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Original article

An Enhanced Framework for Categorization of Fruits Based on Ripeness using Ensemble PSO Model

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Abstract *- Ripeness-based categorization is a vital function after the harvest of fruits to balance the ripening treatment. Ripeness level is the significant factor determining the quality and lifetime of fruits. Various attributes are used to identify the ripeness level, of which the manual method of categorizing based on skin colour is predominantly used. This method is prone to error at many times. This paper implements an Ensemble Particle Swarm Optimization (EnPSO) algorithm to categorize the fruits based on the ripeness level. The comparison reveals that the proposed EnPSO algorithm outperforms the state-of-the-art algorithms used for the same problem. Categorization is done using the decision tree, which provides up to 98% classification accuracy.*

Keywords **-** *Categorization, Ensemble particle swarm optimization, Quality and lifetime, Ripeness level.*

1. Introduction

Fruits are rich in antioxidants, nutrients, vitamins, minerals, and fibre—consuming fruits results in good health in the long run. Fruits should be harvested once they are mature enough to avoid decay during transportation. The transported fruits are stored till they are ripe and consumption ready. The ripeness of certain fruits is challenging to estimate. Change in the colour of fruit skin alone does not assure their ripeness. In order to reduce the wastage of fruits due to changes in taste and quality, ripening stages are to be classified. It also helps to increase the value of fruits supplied in domestic and export markets. It is also essential to categorize the fruits after the harvest process.

This motivates us to propose a framework combining thresholding-based watershed segmentation algorithm and ensembling particle swarm optimization classification mechanism to detect the various ripeness levels. This paper is structured as follows. Section II provides a recent study about ripening-based categorization. In Section III, the proposed EnPSO model for the categorization of ripeness level in fruit is discussed. Experimental results from the proposed EnPSO model are evaluated against other existing models for the same problem in Section IV. Section V winds up the paper along with the scope for future research.

The critical contributions of the proposed EnPSO model are listed below:

- Choice of colour spaces to imitate a manual perception
- Recognition of essential features required for categorization
- Modeling the feature space partitioning using a decision tree
- Fuzzy modelling using the EnPSO algorithm and creation of fuzzy rules
- Comparative study of the proposed EnPSO model with other existing models

2. Related Work

Computer vision is one of agriculture's most actively used technologies to improvise and classify various commodities that many researchers worldwide produce. The recent advancements in computer vision allowed researchers to develop various methods that are used for arranging and ranking the fruits like tomato [1], mango [2], orange [3], peach, apple [4-5], grape, and cherry [6]. Every fruit goes through various stages during ripening, and [7] proposed an algorithm for identifying the quantity of ripeness in chillies and tomatoes at four different stages. RGBD analysis using the pre-trained capsule network was employed [8] for the identification of the ripeness of the fruit using depth filters and a fuzzy interference model built on a support vector machine.

A system model that segregates the fruits as they go through various levels of ripening using CNN [9] and employed RESNET152 [10] for the identification of various levels of ripeness in dragon fruit and also to predict the time to harvest the fruit so that the quality remains the same throughout the process. The main feature employed for classifying the fruit is the inspection of color level by manual or automation techniques. Since the automation model involves many image processing mechanisms and the data set will contain many images, the preferred model for this process is CNN, which uses ReLU to identify features in the final output[11].

An algorithm for recognizing a set of fruits such as apple, peach, cherry, amber-coloured plums and nectarine with almost 100% accuracy in an amorphous data set employing several convolutional, max-pooling, fully connected and Global Average Pooling (GAP) [12] model. The same model identified full-grown tomatoes at a rate of 81.6 %. A method that fuses U-net and YOLO version 3 to identify litchi and litchi stem [13, 14] in dark environments was used. The average accuracy in the low illumination, normal light, and high illumination was 89%, 99% and 96%, respectively.

