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Residual Life Assessment (RLA) Analysis of Apple Disease Based on Multimodal Deep Learning Model

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Abstract: Few works have been carried out for the vision-based Apple disease framework throughout the year. Mainly, apple disease recognition includes two issues: infection identification and disease classification. Because of the advancement of vision-based innovation, we got a better framework for this issue. The datasets are mainly grouped into four categories, i.e., typical, rot, blotch, and scab, the last three being the three major kinds of defects found in apples. The aim is to distinguish these defective apples from the normal ones. In this chapter, we propose an Alex net and VGG-16-based deep learning model for classifying disease in all categories of apples. The performance of the Alex-Net model is 95.56 percent, whereas VGG-16 produces 94 percent accuracy rates. In both models, the highest classification accuracy has been produced for the rot disease apple category.

Keyword: *Apple, Disease recognition, Deep Learning, Training, Transfer learning*

1. Introduction

Apple is a common but nutritious food item. A doctor always advises that to a person to be healthy. Himachal Pradesh and Jammu & Kashmir majorly produce it for the country. With the high volume grown, it gets evident that some part of it is infected, and some might be inconsumable, maybe because of the fertilizers used in cultivation or different types of worms found in the soil. If the farmer that grows it or the consumer buying it wants to pick the uninfected ones, it will take time due to the large quantity produced. Sometimes one might have a defective one in hand but cannot recognize it, and it can be for any product, just not Apple.

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Compared with other non-destructive detecting procedures, machine vision systems dependent on RGB shading cameras indicated more potential for online organic product arranging and reviewing per shading, size, shape, and imperfections because of its ease and fast review speed [1-4]. However, using NIR organized light and NIR camera confounds the image classification and expands the creation expenses of the organic product evaluating framework. Furthermore, as shading, textural, and morphological highlights were often used to examine the deformities of natural products, the acknowledgment precision of those investigations was profoundly subject to the highlights chosen and removed [5].

It would be a great help if there is an application that can do this job for humans, which means by looking at the apple, it could identify the defect or the condition if consumable or not. It could be installed with cameras mounted on the walls of a room storing apples. A day's work can be done in minutes. Now, the bigger picture is how will such an application be built. A neural network needs to be used because these networks work in layers, and the outcomes of multiple data are mutated to obtain the best. The network needs to be trained for the job, and

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it can be done using a dataset containing numerous pictures of apples, both defective and good. The images are supposed to cover all types of diseases found in apples to date. Then the trained model will be tested on a dataset utterly different from the training dataset, which is expected to give a good accuracy value. The rest of this section is as follows. Section 2 describes the related work in the current area. The model of profound learning in portrayed in section 3. The dataset clarifies the proposed framework design in section 4. Section 5 presents the exploratory outcomes and our discoveries. Section 6 elaborate the results and discussion And Section 7 makes a few conclusions and recommendations for future work.

2. Related Work

Recently, a lot of progress has been finished regarding deformity identification. The author proposes a straightforward solution for fruit disease [6]. Disease segmentation using K-means clustering approaches has shown exact recognition results and is widely adopted [7-10]. The quality of fruit depends on the broad internal and external features. The quality parameter such as size, shape, colour, mass, and volume is classified as an external feature [11]– [12]. The sizes of apples are a crucial parameter for outward appearance because the quality of apples is mostly graded by size variability. The estimation of outside rate dependent on size is, in reality, progressively complex because of the sporadic size and shape. The meaning of size is removed dependent on its highlights, strikingly the length, the distance across, and width. The size estimations are increasingly challenging for apples' changeable shape as opposed to oval or round-formed natural fruit products [13].

Recently, the author [14] used wavelet sifting calculation to smooth the gathered apple leaf image, utilizing the shading contrast of the sores and limiting the following analysis to the disease region. The technique is essential for the programmed fast conclusion, counteracting apple leaf infections, and focusing on distinguishing plant illnesses by utilizing the picture highlights of plant sicknesses. Another author [86] has also explored the application of Ultrasound techniques to estimate the quality of apple fruits based on a firmness internal parameter. The experimental setup for determination of apple firmness. In this, a non-destructive ultrasonic system measures velocity and attenuation. The multiple linear regression model (MLRM) correlates the relationship between firmness and ultrasound parameters. They have found that an ultrasound technique is reliable for assessing apple quality. The proposed technology achieves an overall 82 percent accuracy rate. One of the other researchers [14] highlighted the role of velocity and attenuation in changing biochemical composition during the ripening process.

