A Deep Learning Approach to detect the spoiled fruits.

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Abstract: - Fruits are one of the vital sources of nutrients for the mankind and their life span is very less. The fruit spoilage may occur at various stages such as, at the harvest time, during transportation, during storage etc. Freshness is a parameter used for accessing the quality of the fruit. About 20% of the harvested fruits are spoiled due to many factors, before consumption by humans. The spoilage of one fruit has a direct impact on the neighboring fruits. It is also a one of the indicators that gives an estimation of number of days that a fruit can be preserved. Early identification of the spoilage helps in taking the appropriate measures for the removal of spoiled fruits from the whole lot. So that it helps in preventing the spread of spoilage to its adjacent fruits. Deep learning based technological advancements helps in automatically identifying the spoiled fruits. In this work, internal quality attributes of the fruit are not taken into consideration for spoilage detection, only the external attributes are considered. The supervised learning technique is employed for the freshness analysis of two different types of fruits, Apple and Banana. As the 2 varieties are involved, it is a multiclass classification model with 4 classes. One shot detection technique is employed to accurately classify among the good fruit and spoiled fruit. Few images in the dataset are obtained from the kaggle.com and the rest are self - captured images. The dataset is balanced to avoid the biasness in the model. The model is implemented using Yolov4 and tiny Yolov4 frame works. These are one shot detection techniques, can be used for real time deployment. The inferences were obtained on the real time images and video. Confusion matrix is tabulated the performance metrics such as accuracy, F1 Score and recall are discussed with respect to these two techniques.

Key-Words: - Deep Learning, Fruit Spoilage Detection, Artificial Intelligence, Augmentation, one shot detection

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1 Introduction

Fruits are one of the natural sources of food resource that is derived from plants. Everywhere around the world fruits are considered to be healthy food. Fruit consumption by humans gives them a balanced diet. Due to huge demand, farmers are looking towards cultivating the fruit crops by employing the internet of things in agriculture to improve the yield and productivity [1]. The industries making beverages are highly dependent on fruits as their major ingredient [2]. Each variety of fruit has its own lifetime. They can be degraded quickly if not stored in a proper manner. With the technological advancements, application of internet of things in agriculture, various sensors are used to automate the various applications in agriculture[3]. The adapted agricultural practices during the pre-harvest, harvest and the post-harvest stages also have a great impact on the productivity of the fruits [4]. Crop maintenance at each of these stages plays a predominant role. During the pre-harvest stage the major influential factors are pesticide or fertilizer application and weed control. In the harvest stage, maturity of the fruit and firmness are the key parameters to be considered. In the post-harvest stage, storage facilities have a great impact on the life span of the fruit. Improper maintenance of the crop under these stages will result in huge loss. Amongst these factors, pests and diseases are main causes of low yield [5]. After harvest fruits will continue to have the respiratory process thereby, they will still appear fresh for few days. As the days passes fruits will lose its freshness and gradually decay. Apart from these, poor storage and transportation facilities contributes to fruit spoilage [6]. Also, there are chances that the secretions coming out of one spoiled fruit may damage the entire lot, by spreading through the neighboring fruits.

At present, Computer vision has its enormous applications in the field of agriculture, automotive, education, health care etc. Agri-based computer vision applications include, identification of plants and weeds, disease detection in fruit and plant, flower classification, counting of fruits in a tree for yield, sensor data analysis related to agricultural parameters such as temperature, humidity, pH, soil moisture [7]. Machine vision models are the better decision makers, which has become alternatives to human beings [8]. In the case of the human being the decision-making capabilities are dependent on their naked eye vision. Farmers should have a priori knowledge of the diseases to classify them based on their symptoms. Classification can be between the fruit of same type and the classification between different species of fruits [9]. The computer vision techniques extract the features that show the clear indication of the symptoms to predict the fruit diseases. These methods rely on the visual features that appear on the fruit such as shape, color, and texture [10]. Deep learning framework imitates the human brain by using the neural networks for data processing. It requires huge data for training. It gives an improved performance with different types of data. The convolution concept was used to determine the patterns from the image [11]. The deep learning-based object detection and recognition helps in building an efficient classification model for identifying the spoiled fruits from healthy ones.

With this motivation, in this study an automatic classification of diseased fruits from the healthy ones was taken into consideration. Banana is a common man fruit, low cost, multi vitamin rich food [12] and is available in all seasons. It has rich soluble and insoluble fiber content, that helps in easy digestion. It also contains the rich source of nutrients and this fruit is highly recommended for the people suffering from anemia. An apple consumption every day, keeps the doctor away, as per the famous saying, apple and banana fruits were considered in this paper for spoilage detection. The traditional transfer learning approaches classifies only for mutually exclusive dataset. To classify for the non- mutually exclusive dataset one shot detection-based frame works are employed. This paper is organized into six sections. Second section describes the related work. The model architecture of the convolutional neural network (CNN) is explained in third section. The results and discussions were explained in the fourth section. The conclusion is given in the fifth section.

2 Related work

Please, Researchers have developed several machine learning algorithms for object classification using images. This in turn paved the way for the next generation artificial neural networks with deep neural network architectures showing an improved performance when compared to the traditional state of art methods.

Mohd Azlan Abu et. al [13] studied the flower classification using the deep neural network frame on tensor flow. The dataset consisting of 3670 flower images were collected from ImageNet website. The dataset consisting of the five categories comprising of Daisy, Dandelion, Roses, Sunflower, Tulips were trained on MobileNet model with an input resolution of 224x224 RGB images. The trained accuracy obtained with MobileNet 0.50 was greater than that of MobileNet 1.00. The model accuracy was 90%. J.J. Zhuang et.al [14] had developed a machine vision model to identify the citrus fruits in citrus trees. The machine vision model consists of illumination enhancement, foreground region segmentation, region extraction and recognition. The model was trained on the self captured images. The bounding boxes with the minimum enclosure are drawn over the detected fruits in the test data. The model was trained with 100 images. The F1 score obtained was 0.91. David Ireri et. al[15] had proposed a computer vision model to detect the defects in tomatoes and also to perform tomato grading. 200 tomatoes of varying composition of defects were chosen and they were transformed into L, A, B colour space. From each of these mean, range and standard deviation was considered to analyse the colour features, further shape features and text features were analysed. Support vector machine based were used for recognition. For the testing purpose the images are captured with the hikivision camera, connected to computer with Ethernet cable. The model acuuracy was 0.95, root mean square error was 33.5.

