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Identification of Maize Seed Defects using the Yolo-V5 Algorithmic Framework and Object Recognition Paradigms

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ABSTRACT

The maize quality, being one of the most extensively cultivated and planted crops across the globe, takes a central and significant role with respect to rendering farmers and the overall food sector prosperous and successful. Seed quality testing that is manually carried out is usually the norm, but it in turn renders it prone to multiple inefficiencies and chances of errors which can arise at the time of assessment. As land degradation continuing to impose serious risks upon agricultural activities, effective sorting technologies are increasingly essential and necessary to address these issues. Apart from this, maintaining proper and informed seed selection also heightens the production levels along with actively facilitating the practices of sustainable agriculture on a long-term basis. The system presented in this work employs several object recognition paradigms and the Yolov5 algorithmic framework to recognize faults in maize seeds. The work further verifies the performance of the developed model against major metrics of accuracy, precision, F1-score, and mAP. The proposed method employs computer vision algorithms for the recognition and classification of different seed defects, such as cracks, mildew, and discolored seeds. With a remarkable and impressive accuracy rate of up to 98%, the state-of-the-art system can successfully identify and classify abnormalities in seeds, provided it has already been trained on a large and comprehensive dataset that contains many annotated images of maize seeds. The state-of-the-art model called YOLOv5 achieved an extremely high F1-score of 97.7%, a result that reflects its incredible performance, as it was closely followed by another model, YOLOv8, which recorded impressive precision and mean Average Precision (mAP) results of 98.4% and 98.2%, respectively. These outstanding results go to verify and support the enormous potential and success of deep learning technologies in the accurate detection and recognition of defects in maize seeds.

INTRODUCTION

Maize is the staple crop that is an important source of food security and economic progress at the international level. It is cultivated extensively across the world and is an important source of food and income for millions of people (Shiferaw et al., 2011). Maize seed quality plays a major role in crop growth and farmers' livelihoods. Substandard quality seeds may result in poor germination, lower plant health, lower yields, and susceptibility to pests and diseases. Defect detection, traditionally achieved through human vision manually, is an important operation in seed quality control. Physical examination, however, is a human-error-prone and time-consuming task that relies upon a variable and subjective judgment of the quality of seeds (Mutundi et al., 2019). There is a growing demand for high-quality maize seeds requiring an effective and efficient method of detecting faults in seeds. Object detection, a computer vision technique, has proved helpful for object classification and detection from video streams and images (Amit et al., 2020). Although object detection is applied in seed flaw detection, seed flaw recognition can be automated using object identification algorithms whereby seed quality recognition is more efficient and quicker.

The ability to optimize efficacy as well as precision when it comes to maize seed quality assessment puts research into contention. Computerization of seed defect identification will enable farmers and seed producers to easily check seed quality at high speed, thereby enhancing agricultural productivity and attaining food security. Agricultural computer intelligence technology is becoming more and more popular. Artificial intelligence (AI) has become a critical solution tool for many agricultural issues because it has the capacity to learn (Bannerjee et al., 2018). Computer science work on artificial intelligence makes technology able to replicate the capacity of human beings to think by learning and imitating examples. One type of machine learning called "deep learning" uses artificial neural networks to learn from data, as well as to make predictions from data, in vast quantities.

The neural networks are layers of nodes connected to one another, and a single node will carry out an elementary mathematical computation. With the nodes organized in layers in a hierarchical form, the computer system can then calculate more complicated patterns and properties of the input (LeCun et al., 2015; Mitchell, 2007; Hopfield, 1988). The writers of (Gu et al., 2018) believe that in recent years, convolutional neural networks (CNNs) have grown exponentially as a symbol of the technology of deep learning (Kan et al., 2019; Iandola et al., 2014; Szegedy et al., 2017; Qin et al., 2018; He et al., 2016). They are widely applied to image classification. CNNs are inherently feature learning, as opposed to other machine learning methods, because the authors in (Huang et al., 2019), by aggregating low-level features into more abstract, higher-level features.

CNNs have been widely used in agricultural research. For the precise identification and authentication of wheat cultivars, a method using convolutional neural networks (CNNs) and deep learning has been proposed by (Wang et al., 2022). Since Inception V3, DenseNet, and MobileNet architectures were top ranked on test accuracy, the results showed that the proposed approach had high test accuracy ranging from 85% to 95.68% (Laabassi et al., 2021; Afonso et al., 2019; Pang et al., 2020).

The authors in Altuntaş et al. (2019) employed CNNs and hyperspectral imaging to predict and classify maize seed viability. The recognition accuracy of the 2DCNN model using images was 99.96%, and that of the 1DCNN model using spectra was 90.11%. Gao et al. (2020) have suggested Faster R-CNN as a multi-class model for apple detection from highly leaf-covered fruiting-wall trees. The system correctly detected all non-occluded, leaf-occluded, branch/wire-occluded, and fruit-occluded apples. For training, they purchased 800 images and resized them to 12,800. The four-class average precision scores varied between 0.848 and 0.909. It identified an image within 0.241 seconds using an average precision score of 0.879. It is fast recognition that reduces the damage to the fruit and assists robotic picking approaches. Researchers in Tiwari (2021) had suggested a deep learning approach to classify and identify plant diseases based on leaf image captures at varied resolutions. Object detection software was applied in detecting and identifying the rot maize seeds effectively subsequently (Javanmardi et al., 2021). The results verified the superb accuracy of the process and the ability to find and identify the object of concern correctly. Such an approach could provide a base for the enhancement of a seed quality checking device in the future.

The objective of this study is to develop an AI-based system using YOLOv5 for the detection and classification of defects in maize seeds such as cracks, mildew, and discoloration. With the use of deep learning and computer vision, the system is more precise and reliable compared to manual inspection. The efficacy is verified using precision, F1-score, mAP, and accuracy, which fosters further development in agricultural quality control.

MATERIALS AND METHODS

2,064 seeds of three maize varieties served as experimental material for the experiment. The seeds were either faultless or had mildew, insect or equipment damage, or discoloration. Photography was done with an iPhone 5c camera with a resolution of 2448 x 2448 pixels and 8 bits per channel (Treboux et al., 2018). Images of several seed categories are shown in Figure 1. An Intel®XeonTM CPU with a primary frequency of 2.20 GHz and a TeslaT4 graphics card with 16G of memory were used in the experiment's setup. The setup was built on a Linux setup made available by Google Colab, with Python 3.8, PyTorch deep learning framework, and CUDA 11.6 loaded.

