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Onion Classification using Color and Convolutional Neural Network

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Abstract: One of the most critical processes in producing fruits and vegetables is sorting, which is typically done manually in most countries. Onion production is large-scale in India, mainly in Maharashtra's West Region. As a result, it would be more useful in the industry for sorting and grading onions. Food quality detection and grading have benefited from the machine learning application then computer vision techniques. The task of distinguishing infected/uninfected onions from images of their exterior surface is investigated using various methods. One of the supreme important economic sectors in our nation is agriculture and it shows a critical part in our country's economic growth. Agriculture fruits are processed by cutting them from their natural forms, washing, sorting, grading, packaging, and shipping. Grading of onion is a significant step for protecting the quality of fresh-market items. The exterior appearance of the fruits is used to sort agricultural goods. Shape, size, and color are used to grade the items. In this study, HSV ranges are used to categorize onions into red and white colors. A convolutional neural network is also used to categorize the onion pictures into good and damaged quality.

***Keywords*: *CNN, Color, deep learning, HSV, Onion sorting*.**

1. Introduction

One of our nation's best performing industries, farming is essential to the expansion of our economy. Fruits of excellent grade are in great demand due to our nation's expanding population. Agricultural produce is handled in many ways, including cutting fruits and vegetables from the farm, “washing, sorting, grading, packing, transporting, and eventually storing”. Sorting and grading are significant processing which is responsible for protecting the quality of fresh-market items. The texture or exterior appearance of fruits is used to sort agricultural goods.

On the other hand, grading is done based on the overall qualitative aspects of a fruit by taking into account. A variety of qualities such as size, shape, color, and so on. The fruit industry is becoming increasingly discerning, with providers being required to provide superior quality and appearance products. As a result of the growing demand to offer high-quality fruits in a short amount of time, there is a heavy demand of automated fruit grading systems.

India is a rapidly developing country, and cultivation is the strength of the country's early development. The ground is come across encounters as a result of urbanization and globalization principles. Also, knowledge of the need for cultivation must be fostered in the minds of the younger generation. The importance of innovation in the modern world is crucial in many disciplines, yet we still rely on outdated methods in agriculture. A mistaken diagnosis of plant disease results in a significant loss of output, time, money, and product quality. Segmentation approach utilized to be performed directly by trained personnel, but forecasting is becoming more challenging due to the various changes in the environment. As a consequence, vegetable grade can be determined using image processing methods. Due to a scarcity of resources, such as human resources, the quality of fruits then vegetables is now an essential factor, besides grading based on quality is a critical responsibility. The grading procedure will be automated using Computer vision-based technology. The main area of this approach is to use a deep learning algorithm to sort onions by color and quality.

A machine imaging system serves as a low-cost tool that offers dependable operation, quick processing, and precise fruit assessment. Because of the availability of infrastructure, computer vision-based sorting and grading has seen significant expansion in the agriculture industry in both developed and developing nations. The development of clear and meaningful descriptions of physical things from images is known as computer vision. For classification

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problems, deep learning algorithms are more successful. As a result, a (CNN) Convolutional Neural Network may be used in this methodology to categorize onions into good and damaged quality.

2. Literature Survey

Hongshe Dang et al. [1] suggested a picture centered method for classifying then determining the size of fruit. The system uses an “ARM 9 processor” as its main processor and uses image processing methods to identify the size of fruits on the QT/Embedded platform.

John B. Njoroge et al. [2] have produced an image-processing-based programmed classifying technique that emphases on the internal and exterior failings of the fruit. The system is made up of six CCD cameras. They makes the arrangement of cameras to capture the fruit image. four cameras were used ; two on right side and two on left side. The fruits are analyze using image processing to classify according to shape, size and grade.

To determine the colour of the vegetables, Dah-Jye Lee et al. (2011) [4] developed a Direct colour mapping technology. The benefit of this method is that you may adjust colour selections or grading standards depending on the use case. It is an easy technique to use.

D. Savakar et al.[5] presented the fruit grasing system by considering five fruits Orange, mango, apple, chickoo, and sweet lemon. The system utilized 5000 samples of fruit type. For classification, 18 color features and 27 textural features were considered. The proposed system recorded the classification accuracy of 94%, 93%, 92%, and 92%, for Chickoo, apple, sweet lemon, orange, and mango respectively.