Kyamelia Roy et. al [16] developed a frame work to classify the healthy apple and rotten apple. The dataset was obtained from kaggle.com. data pre-processing was performed to generate the binary masks. The enhance UNet was built using the U-Net frame to improve the accuracy. The model was trained with GPU Tesla K80 in google colab. The UNet model achieved 95.36 % validation accuracy, where with the enhanced UNet model the validation accuracy is 97.54. Shiv Ram Dubey et. al [17] developed an apple disease classification model to predict the Apple Blotch, Apple scab, , Apple rot and Normal Apple. In the initial stage, extraction of the region of interest was performed, followed by feature map generation. In the next step distinctive features were extracted. Multi class support vector machine was used for classification. The model achieved an accuracy of 95.94%. Yunong Tian et. al [18] developed a multi class classification model to categorize between the defected and the healthy leaves and fruit. Out of the 11 classes, three of them belong to healthy leaves and fruit categories and the rest of them belong to the diseased leaves and fruit categories. Cycle-GAN was used for augmentation of images. The dataset is trained over Multi-scale Dense Inception-V4, obtained accuracy wad 94.31 % and Multi-scale Dense Inception-ResNet-V2 algorithms with an accuracy of 94.74%. Poonam Dhiman et. al [19], identified the disease severity level in citrus fruits at four levels being low, medium, high and healthy by applying the transfer learning on the VGGnet, giving an accuracy of 99% with severity level low, 98% with high severity level, 97% with medium and 96% with healthy fruit. Benjamin Doh,et.al [20] used svm and ANN to identify the citrus fruit disease based on its characteristics such as color, holes, texture and morphology. The average accuracy of ANN was 89% and 87% with SVM.

Inkyu Sa et. al [21], developed a model with transfer learning on Faster Region-based CNN to detect the presence of fruits in a farm. The multimodal information comprising of Near Infra red and RGB, with 4 channels was given as an input to the network. The bounding box annotation was performed on the images. The model was trained on NVIDIA GPU. The F1 score obtained was 0.83. Heena Shaikh et. al [23], used a six class classifier to classify among apple, pear and bear healthy ones and diseased fruits. In the first step images were annotated using LabelImg in pascal voc format to generate an XML file. 344 images were trained on the faster R- CNN model. The average accuracy was 85. Jamil Ahmad et. al [20], plum images was captured using mobiles phones are fed to the fine tuned CNN to train the model for predicting 5 classes, one class belong to healthy and the other classes belong the defected classes. The overall performance of the model is 88.42%. Ganeshan Mudaliar et. al [24] developed a model to study the classification of ripen tomato and rotten tomato. The data set was taken from kaggle and trained over 500 images with the mobile net. The image output size from pre-processing stage is 32x32, which is then fed to the mobile net. The accuracy of this model is 98.74. Guichao Lin et. al [25], presented a shape matching model based on sub fragment detection and aggregation. Aggregation was done by eliminating the false positives through SVM classifier. The experimental results achieved precision in the range 0.783 – 0.919 for 6 classes.

From the related work it is understood that as the size of the network increases, the training time increases, but the model will produce an improved accuracy when compared to the lighter model. Deep learning models requires enormous data when compared to computer vision techniques, but greater performance can be achieved. One shot YOLO object detection has CNN as backbone, used for real time deployment for object detection.

3 Model Architecture

Convolutional neural network, being a deep learning algorithm in which, based on the objects in the input image, the learning weights are modified. With the help of the filters, CNN can easily obtain the spatial and temporal dependencies.

Convolution, ReLu, Pooling and fully connected layers forms the building blocks of CNN. During this process the dominant features are extracted. Noise suppression is done in the max pooling layer. In the fully connected layer, the nonlinear combination of the dominant features are represented at the output. The basic CNN architecture block diagrams are shown in the following figure 1[8]. LeNet, AlexNet, VGG Net, ResNet, architectures were built using the basic blocks of CNN.

In the convolution layer output is given mathematically as the formulation is defined by (1). where k is the CONV layer, the output feature vector for layer k was denoted by Xnew.

$$X_{new} = \sigma\left(\sum_{i=1}^{n} x_i^k w_i^k + b_k\right) \qquad (1)$$

w_i^k and b_k represents the elements of the filter and bias respectively, denotes the activation function. Rectified Linear unit activation function was applied to increase the nonlinear properties of the network. During this stage, the negative input values are replaced by zero. In the pooling layer, based on the chosen stride value and the window size the max pooling or the average pooling is performed. The feature map obtained from this form the input to the subsequent layers. The above steps are repeated for all the layers.

The flattened input is given to the fully connected layer, to which softmax activation is applied to produce the output in terms of probabilistic value for the each of the classes. This model is implemented in python with tensorflow and keras libraries.

