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Research Article

Red Onion Seed Quality Classification Using Transfer Learning Approaches

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ABSTRACT

Onion (Allium cepa L.) is a very important vegetable grown all over the world and consumed in various forms. Onion is widely used as a condiment to enhance the flavor of food. Red onion seed (A. fistulosum) is grown throughout the world in the wide range of climates temperate to tropical conditions. Globally, it is cultivated in moreover China and Japan. A. fistulosum is grown across Ethiopia in various regions. In 2012, 3,281,574 tons of output were obtained from 30,478 hectares of coverage. Allium fistulosum covers the Amhara area over 8000 hectors, which is 26% of our country. For export, red onion seed is separated based on quality. Red onion seed quality separation or categorization is essential to the trade process. It aids in making people marketable. In Ethiopia, this procedure is carried out manually, which has a number of drawbacks like being less effective, inconsistent, and prone to subjectivity.

To address this problem, we use pre-trained transfer learning model VGG, Google Net, and ResNet50 for quality classification of red onion seed. The main procedures include image preprocessing, resizing, data augmentation, and prediction. The model trained on 470 datasets collected from different agricultural fields in south Gondar libo kemkem and fogera woreda. To increase the dataset, we apply different augmentation techniques. We split the dataset into 80% for training, 10% for validation and 10% for testing. The model classifies the input image with 99%, 100%, 100% and 86% accuracy for VGG19, VGG16, Google Net and Res Net respectively.

Keywords: Allium fitsulosum, Red Onion Seed, Visual Geometry Group, GoogleNet, ResNet, Pretrained Models, Transfer Learning

Introduction

All civilizations began with agriculture. The development of productivity is the main objective[1]. On Earth, agriculture is most important for human sustenance. Many farming practices and equipment have been digitized throughout the years to ensure faster production of higher quality. A productive procedure must be used to cultivate agricultural products because of the increased demand in the farming sector[2].

The onion, or Allium cepa L., is a very significant vegetable that is produced all over the world and used in a variety of dishes[3]. The most frequently farmed species of the genus Allium and the only member of the Alliaceous family is the onion (Allium cepa L.), sometimes referred to as the bulb onion and common onion. More than 130 nations throughout the world grow it. The major onion producers globally are China and India, followed by the United States, the Netherlands, Egypt, and Iran[4].

Red onion seed is grown throughout Ethiopia in various regions. In 2012, 3,281,574 tons of output were obtained from 30,478 hectares of coverage. Allium fistulosum covers the Amhara region above 8000 hectors, which is 26% of our country. The seeds of A. fistulosum were sold domestically and exported to other nations[8].

Although there are studies on the detection of onion diseases, there are few studies on the classification of red onion seed production quality. According to experts in agriculture, the marketing quality of seed production is low. In order to categorize red onion seed production quality into three group's namely healthy, foreign objects, and immature/shriveled grains our study use transfer learning techniques.

Related Work

The paper Automatic and fast classification of barley grains from images propose a deep learning technique for barley classification by collecting 1432 images and labeled into 14 varieties. The paper has done noise removal and augmentation preprocessing techniques. The data is divided in to 80% training, 10% validation and 10% testing. They used transfer learning VGG 16 for feature extraction and classification and they achieved an overall accuracy of 94%[21].

The work Onion agronomy and post-harvest handling Manual describes we can get good quality onion seed production by putting the seed on water using floatation to get quality seed[3]. But this is a traditional system and it takes time as well as needs more manpower .it also needs drying the seed immediately and strainer must be used.

The paper Participatory Evaluation and Demonstration of Onion Spacing in Irrigated Agriculture at Kencho Kebele in Uba Debre Tsehay Woreda, Southern Ethiopia, assess maximum yield of onion using four levels of onion plant spacing (8cm, 10cm, 12cm, and Farmer's practice or planting with own practice) by applying 416.56mm irrigation water with five days interval. The work has been done on the onion variety of Red Creole. Finally the paper recommend that 10 cm is better onion plant spacing by scoring 17.178 t/ha[26]. but the work focus on the yield of onion on its bulb we need to work on the seed yield quality.