Machine vision is part of an engineering expert skill in consolidation with optical and mechanical properties, electromagnetic, and image processing methods. Machine vision frameworks are progressively fast regarding sample image assessment when analysing acoustic and vibration modes. The improvement of the application has increased a lot of enthusiasm for the quality assessment of agricultural products. The volume estimation is essential for fruit to decide the size per specific grading evaluations [18]. At the present stage, the principal worries in this machine vision now explore the capacity of machine vision to classify the agriculture product as far as quality parameters [17]. Till now, research has dealt with the primary practice of quality assessment with methods for machine vision frameworks [18]– [19].

In a computer vision-based system, each image is represented in some particular colour space. Many colour spaces are available in image processing; some common colour space is RGB colour space, HSI colon space, L* a* b* colour space [20-21]. For example, the RGB colour space is frequently utilized in exacting R G B individually of apple fruits which contains the three wavelengths with the composition of red, green, and Blue. As we know, RGB colour space hardware-based colour changes have been done by standard colour value of the particular image that can be identical to the human person in HSI colour space [22]. The machine vision framework plays a vital role in detecting colour, texture, shape, and illumination [23]. Identifying disease or external damage is ongoing with further, more challenging tasks. For instance, the exactness of the machine vision framework to assess the external part of food products depends upon a few elements, including the cultivar, planting area, and postharvest treatment of fruits [24].

The author [25] has presented a computer vision approach to improve productivity. The system comprises a camera, frame grabber, and sample holder components. In this image, samples are kept on a sample holder. Image processing techniques mostly do the quality analysis of fruits and vegetables. This technique consists mainly of four steps, where the first step is to do pre-processing to remove unwanted noise, the second segmentation process is to extract the background of the image sample, followed by feature extraction to extract the parameter responsible for the quality, finally, applying classifiers to detect the performance of the proposed system.

The author [26] first prepared the image acquisition chambers set to grade the apple quality. Various components are arranged in the image acquisition chamber, such as a lamp, focus, camera, reflection material, and sample holder. They have done the quality grading of apples based on three different class labels: Grade I, Grade II, and Grade III. This class is based on the value of color, size, and spot attributes. In the experiment step, the first pre-processing will have done by median filter followed by background extraction using Otsu Threshold techniques. After that, all segmented images are taken, and the spot pixels are extracted by calculating the ratio between the spot pixel and the total apple pixel. Also, colour and shape-based feature is calculated. They have shown that if the value of dominance is less or equal to 117, it falls into the unripe class, or if it is between 117 to 130, it comes under the semi-ripe apple. Otherwise, for more than 130, it falls under the third category, ripe apple. Finally, based on a fuzzy-based rule classifier, apple is classified into Grade I, Grade II, and Grade III.

A design framework was presented by the author [27]. The layout of the system is helpful for fruit grading. In this, the camera captures the image placed on the fruit place device, and the image processor will convert the image into a pixel value. This pixel value will be analysed, and finally, based on the class of quality, an assessment of the fruit will have done. In this, they have taken date fruit from the data sample set. The initial binary threshold method is applied to remove the background noise. The background removal image will process to the next step, where all feature is extracted based on size, shape, and intensity. The assessment and inspection of these mangoes are done manually, which consumes more time and high labour costs. As a solution to this, come into the field of the "non-destructive and automated fruit grading system" with the image processing techniques

The author presents a computer vision framework for Apple grading [28]. This model comprises a CCD camera with lens and filter, a fluorescent lamp, and a PC. All these components are connected via wire. They have labelled the sample apple in small, medium, and large categories. Image dilation and smoothing method were performed on the segmented approach. The relationship between various parameters to grade the apple class is based on distinguishing attributes such as area, diameter, Feret diameter, and roundness. The results show the highest accuracy has been achieved with Feret diameter for large apple classes, whereas less accuracy was received for medium apple classes with roundness parameters.