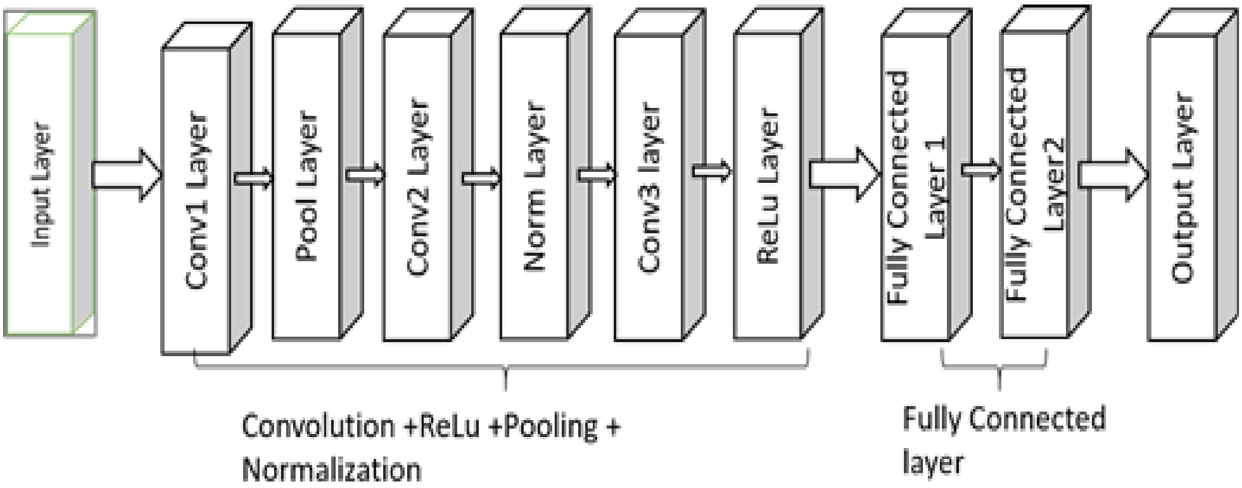


Fig.1: Basic Convolutional Neural Network Architecture

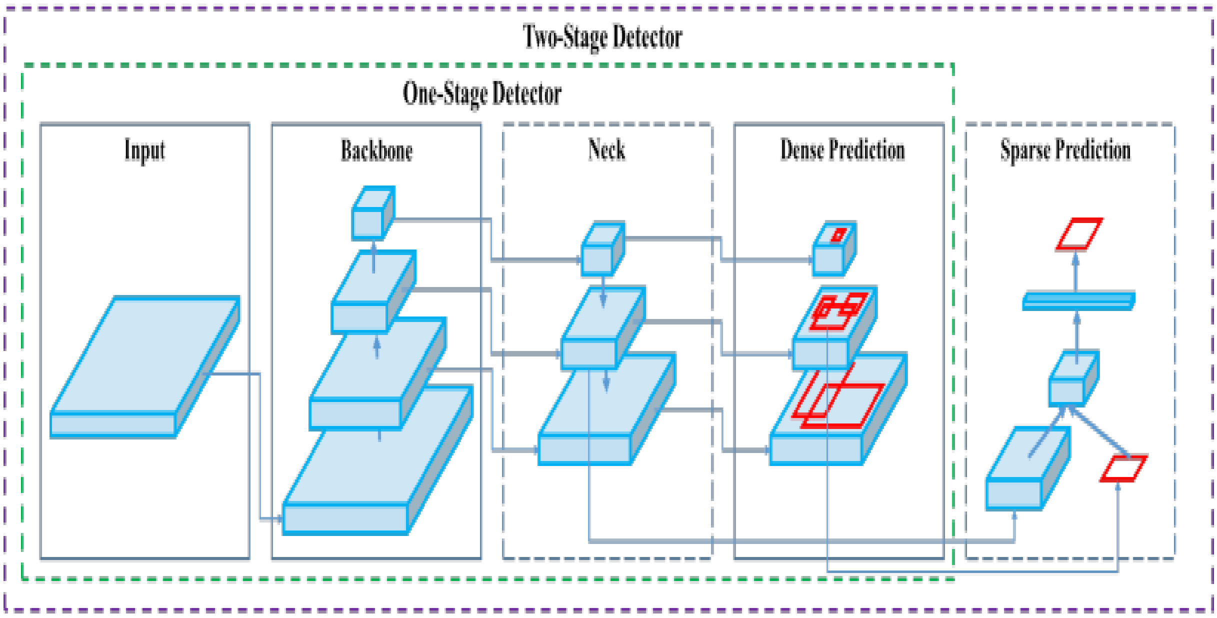


Fig. 2 : Block diagram of an object detector.

3.1 Object detector

In general an object detector consists of the following input, backbone neck and head. The objector detector takes the input as image, patch, image pyramid. Back bone generally contains an architecture built on CNN model. The neck contains the path – aggregation blocks. It forms the feature pyramid network from the backbone Head contains dense prediction of one stage and sparse prediction consisting of two stages. Generally used detectors for one stage are single shot detector (SSD) and YOLO. Two stage detector model uses faster RCNN based models. The object detector diagram is shown in the figure 2 above [26].

3.2 Faster RCNN Architecture:

The faster RCNN consists of, Fast RCNN detector with VGG as the backbone to obtain the object features, a region proposal network to mark the bounding boxes indicating the possible objects in an image. The classification layer is responsible for the class predictions. The width and height of the bounding box can be obtained from the regression layer. The size of the anchor boxes may vary from 128, 512,1024, the aspect ratio 2:1, 1:1, 1:2. It uses multitask loss function [27]. The overview of faster RCNN is shown in figure 3 below [27].

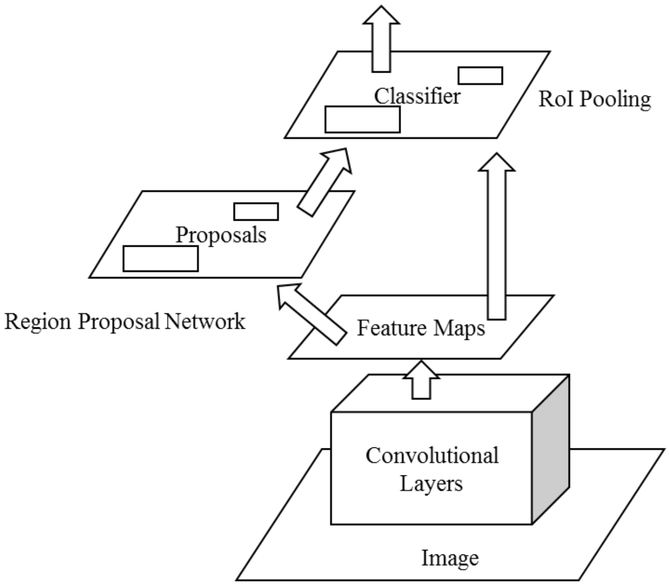


Fig.3: Block diagram of Faster R-CNN unified Network.

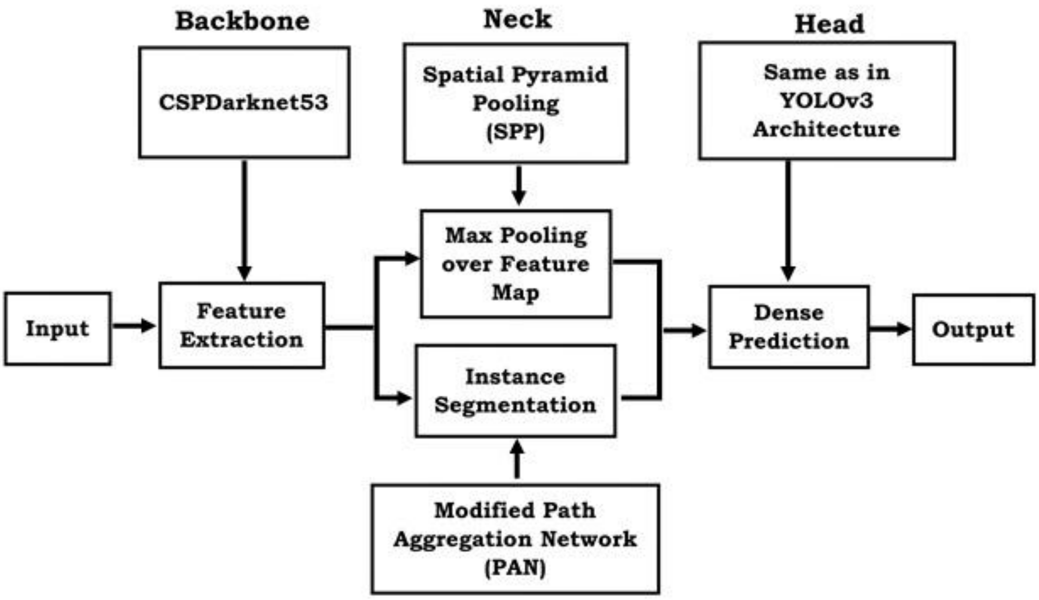


Fig. 4: YOLOV4 block diagram.