Deepa [6] provided a technique for evaluating the characteristics of defected and non-defected fruit grading and classification. There were 200 mosambi fruits in the image database. Design, difficulty, and texture characteristics were calculated. Following PNN classification, it was discovered that the features of form, quantity, and surface contributed 100%, 92%, and 96% of the recognition, accordingly.

For rating the fruits, Mustafa et al.'s [7] new approach was suggested. This article looked at five fruits: mangoes,oranges,apples,bananas,carrots . Size and colour parameters were extracted from fruit photos. Despite having nearly identical shapes and sizes, “morphological characteristics” were used to discriminate among oranges and apples, as well as bananas as well as carrots. In order to prevent confusion among apples and oranges as well as bananas and carrots, colour features were used, increasing accuracy to 79–90%.

The authors of [8] provided an approach for sizing different fruits and classifying them according to their size employing “fuzzy logic”; in this instance, the author suggested utilising “MATLAB” for extraction of features and GUI design.

Machine learning methods were employed by Jamuna et al. [9] to train the model. Extracted features from 900 seeds of cotton. They found that the precision rates of the decision tree classifiers and MLP were 98.7% and 94.22%, respectively, for the classification of seed cotton. Their findings show that, with 52 incorrect categorizations the classifier based on Naive Bayes had the highest error rate, while the selection tree and MLP classifier each had 11 incorrect classifications.

3. Proposed System

The block diagram of the IoT-based Smart farming is as depicted in Fig.1.

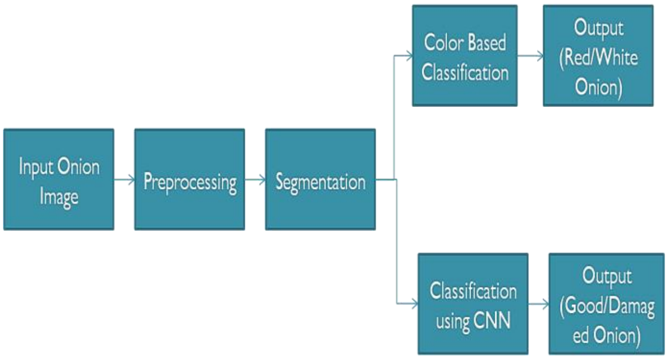
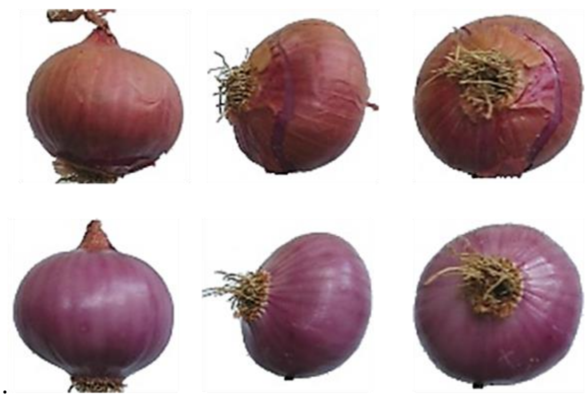


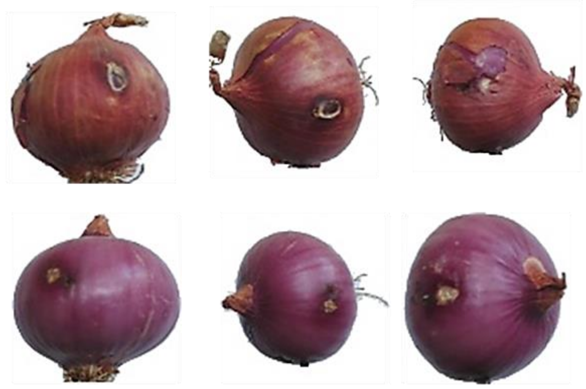
Fig. 1. Block diagram of the proposed system

A. Input Image

The images were taken from the Fruit 360 dataset [10], which may be found on the internet. Images for training and testing are included in the dataset. After planting fruits and vegetables in the shaft of a low-speed motor, a 20-second video was captured (3 rpm). A Logitech C920 camera was used to film the fruits. It's one of the most powerful cameras available. A white piece of paper was placed behind the fruits. The backdrop, however, was not consistent owing to fluctuations in lighting conditions; therefore, we created a specific algorithm to extract the fruit from the backdrop. For this method, we used onion as a criterion. The onion dataset example images are given in Fig.2



(a)



(b)

Fig. 2. Onion sample images of Fruit360 dataset (a) good quality (b) damaged quality

B. Pre-processing

The provided image has undergone pre-processing procedures in order to prepare it for subsequent manipulation. During the pre-processing stage, the image undergoes various image processing operations, including the conversion from “RGB to Gray”. The process of filtering plays a vital role in the pre-processing phase. In this particular scenario, the utilization of the median filter serves the purpose of noise reduction and image smoothing.

