

Prediction And Classification Of Textural Properties On Fruits During Ripening Using Convolutional Neural Network

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Abstract

Non-destructive quality detection and automatic grading are significant in fruit industry. The customary way separates fruits into four level ripening stages dependent on color. The assurance of the ripeness condition of fruits is a fundamental component in the agribusiness research field. In this paper a novel Convolutional Neural network is proposed for prediction and classification of textural properties on fruits during ripening. A PC vision system for ripening classification of fruits is acknowledged commonly dependent on a few cycles. Results and the exhibition of the proposed system are contrasted and different methods, for example, the ANN and SVM. Results uncover that the proposed system has the most noteworthy generally acknowledgment rate, which is 97.5%, among different methods.

Keywords: Convolutional Neural network, computer vision system, ripening classification, ANN and SVM.

1. Introduction

As a result of expanding attention to quality and enhanced perspicacity of purchasers, there is a solid interest for top notch items in both showcasing of horticultural items and in the food business. Throughout the long term, numerous non-destructive testing strategies have been created dependent on mimicking human sensory attributes for quality assessment of agro-food materials. These incorporate visual, acoustic, spectroscopic, and mechanical techniques. As of late, a developing interest and consideration has been paid to hyperspectral imaging as a logical apparatus for quality evaluation of agro-food items.

Data mining techniques can be utilized in agriculture to distinguish various examples for some perplexing errands. There are various investigations that help the utilization of data mining techniques for climate expectation or forecast in the field of agriculture. Data mining techniques are frequently more impressive, adaptable, and productive for exploratory investigation than factual techniques. In the field of agriculture data mining is an arising research strategy, and distinctive data mining techniques are being used. A portion of those techniques are artificial neural networks, choice trees, uphold vector machine, characterization and clustering techniques.

Visual appearance is the primary quality property for foodstuffs and it is additionally the first quality viewpoint searched for by the customers. For fruits, size, shape, texture, color and surface deformities are the essential outer quality credits. Every one of these ascribes are likewise identified with visual appearance of the fruits and agricultural items. Among this visual quality ascribes, color is the main boundaries utilized as a marker of the quality. In this way, greater part of the shoppers first gander at the color of fruits, vegetables and meats to pass judgment on the quality of those foodstuffs.

Strip color is the key quality trait for fruits. It impacts shopper inclinations, yet additionally is identified with dietary benefits of the apples. Strip color is likewise used to recognize one cultivar from the other since every cultivar has explicit color qualities. Different color spaces are frequently used to

characterize color boundaries of fruits. Among them, CIE $L^*a^*b^*$ (CIELAB) determined by International Commission on Illumination is the most widely recognized one.

To improve market acceptance, it is critical to keep peel color uniform of same cluster fruits on the shelf. For the most part, fruit is green when harvested, transported over significant distance, and afterward matured at objective prior to being marketed. The boundary 'time' is utilized to assess the ripening stage (RS), anyway it isn't reasonable to go about as a pointer since some correlative factors, for example, ecological conditions and synthetic specialists can hinder or quicken fruits ripening. During ripening measure, fruit goes through critical color and textural changes. The peel color changes from green to yellow because of the amalgamation of a couple of pigments. Consumers as a rule judge the nature of fruit upon the primary visual evaluation. Color went about as a significant marker of RS of fruit to impacts consumers' acceptability. Normally, peel color is utilized as an indicator of shelf-life for retail conveyance, and surface is a significant piece of eating quality. In the fruit market, as per peel color, the RS of fruits is isolated into seven levels. Fruit with fitting RS on shelves is beneficial to prolong shelf-life and consumer acceptability.



Figure 1: Peel and Color Texture of Different Fruits

2. Existing Methodology

2.1 Artificial Neural Network

Fatma M. A. Mazen and Ahmed A. Nashat proposed Artificial Neural Network for Ripeness Classification. A ripening recognizable proof system that plays out the visual perception of the human administrator in settling on choices at a quick rate. A PC vision system for ripening arrangement of banana fruits is acknowledged commonly dependent on a few cycles. First it underlines the significant sign preparing steps. The algorithm starts with image acquisition. At that point, these images experience preprocessing activities to be prepared for examination. The fundamental module for PC vision machines is the image segmentation followed by image arrangement. An artificial neural network is then utilized for ripening grouping choice, which relies on shading and Tamura statistical surface features.