Image processing is a widely applied technique for sorting fruits in agriculture fields. Author [29] also presents the Machine Vision system for the quality determination of Apple. This framework consists the component such as a Conveyer assembly, an Electric power drive, Fruit samples, an Illumination unit, Light sources, a Camera, a Control unit, Computer, Frame grabber software, and Variable-frequency control. The grading of apples is done based on three categories such as ripe, unripe, and overripe. The author presents an artificial intelligence-based structure for sorting apples [30]. Their study briefly described the role of image processing and AI in sorting the apple. The present model helps capture the image of the apple. Next, it goes for the segmented process, and all feature is extracted to obtain a segmented image of an apple based on colour, mass, and volume feature. Finally, ANN-based regression method quality grading has been done. The proposed system has produced 80 percent accuracy rates for sorting apples.

A hardware and software-based model system is explored to sort an apple by author [31]. They have utilized a conveyor belt, AC motor controller, webcam, sensor and serial commination board. In this model apple sample is kept on conveyor belt, where they pass through webcam device capture the image. This dilatation and erosion operation play an important role to improve the performance of proposed system. Further, Size of apple sample based on calibre determination method. This method extracts the pixel value of images based on weight of respective image 89.5 percentage of accuracy rate is achieved by the proposed system.

The author [32] proposed a framework for learning all processes, such as background removal, feature extraction, training, and classification. This approach is applied to a different scope of issues in the horticultural produce, such as the quality grading of apple. It is indicated that shape, colour, and texture attributes together produce more exact quality grade results. They used a neural network and SVM classifier to grade the apple. The neutral network achieved more accuracy than SVM, with a value of 93.33 percent. Unfortunately, a labour hand-based quality grading of fruit has many disadvantages. Via computerizing the method and utilizing new techniques, the system's performance a neural network and SVM classifier to grade the apple. The neutral network achieved more accuracy than SVM, with a value of 93.33 percent. Unfortunately, a labour hand-based quality grading of fruit has many disadvantages. Via computerizing the method and utilizing new techniques, the system's performance many disadvantages. Via computerizing the method and utilizing new techniques, the system's performance may improve.

In this paper, author [33] has presented a novel framework based on the bio-inspired sensing system for sorting the apple. The proposed method shows a prominent accuracy rate of 92 percent. A similar type of framework is presented by the author [34]. They must grade the apple by regression model based on mass and volume features. The proposed system produces a 91.76 percent accuracy rate for grading apple. towards a coordinated framework for the agriculture industry. These goals will take care of the issues, yet they will likewise give legitimate knowledge of internal and external parameters in the machine vision

3. Deep Learning Models

Deep Learning is a machine learning technique that can classify information more easily using network models like CNN, ANN, etc. It has applications in various fields like audio recognition, image processing, speech recognition, natural language processing, board games, and also medical purposes. The idea is to train a machine using big datasets using different techniques like supervised, semi-supervised, and unsupervised Learning. It is an iterative process using multiple network layers to extract the best features from the raw input. Different algorithms propose simple and time-saving techniques so that the number of layers can be reduced and the best features can be extracted. Mainly we have used two major deep learning models here.

3.1. Alex Net

Earlier datasets like CIFAR and NORB were used, which contained just some thousands of images. However, for real-life applications, including massive datasets like ImageNet, the need for a more capable data learning model has arisen. So here comes Alex Net in the play. It is a Convolutional Neural Network technique proven highly efficient in image recognition. This model's highest error percentage that can be achieved is 15.3%, which says it has a promising accuracy. It consists of eight five convolutional layers and three fully connected like any other CNN.

Some other essential features of Alex Net are:

3.1.1 Rectified Linear Units (ReLU) Non-linearity: It is used because of its ability to complete the job in less amount of time. It is proven to be six times faster than any other technique.

3.1.2 Multiple GPU's: While using such big datasets, the image load must be distributed over multiple GPUs to save training time. This also helps in training big models in an efficient time.

