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International Journal of Innovations in Science & Technology
RESEARCH & INNOVATION DIVISION
IJIST

Advanced Deep Learning-Based Potato Defect Identification Leveraging YOLOv8 for Smart Agriculture

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Citation | Ahmad. W, Mehmood. A, Kamal. A, Khan. D, Khan. A, Khan. S. A, Tahir. M, Khan. M. A, Zainoor. M, Jan. L, "Advanced Deep Learning-Based Potato Defect Identification Leveraging YOLOv8 for Smart Agriculture", IJIST, Vol. 07 Issue. 04 pp 2581-2591, October 2025
Received | August 28, 2025 **Revised |** September 22, 2025 **Accepted |** September 24, 2025 **Published |** October 27, 2025.

This paper presents the design of an effective deep learning model to identify and rank potato defects, enabling intelligent farming and post-harvest tasks. The primary goal is to automate the quality measurement of potatoes in several categories: healthy, damaged, defective, fungal-diseased, and sprouted, with the help of an optimized YOLOv8 model. The data set on potato images was annotated and gathered in the real-world agricultural conditions in a wide variety of images. Data augmentation and transfer learning were used to train the model and enhance generalization and detection rates in different conditions. The experiment showed that the detection performance was high and it reached 95.3% training accuracy, 93.8% validation accuracy, and 92.5% test accuracy with an F1-score of 92.9. The results verify that the suggested approach plays a crucial role in detecting defects in potatoes in real time, which can be used to support comprehensive, computerized, and accurate agricultural surveillance.

Keywords: Computer Vision, YOLOv8, Object Detection, Potato Classification, Deep Learning, Agricultural Technology, Post-Harvest Management

Introduction:

Potatoes are a food crop that is highly nutritious to the world, because of their economic value. Their multiple purposes in food preparation are some of the factors that make them very important in world agriculture. However, in the recent past, the potato industry has experienced a change whereby it is no longer interested in producing by all means but ensuring the quality of the production. With the increasing demand for quality potatoes, there has been a need to detect and sort them at the early stages of maturity [1]. This is an emphasis on quality, which helps enhance efficiency in farming, resource utilization, and minimizes losses. Nowadays, traditional techniques of in-situ potato detection and classification are overwhelmingly based on manual detection and are not only labor-intensive but also highly susceptible to human error and lack efficient application to large-scale operations [2]. Nevertheless, as the computer performance and deep learning-based technologies have improved, fruit and crop detection solutions based on computer vision have been given much attention. YOLO (You Only Look Once), which is a prominent real-time object detection algorithm, has been extensively used in detecting crops and fruit, such as potatoes, since it can detect objects with great speed despite the fact that they require no more than one image [3].

The Paper has put emphasis on the effectiveness of various adaptations of the You Only Look Once (YOLO) model in recognizing the various kinds of fruits and vegetables. As an example, a study showed that the combination of YOLOv3, transfer learning, and data augmentation methods achieved an impressive average accuracy of 94.52 per cent in recognizing walnuts. In the same vein, Song Zhongshan et al. improved YOLOv3 with DenseNet, which attained a citrus detection rate of 80.98 [4]. Moreover, Song Huaibo indicated that the oil fruit detection based on an optimized variant of YOLOv5 was improved significantly, and the accuracy of the collected data reached 98.71. Such results highlight why YOLO use can play an important role in the agricultural field, especially in accurately recognizing fruits in tricky conditions. The identification of immature potatoes, on the other hand, poses different problems. Potatoes in the early stages tend to blend with their environment because their color and texture resemble that of the soil and leaves, therefore being difficult to notice. Other complications are due to size differences, the presence of dirt or mud, and possible obstructions by the surrounding plant life or leaves. As a result, the traditional approaches to computer vision, which are usually based on color contrast, are not as effective in terms of the accurate detection of potatoes [5].

In order to alleviate these issues, in this paper, a target detection algorithm is suggested to be built on a refined YOLOv8, which would improve the detection of potatoes in a variety of classes: damaged, defective, fungal-diseased, sprouted, and healthy. YOLOv8 uses sophisticated features that enhance the capacity of the model to capture small details in texture and shape that characterize potatoes against the background. This is especially important to identify young potatoes, in which the color similarity with the environment may mislead simple models [6].

