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Assessment of Quality of The Wheat Grain Using Image Processing and Mask R-CNN

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Abstract

Wheat, a cereal cultivated worldwide as a staple food and India is the second largest producer of wheat, determining the quality and then categorizing it as storage quality, edible, seeding quality or rotten is a case of deep learning (DL). The main aim of this research study is to develop a system that is capable of classifying the quality of the grain. In this regard, a Mask regional convolutional neural network (Mask RCNN) model is developed. In order to train and test the model, a total of 122 images are created from 2000 grains which are divided into 4 categories. Image processing is employed to extract the texture of the wheat grains from the images. The wheat grains in the image are annotated using the VGG image annotator. Then the JSON files are downloaded in the local disk which are used for training and testing the images by Mask RCNN. The model is trained in batches of images with 500 steps per epoch, a non-max suppression threshold of 0.2 and a learning rate of 0.001. The developed model showed a training and validation loss of 0.0002 and 0.222 respectively. In order to test the practicality of the proposed algorithm, the model is tested for an image of wheat grains with all of the four classes in it which is not yet used for training and testing. The Mask RCNN is able to classify all the classes with an accuracy of 0.923 for storage quality, 0.98 for edible, 0.95 for seedling quality and 1.00 for rotten.

Keywords: Wheat grain, Mask RCNN, Image processing, VGG Annotator.

1. Introduction

Wheat, a cereal cultivated worldwide as a staple food. The seeds of wheat are pounded to get flour from it which is then used for making breads, sweets, and traditional flatbreads etc. In the year 2020, about 761 million tonnes of wheat is cultivated of which India, China and Russia cultivated about 38% of the total production [1]. The wheat exporting countries are competing among themselves based on the quality of wheat. Moreover many countries are committed to improving the wheat quality. Hence, it can be said that the quantity as well as the quality of the wheat are equally important in today's market to protect the consumers from substandard products [2]. In this research paper, the quality of the wheat is assessed using image processing techniques. The present research was inspired by the lack of technical resources for agricultural workers to test the quality of wheat. Today, in comparison with other grains and food products, wheat must meet certain specific standards. At harvesting time, quality control is critical. There will also be varying standards from different customers, depending on what they are using the wheat for. Most flour is made from wheat. Millers assess and blend different wheat varieties to produce flour to exact specifications for each customer and end-purpose. The flour used in one product could be very different from the flour used in another. However, there are three main issues in the current inspection process:

1. Turnaround Time (TAT): Processing Storage Receipt is time consuming and has to be done under 24 hours. Using too many labs is expensive and maintaining consistency becomes difficult.

2. Quality of Work: Human error in evaluating commodities can have a significant impact on valuation of goods. Depositors & banks are very particular about the valuation. In fact, approximately 100 lakh metric tonnes of wheat is wasted every year due to poor storage (especially with undetected spoiled grains).

3. Fidelity: Misappropriation in stock, presence of foreign matter, and other such factors is a major problem when it comes to evaluating goods.

With the advancements made in the field of technology, many researchers are focussing on developing advanced tools to determine the quality of the wheat grains. Traditionally, the quality of the wheat is determined by physical inspection, however it is an inefficient method as it is impossible to physically scrutinize most of the grains. Hence researchers came up with the idea of integrating computer and machine vision for not only assessing the quality but also classifying the good and bad quality wheat grains.

1.1. Motivation and Novelties

In this article, image processing techniques are used to determine the physical properties including length, width, area, aspect ratio, color features such as HSV value to determine the quality. Furthermore, a Mask Region-based Convolutional Neural Network (R-CNN) model is created to classify the wheat grains as storage quality, edible, seeding quality or rotten.

Remainder of the paper is arranged as such. The section 2 of the paper briefly describes the findings of contemporary literature. Section 3 is the material and methodology part that briefly describes the methodology adopted in the paper followed by section 4 which summarizes the results and discussion. Finally section 5 is the conclusion of the paper.

2. Literature Reviews

Assessing the quality of wheat grains is a novel topic and hence very little research paper exists in this domain. However there exists some research to assess the quality of other grains which are summarized in this section of the paper.