3.3 YOLOV4 Architecture

YOLO V4 is a simplified network with a reduced number of learnable parameters when compared the traditional CNN models. You Look Only Once, as indicated by the name, it is a one-shot detector. It is built on the cross stage partial architecture, which is built on the Dense Net, called as CSPDarknet53[28].

It not only does image classification but also performs the object localization. It is represented by a vector consisting of probability of class, centre (x,y) coordinates of the bounding box, height, width of the bounding box, probability of the bounding box classes. The YOLOV4block diagram is shown in the figure 4 above [26].

In the neck part, concatenation was used for the Path Aggregation Network (PAN). Max pooling was performed in the spatial pyramid pooling. Further bag of freebies (BoF) methods helps to improve the accuracy without putting an additional overhead of interference. Bag of Specials (BoS) consists of Mish activation, Cross- stage partial connections and weighted residual connections. Mish activation function will be similar to ReLu and Swish. During the training phase the weights are modified depending on the Complete Intersection Over Union

(CIoU). The loss(L) is mathematically given in equations (2,3) as [25-26]

$$L = S(ß, ßgt) + D(ß, ßgt) + V(ß,ßgt) \quad (2)$$

$$IoU = \text{Intersction Area / Union Area} \quad (3)$$

Where ß is the bounding box, S indicates the overlap area, ßgt is the ground truth bounding box. Analysing the CIoU loss helps in maintaining the consistency of the bounding box aspect ratio. The non-maximum suppression filters the additional bounding boxes on the same object and the keeps only a single bounding box. The uses the IoU and the distance between the centers of two consecutive boxes to determines the redundant enclosures.

3.4 YOLOV4 – Tiny Architecture:

YOLOV4 tiny architecture is built from YOLOV4. This tiny model detects the objects at a faster rate when compared to YOLOV4. Since it is a lightweight model, it will be easily deployed on the real time applications using embedded systems [29-31]. In the backbone it uses CSPDarknet53-tiny. In the cross stage partial network, it employs CSP block, in the cross stage residual edge which divides the feature map into two parts. So that it increases the correlation difference in the gradient information. To reduce the computational overhead it uses Leaky ReLu activation function. Mathematically the Leaky ReLu activation is given by [29]

$$y_k = \begin{cases} x_k & x_k \geq 0 \\ \frac{x_k}{a_k} & x_k < 0 \end{cases} \quad (4)$$

Where $a_k \in (1, +\infty)$

Table 1: YOLOV4 tiny network structure.

Layer	Type	Filters	Size/Stride	Input	Output
0	Convolutional	32	3 × 3/2	416 × 416 × 3	208 × 208 × 32
1	Convolutional	64	3 × 3/2	208 × 208 × 32	104 × 104 × 64
2	Convolutional	64	3 × 3/1	104 × 104 × 64	104 × 104 × 64
3	Route 2				
4	Convolutional	32	3 × 3/1	104 × 104 × 32	104 × 104 × 32
5	Convolutional	32	3 × 3/1	104 × 104 × 32	104 × 104 × 32
6	Route 5 4				
7	Convolutional	64	1 × 1/1	104 × 104 × 64	104 × 104 × 64
8	Route 2 7				
9	Maxpool		2 × 2/ 2	104 ×104 × 128	52 × 52 × 128
10	Convolutional	128	3 × 3/1	52 × 52 × 128	52 × 52 × 128
11	Route 10				
12	Convolutional	64	3 × 3/1	52 × 52 × 64	52 × 52 × 64
13	Convolutional	64	3 × 3/1	52 × 52 × 64	52 × 52 × 64
14	Route 13 12				
15	Convolutional	128	1 × 1/1	52 × 52 × 128	52 × 52 × 128
16	Route 10 15				
17	Maxpool		2 × 2/ 2	52 × 52×256	26 × 26 × 256
18	Convolutional	256	3 × 3/1	26 × 26 × 256	26 × 26 × 256
19	Route 18				
20	Convolutional	128	3 × 3/1	26 × 26 × 128	26 × 26 × 128
21	Convolutional	128	3 × 3/1	26 × 26 × 128	26 × 26 × 128
22	Route 21 20				
23	Convolutional	256	1 ×1/1	26 × 26 × 256	26 × 26 ×256
24	Route 18 23				
25	Maxpool		2 × 2/2	26 × 26 ×512	13 × 13 × 512
26	Convolutional	512	3 × 3/1	13 × 13 × 512	13 × 13 × 512
27	Convolutional	256	1 × 1/1	13 × 13 × 512	13 × 13 × 256
28	Convolutional	512	3 × 3/1	13 × 13 × 256	13 × 13 × 512
29	Convolutional	21	1 ×1/1	13 × 13 × 512	13 × 13 × 21
30	YOLO				
31	Route 27				
32	Convolutional	128	1 × 1/1	13 × 13 × 256	13 × 13 × 128
33	Upsample		2x	13 × 13 × 128	26 × 26 × 128
34	Route 33 23				
35	Convolutional	256	3 × 3/1	26 × 26 × 384	26 × 26 × 256
36	Convolutional	21	1 × 1/1	26 × 26 × 256	26 × 26 × 21
37	YOLO				