2.2 Support Vector Machine

Hou Juncai, Hu Yaohua, Hou Lixia, Guo Kangquan and Takaaki Satake proposed a support vector machine (SVM) method was utilized to characterize the ripening stages by color esteem L^* , a^* and b^* as input data. The ripening stages were arranged by 10-overlay cross approval method of help vector machines with outspread premise function kernel and linear function kernel. The outcomes demonstrated that the color change of center situation of banana finger sufficiently mirrored the adjustments in banana ripening stages. a^* esteem ceaselessly expanded from ripening stage 1 to ripening stage 7, L^* and b^* values expanded from ripening stage 1 to ripening stage 5, and afterward diminished from ripening stage 5 to ripening stage 7. It was hard to perceive the ripening stages utilizing L^* , a^* and b^* values separately. The

motivation behind this exploration was to perceive RS of bananas dependent on strip color in L*a*b* color space utilizing support vector machine (SVM), and to research the immovability change of banana new as RS expanding from RS1 to RS7.

3. Proposed Methodology

The assurance of the ripeness condition of fruits is a fundamental component in the agriculture research field. This is on the grounds that ripeness is identified with quality and it can influence the commercialization of the item. Manual methodology is regularly utilized in item reviewing and quality control, however this prompts lopsided items, higher time cost, and weariness by the human administrators. Subsequently, in this paper proposed, a maturing ID framework that plays out the visual impression of the human administrator in settling on choices at an extremely quick rate. A computer vision framework for aging characterization of fruits is acknowledged commonly dependent on a few cycles. Figure 2 underlines the significant signal processing steps. The fundamental module for computer vision machines is the removing the organic product from foundation and earthy colored spots followed by separating texture features. A Convolutional Neural Network Algorithm is then utilized for aging arrangement choice, which relies on shading and Tamura statistical texture features.

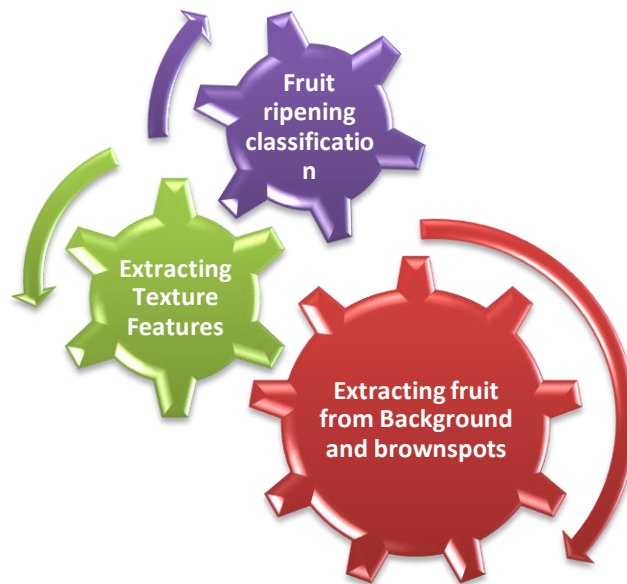


Figure 2: signal processing steps

Extracting fruit from Background and brownspots

A capacity is, at that point, actualized to restore the original input fruit image. This is finished by perusing the developed binary veil image pixel by pixel. A pixel is perceived as a foundation, if its level worth is zero. Something else, compare the level estimation of that pixel with the original one. The second period of this module is to ascertain the ripeness factor of the fruit. The ripeness factor (RF) of the fruit is characterized as:

$$\text{Ripeness Factor (RF)} = \frac{\text{Total Area of the Brown Spots}}{\text{Total Area of the Banana}} \dots\dots\dots (1)$$

where the all-out region of the fruit is given by the all-out number of white pixels of the fruit segmentation cover. To figure the all-out region of the earthy colored spots, another color veil is performed on the fragmented image to recognize the earthy colored spots on the fruit strip. The earthy colored color is described by having $H = 33^\circ$ or 9.29% , $63.7\% \leq S \leq 69.6\%$, and $5.4\% \leq V \leq 62\%$. The absolute zone of the earthy colored spots in the fruit is given by the all-out number of white pixels inside the fruit strip.

Extracting Texture Features

Other than the color-based analysis strategy for ripeness record estimation, texture-based methods help in surface, shape, and fruit class assurance. Statistical texture analysis is the most famous strategy utilized for image acknowledgment. Tamura contrast, coarseness, and heading highlights are three quantitative second-request statistical texture measures for image classification. They depend on psychological investigations of human insight. Contrast, characterized by Eq. 2, quantifies the manner by which dim levels shift in the image and between adjoining pixels and how much their dispersion is one-sided to dark or white.