In the article [3], authors have correlated the quality of rice grains with physical quantities such as the length, width and color features of the grain. They have used vernier calipers with precision of 0.02mm and weighed it on a balance with least count of 0.0001 g. The authors took a laborious and complex way of computing the quality by analyzing the features using Excel software. In the article [4], the authors used stereo vision (SV) to determine the length, width and thickness of wheat grain. The model also employs the SV for detecting the presence or absence of a line or black spot in the wheat grains of a sample. The SV extracts a 3d digital image of the grains. In paper [5], the authors graded the quality of the rice grains based on the size. In the paper, the authors take the digital image of the rice grains with a high resolution camera. The images are converted into binary from which morphological features are extracted. In [6, 7], the author built a neural network (NN) to classify the quality of the grains as good and bad. In the paper [8], the authors built another feed forward NN to count the number of large and small sized seeds. The paper also proposes an image processing model to extract the features of the grains. In [9], the authors proposed a grain quality testing model and an identification model with the help of NN to identify quality of the grains based on their physical appearance. The features are taken as input of the NN which are trained to detect and predict the type, category, impurity and quality of the grains. In the article [10], the authors employed top-Hat transformation to detect the quality of the rice grains. In article [11], the authors have developed an image processing technique to compute the HSV and RGB values of the rice-grains which are then mapped to extract the color of the grains.

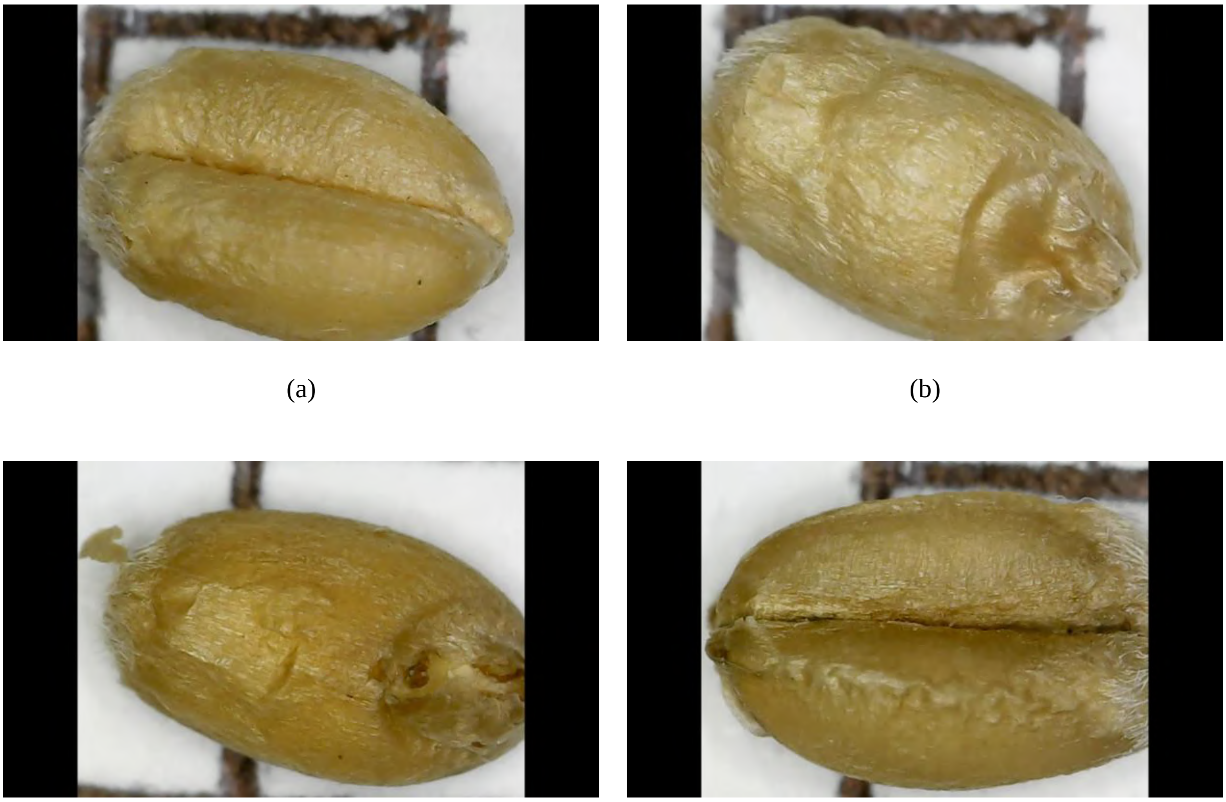
Some other papers are reviewed for compiling the research article. But limiting the literature review part to the most recent and the significant papers.