3.1.3 Overlapping Pooling: Pooling helps in reducing the complexity of the representation by reducing the number of parameters in the network. Overlapping pooling refers to the phenomena when the output of two neighbouring group is same then they can be considered as one hence, reducing the number of parameters. It also finds reduction in error.

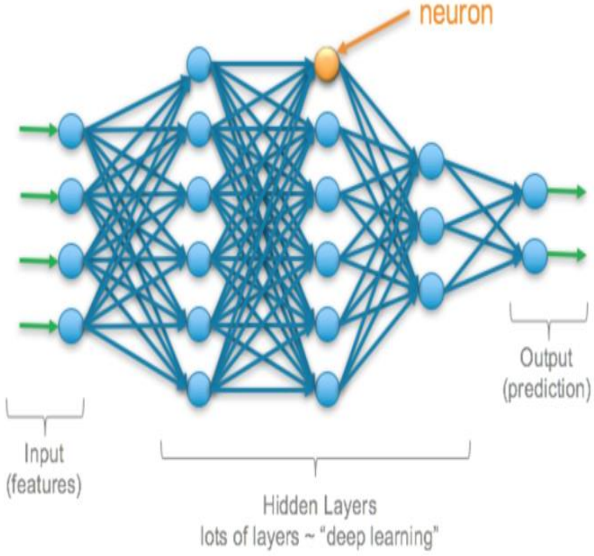

Fig. 1: Neural Network Model

3.1.4 Overfitting: This problem is associated with big datasets, and it can be tackled by using a model large enough and keeping the weights small. It can also make the optimization faster and positively affect overall performance.

3.1.5 Data augmentation: An intelligent technique can increase the training set's data without collecting new data. The goal is to train the dataset best to promise the highest accuracy, and we don't need to order new relative images because that may increase error and overfitting. Because neural networks are more inclined towards that frame that promises best accuracy so one can focus on that one properly and increase the amount of data without affecting the accuracy.

3.1.6 Dropouts: Dropout, as the name suggests, refers to dropping out of random testing units while training the dataset. While the testing phase, a neural network learns new specializations, which also increases the weight of neurons in the model. This could improve dataset training by maintaining the same weight, reducing overfitting, and optimizing performance.

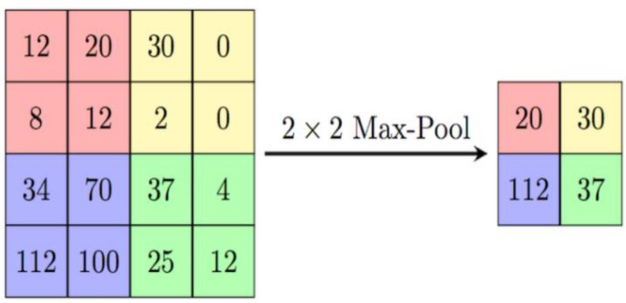

Fig 2: Pooling architecture in NN

3.2 VGG (Visual Geometry Group) Net

VGG-16 is an advancement over Alex Net, promising around 92%. The architecture is almost the same as Alex Net; multiple 3x3 filters replace the large kernel-sized filters. The input to the first convolutional layer is a 224x224 RGB image. Then the image passes through other layers with the filter sized 3x3 (smallest). In a particular configuration, it uses 1x1 conv.

4. Proposed Method

4.1 Image datasets:

There are four kinds of apples for identification and classification. The apple is classified as (a) apple scab, (b) average apple, (c) apple blotch, and (d) apple rot. These images were taken in a fixed foundation instead of under normal conditions. This section chooses the apple image from the informational collection for research. Some disease images appear shown in Fig. 3. All indications pictures were resized to 128 × 128 × 3 for the acknowledgment. After the de-duplication activity, the informational collection contained 240 images. The built dataset was then isolated into preparing and test datasets in a proportion of 8:2 by arbitrarily choosing pictures as indicated by the classification name proportion from the dataset.