$$\text{Contrast} = \frac{\sigma}{(\mu_4)^{0.25}}, \text{ and } \alpha_4 = \frac{\mu_4}{\sigma^4} \dots \dots \dots (2)$$

where μ_4 is the fourth moment about the mean and σ^2 is the difference. Then again, coarseness, characterized in, essentially identifies with distances of eminent spatial variations of gray levels, which is implicitly identified with the number and the size of primitive components shaping the texture. It has the immediate relationship to scale and reiteration rates. It is normal that coarseness of the four fruit classes to be inside a similar reach, since the peel of fruits of the four classes is portrayed by having numerous little primitives, with a serious level of nearby variations of gray levels. In outcome, the coarseness include is rejected from the contribution of the proposed artificial neural network. Another vital quality of the texture image is the disseminating attribute of texture headings. This element alludes the state of texture primitives and their situation rule. The directionality is acquired by looking at the sharp level of a histogram which is built from the slope vectors of all the image pixels. The fruit readiness order algorithm is as per the following:

Compute the texture feature vector, F , for each training fruit image.

$$F = [\text{Contrast Directivity HSV RF}] \dots \dots \dots (3)$$

The thresholds of the HSV color space for the four classes of fruits are acquired dependent on analogy between HTML color codes and different characteristic colors of fruit peels of various classes under an extraordinary illumination. The green fruits are included as having $72^\circ \leq H \leq 78^\circ$, $85\% \leq S \leq 100\%$, and $27\% \leq V \leq \text{half}$. Light green fruits are picked and restored before they have ripened. Toward the start of the ripening cycle, the chlorophyll in the peel separates and the starch inside the fruit is changed over into straightforward sugars. Subsequently, the peel turns yellow tone with earthy colored spots and the fruit relax and turns out to be sweet. The yellow fruit fruits are highlighted as having $50^\circ \leq H \leq 72^\circ$, $70\% \leq S \leq 100\%$, and $79\% \leq V \leq 100\%$. The ethylene gas produced by the fruit makes the yellow shades in fruits rot into brilliant yellow with more earthy colored spots in a cycle called enzymatic sautéing. The brilliant yellow or mid-age fruit is portrayed by $39^\circ \leq H \leq 50^\circ$, $69\% \leq S \leq 96\%$, and $75\% \leq V \leq 100\%$. The last phase of the ripening cycle of the fruit is the yellowish earthy colored or over-mature fruit. The fruit peel

looks profound earthy colored with dim streaks. An alternate measure estimation of the vector F is acquired for each fruit ripening class.

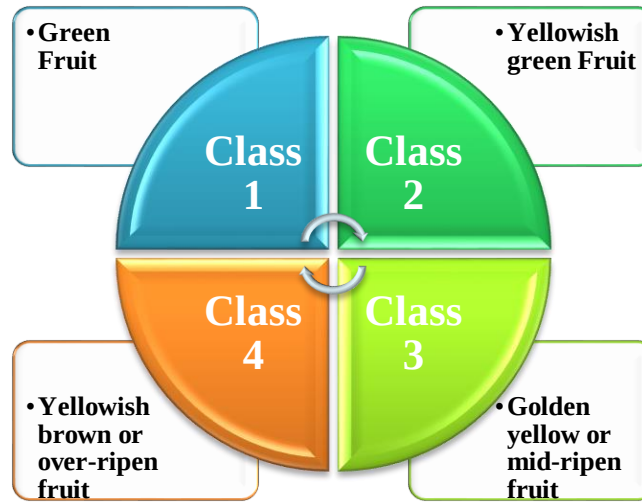


Figure 3: Stages of ripening Fruits

Fruit Ripening Classification using CNN

The network comprises of two convolutional layers, every one of them followed by pooling layers, and two completely associated layers appeared in figure 1. The information layer of the network contains 30,000 neurons as info data, addressing the standard RGB image of size 100×100 pixel. The originally shrouded layer is the convolutional layer 1 which has 64 channels with a kernel of size 3×3 pixels and Rectified Linear Units (ReLU) as an enactment work. The second convolutional layer is the convolutional layer 2 where 64 channels with the kernel size of 3×3 pixels and ReLU were utilized as on the first convolutional layer. The convolutional layer is utilized for the element extraction from input data. Likewise performs convolution activity to little limited zones by convolving a channel with the past layer. The kernel size decides the territory of the channels. A kernel initializer named Lecun uniform is utilized alongside each concealed layer for introducing the weights. ReLU is utilized as an actuation capacity to improve the exhibition toward the finish of all convolutional layers and completely associated layers. In pooling layers 1 and 2, where max pooling is utilized with a pool size of 2×2 alongside a step length of 2. The cushioning utilized here is a similar cushioning which implies that the yield and information highlight maps has similar spatial measurements. Pooling layers limit the spatial size of the yield and controls overfitting. The step characterizes how the convolution activity functions with a kernel when the bigger sizes of an image and complex kernels are utilized. A regularization layer dropout with a likelihood of 0.25 is utilized close to the pooling layer 2 where it arbitrarily turns off 25% of the neurons in the layer during preparing thus diminishing overfitting just as to improve the presentation of the network by making it more robust. This makes the network become able to do better generalization and less compelling to overfit the preparation data.