3. Materials and Methods

In this section of the paper, a brief description about the dataset and the preliminary methodologies adopted is discussed in brief.

3.1. Dataset

The dataset is a set of digital images of wheat grains captured using a micro-camera. In order for the processing to commence, a grain was placed in the allotted area in the prototype. With the help of a micro-camera, images of grains are taken which are kept on a surface of known area. Based on fulfilling the objectives of the present research, the grains were stored in 4 different conditions like stored in a closed area, kept inside the room, soaked once, soaked for 2 days in water. Figure 2 shows the pictures of the wheat grain from the 4 different conditions.



(a) (b) (c) (d)

Figure 1: Picture of wheat grain (a) Stored in closed area, (b) Kept inside room, (c) Soaked for 1 day and (d) Soaked for 2 days

3.2. Methodology

3.2.1. Image processing

Image processing is the process of extracting useful information from an image by performing different operations on it [12]. The different image processing steps which are used in this research paper are as follows:

Grayscale conversion

In this step, the digital images are converted into grayscale images. The grayscale images represent only the information of light intensity. Unlike the RGB images, the grayscale images typically display from the darkest black to the brightest white i.e. the image only consists of black, white, and gray colors [13]. The advantage of converting a RGB image to Grayscale image is that it reduces the computational complexity of the algorithm [14].

RGB and HSV determination

In this step of the paper, the RGB i.e. Red, Green and Blue and HSV value i.e. Hue Saturation Value of of the digital image of the wheat grains is determined using the OpenCV library. The RGB and HSV value of the wheat grain is determined in order to extract the color features of the images.

Pixel intensity

For feature extraction, pixels play a very important role. All the information of a picture is stored in the pixels of the image [15]. Therefore in this step the pixel intensity is adjusted so that maximum information could be obtained from the images.

Edge detection

Edge detection in image processing is the way of detecting the boundaries of objects in the images [16]. The process of edge detection works by detecting the discontinuities in brightness of the objects. This process is mostly used for data extraction. Canny edge detection [17] technique is used for detecting the edge of potholes in the project.

Contour detection

Contour detection can be defined as the process of joining all the continuous points along the boundary of the objects within an image that are having the same color and intensity [18]. The shape features can be extracted from the contour detection