Figure 1: All Categories of Maize Seeds Worse, Bad, Excellent, Good

YOLOv5 Model Structure

A strong one-stage recognition of objects model with a rapid time frame for inference is the YOLOv5. The two-stage series models' normal recalculation of candidate areas is eliminated. The four distinct structures that make up the YOLOv5 architecture are the YOLOv5s, YOLOv5m, YOLO v5x, and YOLOv5l. Their networks disintegrate in the manner described above. The Backbone, Neck, and Head comprise the YOLOv5 baseline architecture is depicted in figure 2. One of the key technologies for combining fine-grained images to create image attributes is the CNN. The 2D convolution, regularization, and SiLU activation operations are carried out by the conv module, which serves as the architecture's central unit for convolution. By incorporating gradient changes in the feature graph, the primary feature extraction structure, the c3 module, minimizes model size, FLOPs, and parameters while retaining inference speed and accuracy. While feature maps are upsampled in the additional sample module, characteristic maps of various sizes are joined in the combined module. The SPP module at layer 9 of the backbone converts characteristic patterns of all sizes into fixed-size characteristic vectors, therefore broadening the perceptual span of the network. The Neck framework improves the transfer of information along the manufacturing path by distributing modest qualities effectively with the characteristics hierarchy network and merging more complex characteristics with path aggregation networks. With adaptive pooling, the amount of valuable data from every characteristic layer is maximized by connecting pyramidal characteristics, route collection systems, and additional features. By combining reliable semantic information from lower layers with precise placement signals from upper layers, object localization accuracy is improved. The Head structure's three detecting layers enable it to recognize objects of different sizes. For every one of these detection layers, an input pixel feature map measuring 80 by 80, 40 by 40, and 20 by 20 pixels is needed. This experiment creates a 36-channel linked vector for each layer that has three anchoring boxes, four classifications, one assurance threshold, and four restriction box points. In this research, there were a total of four targets for detection. Target categories and predicted boundary boxes were made and tagged in the originating photographs to identify the picture targets.

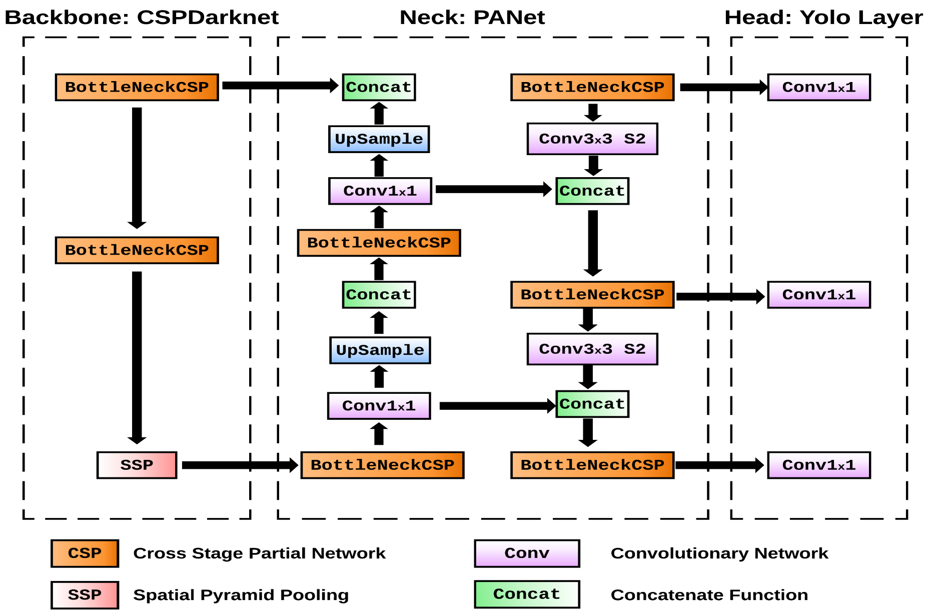

Figure 2: Yolo 5 model architecture

Data acquisition

There were 1648 maize cases taught in all. Considering the degree of severity of the flaws in the seeds, the data is split into four groups. The maize image annotation for the four classifications: “Excellent,” “Good,” “Bad,” and “Worse” are depicted clearly in figure 3.

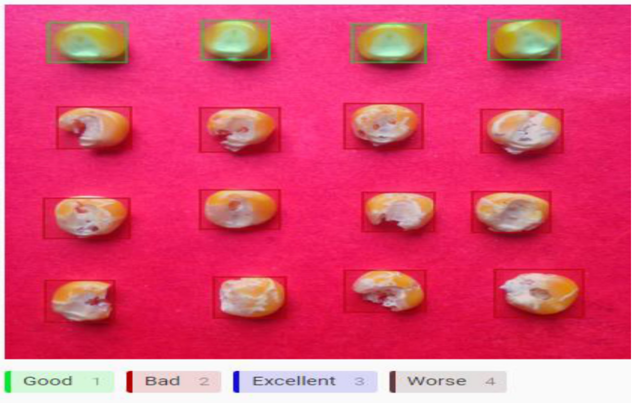

Figure 3: Maize image annotation

Each photo has 16 maize seeds and is taken in an image deck. The model was put to the test using images of 256 more seeds, and it was then confirmed using pictures of another 160 seeds. The acquired pictures are displayed in Figure 1. The LabelStudio program was used to tag both healthy and sick seeds using PyTorch’s YOLOv5 standard.

Data labelling

Because object detection is a supervised learning task, annotating the data is necessary to allow the algorithm to recognize the ground truth boxes for each detected image. Label-studio is the program that was utilized to annotate the document. The PyTorch YOLOv5 format was used to designate both defective and non-defective seeds. Figure 4 depicts the annotation procedure, and Figure 5 shows the annotation file that was created from the maize image in Figure 4.