The weighted average approach is used to convert RGB to grayscale. The standard averaging procedure is ineffective because of a brightness issue. To convert an RGB image to a grayscale, we utilize the weighted average approach. Because red has the longest wavelength of all three hues, green is the hue that has a shorter wavelength than red and has a more relaxing impact on the eyes. We must reduce the contribution of red color, raise the contribution of green color, and place the contribution of blue color in the middle. As a result, the equation

$$Grayscale\ Image = (0.3 * \mathrm{R}) + (0.59 * \mathrm{G}) + (0.11 * \mathrm{B}) \quad (3.1)$$

According to this equation, Red contributes 30%, green contributes 59 percent, which is the highest of the three colors, and Blue contributes 11%.

The technique of reducing noise from images is known as filtering. During image acquisition, the camera's images are mainly influenced by several types of noise. To date, a variety of filtering strategies have been described and tested to see if they were appropriate for a range of applications. If an image has been damaged by impulsive noise, nonlinear filtering techniques are used. These nonlinear filtering approaches also take into account the nonlinear structure of the human visual system. Because salt and pepper noise appears as white and black dots layered on an image, median filtering is particularly effective in the presence of the noise. The median of the pixel's neighborhood under consideration is calculated and assigned to the exact location in the output image via median filtering. To eliminate noise from the images, the median filter was utilized.

C. Color-based onion classification

In this approach, the RGB image is converted into HSV colorspace. The Red and white color has different HSV ranges. Lower range of HSV color for red color onion is calculated as (50,90,20) while higher range of HSV is (120, 150, 170). The segmented image has proceeded for the calculation of a number of white pixels i.e. area. if the area is greater than the threshold value set by the user then it is concluded as red onion otherwise white onion.

D. Classification using CNN

The deep convolutional network, which involves three features learning, selection, and classification, recognizes seven states of facial emotions. However, having more than two layers was difficult to train, as this model contains many layers it is trained using GPU. CNN is a single among the neural network subtypes algorithms that is most popular for image classification problems. CNN algorithm consists of convolution, Max pooling, flattening, and fully connected layers. Fig. 3. shows the generalized architecture of CNN.

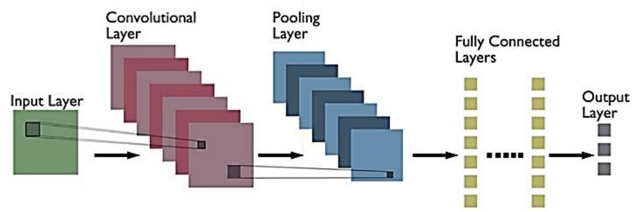


Fig. 3. Architecture of CNN

1) Convolutional Layer (CL): It is the primary block of the CNN. It aims to extract the different features from the images. It convolve the kernel with input image and makes the small images. To obscure the input image, a set of learnable neurons is employed. It creates a feature map in the output image, which is then sent as input data to the next Convolutional layer. It's written mathematically as

$$G[m,n] = (f * h)[m,n] = \sum_j \sum_k h[j,k] f[m-j, n-k] \quad (3.2)$$

where f = “input image” and h = “kernel”. The result “matrix's row and column indexes” = m and n, respectively.

2) ReLU Layer: ReLU is a “non-linear operation” that consists of units based on rectifiers. The operation is performed on a “per-pixel” basis, known as element-wise, where all non-positive values in the “feature map” are replaced with zero. It results in an increase in the non-linearity observed within the dataset. Let assume that the input to the neuron is denoted as x, and the rectifier function is defined as.

$$f(x) = max(0, x) \tag{3.3}$$

3) *Pooling Layer:* The pooling layer extracts the most important features by reducing the feature map size. Each region of a feature map is downsampled using a nonlinear method such as min, max, and average. This layer provides the data with high generalization, fast convergence, and min distortions.