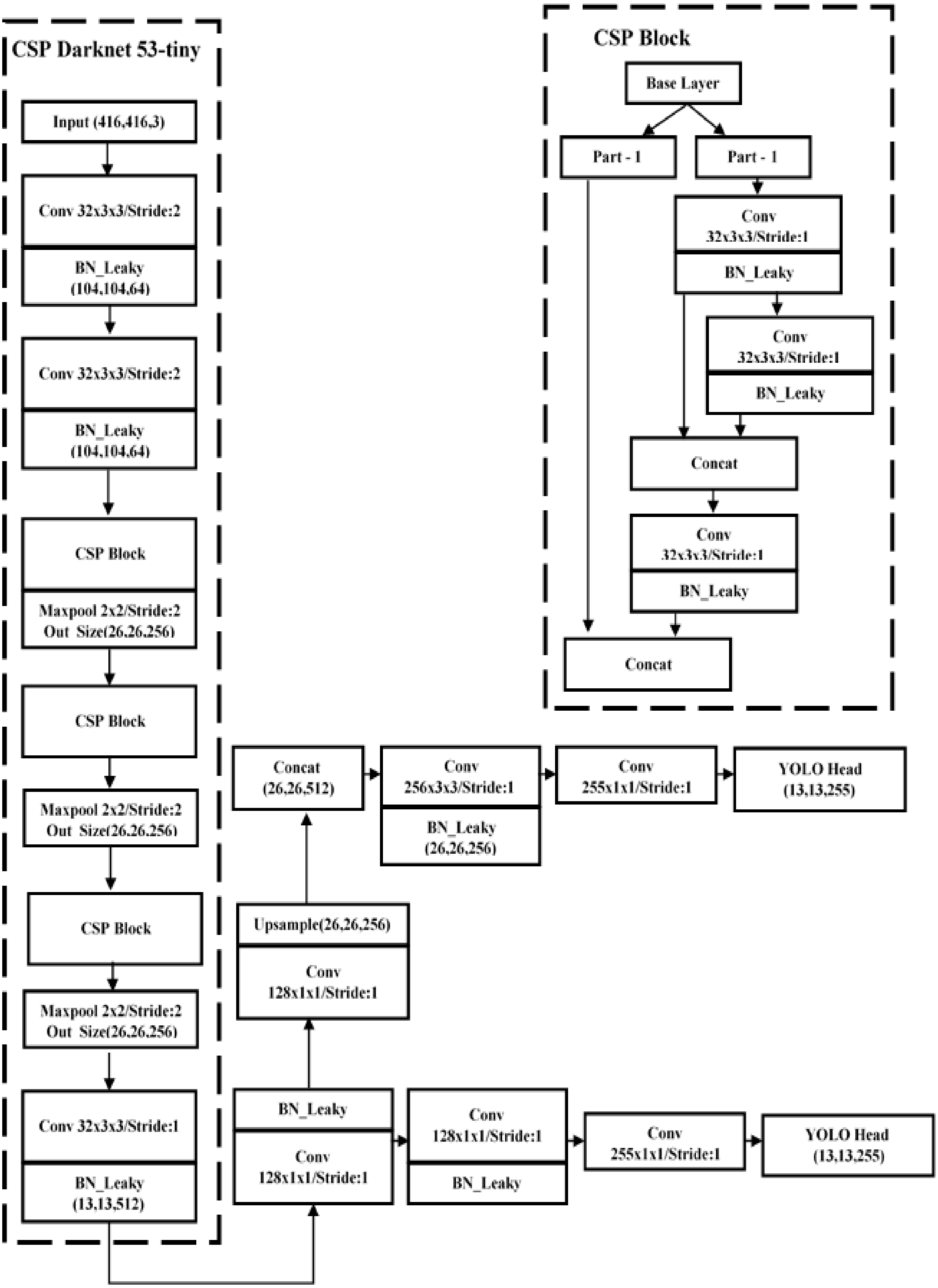


Fig.5: Block diagram of YOLOV4 tiny model.

The feature pyramid network with different scales are used to increase the object detection speed. In the tiny model SPP and PAN are not used. The detections are predicted using 13x13 and 26x 26 feature maps. The block diagram of YOLOV4-tny model is shown in the figure 5 below [32].

Initially the image is divided into SxS grids, in each grid the objects are detected using bounding boxes. Depending on the availability of the objects in the grid, SxSxB bounding boxes are generated. This process is repeated for the entire image. The object is predicted only if the centre of the object related bounding box is present inside the grid. The bounding box is retained only if it satisfies the confidence threshold value. Then intersection over unions, non-maximum suppression is applied same as YOLOV4 to retain a single bounding box over a single image. The network structure of YOLOV4 tiny model is shown in Table.1 above [33].

The average precision in YOLOV4 is increased by 10% when compared to YOLOV3. The YOLOV4 contains 139 convolutional layers whereas YOLOV4 tiny contains 29 convolutional layers. The accuracy of the YOLOV4 tiny model is two-third of YOLOV4 model on MS COCO dataset. YOLOV4 tiny is preferable in applications where there is a requirement of faster processing in real in real time.

4 Results and Discussion

Two types of fruits, apple and banana, which are healthy and diseased were considered for the study. The classification and localization were performed using YOLOV4 tiny and YOLO algorithms. This is a multi-class classification problem with four classes being good apple, bad apple, good banana and bad banana. A total data set of 800 images were used. The complete data set was split into train and test. A total of 800 images with 200 images from each class are collected. Few images were captured manually using a mobile phone and few are collected from kaggle.com /fruit 360. The same data set trained over two frame works YOLOV4 tiny and YOLO. The dataset was annotated with the bounding boxes using lablelImg Software. The labelImg generates the .txt file consisting of data related to class and bounding box coordinates. The data augmentation was performed on the images to increase the data set. The images are rotated by 90 degrees and 270 degrees. The following figures [6 -7] gives an overview of the loss in two models. The model was trained using google colab pro. At the end of 6000 iterations the current average loss of the two models is shown in the Table 2. below:

Since YOLOV4 tiny is a lightweight model in which the loss convergence is faster. Since the number of convolution layers in the tiny yolov4 less, the trainable parameters is also less. Therefore, the time taken by for each iteration is less when compared to YOLOV4 model.

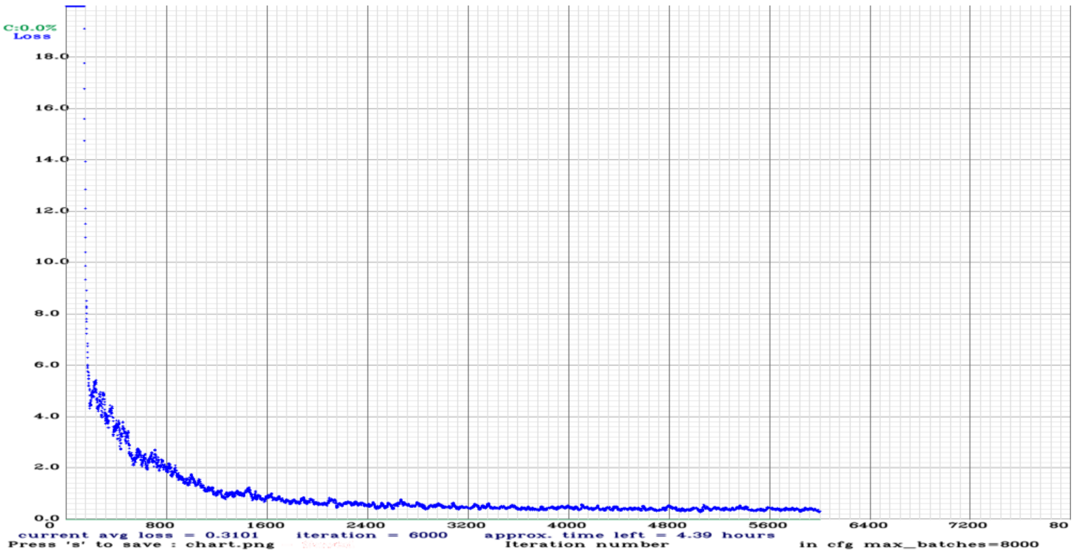


Fig. 6 YOLOV4 loss convergence with number of iterations during training

Table 2: Average loss during training.