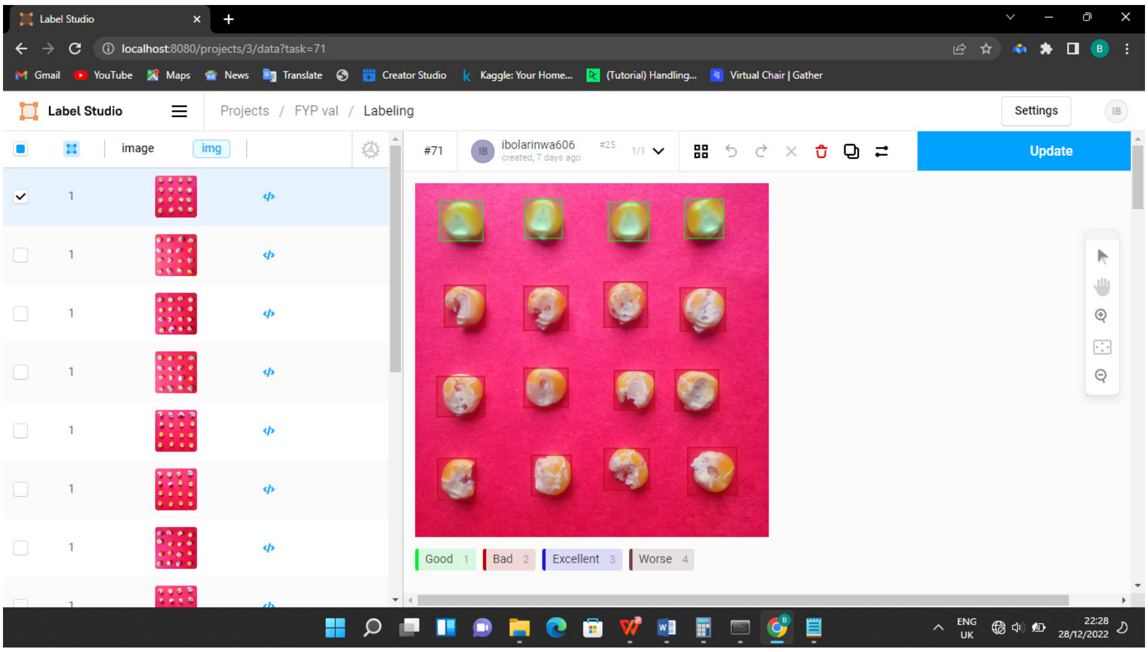

Figure 4: Annotation using label-studio

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2 0.11229314420803782 0.13356973995271867 0.12056737588652482 0.1252955082742317
0 0.34751773049645396 0.1264775413711584 0.13238770685579196 0.14420803782505912
0 0.5791962174940898 0.12293144208037825 0.1276595744680851 0.13238770685579196
0 0.8297872340425532 0.12411347517730494 0.13238770685579196 0.1300236406619385
0 0.11465721040189125 0.3687943262411348 0.13947990543735225 0.13711583924349885
0 0.35697399527186763 0.3723404255319149 0.1276595744680851 0.1300236406619385
0 0.5886524822695036 0.36643026004728135 0.1276595744680851 0.1276595744680851
0 0.8096926713947988 0.3723404255319149 0.1300236406619385 0.1300236406619385
0 0.1193853427895981 0.6111111111111112 0.13947990543735225 0.1158392434988l797
0 0.35224586288416077 0.5898345153664303 0.1276595744680851 0.1347517730496454
0 0.58274231678487 0.6134751773049645 0.12056737588652482 0.1347517730496454
0 0.8203309692671396 0.6182033096926713 0.13238770685579196 0.1252955082742317
0 0.12293144208037825 0.8144208037825059 0.13238770685579196 0.1252955082742317
0 0.36643026004728135 0.8191489361702127 0.1276595744680851 0.1252955082742317
0 0.6016548463356974 0.8156028368794327 0.13947990543735225 0.13711583924349885
0 0.8439716312056739 0.8309692671394799 0.13711583924349885 0.14420803782505912
```

Figure 5: Maize image generated annotation file

Data Preprocessing

Data augmentation: Because mosaics are a crucial component of YOLOv5, the process of implementing them was automated. Mosaics are created by randomly selecting four sources, resizing them to the same size, and fusing them together to create a larger image as depicted in figure 6. This process is like tiling. The bounding boxes of the objects in the tiles are then adjusted as necessary before the bigger image is arbitrarily divided into four comparable tiles. Mosaics can help the model detect items in difficult environments and reduce overfitting by increasing the diversity of the training. Additional augmentations are made using the albumentations library (kaggle, 2023). Data augmentation during training and Screenshot showing training summary are depicted clearly in figures 7 and 8 respectively. Other augmentation techniques include blur, median blur, random resized crop, gray, random brightness contrast, and random gamma. Image quality was also decreased in the augmentation to account for low quality photographs when making deductions from data that the model has never seen previously.