The work Adaptability and yield performance evaluation of onion (Allium cepa L.) varieties in Jimma zone, Southwestern Ethiopia assess adaptation trial of three improved onion varieties (Nanthus, Adama red and Bombe red) with one local check was done in Jimma zone at Agaro Agricultural Research Sub-center using RCBD design for two consecutive seasons. finally, Bombe red variety performing well adapted and provided highest yield in both cropping seasons with the overall result yield performance of 71.51 tons/ha[28]. But the work focusses on yield performance of bulb so, we need to assess the quality of onion seed production.

Research Methodology

Proposed System

This chapter gives a detailed information about the architecture of the system, concepts and algorithms used, evaluation metrics and their representation related to the study, and finally software tools and libraries used to carry out the implementation.

System architecture: In the following figure the architecture for an implementation of the proposed system is depicted **(Figure 1)**.

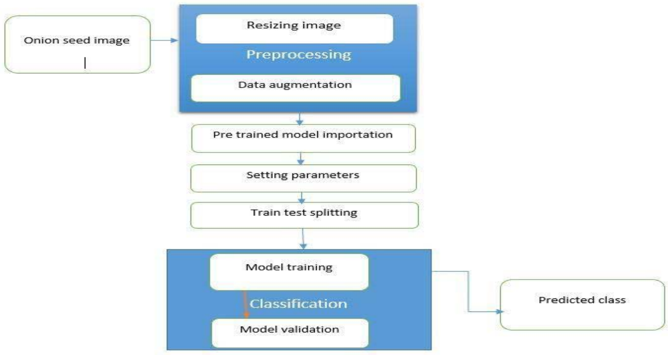


Figure 1: Proposed architecture.

Data collection and dataset preparation: The first step was to acquire images of the onion seed. This study includes images collected from Agricultural fields in south Gondar by the help of experts listed in the table. Experts annotate or label the image with respect to their class using mechanism like color and weight. A total of 470 pictures of the onion seed was acquired. All images were in RGB color and JPEG format.

The images were classified into 3 classes: healthy, immature shriveled grain, and foreign matter. The data classified was divided into training set and testing set. The training set was used to train the neural network and the test set was used to test the system. 70% of the data was allocated to training, 15% allocated to testing and 15% for validation. Three transfer learning models VGG, Google Net and ResNet 50 were used to train and validate the images through transfer learning. The experts involved in the annotation of our dataset.

Data augmentation for proposed model: To increase number of images the study implement augmentation. We implement image data generator to supplement data **(Table 1)**. And the images that preprocessed data are augmented.

Table 1: Parameters we use for the augmentation.

Image_data_generator_augmentation techniques	Values
Rotation range	40
Width shift range	0.2
Height shift range	0.2
rescale	1./255
Shear range	0.2
Zoom range	0.2
Horizontal flip	True
Brightness range	[0.2,1.2]
Fill mode	'nearest'

Model training and validation: Training Parameter of the Network: In choosing the set of training parameters used for the training of the model, a series of trial and error was carried out. Adam optimizer were used. The number of epochs chosen was also set at 15. The learning rate of 0.001 was chosen as the network achieved a higher Accuracy in it **(Table 2)**. ReLU was used for the activation function and SoftMax used for the classification task. Since the final layer of the networks used is a classification layer, the loss function used is the cross-entropy loss. The training parameters used for training the model are listed in Table below.

Table 2: Parameters we use for the work.

Parameter	Unit
Epochs	10
Batch size	256
Width, height, depth	224 ,224 ,3
Activation function	Soft max
Loss function	Categorical cross entropy
Optimization algorithm	Adam optimizer
Learning rate, patience, verbose	Learning rate schedule,25 patience, 1
Early stop, random state	5,0

Experiment

Data set: There is no readymade dataset in red onion seed for this type of research; as a result, we have prepared our own dataset to evaluate the performance of the proposed system.to do so, Image acquisition is done using a SONY camera (DSC-W800). The distance between the camera and the sample was fixed at 15 cm and the images taken are all 24-bit color JPEG format. The images were taken at a resolution of 5152 * 3864 pixels. During background color selection, we compared a red, and blue colors. We observed that the blue color makes a good contrast with the foreground objects and achieved better quality. A total of 470 of red onion seed kernels are prepared to train and validate the proposed model. All the data are collected from agricultural fields in south Gondar libo kemkem and fogera woreda. These 470 red onion seed sample constituents are separated/labeled into their corresponding 3 classes by agricultural experts of those woreda **(Table 3)**. Therefore, we finally have 3 classes of images which are healthy, immature and foreign matters.