Though these naive models provided a reasonable level of accuracy and performance, they demanded an extensive data set in prior, which is a time-consuming process to collect. The performance of these models tends to decrease if the dataset contains fruit images that are overlapping, occluded or vary with light intensity. These factors prompted us to identify a new method that helps identify the level of ripeness in a wide range of fruits with a very minimal dataset and addresses the above issues. Numerous linear and nonlinear processes are feasible due to the high flexibility of the processing of digital images technique. The tools for processing digital photos that have been created have been used on photographs from many fields. In this work, we addressed a variety of applications, including image enhancement and restoration, healthcare, sensors, automation, colour processing, pattern and character identification, processing video, agriculture, fingerprint fingerprinting, signatures identification, etc [17]. Machine learning algorithms can predict and estimate crop yields, which is crucial for farming users. As a result, the suggested system was created, which examines macronutrients (NPK), pH, electrical conductivity in the soil, and temperature to advise the best crops. Rotation of crops, crop yield predictions, and fertiliser advice are all collaboratively built into the suggested system. The ensemble classification technique is applied to the farm dataset to identify suitable crops [18-20]. According to the evaluation performed using the data mining method, the study suggests helping farmers assess the soil quality. As a result, the technique focuses on examining the soil's condition to forecast the crop that will grow best in every type of soil and to maximize the yields of crops by suggesting the right fertilizer [21-23]. For categorization in mining information, decision trees are a well-known technique. The primary flaw of the C4.5 method is that it favours characteristics with more values, but the CART algorithm results in categorization errors whenever the desired attribute's range is too broad. A collection of soil sample test data is used to evaluate the model. Test results demonstrate that the improved decision tree method has a greater level of accuracy in classification. The division of soil into groups or classes, with each exhibiting comparable properties and perhaps similar behaviour, is known as classifying [24-27]

3. Proposed EnPSO Methodology

A fuzzy model for ripening level categorization of mango is shown in Fig. 1. The pictures of the mangoes are captured using a digital camera, and the image is fed as input for thresholding using the Gaussian Otsu thresholding model. The watershed algorithm is applied to the thresholded monochrome image to extract the strawberry region.

This model is developed by imitating the human judgment on the ripening of strawberries from their external appearance. Correlation-based Feature Selection (CFS) method identifies the important class features with correlation and ignores the rest. It separates a subset of features from the collection of features based on Eq. (1).

$$F_s = \frac{l \times \overline{r_{af}}}{\sqrt{l+\left(l \times (l-1)\right) \times \overline{r_{mf}}}} \tag{1}$$

where $'l'$ represents the feature count, $\overline{r_{af}}$ is the average correlation between a feature class and $\overline{r_{mf}}$ is the mean feature-to-feature correlation. The parameters of EnPSO are restructured using Eqs. (2) and (3).

$$v_i^{n+1} = w * v_i^n + C_1 * R_1 \left(xBt_i^n - x_i^n\right) + C_2 * R_2 \left(gBt_i^n - x_i^n\right) \tag{2}$$

$$x_i^{n+1} = x_i^n + v_i^n \times n \tag{3}$$

Where xBt and gBt are the best positions concerning an item and group, n represents the iterations, and C1, C2, R1, and R2 represent the non-negative integers and random parameters, respectively, between 0and 1. A multiple-class training dataset with 'l' attributes is chosen, and a simple arbitrary sampling technique is computed on a multiple-class training dataset. A simple random sampling method results in the dataset $D_{ran\text{-}sam}$. The globally finest attribute is computed using Eqs. (1) – (3) and appended to the reduced attributes subset ($F_{bt\text{-}sbst}$). The process of obtaining the best attribute is iterated until the highest iterations of the upper limit or lowest error criteria are hit. The EnPSO makes use of the extracted $F_{bt\text{-}sbst}$ for further categorization. Using a fusion rule, the EnPSO combines the predictions from Straightforward Logistics and Naïve Bayes classification algorithms. Finally, EnPSO gives categorization prediction.