3.2.2. Mask R-CNN

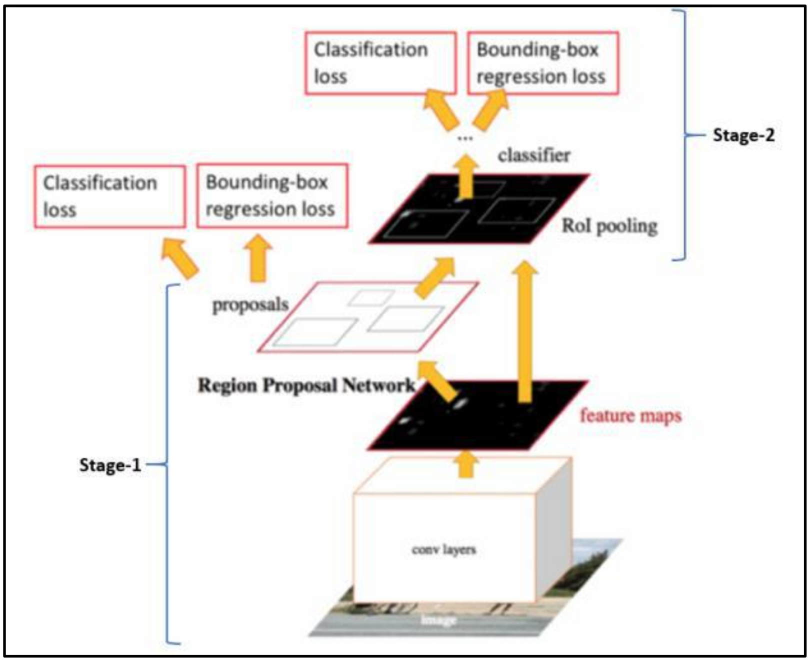


Figure 2: Visual representation of the Mask RCNN

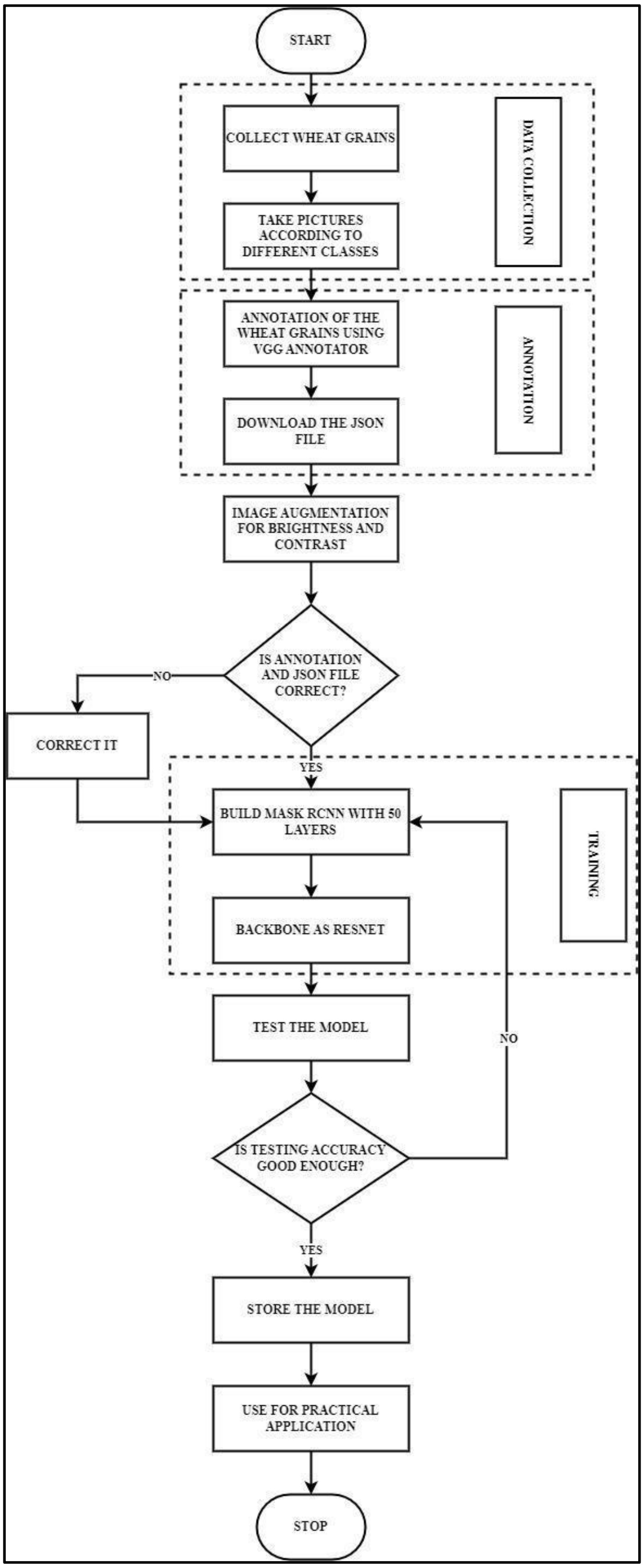


Figure 3: Flowchart of the proposed methodology.

Mask Regional-based Convolutional Neural Network or Mask R-CNN is an advanced modern DL methodology built for object detection by instance segmentation. Mask R-CNN works in two stages [19]. The first stage of the Mask RCNN consists of 2 networks where the first network is the backbone and the second network is region proposal network. These networks run once per image to give a set of regions in the feature map which contain the object to be identified [20]. The second stage of the Mask RCNN is to predict the object class for the annotations. The proposed regions can be of different sizes whereas for classification requires a fixed size vector. Hence, these proposed regions are fixed by using either RoI pool or RoIAlign method [21]. The visualization of Mask RCNN and flowchart for the proposed methodology is shown in figure 2 and 3 respectively.