Table 3: Number of datasets used in each class.

No	Class	Number of datasets
1	Healthy	150
2	Immature shriveled grain	160
3	Foreign matter	160
Total		470

The original data is augmented to 4000 using this type of augmentation techniques rotation range, width and height shift range, rescale, shear range **(Figure 2)**, horizontal flip brightness range and fill mode for class balancing we remove some images for the model after that we have 3942 images for the model. After augmenting the data, we do train-test splitting shown in below.

```
[ ] print("Number of training data :",len(X_train))
    print("Number of testing data :",len(X_test))
    print("Number of validation data :",len(x_validate))

    Number of training data : 2759
    Number of testing data : 591
    Number of validation data : 592
```

Figure 2: Train test splitting of augmented data.

Implementation: Python programming language used in developing the prototype. The implementation is done in Google colab. We choose Google colaboratory it allows to write and execute arbitrary python code through the browser, and is especially well suited to machine learning and data analysis. We also used Colab because it is a hosted Jupyter notebook service that requires no setup to use, while providing access free of charge to computing resources including GPUs **(Table 4)**. The hardware accelerator or the device we used in Google colab is GPU because the available device in Google colab is GPU. The main library packages used during implementation are listed in the table below.

Table 4: Libraries used in during implementation.

Library	Version	Description
Keras	2.8.0	Open source developing and evaluating deep learning models
Opencv	4.1.2.30	Open-source library for computer vision, machine learning, and image processing
Scikit_learn	1.0.2	Free software for data analysis in machine learning
Scikit_image	0.18.3	Open source designed for image processing

Result and Discussion

Evaluation on the performance of the proposed red onion seed quality classification is conducted on VGG16, VGG19, Google Net and ResNet50 classifiers to determine the best performing classifier based on the criterion of classification accuracy. On the next sub sections, we present their results.

VGG 19 model

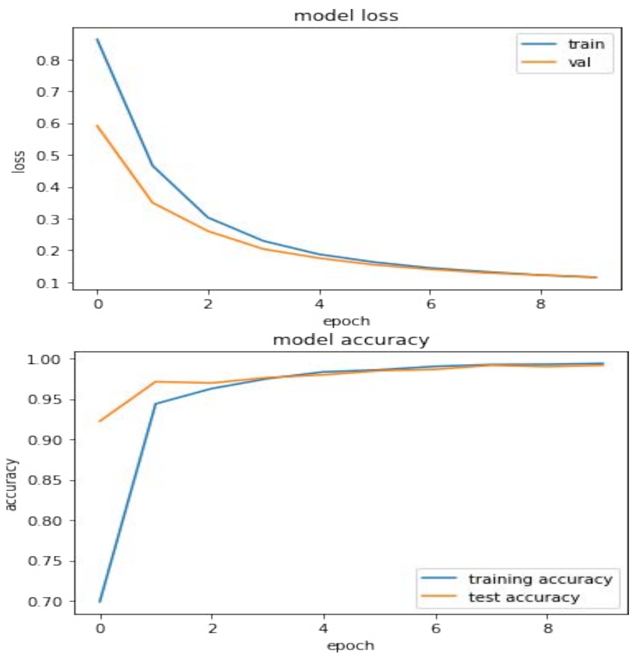
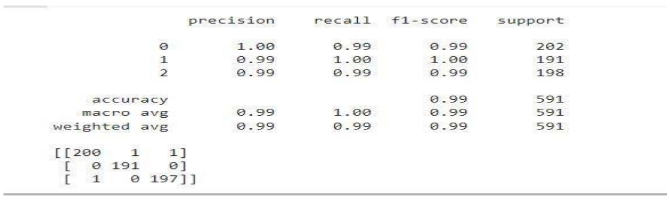


Figure 3: VGG validation accuracy and loss results.

VGG19 has given a validation accuracy of 99.155%, test accuracy of 99.49% and training accuracy of 99.38%. It took about 152 minutes for training. Validation loss started from 0.5909 and reduced to 0.1148 by the end of the final iteration **(Figure 4)**. Finally, as we can see from the above two plots the validation accuracy line is almost in sync with the training accuracy line and at the same time, the validation loss line is also in sync with the training loss. The confusion matrix is shown below.



	precision	recall	f1-score	support
0	1.00	0.99	0.99	202
1	0.99	1.00	1.00	191
2	0.99	0.99	0.99	198
accuracy			0.99	591
macro avg	0.99	1.00	0.99	591
weighted avg	0.99	0.99	0.99	591

```
[[200   1   1]
 [  0 191   0]
 [  1   0 197]]
```

Figure 4: VGG19 confusion matrix.