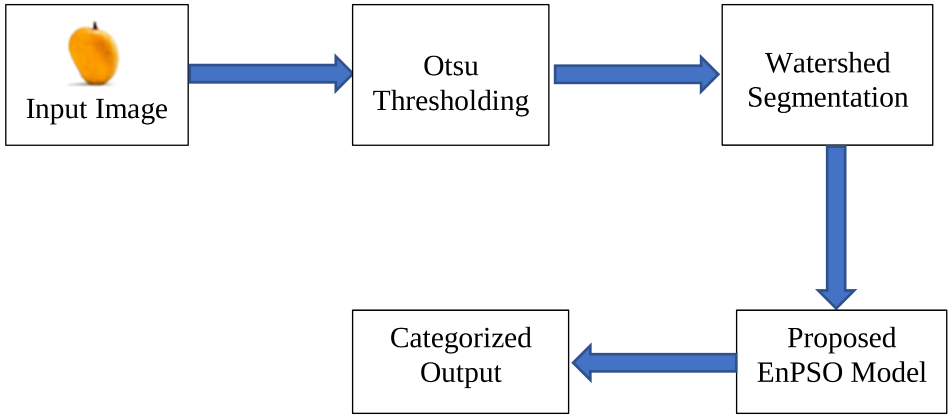

Fig. 1 Proposed EnPSO model

3.1. Gaussian Otsu Thresholding

Thresholding is used to split the objects from the surroundings in the picture. Various thresholding algorithms are used to set the best threshold value. In Otsu's thresholding method, shown in Fig. 2, the algorithm iterates through all the possible threshold values and lists a measure for the pixels on each threshold side.

This assigns values to pixels in the background and the pixels in the foreground to decide about the threshold, which is supposed to be at its minimum. The optimal value is calculated by diminishing the total of the weighted group variances. The probability is used to assign weights for the respective groups. Pi is the probability of the observed color values, i=1,…, K.

$$P_i = \frac{number\{(r,c)|image(r,c)=i\}}{(R,C)} \tag{4}$$

R, C denotes the row and column count of the picture. The variance is calculated as follows:

$$\sigma_w^2 = \omega_b(n) * \sigma_b^2(n) + \omega_f(n) * \sigma_f^2(n) \tag{5}$$

where, $\omega_b(n), \mu_f(n)$ and $\sigma_b^2(n)$ are the weight, average and variance of class Co with intensity 0 to n, respectively. $\omega_f(n), \mu_f(n)$ and $\sigma_f^2(n)$ are the weight, average and variance with intensity n+1 to 1, respectively. The value of mean and variance are calculated as follows:

$$\omega_b(n) = \sum_i^n P_i \tag{6}$$

$$\omega_f(n) = \sum_{i=n+1}^k P_i \tag{7}$$

$$\sigma_b^2(n) = \frac{\sum_i^n \left(1-\mu_b(n)\right)^2 * P_i}{\omega_b(n)} \tag{8}$$

$$\sigma_f^2(n) = \frac{\sum_{i=n+1}^k \left(1-\mu_f(n)\right)^2 * P_i}{\omega_f(n)} \tag{9}$$

$$\mu_b(n) = \frac{\sum_i^n i * P_i}{\omega_b(n)} \tag{10}$$

$$\mu_f(n) = \frac{\sum_{i=n+1}^k i * P_i}{\omega_f(n)} \tag{11}$$

Gaussian Otsu's method expands Otsu thresholding and is based on a class variance of the foreground and background regions. This is faster than Otsu's method as it calculates the highest value between class variances, whereas the minimal value is chosen within the class variance. The between-class variance is computed as given in the equation.

$$\sigma_{Bt}^2(n) = \sigma^2 - \sigma_\omega^2(n) = \omega_b(n) * (\mu_b(n) - \mu)^2 + \omega_f(n) * \left(\mu_f(n) - \mu\right)^2$$
$$= \omega_b(n) * \omega_f(n) * \left(\mu_b(n) - \mu_f(n)\right)^2 \tag{12}$$

Where, σ^2 and μ are total variance and total mean, respectively.

3.2. Watershed for Segmentation

This classical algorithm used for image segmentation is constructive when mining overlapping objects in images. The watershed algorithm needs user-defined markers to be defined. These markers are derived from Otsu's thresholding. Based on these, the algorithm considers pixels in the image as local elevation. The algorithm starts from the markers and moves outwards till the valleys of diverse markers meet each other.