Model	Current average loss at 6000th iteration	Time taken for 6000 iterations
YOLOV4	0.3101	12 hours
YOLOV4 tiny	0.0530	2 hours

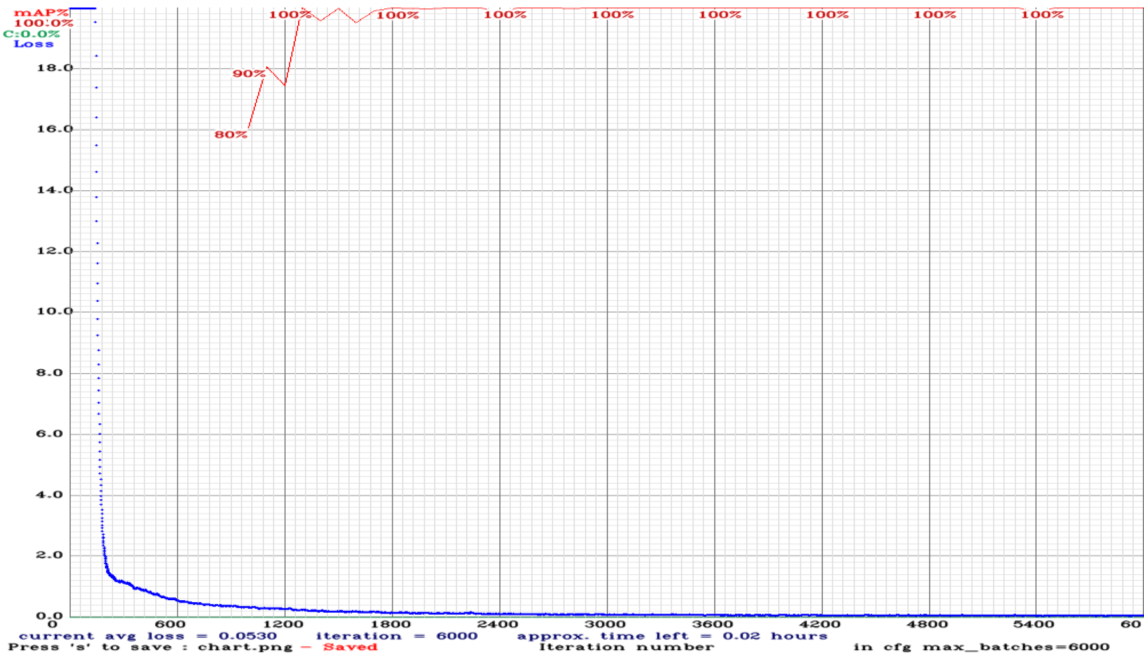
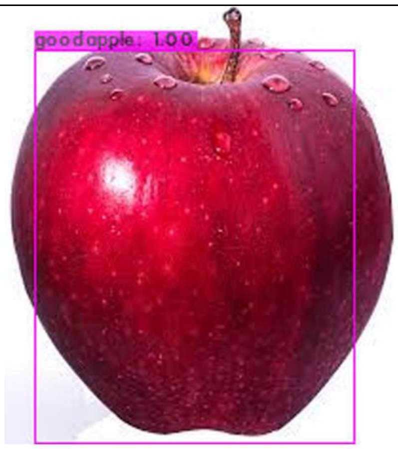


Fig. 7 YOLOV4 tiny model loss convergence with number of iterations during training.

Table 3: Predictions on test images

Sno	Test image		Predicted class
	YOLOV4	YOLOV4tiny	
1			Good apple
2			Bad apple

3			Bad apple
4			Bad banana
5			Bad banana
6			Good banana

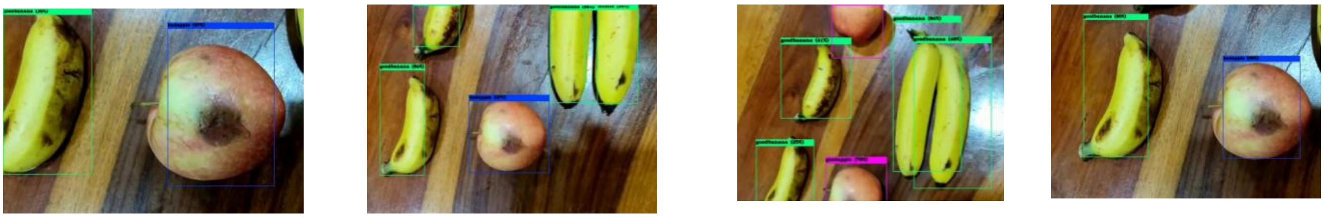


Fig.8(a, b, c, d): Extracted frames of video prediction on YOLOV4 tiny.

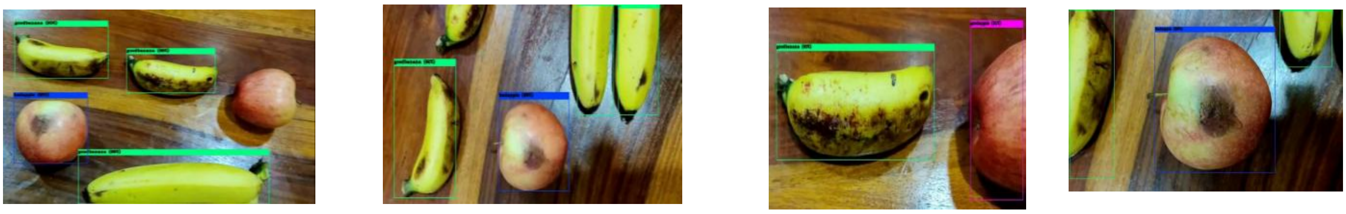


Fig.9 (a, b, c, d): Extracted frames of video prediction on YOLOV4.

Table.3 shows image predictions, figures 8, 9 shown above describes the predictions on the video, few frames are extracted for both the YOLOV4 tiny and YOLOV4 models. Green colored bounding box indicates the good banana, the blue colored bounding box indicates the bad apple, pink color bounding box indicates that the predicted object is a good apple.

The confusion matrix is tabulated to describe the performance of the model for the test images. It gives the analysis about the predicted data against the target data. The Table 4 and Table 5describes the confusion matrix for fruit classification model with YOLOV4 and YOLOV4 tiny algorithms from which the accuracy and F1 score was calculated.