4) *Flatten Layer:* Upon the completion of the initial two steps, it is expected that a pooled feature map has been obtained. As indicated by its nomenclature, the pooled feature map will be transformed into a columnar shape.

5) *Fully Connected Layer (FCL):* By employing these traits and the training dataset as a model, the FCL is intended to classify the input image into several categories. The FCL's output probabilities are summed up and equal 1, therefore 1. Softmax is used as the "activation function" to ensure this. A vector of arbitrary real-valued scores is reduced by the Softmax function to a single value that sums to one.

6) *Vgg16:* The vgg16 algorithm's structure is seen in

Fig. 4.

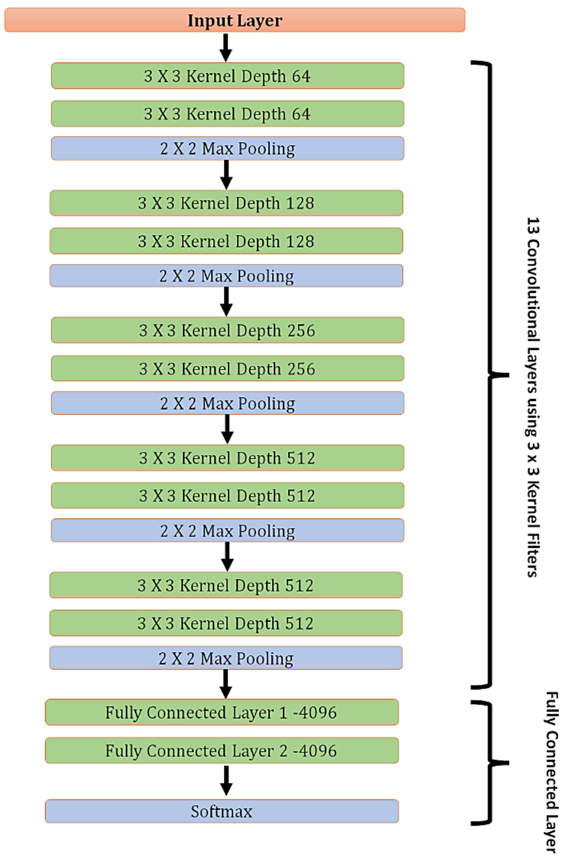


Fig. 4. Model architecture of VGG-16

- The 1St and 2nd CL are 64 feature "kernel filters", every 33 pixels in diameter. The RGB picture with layer 3 source image's sizes become 224x224x64 after going through the first and second convolutional layers. The result is subsequently sent with a stride of 2 to the max-pooling layer.
- The "124 kernel filters" in the 3rd and 4th CL have a filter size of 3X3. After these two layers, a "MPL with stride two" is applied, and the output is shrunk to 56x56x128.
- The 5th, 6th and 7th layers are all "convolutional layers with 3X3 kernel size." All layers uses "feature map" of size 256 and MPL with "stride 2".
- The kernel size of the 8th to 9th CL is 3x3. Each of these CL sets contains 512 kernel filters. A MPL with a stride of 1 follows these layers. The 14th and 15th layers are 4096-unit FCL, followed by a 1000-unit softmax layer (16th layer).

4. Results

The proposed onion grading system's outcomes are assessed using qualitative and quantitative methods. The outcomes of the given onion grading system are evaluated using both qualitative and quantitative approaches.

E. Qualitative Analysis

The purpose of qualitative analysis is to describe the detailed information and description of the results. Qualitative analysis allows for subtle distinctions since the data does not have to be crammed into a certain number of classifications. The analysis is capable of detecting ambiguity in human language. Fig.6 depicts the result of the onion sorting mechanism.