$$\sigma(z) = (1 + \exp(-z))^{-1} \quad (4)$$

After the dropout, a level layer is utilized which changes over the 2D channel lattice into 1D element vector prior to going into the completely associated layers. The following shrouded layer is the completely associated layer 1 comprises of 500 neurons with a dropout of 0.5 and ReLU. Again a dropout with a probability of 0.5 is utilized between the yield layer and the last concealed layer. At long last, the completely associated layer 2 or the yield layer contains 25 neurons where softmax classifier enactment is utilized to predice the yield of the model and addresses 25 unique classes of fruits.

$$\sigma(z)_j = \frac{e^{z_j}}{\sum_{k=1}^k e^{z_k}} \text{ for } j=1, \dots, k \quad (5)$$

In deep neural network, optimizer assumes an indispensable part and assists with diminishing or increment the blunder capacity of the model. For preparing our network we utilized Adam optimizer. Adam represents Adaptive Moment Estimation which processes versatile learning rates for hyper-parameter. The Adam advancement algorithm is direct to execute, requires little memory, fitting for issues with scanty angles and computationally compelling. Besides, it is extensively utilized in numerous deep learning applications like computer vision and characteristic language handling. For our CNN model, we utilized Adam optimizer with a learning pace of 0.002, cluster size of 15 and 15 ages. For diminishing the model's preparation mistake a little learning rate is vital. For assessing the occasions, Adam conveys dramatically rotting midpoints and registered on the angle as:

$$n_t = \beta_1 * n_{t-1} + (1 - \beta_1) * g_1 \quad (6)$$

$$s_1 = \beta_2 * s_{t-1} + (1 - \beta_2) * g_t^2 \quad (7)$$

Where n_t and s_t are the first and second moments, g_t is the gradient, β_1 and β_1 are the hyper-parameters. For performing the weight update:

$$w_t = w_{t-1} - \eta * \frac{\hat{n}}{\sqrt{s} + \epsilon} \quad (8)$$

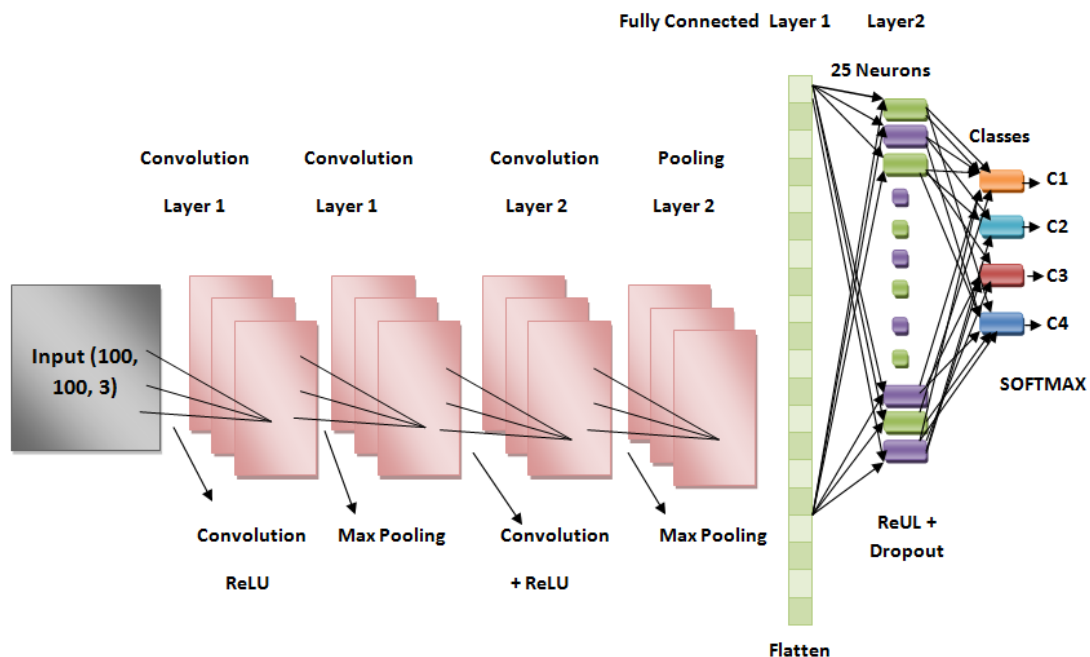


Figure 4: Schematic architecture of the CNN

To compute the model performance, error rate need to be calculated. We have used categorical cross-entropy cost function as a loss function in equation (9) and cost function is defined in (10).

$$L_i = -\sum_j t_{i,j} \log(p_{i,j}) \quad (9)$$

$$C(w, b) = \frac{1}{2n} \sum_x [y(x) - a^2]^2 \quad (10)$$

Where w is the cumulation of weights in the network, b is all the inclinations, n is the all-out number of preparing inputs and an is the real output. C(w,b) is non-negative as all the terms in the whole is non-negative. Figure 5 shows the flowchart of our proposed neural network framework for preparing and testing fruit fruits.