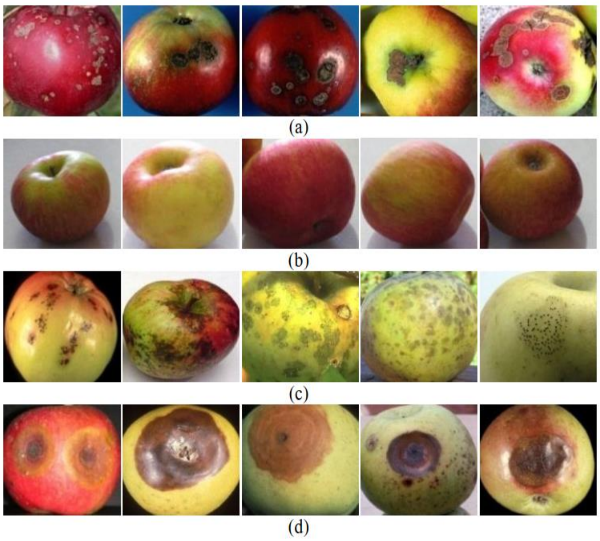

Fig 4: Example data set images (a) apple scab, (b) normal apple, (c) apple blotch, and (d) apple rot

4.3 Training

We must prepare a training set of image data for a network model. It should be large enough to test all the meaningful possibilities or possess all the test set's characteristics. Here, we have introduced two models, I.e., Alex Net and VGG-16 using supervised learning methods on an NVIDIA GeForce GTX 1050 graphic processor, which gives different accuracies. We have used a training set of over 2000 images containing 500 images for each rot, blotch, and scab disease, including additional features.

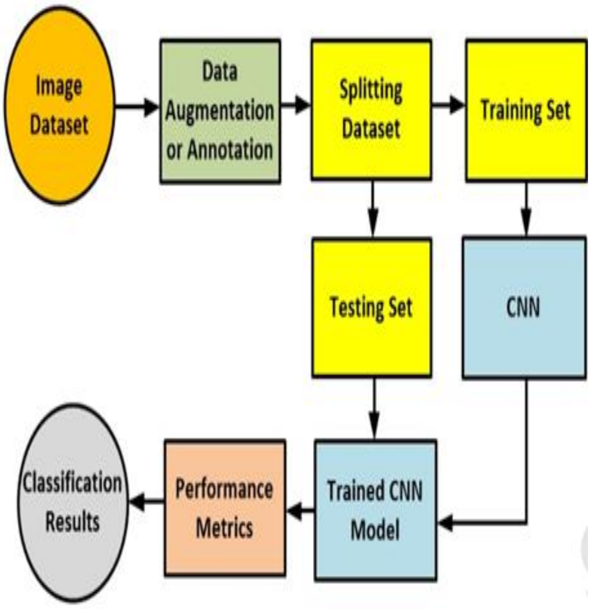

Fig. 4: Block diagram of a deep learning-based recognition model

4.5 Validation

It consists of about 20 percent of all the data used. Sometimes validation is performed in the training phase so that parameters can be tuned for selecting the best model. Overfitting is checked in the proof set to eliminate errors or for future predictions. The details of the data argument in both Alex Net and VGG-16 are described in Tables 1 and 2.

Table 1: Before Data Augmentation

Model	Dataset	Training	Testing
Alex Net	Blotch	61	10
	Normal	65	10
	Rot	76	9
	Scab	66	11
VGG-16	Blotch	61	10
	Normal	65	10
	Rot	76	9
	Scab	66	11

Table 2: After Data Augmentation

Model	Dataset	Training	Testing
Alex Net	Blotch	479	70
	Normal	526	69
	Rot	612	77
	Scab	526	63
VGG-16	Blotch	479	70
	Normal	526	69
	Rot	612	77
	Scab	526	63

5. Experimental Setup:

We implemented the proposed method for classifying apple disease using the Deep learning model. Below, Table 3 and Table 4 briefly explain the implementation and corresponding results. In Alex Net before Image Augmentation, we used an optimizer as Adam with a batch of 4, each size 12. As we have used the Adam optimizer, the momentum is not considered by default, and the learning rate is 0.01. Similarly, after Image Augmentation for Alex Net, the optimizer we have used is the same, i.e., Adam with 22 batches with each batch size of 15. The momentum and learning rate are the same as before.