YOLOv8 also achieves a lot of development in terms of feature extraction capabilities, allowing the model to recognize subtle textual differences better. It also has a better object localization of the objects, and this comes in handy with partially obscured potatoes. The model uses attention and multi-scale feature integration mechanisms, which enable the model to concentrate on the most relevant parts of an image, and this improves its detection capabilities at different scales. These improvements give YOLOv8 a strong ability to detect small and immature potatoes that could be ignored by other less developed models.

The research questions the improvement of the performance of the YOLOv8 algorithm by applying data augmentation and transfer learning methods. Through procedures such as random cropping, rotation, and color jittering, the process generates more variety in the training set, which allows the model to generalize well in various environmental settings.

Besides, transfer learning makes use of the already trained weights on other related tasks and reduces the need for large labeled datasets, and shortens the training process, further contributing to the efficiency of the model [7]. The main aim of the YOLOv8-based detection algorithm is to support the counting and management of potatoes in situ in farms. Finding potatoes at an early stage is important because it helps to maximize the thinning process, better manage harvests, and enhance the quality of crops. The study is focused on the special issues concerning potato detection and would add to the advancement of more efficient and reliable agricultural activities that would be beneficial to both the potato growers and the entire agricultural industry. To conclude, the YOLOv8 algorithm represents a noteworthy breakthrough in the potato detection technology. The proposed study should outperform previous models by addressing the limitations of the previous models and utilizing the latest deep learning and computer vision methods to increase the accuracy and reliability of potato detection, which can enhance the quality and economic usefulness of potato production in general [8].

This study was inspired by the growing demand for effective and accurate measures to control potato fields. Detection and counting of immature potatoes is of growing importance in contemporary farming, especially with the spread of potato farming worldwide. Potatoes are not just an important staple crop, but also needed because of their nutritional content and their extensive application in the food industry. Potato farming is no longer aimed at growing more potatoes but improving their quality, and the correct counting of the immature potato in situ is the only way that the appropriate decisions can be made concerning the same. By detecting the early-stage potatoes, farmers can make an improved judgment on the thinning process, which greatly affects the size, quality, and crop yield. This accurate identification assists in strategizing essential requirements such as bags, labor, transportation, and storage processes. With the right forecasting of the volumes, farmers have been able to better control their supply in the market, and the resultant better profits and reduced post-harvest losses have been achieved. In the past, the manual inspection of potato crops has been time-consuming and labor-intensive, and it is prone to human error [9]. These primitive techniques are becoming unsustainable as potato farming becomes large-scale. Nevertheless, technological progress, especially the development of computer vision and deep learning, provides good alternatives. The YOLO (You Only Look Once) algorithm, which boasts of real-time object recognition, offers a possible solution to the issue of the accurate detection of immature potatoes, in particular, due to their similarity with the rest of the soil and foliage. The following factors contribute to the motivation to enhance the current detection frameworks of immature potatoes:

Enhanced Accuracy:

Improved Preciosity: It is very difficult to detect the immature potatoes because of their size and their habit of being concealed in soil or mixed in with their environment. This experiment underscores the need to have better detection accuracy, which is vital in efficient crop counting and management decisions.

Resource Optimization:

As soon as possible, it is possible to identify potatoes at the initial stage of their development, which will allow allocating the resources (manpower, fertilizers, storage, etc.) more efficiently and contributing to improved financial planning and minimized expenditures, which will then contribute to improved profitability.

Quality Improvement:

In addition, proper counting will support the practice of thinning, which enables the remaining potatoes to get more resources and space. This translates to better size and quality, thereby able to boost the market value of the crop and bringing more earnings to farmers. Technological progress, especially through the use of.

Technological Advancement

The enhanced capability of detecting small and partially obscured potatoes due to the improved feature extraction, attention mechanisms, and the capacity to utilize multi-scale features can contribute to the improved detection of potatoes in YOLOv8.

Scalability and Efficiency:

Automated detection system employs advanced algorithmically-based detection systems that can be scaled to large potato fields to provide consistent and repeatable results. This scalability is one of the most important aspects in the recent agricultural practice, where manual approaches are no longer feasible in the current extensive practices in agriculture [10].