Algorithm for Textural properties on Fruits during ripening

Step 1: Input Images

Step 2: Extract fruit from Background and brown spots

Step 3: Initialize Cr, Cn, D, H, RF

Step 4: Extracting Texture Features (Coarseness (Cr), Contrast (Cn), Directivity (D), Hue color space (H)).

Step 5: Fix the minimum and maximum values of the Texture Features according to the Fruit

Step 6: Calculate the fruit ripeness coefficient (RF)

Step 7: Check the Coarseness (Cr) with minimum and maximum values of the texture features

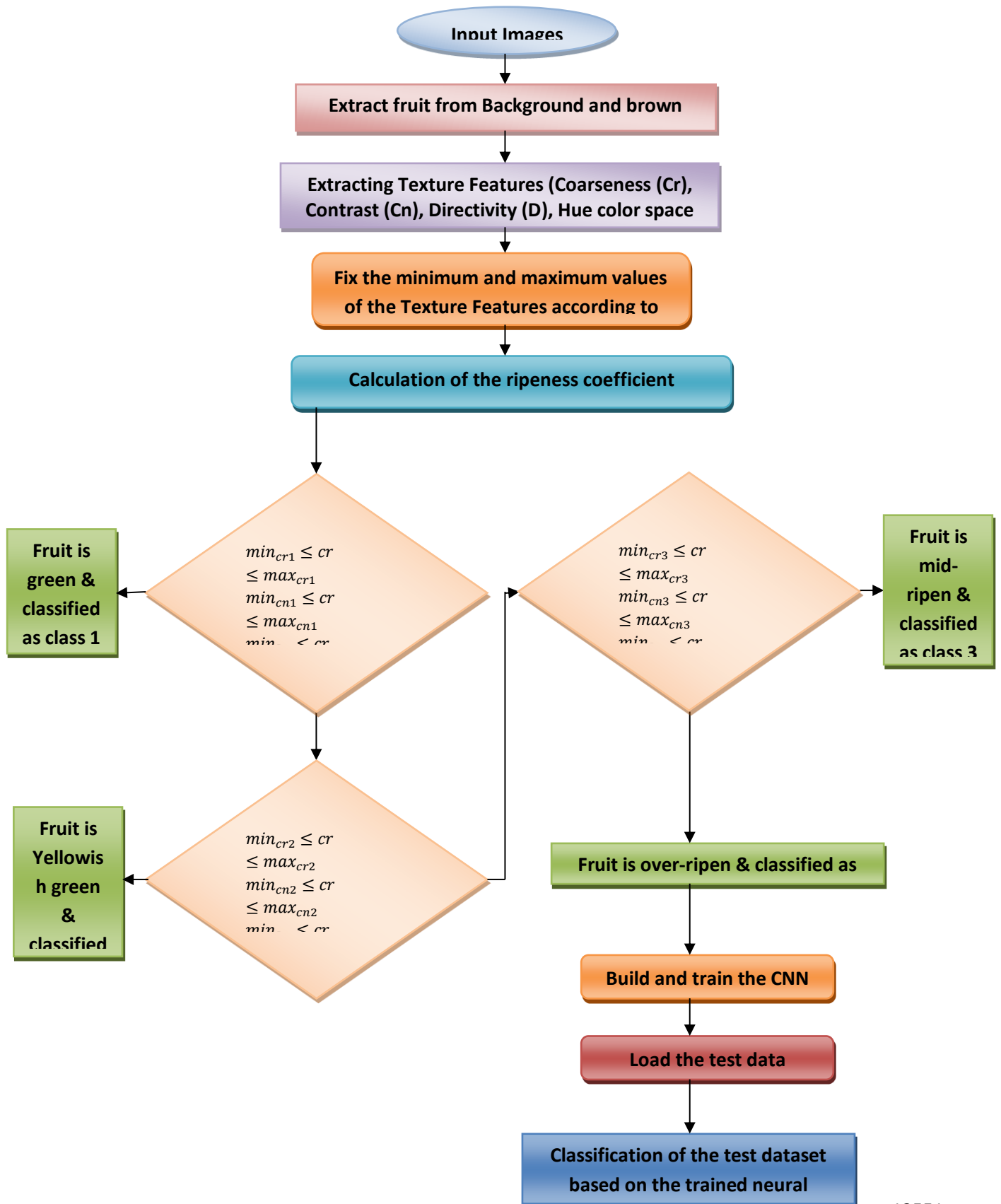
Step 8: Classify the fruit class (class 1 or class 2 or class 3 or class 3)