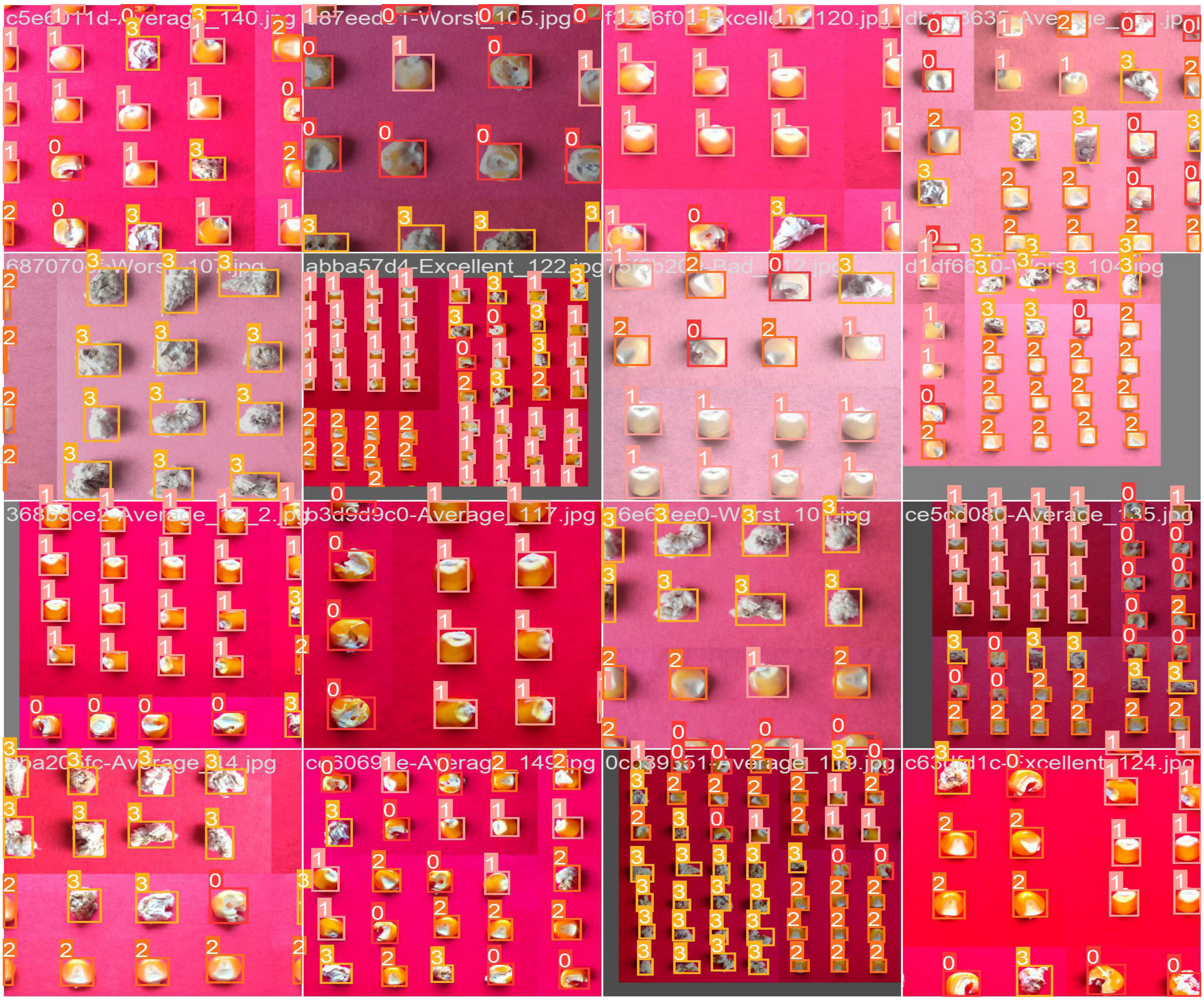


Figure 6: Mosaic augmentation for maize seeds

Training, validation and test sets

The maize dataset consists of three sets: training, validation, and test sets. YOLOv5 is trained on the training set, and its performance is evaluated using the validation and test sets. 1.648, 256, and 160 photos were used for each of the three sets in this investigation, which were split into training, validation, and testing sets with corresponding weights of 80%, 15%, and 5%. Several data augmentation techniques, including resizing, movement, width and height negate, trimming and scaling boundaries, diagonal flip, brightness and channel-related offset, and neighborhood fill designs, were applied to the data used for training with the objective of improving the diversity of the dataset. This tactic guarantees the framework's flexibility and effectively combats overfitting.

Experimental environment and training parameters

The experimental setup consisted of a Tesla T4 graphics card with 16 GB of memory, a 2.20 GHz Intel® XeonTM CPU, and 16 GB of RAM. Python 3.8.5, PyTorch 1.10.1, and the TorchVision 0.11.2 artificial neural network library were used to set up the training environment. The deep neural network acceleration package CUDA 11.6 was also used.

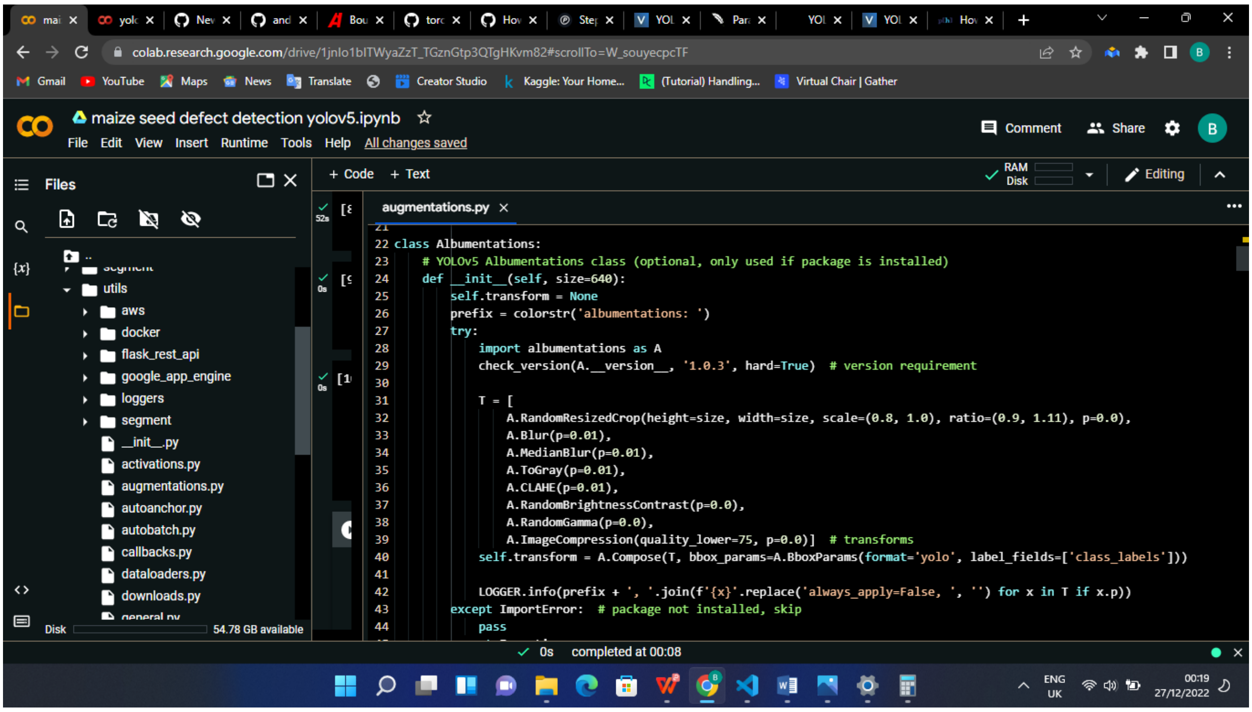


Figure 7: Data augmentation during training

Training parameter settings

YOLOv5 with BCELoss as the loss function and SGD as the optimizer was chosen for the network training (Javanmardi *et al.*, 2021). Initial settings for the input picture size and learning rate were 640 × 640 pixels and 0.0042, respectively, before being changed to 0.15. The coefficient of degradation has been configured at 0.00056 and the momentum value at 0.845. A warm-up parameter was also utilized to make sure the model got access to the data prior to training. All other parameters were set to their default values.

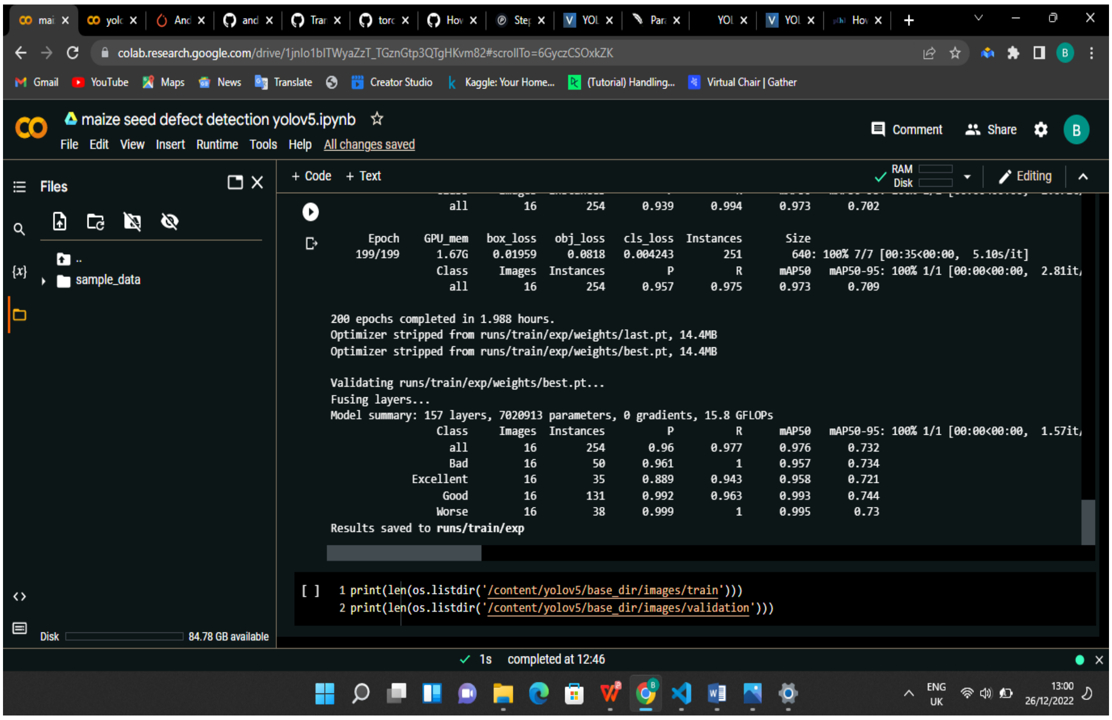


Figure 8: Screenshot showing training summary

Experimental Results and Analysis Model

Evaluation Metrics: The defect detection model was thoroughly examined by the researchers together with the other contemporary techniques described in the paper. Equations (1) through (5) give distinct formulas for every statistic, including mean precision (AP), accuracy (A), F1-score (F1), precision (P), and recall (R).

Several precautions were taken throughout the assessment.

$$R = \frac{TP}{TP + FN} \quad \text{Equation 1}$$