4. Results and Discussion

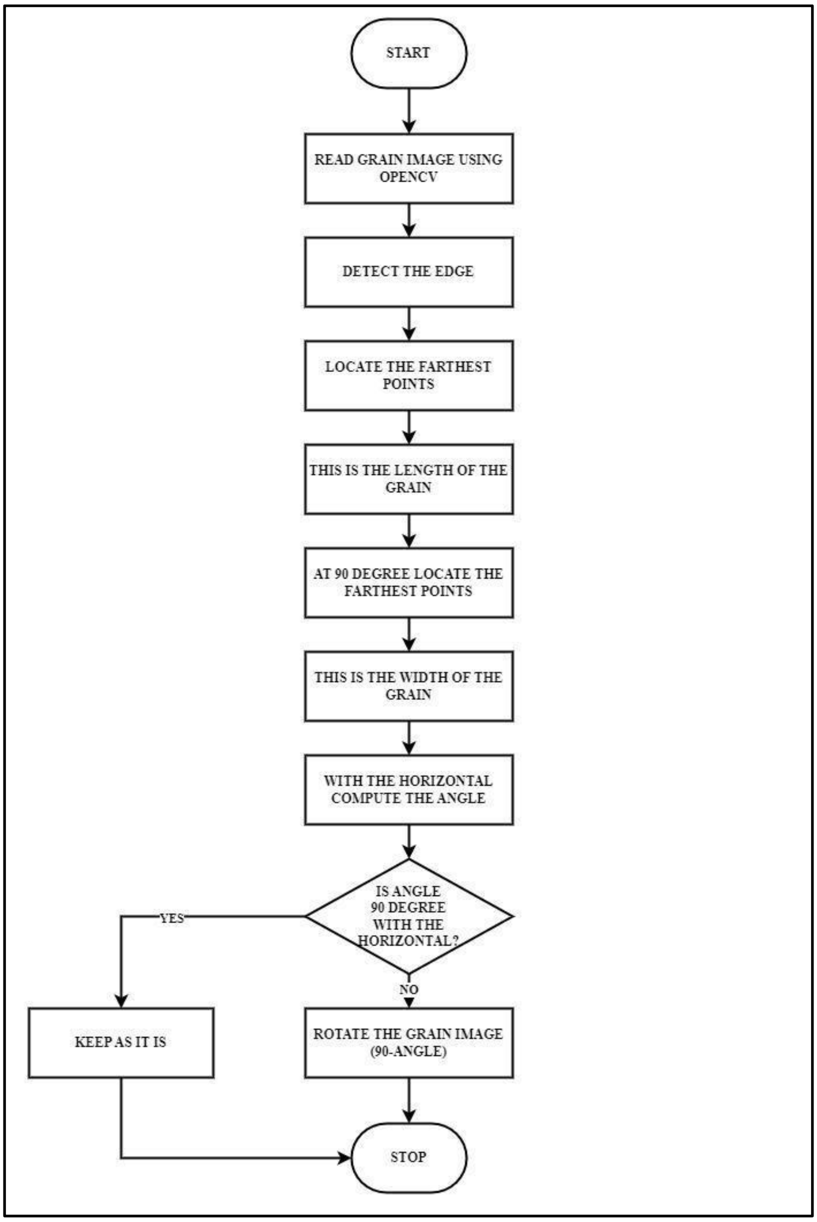


Figure 4: Flowchart for rotating the grain vertically

The first step of the analysis is data collection. In this step, 2000 grains of wheat are collected and separated into 4 groups of 500 grains each. The first group is stored in a closed area, the second group is kept inside a dark room, the third group is soaked in water for 24 hours and the fourth group is soaked in water for 48 hours. For the Mask RCNN model that is developed in the dataset, the first group represents the storage category quality, the second group represents the edible group, the third set represents the seedling grada and the fourth group represents the rotten wheat grains. The second step of the analysis is taking digital images of the wheat grains using a micro-camera. Total of 120 images were created.

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The third step of the analysis is using image processing on the digital image of the wheat grains to detect the height and width of the grains and vertically arrange the grain if the grain image is aligned horizontally. The flowchart for the third step is shown in figure 4.

The fourth step of the analysis is annotating the image of the wheat grains using the VGG image annotator and saving the JSON files to the local disks. In the next step the images are augmented to account for brightness and contrast.

In the next step the images are trained and tested with the annotated JSON files and classified into different categories such as wheat grain as storage quality, edible, seeding quality or rotten. In order to train and test the images of wheat grains the Matterplot of Mask RCNN [22] is implemented using the Keras and Tensorflow. The program is run on a Jupyter Notebook of Windows 10 having a 64-bit PC with 8GB RAM and i5, 1.6GHz processor. The model is trained in batches of images with 500 steps per epoch, a non-max suppression threshold of 0.2 and a learning rate of 0.001.

