constructed with or without weights. The features of the kernel are used to generate the model file in SVM.

Binary SVM

Step 1: Input sample set T = { (x_i, y_i) }i=1 to l. where feature vector is represented by xi and classes are represented byy$_i$.

Step 2: Generate the kernel matrix with the features.

Step 3: Choose a suitable penalty parameter and positive component.

Step 4: Formulate the decision function utilizing Equation (8)

F(x) =sgn ($\sum_{i=1}^{l} y_i p_i \times K(x_i, x) + b^*$) (8)

Where b* is a positive component.

The weights of the features are used to replace the diagonals of the kernel matrix in SVM algorithm based on a weighted feature (WFSVM) which is a major difference between SVM and this one [19].

In the testing step, the feature set of the test set is used to test the trained SVM and WFSVM. From the testing set of databases, the features are extracted to generate the kernel matrix without diagonal weights. This matrix is given as an input to WFSVM for classification. In SVM, classification is done by directly validating the features of various kernels.

In this work, a generic post-processing module is introduced. It can be combined with the output of CNN and SVM for fine-tuning the segmentation. It does not require data set specific tuning. Known as region growing refinement (RGR) is explained in [20]. The images are segmented into regions by using the score map of CNN. The segmentation is done with a high confidence object, high confidence background, and uncertainty region. Appearance-based region growing is used to classify the pixels present within the uncertainty region are of the initial seeds, which are sampled in random from the high confidence regions. The identical pixels are grouped into clusters by RGR algorithm with multiple Monte Carlo region growing steps. Then, it carries out common polling for the classification of every cluster based on the presence of flowers.

E. Weighted majority algorithm

Weighted Majority Algorithm (WMA) is used to formulate prediction algorithms like classifiers, learning algorithms and real-life expert professionals in machine learning. The approach supposes that it doesn't have the idea about the accuracy of the algorithms present in the pool, the performance of the one or more algorithms in the pool will be better.

In binary decision problems, the algorithms in the pool are given with a positive weight. The weighted vote from all the algorithms in the pool is combined by the compound to predict the highly voted algorithm.

The multiplicative weights update method is very generic, and is applied in various subjects, including, but not confined to

• resolving linear and convex programs

• Playing games

• Learning graphical models

• Sparsification, linear systems

• Analyzing evolutionary algorithms

The high-level concept is that the algorithm maintains a distribution of weights over the pool of functions H, and then updates the weights of the functions by iteration, which makes errors with a multiplicative update rule. The first variant to be analyzed in this work is called the weighted majority algorithm.

Algorithm:

Step 1: At t=0, the algorithm initializes all weights to 1, i.e. ∀h∈ H, $w_h^{(0)} = 1$.

Step 2: At time step t, on input x_t, let

$$w_+ = \sum_{h\in H: h(x_t)=+1} w_h^{(t-1)} \quad (9)$$

$$w_- = \sum_{h\in H: h(x_t)=-1} w_h^{(t-1)} \quad (10)$$

If $w_+ \geq w_-$, the algorithm produces an output 1, else the algorithm produces an output -1.

Step 3: Once the correct answer y_t for x_t is received, for every h∈H, which has made an error on x_t, i.e. h(x_t) 6= y_t, the algorithm updates the weight of h as below:

$$w_h^{(t)} = \frac{1}{2} . w_h^{(t-1)} \quad (11)$$

Theorem 1. For any input sequence, if M refers to the number of errors done by the weighted majority algorithm, and m stands for the number of errors done by the best algorithm in H, then

$M \leq 2.4(m + \log|H|)$ (12)

The analysis given below adopts a generally employed mechanism in the analysis of online algorithms. The concept is to select an appropriate probable function and analysis its evolution with time.

The sum of weights at time step t is used as a general candidate for the potential function:

$$w^t = \sum_{h\in H} w_h^{(t)} \quad (13)$$

It is to be noted that W^0 = |H|. Moreover, as the best function would have made at most m errors after t steps, it follows that

$$W^t \geq \frac{1}{2^m}$$

(14)

On the other side, it is to be noticed that if the algorithm makes an error on x_t, and if H^t_{bad} represents the set of functions in H, which made an error on x_t, then it has to be the case that

$$\sum_{h\in H^t_{bad}} w_h^{(t-1)} \geq \frac{w^{t-1}}{2} \quad (15)$$

As the weighted majority algorithm will slow down the weight of each function in H^t_{bad} by half, it may be concluded that

$$W^t \leq \frac{3}{4}.W^{t-1} \quad (16)$$

In case the weighted majority algorithm makes M errors in t time steps, it may be concluded that

$$W^t \leq \left(\frac{3}{4}\right)^M .W^0 = \left(\frac{3}{4}\right)^M .|H| \quad (17)$$