Table 4: Confusion matrix of the fruit classification model with YOLOV4 algorithm

		Predicted Outputs			
Actual Class		Good apple	Bad apple	Good banana	Bad banana
	Good apple	24	1	0	0
	Bad apple	2	23	0	0
	Good banana	0	0	22	3
	Bad banana	0	0	1	24

Table 5: Confusion matrix of the fruit classification model with YOLOV4tiny algorithm

		Predicted Outputs			
Actual Class		Good apple	Bad apple	Good banana	Bad banana
	Good apple	22	3	0	0
	Bad apple	5	20	0	0
	Good banana	0	0	21	4
	Bad banana	0	0	2	23

The results obtained from Table 4 and Table5 shows that there is no misclassification between the apple and banana with both the models. The distinctive features between the apple and banana are more therefore the predictions does not classify the apple as banana and vice-versa. In the case of classification between the same species being healthy and spoiled there is more correlation. Since the tiny YOLOv4 model has the less architecture when compared to the full model, the misclassification is more between the same species. From the confusion matrix the accuracy, F1 score, Recall are calculated as shown in the equations 5,6,7,8.

$$\text{Accuracy} = \frac{True\ positive\ + True\ Negative}{True\ positive + True\ Negative + False\ Positive + False\ Negative} \quad (5)$$

$$\text{Precision} = \frac{True\ positive}{True\ positive + False\ Positive} \quad (6)$$

$$\text{Recall} = \frac{True\ positive}{True\ positive + False\ Negative} \quad (7)$$

$$\text{F1 score} = \frac{2 * Precision * Recall}{Precision\ +\ Recall} \quad (8)$$

From Table 6, it is observed that the as the network architecture is more, the number of trainable parameters increases, performance metrics parameters shows improvement. The accuracy and F1 score of the YOLOV4 algorithm is higher in comparison with YOLOV4 tiny when trained for 6000 iterations.

Table 6: Comparison of performance metrics for YOLOV4 and YOLOV4tiny.

	Accuracy	Precision	Recall	F1score
YOLOV4	0.94	0.938	0.92	0.927
YOLOV4tiny	0.87	0.86	0.86	0.86

5 Conclusion

In this paper apple and banana are classified between the healthy and the diseased ones. Deep learning YOLO algorithms will give higher accuracy and precise object detection in comparison with traditional CNN models. The dataset is trained on YOLOV4 and the light weight model YOLOV4 tiny. Since YOLOV4 tiny has a smaller number of convolution layers in comparison with the YOLOV4, it consumes less time for training. For this dataset, after 6000 iterations the average loss in YOLOV4 tiny is less when compared to YOLOV4. Predictions are done for the same set of images in YOLOV4 and YOLOV4 tiny, it was observed that accuracy of the YOLOV4 tiny model is slightly lesser than the YOLOV4. For a given test image the confidence score of identifying the object in YOLOV4 is higher than YOLOV4 tiny, but faster predictions occur in YOLOV4tiny as it a lightweight model so it can be easily deployed in embedded systems for real time applications. Therefore, there is a trade- off between the time consumption, confidence level in classification and accuracy. For a small-scale applications YOLOv4 tiny is a good choice. In Future, the model can be extended for other category of fruits by re-training the model with relevant dataset and can be deployed on embedded platform for real time fruit grading.

Declaration of Interests

The authors declare that there is no conflict of interest.

References:

[1]. Priyanka Kanupuru, N. V. Uma Reddy, "Survey on IoT and its Applications in Agriculture," 2018 International Conference on Networking, Embedded and Wireless Systems (ICNEWS), pp. 1-5, 2018. doi: 10.1109/ICNEWS.2018.8903969.

[2]. L. Wu, H. Zhang, R. Chen and J. Yi, "Fruit Classification using Convolutional Neural Network via Adjust Parameter and Data Enhancement," 2020 12th International Conference on Advanced Computational Intelligence (ICACI), pp. 294-301, 2020. doi: 10.1109/ICACI49185.2020.9177518.

[3]. Kanupuru Priyanka, Nadig Vijayendra Reddy Uma Reddy, “Multi node based smart monitoring system with motor dry run avoidance for sustainable agriculture”. Instrumentation Mesure Métrologie, Vol. 20, No. 1, pp. 39-47, 2021. https://doi.org/10.18280/i2m.200106.

[4]. Vishal Meshrama , Kailas Patil , Vidula Meshrama , Dinesh Hanchate b , S.D. Ramkteke, “Machine learning in agriculture domain: A state-of-art survey”, Artificial Intelligence in the Life Sciences, Elsevier, Vol. 01, pp. 25761-25783, 2021. https://doi.org/10.1016/j.ailsci.2021.100010.

[5]. Guy Blomme, Miguel Dita, Kim Sarah Jacobsen, Luis Pérez Vicente, Agustin Molina, Walter Ocimati, Stephane Poussier, Philippe Prior, (2017) "Bacterial Diseases of Bananas and Enset: Current State of Knowledge and Integrated Approaches Toward Sustainable Management", Frontiers in Plant Science, Vol. 08, pp. 1 – 25. https://doi.org/10.3389/fpls.2017.01290.

[6]. Arif U Alam , Pranali Rathi, Heba Beshai , Gursimran K,Sarabha and M, Jamal Deen, "Fruit Quality Monitoring with Smart Packaging", Sensors, vol.21, pp. 1 – 20, 2020, https://doi.org/10.3390/s21041509.

[7]. Juliana Aparecida Fracarolli, Fernanda Fernandes Adimari Pavarin , Wilson Castro and Jose Blasco, "Computer vision applied to food and agricultural products", Revista Ciência Agronômica, , Special Agriculture 4.0, vol.51, pp. 1 – 20, 2020, doi:10.5935/1806-6690.20200087.

[8]. Dayanand Savakar, "Identification and Classification of Bulk Fruits Images using Artificial Neural Networks", International Journal of Engineering and Innovative Technology (IJEIT), vol.01,No. 3, pp. 36-40, 2012.

[9]. Rojas-Aranda J.L., Nunez-Varela J.I., Cuevas-Tello J.C., Rangel-Ramirez G. Fruit Classification for Retail Stores Using Deep Learning. In: Figueroa Mora K., Anzurez Marín J., Cerda J., Carrasco-Ochoa J., Martínez-Trinidad J., Olvera-López J. (eds) Pattern Recognition. MCPR 2020. Lecture Notes in Computer Science, vol 12088, 2020. Springer, Cham., https://doi.org/10.1007/978-3-030-49076-8_1.

[10]. Muhammad Attique khan, Tallha Akram, Muhammad Sharif, Tanzila Saba, "Fruits diseases classification: exploiting a hierarchical framework for deep features fusion and selection", Multimedia Tools and Applications, Springer, Vol. 79, pp. 25763–25783, 2020. https://doi.org/10.1007/s11042-020-09244-3 .

[11]. Sai Sudha Sonali Palakodati , Venkata RamiReddy Chirra, Yakobu Dasari , Suneetha BullaYk, "Fresh and Rotten Fruits Classification Using CNN and Transfer Learning", Revue d'Intelligence Artificielle, vol.34, No.05, pp. 617-622, 2020. https://doi.org/10.18280/ria.340512.

[12]. K. Lakshmi Narayanan , R. Santhana Krishnan , Y. Harold Robinson , E. Golden Julie , S. Vimal , V. Saravanan , and M. Kaliappan, Banana Plant Disease Classification Using Hybrid Convolutional Neural Network", Computational Intelligence and Neuroscience , vol. 2022, Article ID 9153699, 13 pages, 2022. https://doi.org/10.1155/2022/9153699.