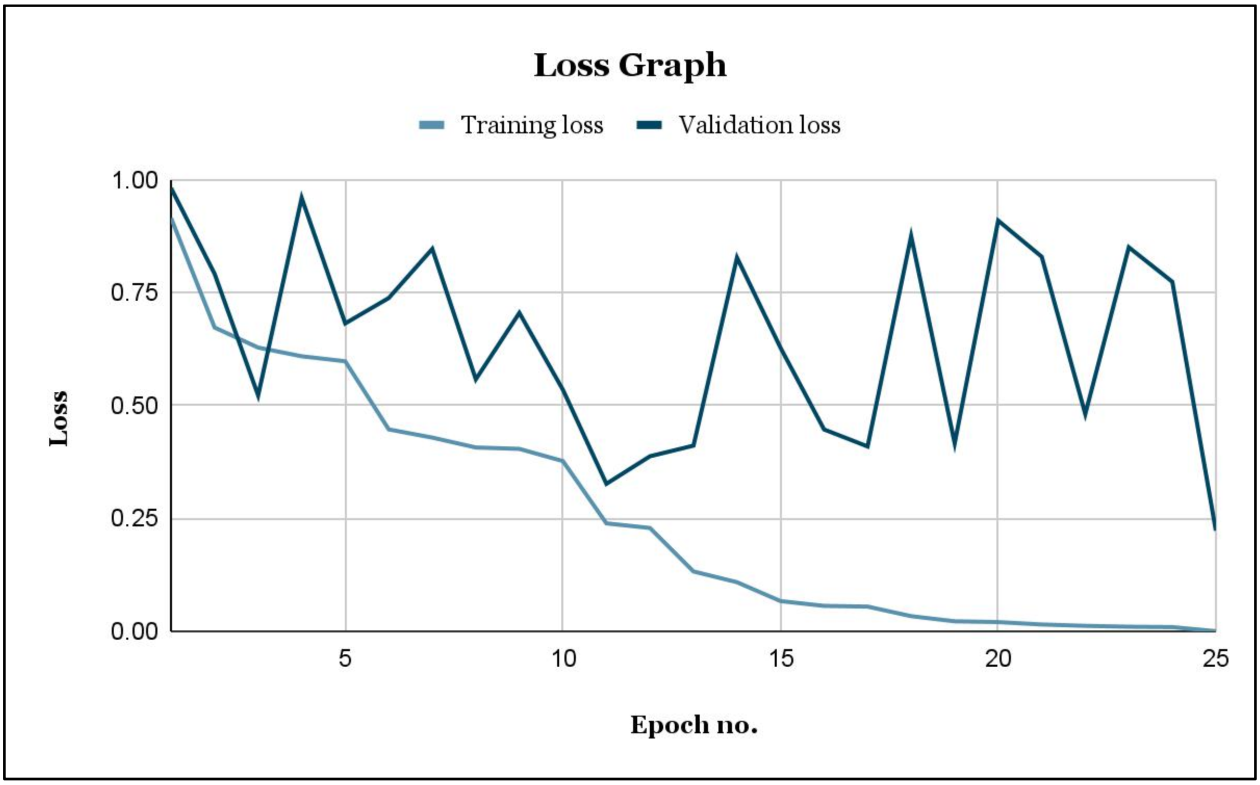

Figure 5: Training and validation loss of the Mask RCNN

In the Mask RCNN, the weights and the bias are the learnable parameters which are initialized at random in the first epoch and then trained with the pre-trained weights for the COCO dataset (http://cocodataset.org/#home). The images are trained for 25 epochs and the training and validation loss graphs are shown in figure 5.

From figure 5, it is observed that the training loss for the first epoch was 0.915 which was reduced to 0.0002 at the 25th epoch. On the other hand, the validation loss for the developed model was 0.981 for the 1st epoch which was reduced to 0.222 at the 25th epoch. A classified image of the wheat grains is shown in figure 6.