Step 9: Build and train the CNN

Step 10: Load the test data

Step 11: Classification of the test dataset based on the trained neural network

Step 12: Output classified Images



4. Experimental Result

Sensitivity and precision

Sensitivity and precision are two statistical execution measures for order tests. Sensitivity is characterized as the capacity of the expectation model to choose the example of a specific class from the dataset. It is the proportion of the real certain classes which are effectively distinguished. Then again, precision is characterized as the proportion of the anticipated positive classes which are accurately distinguished. They are given by:

$$\text{Sensitivity} = \frac{TP}{(TP+FN)} \quad (11)$$

$$\text{Precision} = \frac{TP}{(TP+FP)} \quad (12)$$

TP, FP, and FN are the numbers of the true positive, the false positive, and the false negative predictions for the considered class, respectively.

1. Class Sensitivity in %

Actual class	ANN	SVM	CNN
Class 1	100	100	100
Class 2	100	82.4	100
Class 3	86.6	100	94.5
Class 4	100	100	100

Table 1: Table of class sensitivity of different algorithms

Table 1 represents class sensitivity values of different algorithms. Proposed (CNN) values are compared with Existing values of ANN and SVM. Their proposed values are higher than compare with other existing values.

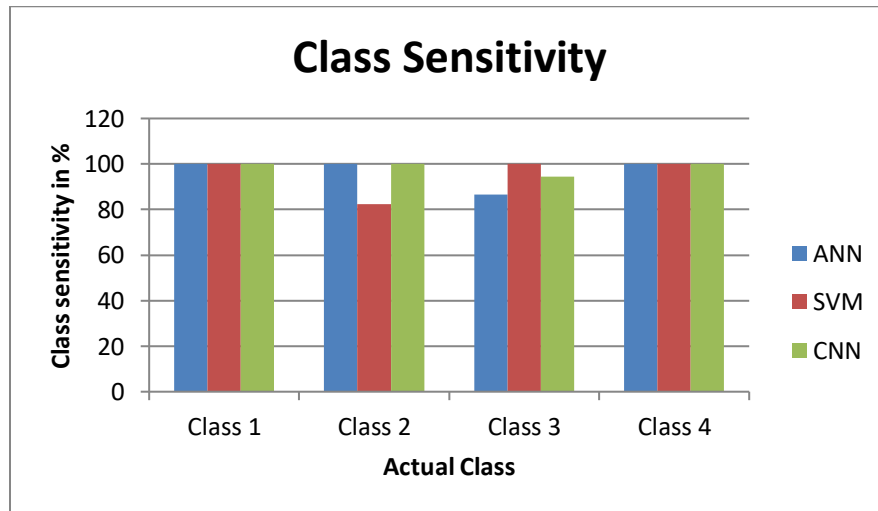


Figure 5: Comparison chart of class sensitivity of different algorithms

Figure 5 represents the class sensitivity values are compare with them. Here the proposed novel CNN is compared with existing ANN and SVM classifiers. Class 1, class 2 and class 4 sensitivity is 100% and class 3 has 94.5 Overall sensitivity values are higher than existing methods as shown in this diagram. Existing 1 is a lower than compare with existing 2 and proposed values.

2. Class Precision in %

Actual class	ANN	SVM	CNN
Class 1	100	100	100
Class 2	100	81.1	100
Class 3	83	100	95.5
Class 4	100	100	100

Table 2: Table of class Precision of different algorithms

Table 2 represents class precision values in this table. Proposed (CNN) values are compared with Existing values of ANN and SVM. Their proposed values are higher than compare with other existing values.