The watershed algorithm assumes a drop of water plunging onto the image surface flows down and reaches the respective valley. The route covered by the drop is the connectivity and is the narrowest pathway between the fall point and the valley.

All the connected entities that end up in the same valley make a watershed. For images with minimal plateaus, the algorithm needs only three complete iterations. However, four iterations of the entire image are needed to mark all the watersheds for images with non-minimal plateaus.

The steps in the watershed algorithm are summarized below:

Iteration 1

- Every element of the picture is marked with the position of the smallest minor adjacent element. In the absence of those elements in the region, the present one is considered an element of the plateau.
- Removal of non-minimal plateaus.

Iteration 2

- The adjacent values of every element noted as a plateau are checked. If a neighbouring element is not noted as a plateau and has the same value as the element, this neighbour is pushed into a queue and neighbours of this element are checked.
- The elements are removed from the queue until the neighbouring elements' queue becomes empty. The neighbors noted as a plateau is checked and marked by recording the position of the removed element. All these elements are pushed into the queue.

Iteration 3

- The minor plateau elements are marked with respective values.
- Each element that is a plateau is marked with a marker pointing to the location of the element itself.
- The adjacent pixels of the current element are considered, one by one, which have already been traversed and have identical values.
- For the present element and its neighbor, path consolidation is performed by traversing the path along the markers, from the current element to that element discriminated with a value pointing to itself, and allocating the marker value of the finite element on it, to each marker of the elements of the path.
- The final step is plotting the consolidated paths' final elements with the most negligible value from their markers.

Iteration 4

- The path consolidation is done for every image element. The elements are marked with finite element markers of the path traversed.

3.3. Extraction of Key Features

The colour of the peel plays a vital role in the categorization of the level of fruit ripening. The fruit is green if it is yet to ripe, while it is yellow as the fruit ripens, and an over-ripened fruit is yellow with more brown spots. In the HSV colour model, the hue channel denotes the actual colour of the fruit peel. Bi-colour spaces are used to ascertain the particulars of the accurate colour of the fruit peel and to identify the area of terminally matured spots on the fruit. HSV colour space has a better correlation with the human observation of colours and is found to be invariant to changes in illumination. The Hue channel of HSV and adversary colours of CIELa*b* colour space are employed for extracting features of the fruit skin. A region of interest (ROI) is framed, and the hue value of the most remarkable peak is the actual colour of the fruit skin.

The proportion of terminally matured areas in the fruit is identified using ‘a*’ and ‘b*’ channels. The peak of the 100 bin hue histogram is noted down. The peak's hue value is calculated, providing the dominant colour present in the fruit peel. The brown spots are randomly distributed concerning position, region and shades of colour.

The source illumination effect is added to the device-independent colour spaces, referred to as the reference white point. The source adds a hue to the original image per the illuminant’s shade temperature. For instance, Sun’s ray during dawn or dusk adds a yellow hue to an image, whereas light in the middle of the day adds a blue hue. The peak value of hue and Normalized Brown Area (NBA) are extracted as features for categorization. Areas of brown are the brown pixel count in the cluster. In order to deal with variance, the normalized value of the region of brown is calculated as

$$NBA = \frac{a_t}{\sum_{i=1}^{l} a_i} \tag{13}$$

where ‘a’ refers to the count of pixels in the cluster, ‘t’ is the cluster with the brown region, and ‘l’ represents the cluster count. Fruit ripening is an ongoing process with minor modifications to the fruit peel. The consecutive stages of fruit pose vagueness in deciding the class the fruit belongs to. Therefore, the classification of ripening levels can be done using ensemble learning techniques.

3.4. EnPSO Implementation

Recognition of the same stage of ripening is a problem of multiclass classification. Since the ensembles categorize the stages better than single machine learning algorithms, an ensemble approach which is a mixture of Voting, CFS method, PSO algorithm and arbitrary sampling method, is used[28]. CFS identifies the significant attribute subset and ignores insignificant attributes from the input dataset. This step is performed to augment the performance of machine learning algorithms. CFS uses correlation-based heuristic estimation and selects the attributes with high correlation within the class. PSO is a bio-inspired algorithm that mimics the message passing among group members and distributes essential information. It is widely applied to optimization problems. In this algorithm, particles search for the best feasible solution. Each particle has its 'best' achieved location and the group's 'best' location. However, the particles move randomly.