Combining (14) and (17), the relationship desired between M and m is expressed as:

$$\left(\frac{4}{3}\right)^M \leq |H|.2^m \quad \text{m} \quad (18)$$

$$\Rightarrow M \leq log_{\frac{4}{3}}(2)(m + \log|H|) \quad (19)$$

IV. RESULTS AND DISCUSSION

In different environments and with different capture angles the flower images are collected. The datasets Apple A consists of images of apple trees. The images are gathered in a USDA orchard on a sunny day. A portable camera is used to collect an Apple A is set with 147 images. 100 images are randomly selected from this dataset for training purposes. Another 30 images are selected randomly to construct a testing set.

These flowers in the dataset various with size, occlusion by leaves and branches and cluttering. The mean area of the flower is 10, 730 pixels, but with a standard deviation of 17,150 pixels. From Apple A, a dataset, a utility vehicle enabled with a background unit was utilized for imaging to avoid trees in other rows in the images. The dataset specifications are explained as below:

Dataset specification:

Name of the dataset: Apple A
Number of images: 100 (train) + 30 (val)
Weather: Sunny
Background panel: no
Camera model: canon EOS 60D
Resolution: 5184 x 3456
Camera support: Hand-Held

The AppleA dataset has a resolution 4.3x. The images in these datasets are split into portraits of 155 x 155 pixels, instead of the 321 x 321 pixels portraits utilized for AppleA. This research work compares different classification such as SPPX+CLARIFAI, DEEPLAB+RGR with this proposed ECF algorithm.

This research work assessed the proposed technique on the dataset openly available: Apple A. The comparison between various kinds of classification is explained in the section below in detail. The performance of different approaches studied is assessed with the well-known precision, recall, accuracy and *F*-score measures, whose standard definitions are as expressed as follows:

$$\text{Precision} = \frac{TP}{(TP+FP)} * 100 \quad (20)$$

$$\text{Recall} = \frac{TP}{(TP+FN)} * 100 \quad (21)$$

$$\text{F – Measure} = \frac{2TP}{(2TP+FP+FN)} * 100 \quad (22)$$

$$\text{Accuracy} = \frac{(TP+TN)}{(P+N)} * 100 \quad (23)$$

Figure 3(a) shows the input image sample, Figure 3(b) shows the fruit flower segmentation results of the DEEPLAB+RGR algorithm and finally Figure 3(c) shows the fruit flower segmentation results of the proposed work. The overall comparison results of all metrics are shown in table 1.

Table 1. Performance comparison metrics vs. fruit flower detection methods

Methods/ metrics	Precision (%)	Recall (%)	F1-Measure (%)	Accuracy (%)
SPPX+CLARIFAI	81.19	83.4	82.295	83.25
DEEPLAB+RGR	87.24	87.1	87.17	88.98
ECF	91.25	90.23	90.74	92.15

Figure 3(a). Original image

Figure 3(b). Segmentation image results of DEEPLAB+RGR algorithm

Figure 3(c). Segmentation image results of ECF algorithm

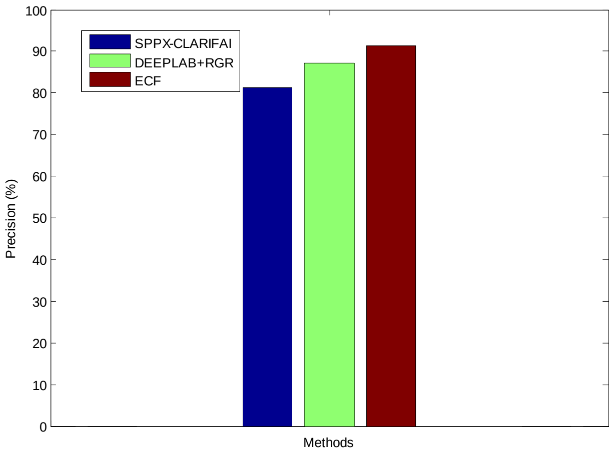

Figure 4. Precision comparison vs. fruit flower detection methods

Figure 4 illustrates the comparative analysis carried out between different classification approaches in terms of precision. In this, the proposed technique, a precision of 91.25% is achieved, which is high in comparison with the other two available techniques SPPX+CLARIFAI and DEEPLAB+RGR yielding 81.19% and 87.24% correspondingly.