[13]. Mohd Azlan Abu , Nurul Hazirah Indra , Abdul Halim Abd Rahman , Nor Amalia Sapiee and Izanoordina Ahmad, "A study on Image Classification based on Deep Learning and Tensorflow", International Journal of Engineering Research and Technology, vol.12, No.4, pp. 563-569, 2019.

[14]. J.J. Zhuanga , S.M. Luoa , C.J. Houa , Y. Tanga , Y. Heb , X.Y. Xuec, "Detection of orchard citrus fruits using a monocular machine vision-based method for automatic fruit picking applications", Computers and Electronics in Agriculture, vol.152, pp.64-73, 2018. https://doi.org/10.1016/j.compag.2018.07.004.

[15]. David Ireri, Eisa Belal, Cedric Okinda, Nelson Makange, Changying Ji Gzjf, "A computer vision system for defect discrimination and grading in tomatoes using machine learning and image processing", Artificial Intelligence in Agriculture, vol 2, pp 28 – 37, 2019. https://doi.org/10.1016/j.aiia.2019.06.001.

[16]. Roy, K., Chaudhuri, S.S. & Pramanik, S. "Deep learning based real-time Industrial framework for rotten and fresh fruit detection using semantic segmentation" Microsystem Technologies, Vol. 27, pp. 3365–3375, 2021. https://doi.org/10.1007/s00542-020-05123-x

[17]. Shiv Ram Dubey, Anand Singh Jalal, "Apple disease classification using color, texture and shape features from images", Signal, Image and Video Processing volume, Springer, Vol. 10, pp. 819–826, 2016. https://doi.org/10.1007/s11760-015-0821-1.

[18]. Tian Yunong, Li En, Liang Zize, Tan Min, He Xiongkui, "Diagnosis of Typical Apple Diseases: A Deep Learning Method Based on Multi-Scale Dense Classification Network", Frontiers in Plant Science, Vol. 12, , pp. 1-12, 2021. https://doi.org/10.3389/fpls.2021.698474.

[19]. Dhiman, Poonam, Vinay Kukreja, Poongodi Manoharan, Amandeep Kaur, M. M. Kamruzzaman, Imed B. Dhaou, and Celestine Iwendi. "A Novel Deep Learning Model for Detection of Severity Level of the Disease in Citrus Fruits" Electronics, Vol 11, no. 3: 495, pp 1-14. 2022. https://doi.org/10.3390/electronics11030495.

[20]. B. Doh, D. Zhang, Y. Shen, F. Hussain, R. F. Doh and K. Ayepah, "Automatic Citrus Fruit Disease Detection by Phenotyping Using Machine Learning," 2019 25th International Conference on Automation and Computing (ICAC), pp. 1-5,2019. doi: 10.23919/IConAC.2019.8895102.
[21]. Inkyu Sa, Zongyuan Ge, Feras Dayoub, Ben Upcroft, Tristan Perez, Chris McCool, "DeepFruits: A Fruit Detection System Using Deep Neural Networks" sensors, vol.16, No. 08, pp. 1-23, 2016. https://doi.org/10.3390/s16081222.
[22]. Heena Shaikh, Yashashree Wagh, Siddhesh Shinde, Shankar M. Patil, "Classification of Affected Fruits using Machine Learning", International Journal of Engineering Research & Technology (IJERT), vol.9, no.7, pp. 1541-1547,2021.
[23]. Jamil Ahmad , Bilal Jan , Haleem Farman , Wakeel Ahmad and Atta Ullah, "Disease Detection in Plum Using Convolutional Neural Network under True Field Conditions", Sensors, Vol. 20, no.9, pp. 1–18, 2020. https://doi.org/10.3390/s20195569
[24]. Ganeshan Mudaliar, Rashmi Priyadarshini B.K, "A Machine Learning Approach for Predicting Fruit Freshness Classification", International Research Journal of Engineering and Technology (IRJET), Vol. 08, no. 05 , pp. 2979-2983,2021.
[25]. Guichao Lin, Yunchao Tang, Xiangjun Zou, Jiabing Cheng, Juntao Xiong, "Fruit detection in natural environment using partial shape matching and probabilistic Hough transform", Precision Agriculture, Vol.21, pp. 160–177, 2020. https://doi.org/10.1007/s11119-019-09662-w.
[26]. Alexey Bochkovskiy, Chien-Yao Wang, Hong-Yuan Mark Liao, "YOLOv4: Optimal Speed and Accuracy of Object Detection", arXiv:2004.10934v1,2020.
[27]. Shaoqing Ren, Kaiming He, Ross Girshick, Jian Sun, Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks, arXiv:1506.01497v3, pp 1-14,2016.
[28]. Protik, Adban & Hossain, Amzad & Siddique, Shahnewaz,"Real-time Personal. Protective Equipment (PPE) Detection Using YOLOv4 and TensorFlow", 2021 IEEE Region 10 Symposium (TENSYMP), pp. 1-6, 2021. DOI: 10.1109/TENSYMP52854.2021.9550808.
[29]. Anna Kuznetsova, Tatiana Maleva and Vladimir Soloviev, Using YOLOv3 Algorithm with Pre- and Post-Processing for Apple Detection in Fruit-Harvesting Robot", Agronomy, Vol. 10, no. 1016, pp. 1-19, 2020. doi:10.3390/agronomy10071016.
[30]. WenYu Feng,1 YuanFan Zhu,2 JunTai Zheng,1 and Han Wang, "Embedded YOLO: A Real-Time Object Detector for Small Intelligent Trajectory Cars "Mathematical Problems in Engineering, vol. 2021, Article, pp. 1-11, 2021. https://doi.org/10.1155/2021/6555513.
[31]. Dongwei Guo, Lufei Cheng, Meng Zhang,Yingying Sun, "Garbage detection and classification based on improved YOLOV4", Journal of Physics: Conference Series, 2024 012023, pp. 1-8, 2021. doi:10.1088/1742-6596/2024/1/012023.
[32]. Zicong Jiang1 , Liquan Zhao , Shuaiyang Li And Yanfei Jia, "Real-Time Object Detection Method based on improved YOLOv4-tiny", Computer vision and pattern recognition, pp.1-11, 2020. https://doi.org/10.48550/arXiv.2011.04244 .
[33]. Silva, L.A.; Sanchez San Blas, H.; Peral García, D.; Sales Mendes, A.; Villarubia González, G. "An Architectural Multi-Agent System for a Pavement Monitoring System with Pothole Recognition in UAV Images", Sensors vol. 20, no. 21, pp. 1-23. 2020, https://doi.org/10.3390/s20216205.

Contribution of individual authors to the creation of a scientific article (ghostwriting policy)

Priyanka Kanupuru contributed for the execution of algorithms and analysis of results.

N V Uma Reddy contributed for the analysis of results.