Proposed EnPSO Algorithm
Inputs:
D_{Train} = { Sa,Fe,Cl}, Sa= {$s_1,s_2,.....s_k$}, Fe= {$f_1,f_2,....f_l$}, Cl= {$c_1,c_2,....,c_n$}
Algorithm:

Step 1:
Apply random sampling on D_{Train} and generate $D_{ran-sam}$
Step 2:
Initialize $F_{bt\text{-}sbst} = \phi$, $xBt_i = fit_1$, $gBt_i = fit_1$
While (max iteration || min criteria is not achieved):
for each i from 1 to l_i
Calculate the current fitness value using (1)
If the recent value is better than xBt_i, then xBt_i = current value
If the current value of gBt_i is better than xBt_i, then $gBti, = xBt_i$,
For each dimension from 1 to n:
Modify the best position of the ith particle
Modify the global best position of the ith particle
Modify the velocity position of the ith particle using (2)
Modify the position of the ith particle using (3)
The best feature is then selected and appended to $F_{bt\text{-}sbst}$
Step 3:
For each i from 1 to N (Max algorithms):
Employ Machine Learning categorization algorithm on attributes$D_{ran-sam}$ with $F_{bt\text{-}sbst}$
Obtain categorization prediction from Machine Learning categorization algorithm using $F_{bt\text{-}sbst}$
Step 4:
Calculate categorization prediction using ensemble vote to obtain the overall prediction using $F_{bt\text{-}sbst}$
Step 5:
Display the categorization prediction using $F_{bt\text{-}sbst}$

The training dataset with 'l' features is selected first. Plain arbitrary sampling is employed on the dataset to find homogeneous class distributions. CFS computes the mean attribute-class correlation and means feature-feature inter-correlation. Every probable solution to the problem is treated as a particle. Every particle moves in the available search space to obtain an optimal solution. The entire swarm searches for the solution by refreshing the location of each particle, considering their understanding and the nearby particles.

The classification algorithm that is chosen is logistic regression. Also, Naïve Bayes is applied to get classification prediction. Voting fuses the predictions of logistics and Naïve Bayes by employing a fusion rule. The choice of a suitable fusion rule is significant in ensemble design. Fusion rules are rules of the likelihood that guess and estimate the prediction of a ripening stage[29]. The entire set of classes in the ensemble is assumed as equally probable.

The product rule of likelihood guesses the likelihood of a ripening stage by merging the posterior likelihoods of a machine learning algorithm which employs the product of probabilities. The average rule assigns a sample to a ripening stage class if the average of posterior likelihoods is the highest. In majority voting, the votes obtained for a particular hypothesis are calculated. Different machine learning algorithms calculate the likelihood of being in a particular ripening stage. Hence, the ripening stage with the highest votes is chosen. In case of no errors or missing values in the dataset, the minimum likelihood rule is selected.

4. Results and Discussion

The banana and mango image data from a website for all ripening stages, such as unripe, partially ripe, ripe, and overripe, is collected manually, as shown in. The 'n'-fold univariate n strategy in the proposed work divides the dataset into 'n' pieces—the proposed strategy results in 'n' average evaluation results. Thus, the present work evaluates each experiment using the 'n'-fold univariate strategy. The performance of EnPSO is analyzed based on classification accuracy, precision, and sensitivity for various fruits and compared with the existing models such as RESNET-50, DENSENET-121 and PSO[30]. The proposed model is evaluated for six different fruits, and the results are shown and compared using accuracy, specificity and precision. Accuracy represents the proportion of rightly predicted count of samples concerning the total count.

$$Accuracy = \frac{\text{TP+TN}}{TP+FP+TN+FN} \tag{14}$$

Here, TP and TN represent True Positives and True Negatives, whereas FP and FN denote False Positives and False Negatives. Specificity denotes the part of true negatives among the total false positives and true negatives.