Table 3: Alex net

Parameter	Values before IA	Values after IA
Optimizer	Adam	Adam
Batch	4	22
Batch size	12	15
Momentum	-	-
Learning	0.01	0.01

For VGG-16, we have used SVG optimizer before and after image augmentation. Before augmentation, the number of batches implemented is 8, with a batch size of 0.9, a momentum of 0.9, and a learning rate of 1. Similarly, for after-image augmentation number of batches implemented is 33, with a batch size of 13.

Table 4: VGG-16

Parameter	Values before IA	Values after IA
Optimizer	SVG	SVG
Batch	8	33
Batch size	12	13
Momentum	0.9	0.9
Learning rate	1	1

5.1 Performance Metric:

In the section we have analysed deep learning model for identification and classification of apple disease. The performance measure of the proposed system was introduced given as:

$$\mathbf{CA} = \frac{\begin{array}{c}Total\ numer\ of\ fuits/vegetables\\ correctly\ classified\ image\ used\ for\ testing\end{array}}{\begin{array}{c}Total\ number\ of\ fuits/vegetables\\ image\ used\ for\ testing\end{array}} * 100 \qquad (1)$$

$$\mathbf{Precision} = \frac{total\ value\ of\ true\ positive}{\begin{array}{c}total\ value\ of combination\ with\\ true\ positive\ and\ false\ positive\end{array}} * 100 \qquad (2)$$

$$\boldsymbol{Recall} = \frac{total\ value\ of\ true\ positive}{\begin{array}{c}total\ value\ of combination\ with\\ true\ positive\ and\ false\ negative\end{array}} * 100 \qquad (3)$$

$$\boldsymbol{F-Score} = 2.\ \frac{Precision.recall}{Precision+recall} * 100 \qquad (4)$$

6. Results and Discussion:

For Alex Net and VGG-16, we used around 270 training datasets before image augmentation, while for testing, we used 40 data sets. In Alex Net, before augmentation, we got an accuracy of 86.11% by implementing 200 epochs, and it took around 2 hours for execution. In VGG-16, the precision we got before image augmentation was 88.88% after executing with 150 epochs, and it took about 4 hours to complete. After image augmentation, we got a dataset of over 2000 images for training and over 200 for Alex Net and VGG-16 testing. In Alex Net, it took around 3hrs to complete its execution of 100 epochs with an accuracy of 94.44%. While in VGG-16, it took 7hrs to complete 150 with weighted accuracy of 94%. Table 7 and 8 shows the Evolution of each class with its precision, recall, and f-score for both models before and after Image Augmentation. Both model VGG models proved better results, with a value of 88.88 compared to Alex's net model. The details of all classes of apples with different performance model results have shown in Table 5 and Table 6.

Table 5: Before Image Augmentation

Model	**Accuracy**	**Dataset**	**Precision**	**Recall**	**F-Score**
Alex net	86.11	Blotch	80	80	80
		Normal	91	100	95
		Rot	100	82	90
		Scab	70	78	74
VGG - 16	88.88	Blotch	89	80	84
		Normal	91	100	95
		Rot	82	82	82
		Scab	89	89	89

Table 6: After Image Augmentation

Model	**Accuracy**	**Dataset**	**Precision**	**Recall**	**F-Score**
Alex net	95.55	Blotch	100	97	99
		Normal	100	100	100
		Rot	100	94	97
		Scab	90	100	95
		Blotch	94	86	90
VGG-16	94.00	Normal	100	100	100
		Rot	94	97	96
		Scab	88	92	80

7. Conclusion

In this paper, we have proposed deep learning model-based approach to the classification of different categories of the apple. Here, we have considered two other models, Alex Net and VGG, to solve apple disease recognition. The deep learning model will build, and various performance metric has been implemented to check the performance of the proposed system. The metrics used are performance accuracy, Precision, recall, and F-score. The results show that the Alex Net model is more accurate than VGG-16 after the segmentation. The performance of the Alex Net model is 95.56 percent, whereas VGG-16 produces a 94 percent accuracy rate. In both models, the highest accuracy has been made for the Rot disease apple category.

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