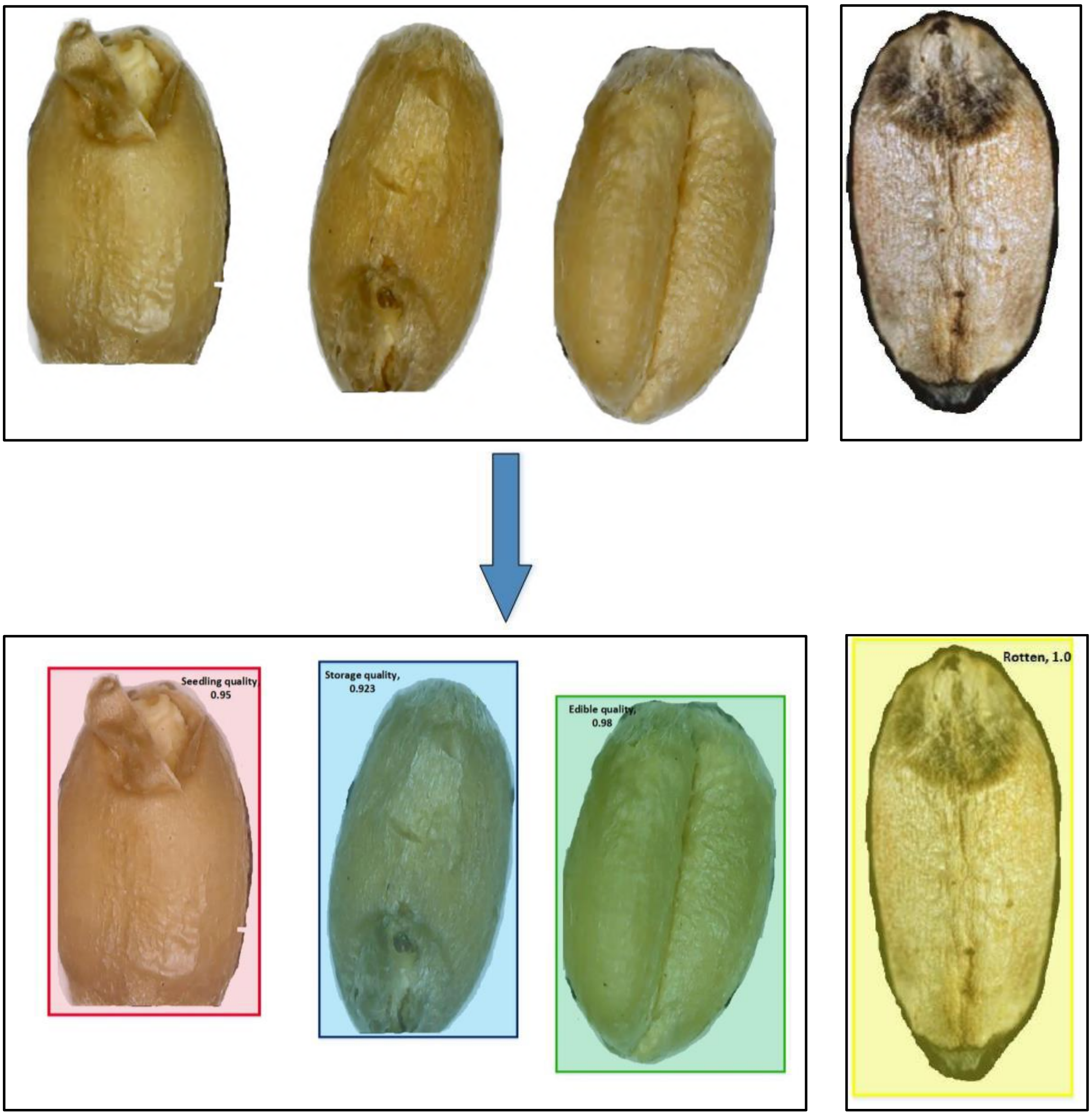

Figure 6: Classified image of the wheat grains

The Mask RCNN developed is tested for images of wheat grains from each class which are not used for training. The develop model is capable of predicting the seedling quality, storage quality, edible quality and rotten wheat grain with 95%, 92.3%, 98% and 100% accuracy respectively.

5. Conclusion

The comprehensive intention of the present study is to develop a Mask R-CNN model to classify the wheat grains as storage quality, edible, seeding quality or rotten. In order to achieve the objective of the paper 2000 wheat grains were collected and divided into 4 groups. A total of 122 images of the wheat grains are taken and with the help of image processing the texture of the wheat grains are extracted. The images are annotated using VGG image annotation tool and the JSON file is stored in the local disk. Then with the help of Matterplot of Mask RCNN. The model is trained in batches of images with 500 steps per epoch, a non-max suppression threshold of 0.2 and a learning rate of 0.001. The developed model showed a training and validation loss of 0.0002 and 0.222 respectively. The model is tested for an image of wheat grains with all of the four classes in it. The Mask RCNN is able to classify all the classes with an accuracy of 0.923 for storage quality, 0.98 for edible, 0.95 for seedling quality and 1.00 for rotten. The Mask R-CNN model is capable of testing the wheat grains.

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