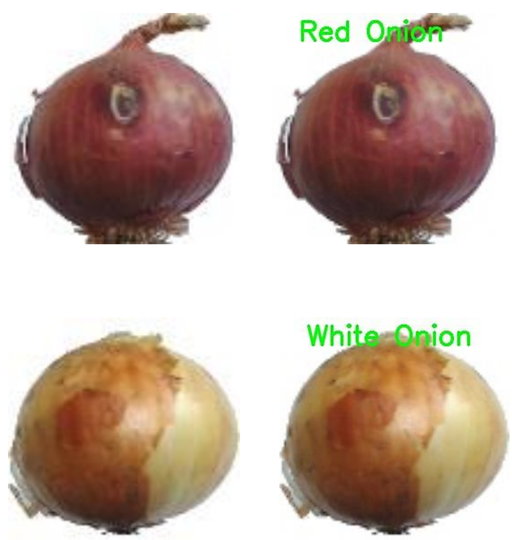
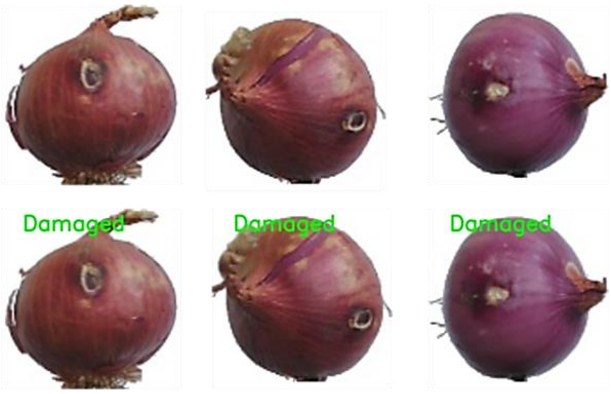
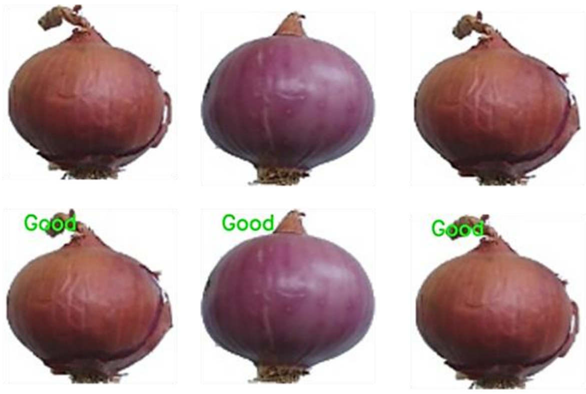


Fig. 5. Color based onion classification of (a) Red Sample (b) White Sample



(a)



(b)

Fig. 6. Output of onion grading system (a) Damaged onion samples and respective output (b) Good onion samples and respective output

In the first section, the damaged sample of onion is taken as an input to the system. In the second section, good onion samples are taken as input and observe in the system's output. From examination of the proposed system's quality, it is observed that the system shows the best results. It can accurately detect the quality of the onion.

The database distribution for the training and validation is as shown in TABLE I.

TABLE I. DATABASE DISTRIBUTION

	Total	**Good**	**Damaged**
Training	961	582	379
Testing	239	145	94

F. Quantitative Analysis

In the realm of quantitative research, the methodology involves identifying specific characteristics, quantifying them, and potentially developing more complex statistical models to explain the observed phenomena. The generalizability of the findings can be extended to a broader population, and meaningful comparisons between two datasets can be made provided that a reliable sample and appropriate statistical methods are employed. Hence, the utilization of quantitative analysis enables us to differentiate between instances that are mere chance happenings and those that are more probable to be reliable representations of the behavior of a language or its variant. The analysis of a specific language variant is a more straightforward process that produces accurate visual representations of the frequency and rarity of specific occurrences, as well as their relative prevalence or deviation from the norm.

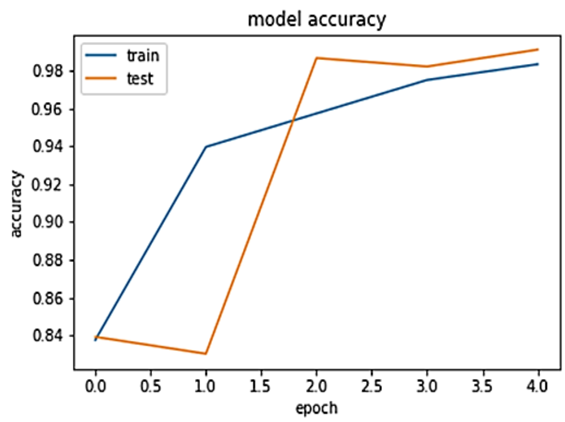
Using an accuracy parameter, the quantitative analysis of the suggested system is computed. The facial recognition system's accuracy is shown by the equation (Eq.5.1).