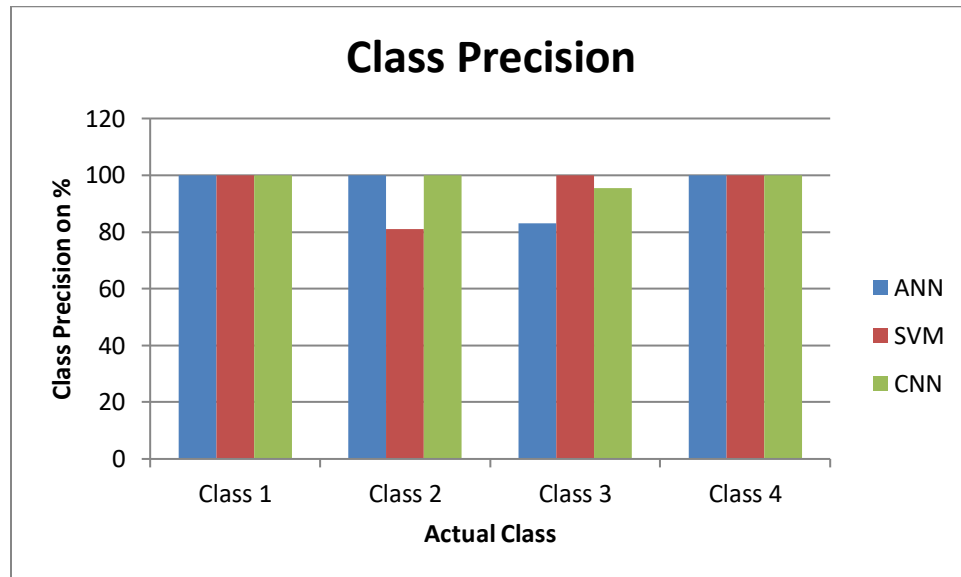


Figure 6: Comparison chart of class Precision of different algorithms

Figure 6 represents the runtime values are compare with them. All values are only positive. The proposed values are higher than in this diagram. Existing 1 is a lower than compare with existing 2 and proposed values.

Specificity and overall class prediction

Specificity and in general class prediction accuracy are other helpful statistical estimates that depict the exhibition of a classifier. They are utilized for twofold classifiers. Specificity is characterized as the proportion of genuine negative classes (all aside from the positive class) which are accurately recognized, while generally class prediction accuracy is characterized as the proportion of the absolute number of predictions that were right.

They are given by:

$$\text{Specificity} = \frac{TN}{(TN+FP)} \quad (13)$$

$$\text{Overall Prediction Accuracy} = \frac{TP+TN}{(TP+TN+FP)} \quad (14)$$

Binary confusion matrix for proposed CNN:

Actual Class	Predicted class		
Class 1 Not Class 1	Class 1	Not Class 1	
	TP = 12	FN = 0	Sensitivity=100%
	FP = 0	TN = 77	Specificity=100%
	Precision =100	Negative predictive value=100%	Overall prediction accuracy=100%
Class 2 Not Class 2	Class 2	Not Class 2	
	TP = 28	FN = 2	Sensitivity=93.2%
	FP = 0	TN = 59	Specificity=100%
	Precision =100	Negative predictive value=100%	Overall prediction accuracy=97.7%
Class 3 Not Class 3	Class 3	Not Class 3	
	TP = 18	FN = 0	Sensitivity=100%
	FP = 11	TN = 78	Specificity=97.1%
	Precision =88.5	Negative predictive value=100%	Overall prediction accuracy=97.5%
Class 4 Not Class 4	Class 4	Not Class 4	
	TP = 30	FN = 0	Sensitivity=100%
	FP = 0	TN = 58	Specificity=100%
	Precision =100	Negative predictive value=100%	Overall prediction accuracy=100%