$$P = \frac{TP}{TP + FP} \quad \text{Equation 2}$$

$$A = \frac{TP}{TP + FN + FP} \quad \text{Equation 3}$$

$$F1 = \frac{2 \times P \times R}{P + R} \quad \text{Equation 4}$$

$$AP = \frac{1}{n}\sum_{i=1}^{n} P_i \left(P_i = \frac{1}{n}P_1 + \frac{1}{n}P_2 + \cdots + \frac{1}{n}P_n\right) \quad \text{Equation. 5}$$

The terms "true positive," "false positive," and "false negative" in equations (1) through (3) denote, respectively, the percentage of accurately determined positive occurrences, "wrongly identified negative instances," and "correctly rejected positive instances."Equation (4)'s F1, a recall and accuracy combined statistic, provides a more precise assessment of the model's performance. Mean average precision (mAP) is computed using a connection over unification (IoU) criteria whose value is 0.5, in the same way as AP is computed. Equation (5) states that the average accuracy of the classes is calculated by averaging the N P values for an assortment of N correctly determined specimens. Every sample that was properly identified corresponds to a P value.

RESULTS AND DISCUSSION

In this research, a computer vision object recognition model to identify irregularity in maize seeds was developed. The model was trained and tested on more than 1000 images with the same number of healthy and defective seeds. The model output was compared with other state-of-the-art algorithms for seed defect detection, i.e., YOLOv7 and YOLOv8. This section gives the summary of results and comparison of model performance across various scenarios.

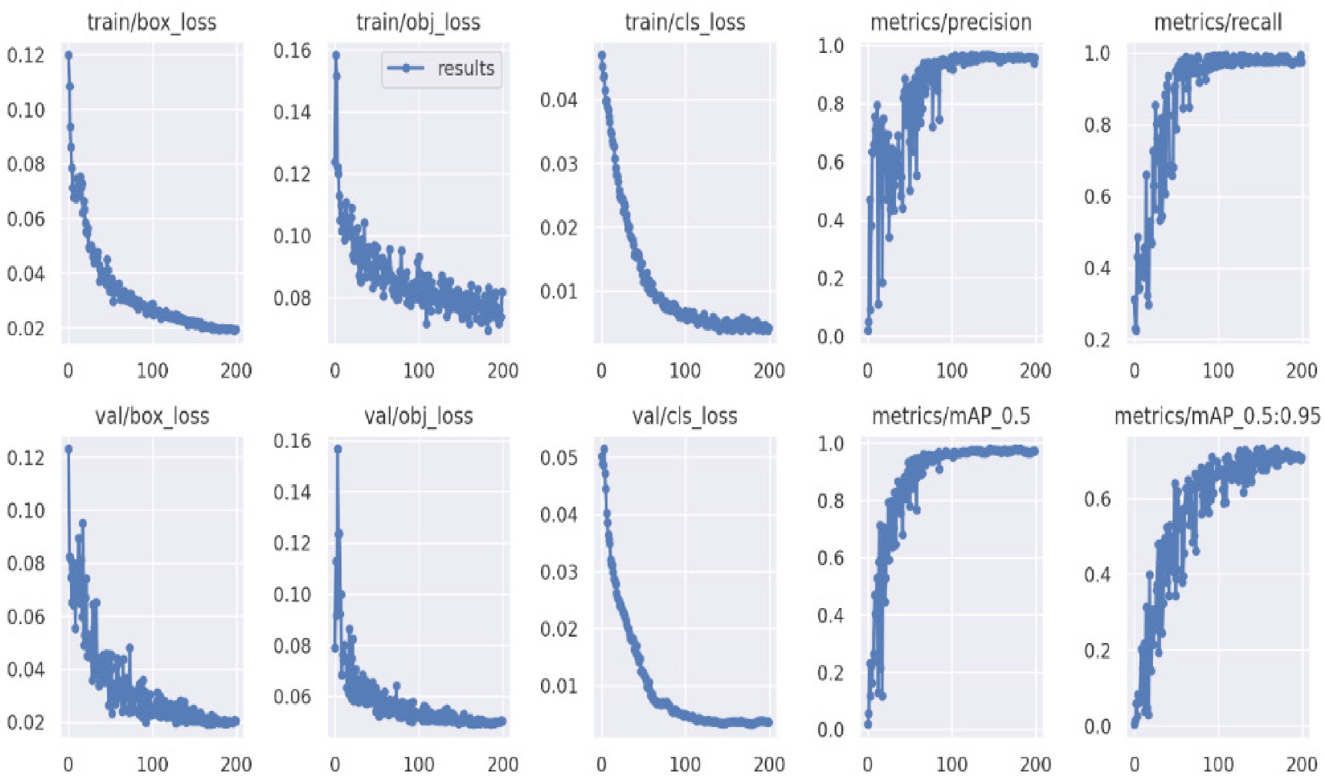


Figure 9: Metric charts for the YOLOv5 model

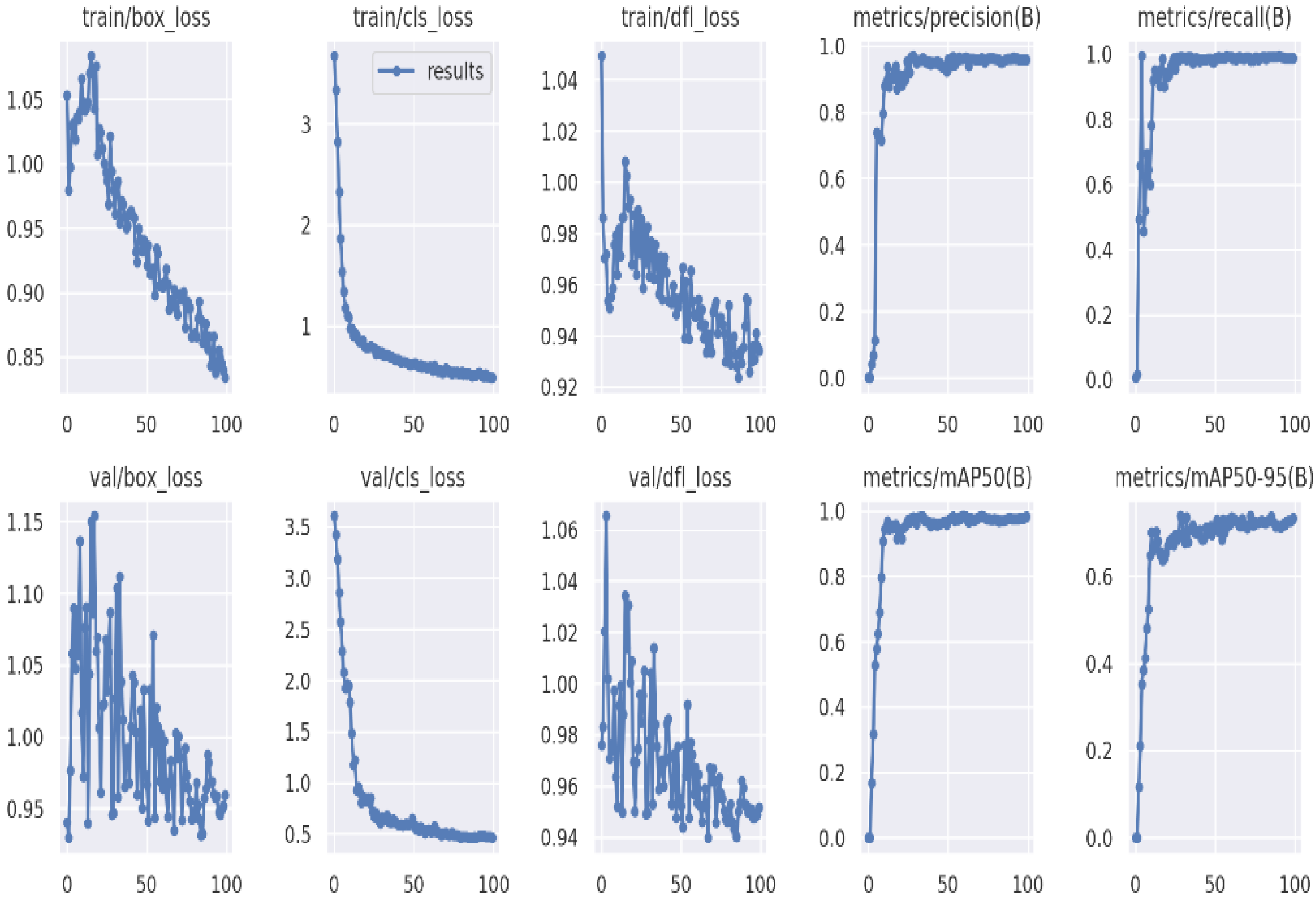


Figure 10: Metric charts for the YOLOv8 model

Comparison with other approaches

We also compared our YOLOv5 model with other state-of-the-art approaches to seed defect detection, including YOLOv7 and YOLOv8. We employed the same dataset and evaluation parameters as other studies to ensure that the comparison would be equitable.

YOLOv7

Table 1: Evaluation of the YOLOv7 model

Metrics (%)	Excellent	Good	Bad	Worse	All
P	89.7	100	96	99.9	96.4
R	100	96.9	100	100	99.2
F1	94.57	98.42	97.9	99.9	97.7
mAP	92.4	98.9	96	99.5	96.7

YOLO v5

Table 2: Evaluation of the YOLOv5 model

Metrics (%)	Excellent	Good	Bad	Worse	All
P	89	99	96	99	96
R	94	96	97.7	100	96.9
F1	94.57	98.42	97.9	99.9	97.7
mAP	95.8	99.3	95.7	99.5	97.6

YOLOv8

Table 3: Evaluation of the YOLO v8 model

Metrics (%)	Excellent	Good	Bad	Worse	All
P	88.4	100	96.1	99.8	96
R	97.1	95.5	100	100	98.2
F1	92.54	97.7	98	99.9	97