$$Accuracy = \frac{No\ of\ faces\ correctly\ detected}{Total\ no\ of\ samples} \quad (5.1)$$

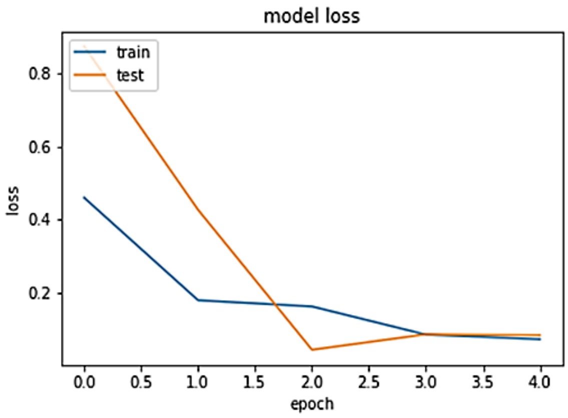
The Presentation analysis of the onion classifying scheme is as shown in Fig. 7.

```
Epoch 1/5
31/31 [==============================] - 1484s 48s/step - loss: 0.7572 -
acc: 0.7159 - val_loss: 0.8756 - val_acc: 0.8393

Epoch 00001: saving model to facedetect.hdf5
Epoch 2/5
31/31 [==============================] - 1341s 43s/step - loss: 0.2396 -
acc: 0.9286 - val_loss: 0.4274 - val_acc: 0.8304

Epoch 00002: saving model to facedetect.hdf5
Epoch 3/5
31/31 [==============================] - 1339s 43s/step - loss: 0.1537 -
acc: 0.9599 - val_loss: 0.0436 - val_acc: 0.9866

Epoch 00003: saving model to facedetect.hdf5
Epoch 4/5
31/31 [==============================] - 1330s 44s/step - loss: 0.1275 -
acc: 0.9677 - val_loss: 0.0859 - val_acc: 0.9821

Epoch 00004: saving model to facedetect.hdf5
Epoch 5/5
31/31 [==============================] - 1395s 45s/step - loss: 0.0341 -
acc: 0.9924 - val_loss: 0.0836 - val_acc: 0.9911

Epoch 00005: saving model to facedetect.hdf5
dict_keys(['loss', 'acc', 'val_loss', 'val_acc'])
```

(a)



(b)



(c)

Fig. 7. Quantitative analysis (a) Training progress (b) Accuracy plot (c) Loss plot

The quantitative analysis of the proposed system is tabulated in Table II.

TABLE II. DATABASE DISTRIBUTION PERFORMANCE ANALYSIS OF TRAINING OF THE SYSTEM

Epoch	**Training Accuracy**	**Training Loss**	**Validation Accuracy**	**Validation Loss**
1	0.7159	0.7572	0.8393	0.8756
2	0.9286	0.2396	0.8304	0.4274
3	0.9599	0.1537	0.9866	0.0436
4	0.9677	0.1275	0.9821	0.0859
5	0.9924	0.0341	0.9911	0.0836

The performance Table II. shows the performance of the training and validation of the system. The training and validation accuracy of the system increases while training and validation loss decreases at each epoch. At the last fifth epoch, the training accuracy and loss are observed as 0.9924 and 0.0341, respectively, while the validation accuracy and loss are observed as 0.9911 and 0.0836, respectively. The accuracy obtained is best and satisfactory.

Observing ethical standards

Competing Interests. The corresponding author declares that there are no competing interests on behalf of the other writers.

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5. Conclusion

In this approach, we present the onion grading system using a convolutional neural network with the help of the Vgg16 transfer learning model. The Fruit360 dataset is used for the evaluation of the system. The dataset consists of red onion and red peeled onion. The dataset is split into 80% for training and 20% for testing purposes. The CNN architecture with vgg16 pre-trained network is used to train the classification model. The training performance of the system shows excellent results. At the last fifth epoch, the training accuracy and loss are observed as 0.9924 and 0.0341, respectively, while the validation accuracy and loss are observed as 0.9911 and 0.0836, respectively. Also, the qualitative analysis of the system shows promising results.

In the future, this model can be trained for more samples of the onion, including white onions. The system can also be implemented for more vegetables/fruits.

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