Table 3: Binary confusion matrix for proposed CNN

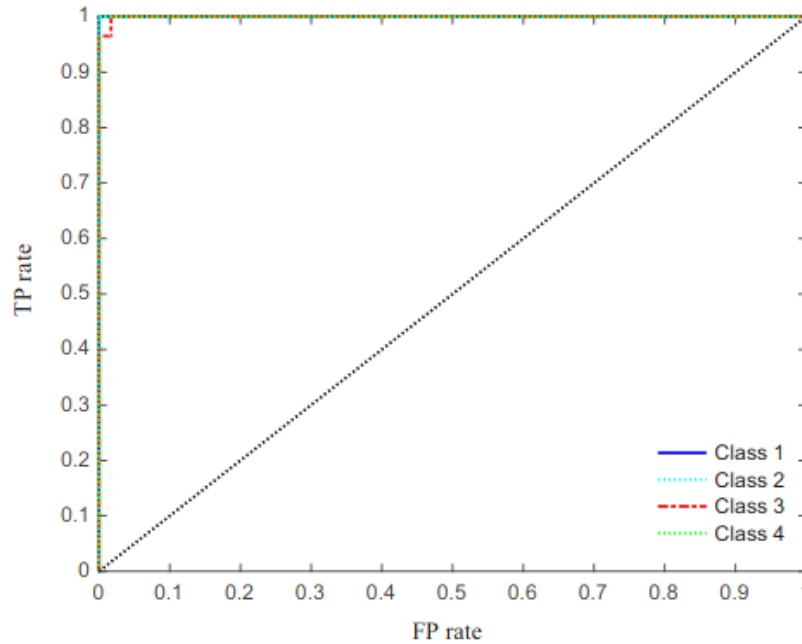


Figure 7: Receiver operating characteristic (ROC) curves for proposed CNN

Binary confusion matrix for SVM

Actual Class	Predicted class		
Class 1 Not Class 1	Class 1	Not Class 1	
	TP = 12	FN = 0	Sensitivity=100%
	FP = 0	TN = 77	Specificity=100%
	Precision =100	Negative predictive value=100%	Overall prediction accuracy=100%
Class 2 Not Class 2	Class 2	Not Class 2	
	TP = 28	FN = 2	Sensitivity=100%
	FP = 2	TN = 57	Specificity=100%
	Precision =100	Negative predictive value=100%	Overall prediction accuracy=100%
Class 3 Not Class 3	Class 3	Not Class 3	
	TP = 18	FN = 0	Sensitivity=100%
	FP = 11	TN = 78	Specificity=97.1%
	Precision =88.5	Negative predictive value=100%	Overall prediction accuracy=97.1%
Class 4 Not Class 4	Class 4	Not Class 4	
	TP = 30	FN = 0	Sensitivity=100%
	FP = 2	TN = 56	Specificity=97.5%
	Precision =100	Negative predictive value=100%	Overall prediction accuracy=91.5%

Table 4: Binary confusion matrix for SVM

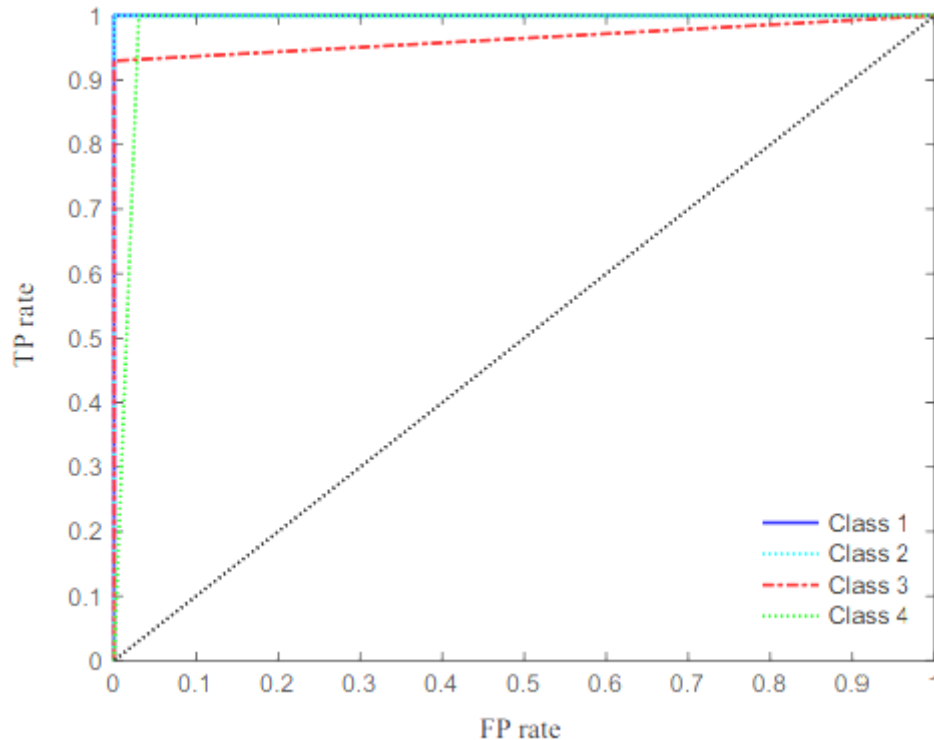


Figure 8: Receiver operating characteristic (ROC) curves for Existing SVM

Receiver operating characteristic (ROC) is a measurement used to check the nature of the classifier. It is the TP rate or the affectability against the FP rate or (1-particularity), which is the likelihood of bogus caution, for the various conceivable cut-purposes of the test dataset. The proposed CNN classifier is entirely precise for classes 1, 2, and 4, since the territory under the ROC bend equivalents to one. Then again, the SVM is totally precise for classes 1 and 2, since the region under the bend is one. Be that as it may, it is less exact than the CNN classifier for different classes, since the zone under the bend for the second rate class for the fourth class.

5. Conclusion

A Convolution neural network-based system for the classification of ripeness condition of fruits has been talked about. This specific utilization of computer vision could empower the advancement of a generally basic and automated system to sort fruit as per various degrees of development. The system has ideal execution as contrasted and other regulated classification algorithms as the CNN and SVM classifiers. The general class acknowledgment exactness of 100% is acquired for the green and overripen classes, while it is 97.7% for the yellowish green and 97.5% for the mid-ripen classes.

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