mAP	95.7	99.3	98.9	99.5	98.4

Tables (1) to (3) are contrasting the models that we have picked, with the YOLOv5 and YOLOv8 models somewhat superior to the YOLOv7 model. The conduct of the varied measurements on the YOLOv5 and YOLOv8 models is alarmingly comparative and about equal if we view the averaged measures. While the YOLOv8 model's precision and mAP scores are better than the YOLOv5 model's (98.4 and 98.2, respectively), the YOLOv5 model's F1-score is higher than the YOLOv8model's (97.7). The YOLOv8 model converges more quickly than the YOLOv5 model; whilst the lowest values for the YOLOv5 model are reached after around 200 epochs, they are reached after about 100 epochs for the YOLOv8 model.

Table 4: Studies with similar metrics

Study	Precision	Recall	F1	Accuracy
Wazir & Fraz, (2022)	98.2	98.1	98.1	98.1
Yao et al, (2021)	95.63	95.29	95.46	

Table 4 provides a review of the literature used in this inquiry. The authors of Wazir & Fraz, (2022) presented a unique technique that uses a deep convolutional neural network (CNN) as a universal feature extractor to automatically classify various kinds of maize seeds. Their model showed a 98.1% F1 score, 98.1% recall rate, 98.2% precision rate and 98.1% 98.1% accuracy rate.

Yao et al. (2021) used a two-pathway CNN with a watershed method, achieving 95.46% F1 score, 95.63% recall, and 95.29% precision. Its high accuracy has a major impact on the detection of defective maize seeds, which are crucial for food security. The method allows seed companies to detect and remove defective seeds with ease and higher yield and sustainability. YOLOv8 is also used in the research as a powerful deep learning model that is highly accurate for object detection. Flipping, rotation, and scaling techniques were used in anomaly detection using augmentation methods. The study offers an efficient automated technique of maximizing agricultural output. Future studies might use the approach in other industries and crops. Graphs of training/validation loss, precision, recall, and mAP are presented in figures 9 through 20 for YOLOv5, YOLOv7, and YOLOv8 models.

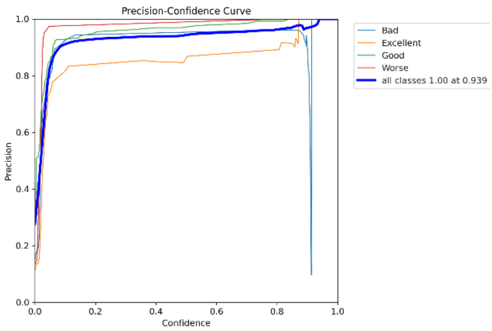


Figure 11: Precision curve for the YOLOv5 model .

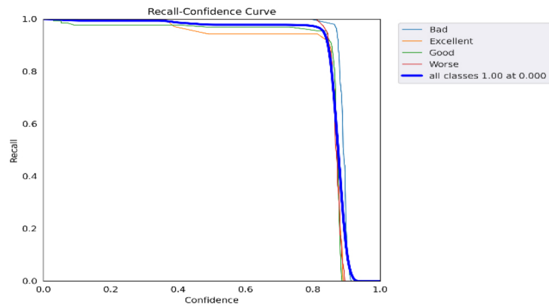
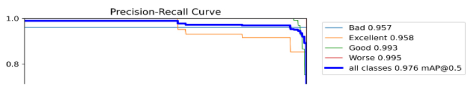
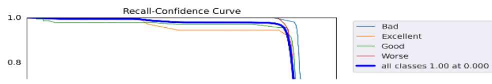
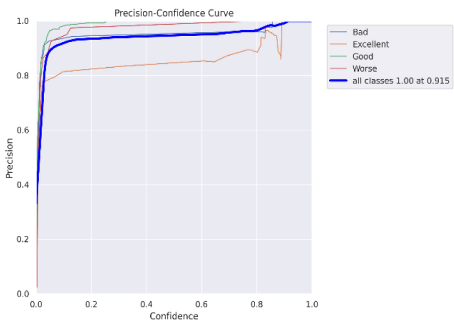


Figure 12: Recall curve for the YOLOv5 model







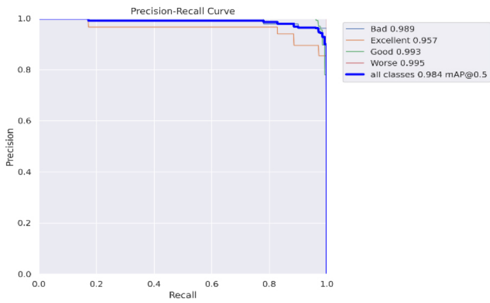


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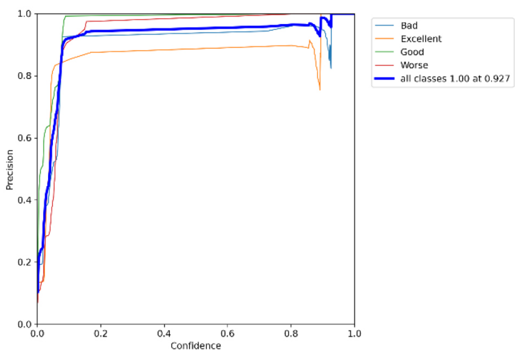