$$Specificity = \frac{\text{TN}}{TN+FP} \tag{15}$$

The precision determines the proportion of correctly predicted positive samples to total positive samples.

$$Precision = \frac{\text{TP}}{TP+FP} \tag{16}$$

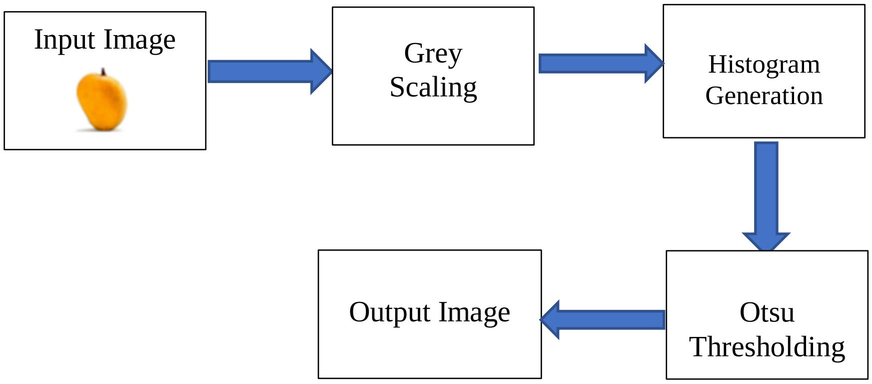

Fig. 2 Otsu thresholding model

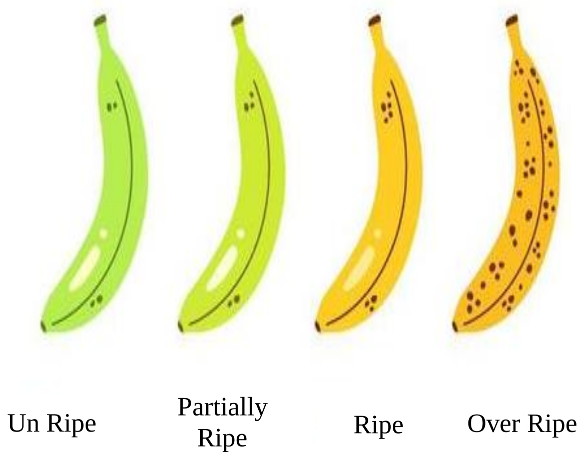

Fig. 3 Sample banana image four levels

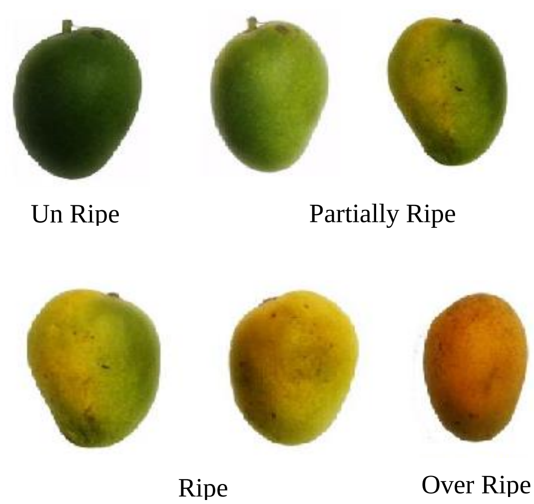

Fig. 4 Sample mango image four levels

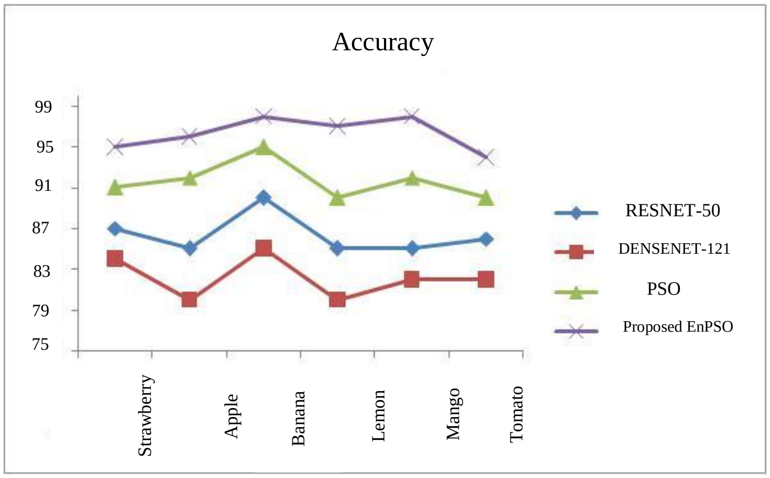

Fig. 5 Accuracy comparison

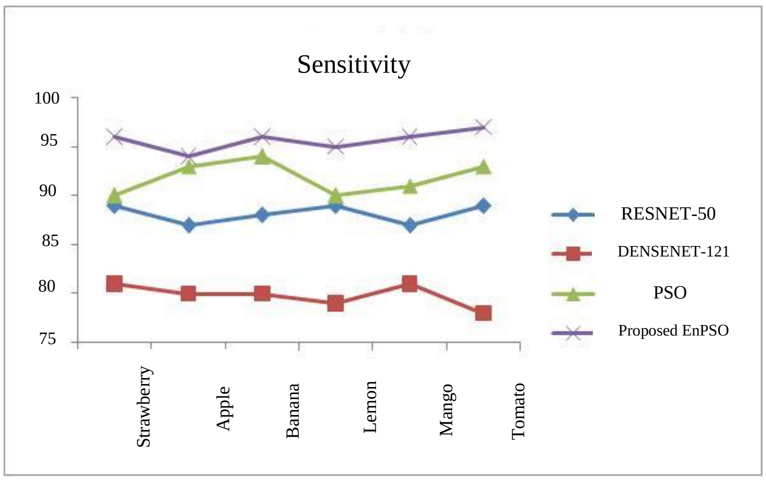

Fig. 6 Sensitivity comparison

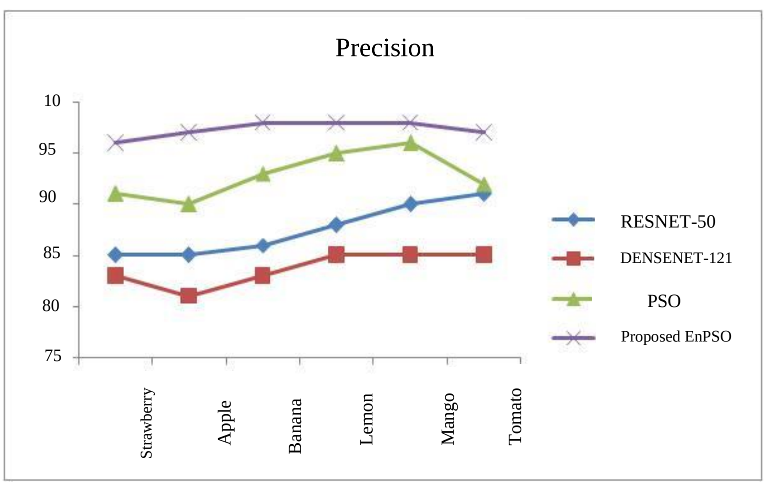

Fig. 7 Precision comparison

5. Conclusion and Future Scope

An Ensemble-based PSO algorithm for the identification of fruit ripeness level is proposed in this paper. The proposed EnPSO model used the Otsu algorithm for image thresholding and watershed segmentation, extracting features from the image data. Once the features are extracted, the EnPSO algorithm predicts the ripeness level. The results of the proposed EnPSO study show that Ensemble CNN models that produce the results based on voting have the maximum accuracy in categorizing the input test data compared to other deep learning models. However, there are still limitations of the proposed model, which entails further study. In the proposed EnPSO system, categorization is exclusively dependent on the outer look of the fruit, and it only utilizes a solitary view of the fruits' pictures. Other factors, such as occlusion and illumination, may degrade the model's performance, which has to be examined in the future.

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