As we observe from the above confusion matrix in class 0 or foreign matter there is 200 correctly predicted instances while 1, 1 are incorrectly predicted in class 1 and class 2, in class 1 or healthy there is 191 correctly predicted instances while no incorrectly predicted instances and in class 2 or immature 197 instances are correctly predicted with 1, incorrectly predicted instances in class 2.

VGG16 model

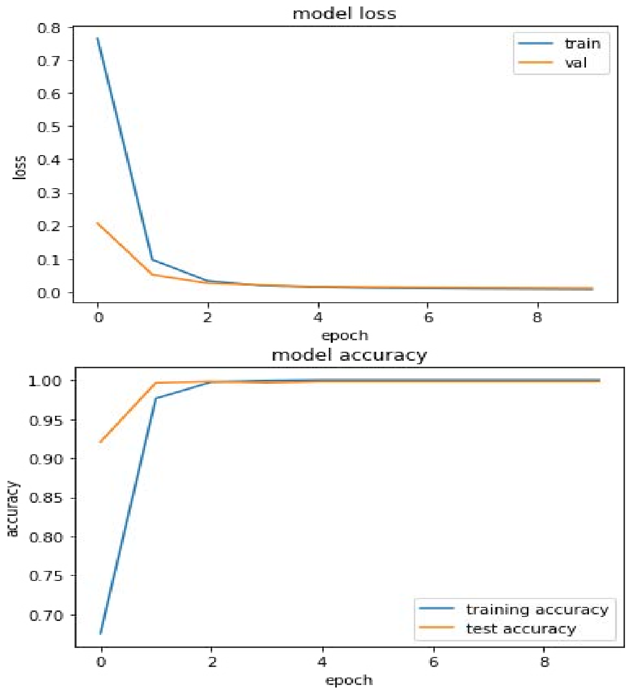
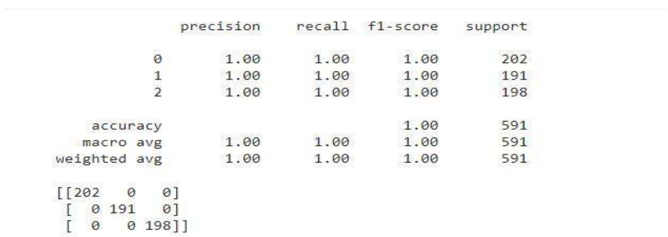


Figure 5: VGG16 validation accuracy and loss results.

VGG16 has given a validation accuracy of 99.831%, test accuracy of 100% and training accuracy of 99.93%. It took about 138 minutes for training and validation loss started from 0.2068 and reduced to 0.0103148 by the end of the final iteration. The confusion matrix is shown below **(Figure 6)**.



	precision	recall	f1-score	support
0	1.00	1.00	1.00	202
1	1.00	1.00	1.00	191
2	1.00	1.00	1.00	198
accuracy			1.00	591
macro avg	1.00	1.00	1.00	591
weighted avg	1.00	1.00	1.00	591

```
[[202   0   0]
 [  0 191   0]
 [  0   0 198]]
```

Figure 6: VGG16 confusion matrix.

All the instances in each class are correctly predicted along with its class.202 instances of class 0 or foreign matter are correctly predicted while there is no incorrectly predicted instances, 191 instances of class 1 or healthy are correctly predicted with no incorrectly predicted instances and 198 instances of class 2 or immature are correctly predicted with no incorrectly predicted.