Figure 15: Precision curve for the YOLOv8 model

Figure 16: mAP curve for the YOLOv5 model



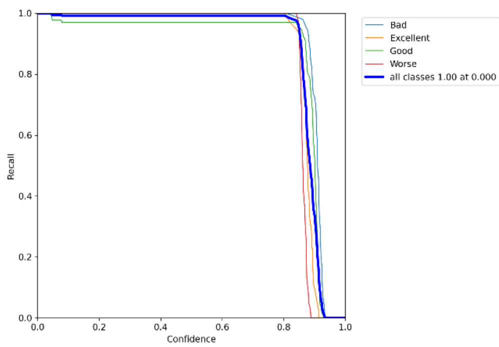


Figure 17: Precision curve for the YOLOv7 model

Figure 18: Recall curve for the YOLOv5 model

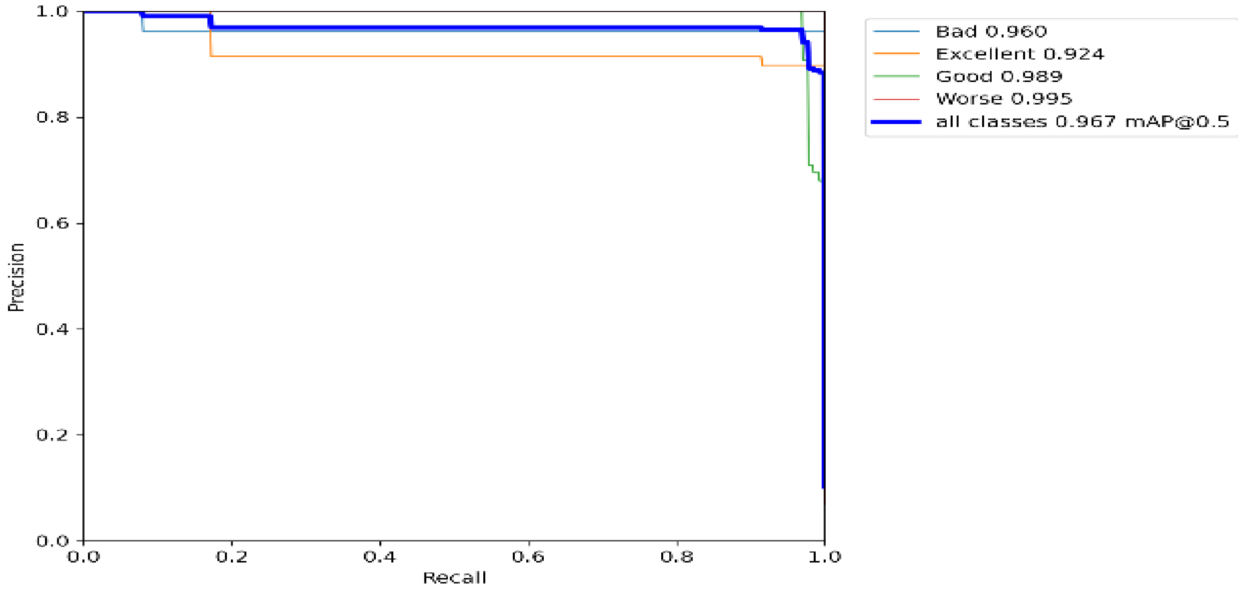


Figure 19: Map curve for the YOLOv5 model

Confusion matrix

The confusion matrix shows how accurate the predictions are between all 4 classes is depicted in figure 20.

- The YOLO v5 model correctly classifies all instances of '**Bad**' maize seeds
- The YOLO v5 model classifies 91% of seeds which belong to the '**Excellent**' class correctly
- The YOLO v5 model classifies 97% of seeds which belong to the '**Good**' class correctly
- The YOLO v5 correctly classifies all instances of the '**Worse**' class
- The YOLO v5 classifies 3% of instances in the '**Excellent**' class as '**Good**'
- The YOLO v5 classifies 9% of instances in the '**Good**' class as '**Excellent**'

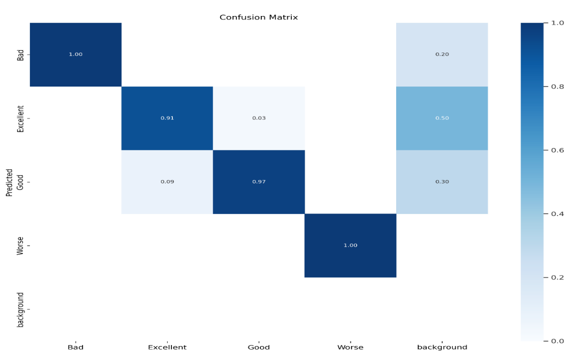


Figure 20: Confusion Matrix

Visualisation feature

Understanding the inner workings of a deep neural network can be made easier by visualizing feature maps. The neural network employed in this study's analysis has 24 layers, and each layer has between 32 and 512 convolutional kernels. The investigators could see how features were represented for each layer by choosing typical feature maps. A visual representation of the features that the model discovered is shown in Figure 21. Researchers can study the resulting representation to see how the network harvests traits at each layer during model training. This can show where the model might have faults and indicate where it needs to be strengthened. Generally speaking, researchers may find that visualizing neural network models is an excellent method for better understanding how deep models develop and for boosting their effectiveness. Based on the given feature maps, convolutional neural network kernels for tiers 0 to 1 were trained to retrieve picture margins and seeds of maize margins. Observing how several convolutional kernels focus on different regions—such as the edges of fault zones, seeds, or both—is fascinating. While convolutional kernels focused on gathering textural information, layers 2 through 4 were better at depicting the seeds' basic structure. However, the edge and texture information faded, and the resulting image's contour altered from fine to coarse in the characteristic maps that the 5- to 6-layer network produced. It was hard to discern between the texture and edge information of the seeds due to the increasing complexity of the feature representation between layers 7 and 23. Consequently, as the number of network layers and filters rises, the features of the network can be thought of as translating minimal to multifaceted features.