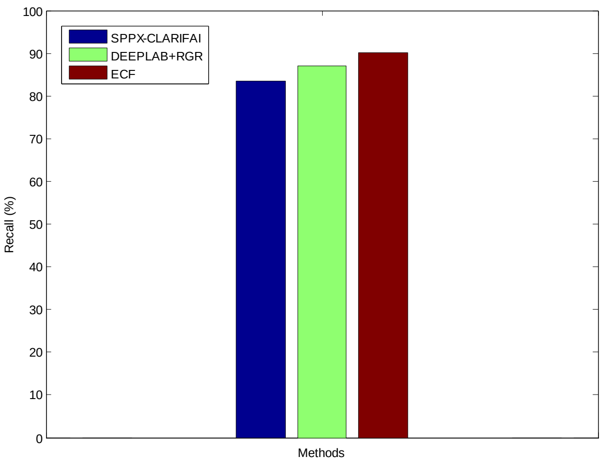

Figure 5. Recall comparison vs. fruit flower detection methods

Figure 5 illustrates the comparative analysis carried out between different classification techniques in terms of recall. In this, the proposed technique yields a recall of 90.23%, which is high in comparison with the other two available techniques SPPX+CLARIFAI and DEEPLAB+RGR corresponding recall rates of 83.4% and 87.10%.

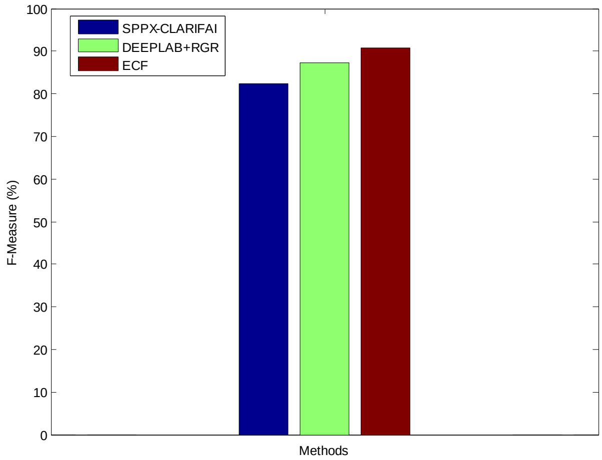

Figure 6. F1-measure comparison vs. fruit flower detection methods

Figure 6 illustrates the comparative analysis of different classification techniques in terms of F-measure. In this, the proposed technique gives the F1-measure 90.74%, which is high in comparison with the other two research technique SPPX+CLARIFAI and DEEPLAB+RGR, which yield 82.295% and 87.17% correspondingly.

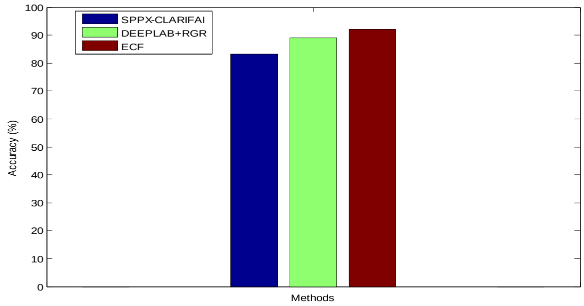

Figure 7. Accuracy comparison vs. fruit flower detection methods

Figure 7 illustrates the comparative analysis carried out between different classification approaches in terms of accuracy. In this, the proposed technique achieves 92.15% that is high in comparison with the other two available techniques SPPX+CLARIFAI and DEEPLAB+RGR that give 83.25% and 88.98% correspondingly.

V. CONCLUSION AND FUTURE WORK

This research approach introduces an ensemble classification framework for the semantic segmentation. Since the advance prediction of fruit yield is vital for the agricultural sector for the calculation and fixing of the product cost in the future, the prediction of fruit yield per orchard is carried out by the detection of flower intensity. It makes use of a modified bat optimization algorithm for generating maps of flowers in block-level using the generation of the direct map. After this, the ensemble classification is carried out with the help of the Support Vector Machine (SVM) classifier and Enhanced Convolutional Neural Network (ECNN) for semantic segmentation. To improve the sensitivity it refines the network employing RGR. These are then finely tuned applying the weighted majority algorithm.

The newly introduced framework called ECF is then compared with different classification techniques and the proposed technique with the help of result metric such as, precision has 91.25%, recall has 90.23%, F-measure has 90.74% and the accuracy has 92.15%. As an objective for the future, it requires improvement in terms of the performance factors that are performed by including a few technologies/concepts such as filtering and preprocessing approaches to attain a better outcome.

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