Google Net Model

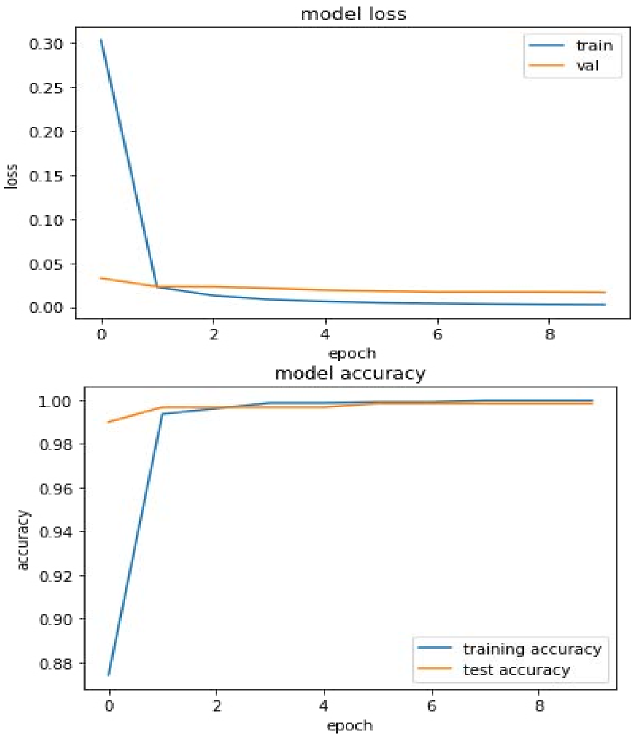
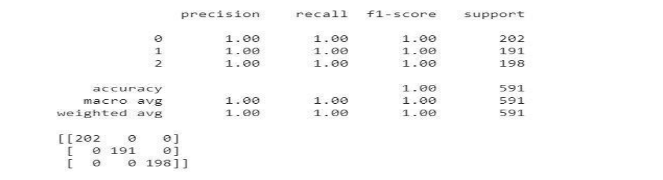


Figure 7: InceptionV3 validation accuracy and loss results

Inception V3 has given a validation accuracy of 99.83 %, test accuracy of 100% and training accuracy of 99.96%. It took about 142 minutes for training and validation loss started from 0.0325 and reduced to 0.0165 by the end of the final iteration **(Figure 8)**. The confusion matrix is shown below in.



	precision	recall	f1-score	support
0	1.00	1.00	1.00	202
1	1.00	1.00	1.00	191
2	1.00	1.00	1.00	198
accuracy			1.00	591
macro avg	1.00	1.00	1.00	591
weighted avg	1.00	1.00	1.00	591

```
[[202   0   0]
 [  0 191   0]
 [  0   0 198]]
```

Figure 8: InceptionV3 confusion matrix.

All the instances in each class are correctly predicted along with its class.202 instances of class 0 or foreign matter are correctly predicted while there are no incorrectly predicted instances, 191 instances of class 1 or healthy are correctly predicted with no incorrectly predicted instances and 198 instances of class 2 or immature are correctly predicted with no incorrectly predicted.

ResNet50 Model

ResNet50 has given a validation accuracy of 87.16 %, test accuracy of 86.29% and training accuracy of 87.31%. It took about 180 minutes for training and validation loss started from 0.5435 and reduced to 0.5376 by the end of the final iteration **(Figure 10)**. The confusion matrix is shown below.

As we observe from the confusion matrix 170 instances are correctly predicted as class 0 or foreign matter while 1, 31 are incorrectly predicted in class 1 and class 2 respectively, 169 instances are correctly predicted as class 1 or healthy while 2, 20 are incorrectly predicted in class 1 and class 2 respectively and 171 instances are correctly predicted as class 2 or immature while 26, 1 are incorrectly predicted in class 0 and class 1 respectively.

In this study, we propose quality separation for red onion seed that works in similar manner to manual quality separation procedures by exploring image processing techniques and supervised learning algorithms. The proposed model was tested on verified sample data collected from libo kemkem and fogera woreda agricultural fields by experts of those woreda. We used accuracy measurement to test the performance of the developed model. The experiments were done using pre-trained convolutional neural network model VGG, GoogleNet, resnet50. The performance of red onion quality classification has been determined through accuracy rate. Validation accuracy of VGG 19, VGG16, GoogleNet, and ResNet50 is 99.155%, 99.831, 99.83%, and 87.16% respectively. We have shown that our proposed system and the models we used for quality separation of red onion seed sample constituent achieved their intended purposes **(Table 5)**. This is shown by a very high level of classification accuracy we achieved. From the three classifiers VGG16 achieved better validation accuracy than other.