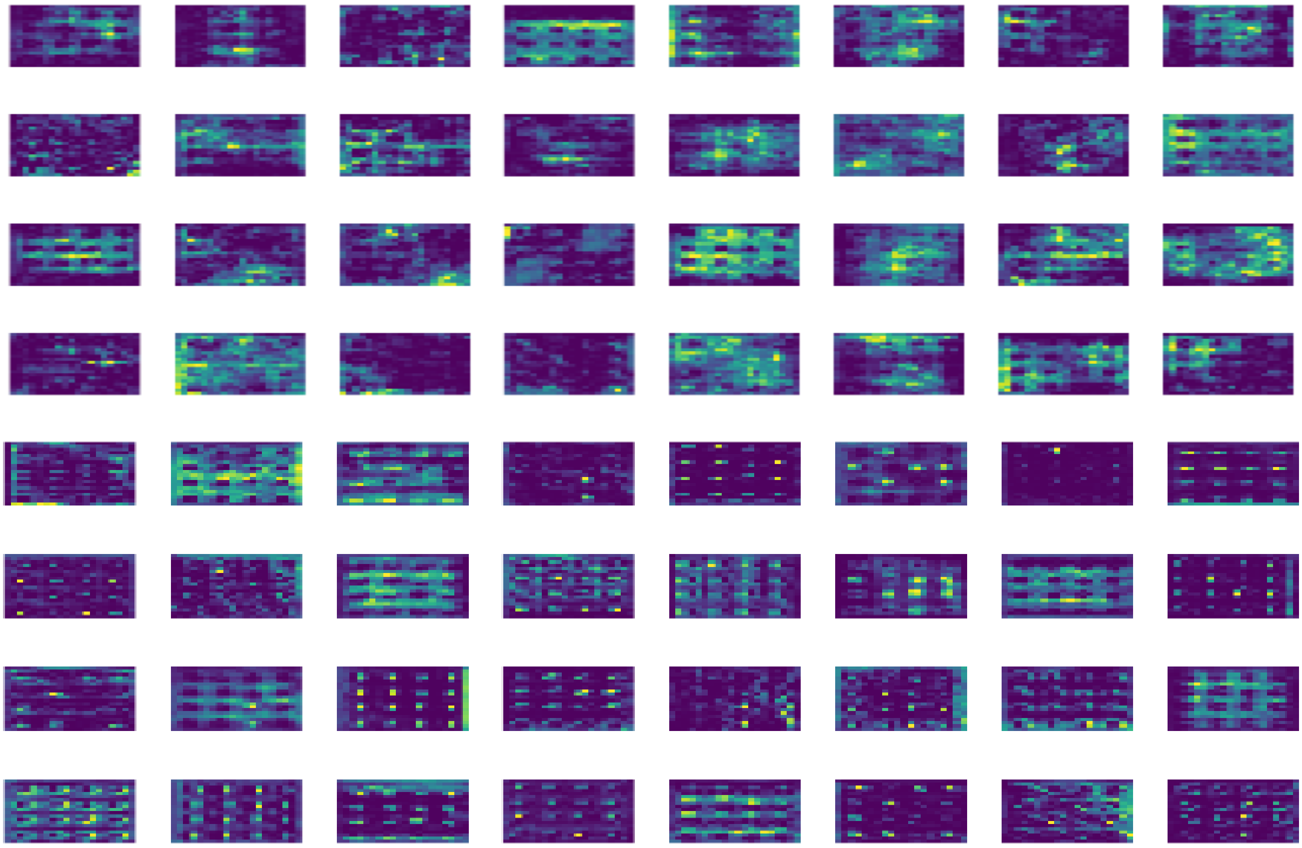


Figure 21: Visualization map

Model inference

After training was completed, inference was performed to predict bounding boxes and correctly classify seeds in images that the model has never seen before, the inference was performed using the detect.py script in the YOLOv5 repo.. Figures 22 and 23 show, respectively, the inference image before the inference was made and the anticipated bounding boxes and their confidence scores after the inference.

Figure 22: Inference Image

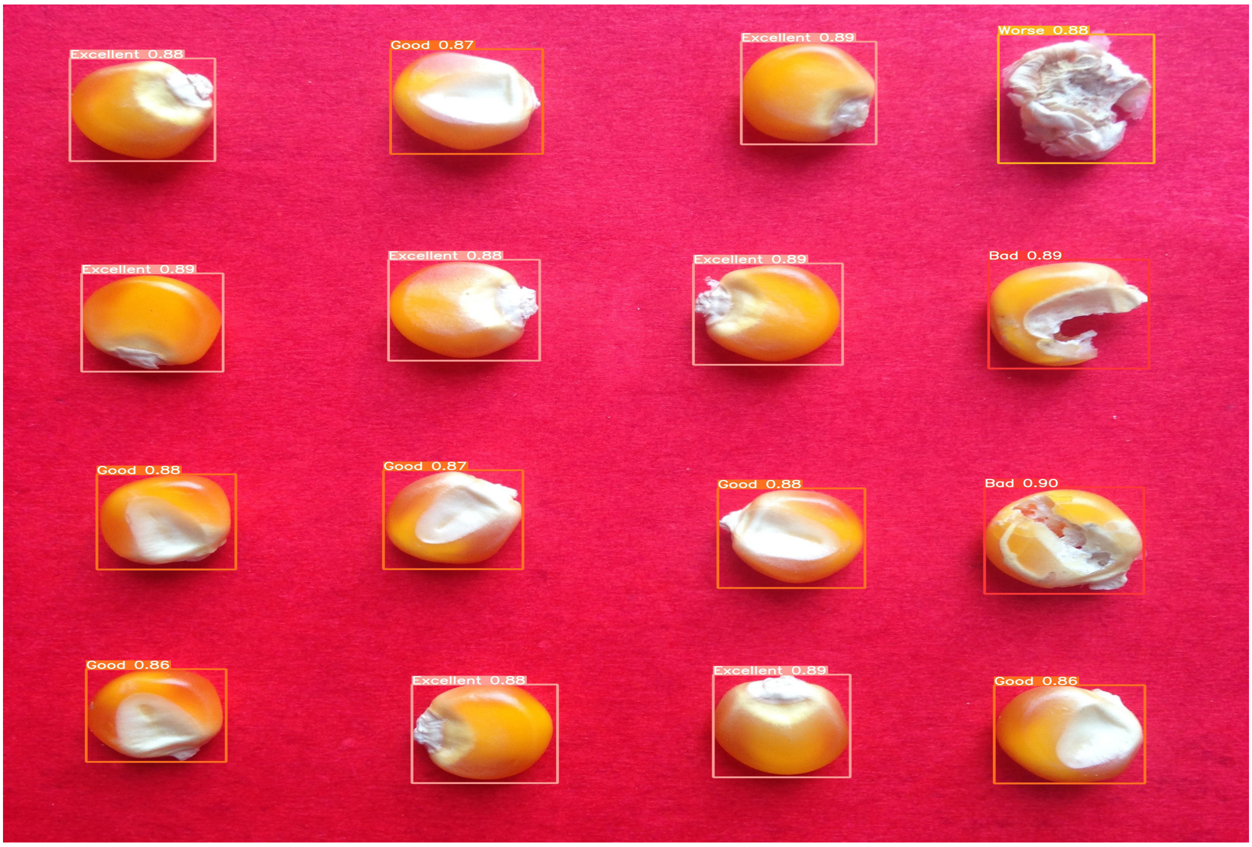


Figure 23: Inference Image after the inference

CONCLUSION AND RECOMMENDATION

We have presented a deep learning-based technique for identifying anomalies in maize seeds, to sum up. We used a number of YOLO implementations and compared their efficacy to figure out which version of YOLO performed the best. Our research demonstrates that the YOLOv8 model performed better than the other models put to the test, obtaining the best accuracy in detecting defects in maize seeds. The model could accurately spot a range of faults, including fractures, stains, and deformities, with an accuracy of up to 97%. Furthermore, we have demonstrated the benefit of visualizing how the network collects features in order to better understand potential problems with the model and improve performance.

Thanks to the feature maps we were able to gather from the model's intermediate layers, we were able to understand more about how the model adaptations to recognize various features at each layer. Our study provides a practical way for using computer vision to detect faults in maize seeds, which can be applied in the agricultural sector to improve seed quality and increase yields. By using other cutting-edge techniques like data augmentation and transfer learning, the proposed method can be made even more effective. In recommendation, the data should be expanded to include different maize types, defect types, and environmental conditions to improve model robustness. Bringing on board agricultural experts will ensure defect annotations are both accurate and practical in use. This will improve both model performance as well as practical usability.

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