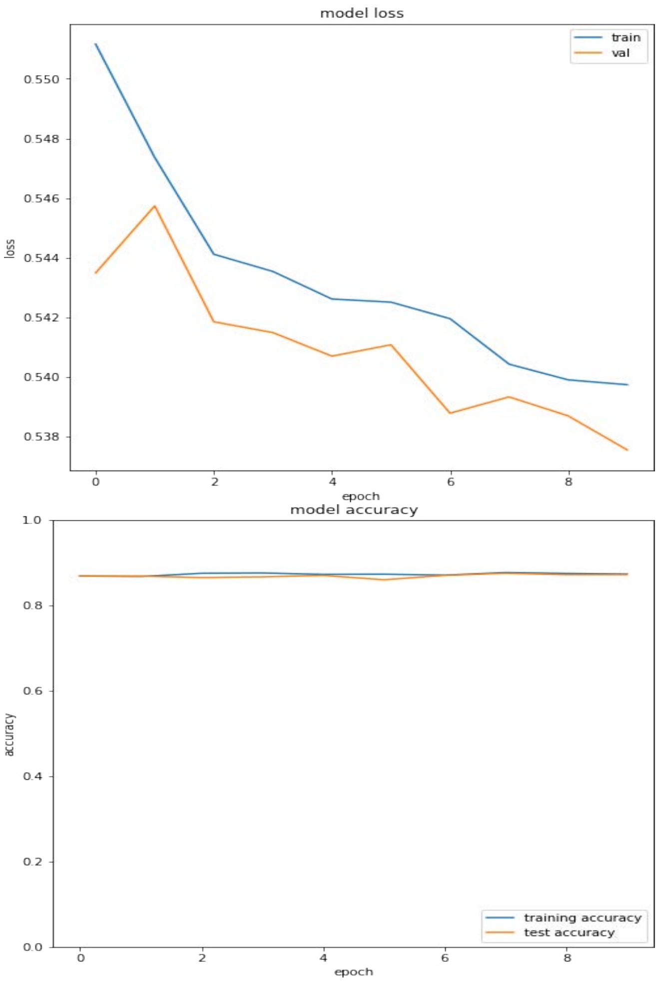


Figure 9: ResNet50 validation accuracy and loss results.

```
              precision    recall  f1-score   support

           0       0.86      0.84      0.85       202
           1       0.99      0.88      0.93       191
           2       0.77      0.86      0.81       198

    accuracy                           0.86       591
   macro avg       0.87      0.86      0.87       591
weighted avg       0.87      0.86      0.87       591

[[170   1  31]
 [  2 169  20]
 [ 26   1 171]]
```

Figure 10: ResNet50 confusion matrix.

Conclusion

Onion is very important vegetable grown all over the world used as food flavor. For export, red onion seed is separated based on quality. Red onion seed quality separation or categorization is essential to the trade process. To increase the revenue the major threats that hinder red onion seed quality should be controlled and assessed. In this thesis work we explored image processing methods and supervised learning algorithms for quality classification of red onion seed automatically using computer system. A thorough discussion on image processing in general, starting from the definition of image to the current state-of-the-art findings, methodologies and architectures were conducted. Fundamental steps in digital image processing are discussed and analyzed briefly along supervised learning algorithms.

Table 5: General comparison between the results.

Networks	Validation accuracy	Training accuracy	Testing accuracy	Average accuracy	Training time(min)
VGG19	99.155%	99.38%	99.49	99%	152
VGG16	99.831	99.93%	100%	100%	138
GoogleNet (Inception_V3)	99.83%,	99.96%	100%	100%	142
ResNet50	87.16%	87.31%	86.29%	86%	180

From the very beginning the proposed system needs a dataset. We collect the dataset from north Gondar in libo kemkem and fogera woreda with the assist of those woreda agricultural experts. Before feature extraction from the acquired images image preprocessing resizing and data augmentation were done first to better and accurately locate each red onion seed kernels in the image. The main purpose of this research work is to develop automatic red onion seed quality assessment using transfer learning techniques. For this reason, we proposed system architecture which includes preprocessing like resizing, data augmentation and identification components.

In order to create red onion seed quality classification model, we create a labeled training dataset that namely healthy, immature shriveled grain and foreign matters. The labeling task is done by the domain expert from libo kemkem woreda in southern Gondar. After all, the quality inspection model trained on it in the training phase. The image dataset is split into training and testing datasets. The training dataset contains 70% of the total dataset and 30% for validation and testing by employing pre-trained CNN model which is VGG (19, 16), GoogleNet and ResNet50. Accuracy evaluation technique was utilized for the evaluation purpose.

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