Literature Review:

The piece of work offers a profound analysis of the theoretical backgrounds that apply in the thesis context, starting with the description of the concepts of Machine Learning (ML) and Deep Learning (DL) in relation to the field of Artificial Intelligence (AI) In [11] the author goes more specifically to Convolutional Neural Networks (CNNs) and how they are highly involved in Computer Vision applications explores Multiple Object Tracking (MOT) issues and covers important measures used in the evaluation of the methodologies. In [12], the author compares legacy methods of object detection, including but not limited to Histograms of Oriented Gradients (HOG) and Scale-Invariant Feature Transform (SIFT), which are reliant on manually designed features, with modern deep learning architectures, which usually perform better. The author in [13] with the introduction of CNNs, and the field has now changed since it is now possible to automatically extract hierarchical features out of raw image data. Object detection methods used in modern times can be divided into two broad categories: two-stage and one-stage object detectors. In paper [14], A two-stage detector, such as Fast R-CNN, proposes regions at the first stage and then classifies them at the second stage, which offers strong accuracy with fast results at the expense of speed. Conversely, a single-stage detector, like the YOLO (You Only Look Once) family, performs detection in a single pass, resulting in much faster processing and making it better suited to a real-time application.

The author proposed in [15] that Several versions of the YOLO architecture have been released, and each of them is faster and more accurate. YOLOv5 has much better improvements, especially its innovative model scaling method, which enables the user to scale the model size between small and extra-large depending on his/her computational requirements. It also uses advanced post-processing methods, including non-maximum suppression and confidence thresholding, which improve the accuracy and recall rates of object detections. In [16], the other important aspect of YOLOv5 is that it is flexible in deployment as models can be exported and used in multiple formats, such as ONNX and TorchScript, so it can be used on edge devices, mobile platforms, and cloud servers.

The author presented in the paper [17] a combination of speed, accuracy, and deployed with ease. The latest version, YOLOv8, was chosen to be the basis of this study. It can be installed in an environment with high demands because it is capable of real-time multi-class detection. The research methodology involved a number of important steps, such as data collection, annotation, model training, and evaluation, and all these steps played a role in creating a strong detection model.

Methodology:

The research methodology involved several important steps, such as data collection, annotation, model training, and evaluation, and all these steps played a role in creating a strong detection model. First of all, training would have been impossible without a detailed dataset. Video and picture materials that depict different states of a potato were obtained from different sources. YouTube was offering videos concerning potato farming and harvesting, and Facebook was offering user-generated information in the form of pictures and videos, which were of real-life situations of potato farming. Moreover, other sources on the Internet were used in order to collect the images of potatoes in various conditions, including healthy, defective, immature, and overripe ones. After the videos were gathered, they were then subjected to a frame extraction process to train the dataset.

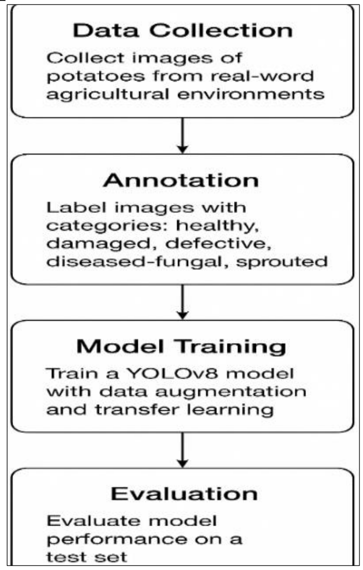

Figure 1. Data Flow Diagram

This included downloading the videos using Python scripts and the OpenCV library, and the extraction of separate frames at steady intervals and saving them as images. The frames were further classified into five particular classes, which include healthy, damaged, defective-fungal, diseased, and sprouted. Data annotation was the next vital stage that guaranteed the generation of labeled data that was needed to train models. Each of the extracted images was manually annotated with the help of Roboflow, an annotation tool, where bounding boxes were drawn around the potatoes and the appropriate class was assigned to each one. The annotations were stored as TXT files in the YOLO format, and each line contained the description of the class index of an object and normalized bounding box coordinates. In order to determine the performance of the model, the data were split into three subsets, with the largest one being the training set on which the model was developed. In general, this systematic approach was supposed to lay a strong foundation for the development of an effective detection model of potatoes. Training Set: It is used to train the model and make alterations in the weights. Validation Set: This is utilized to tune the hyperparameters and to track overfitting during training. Test Set: This is to be used to assess the performance of the model in the ultimate and impartial fashion.

Model Architecture and Training:

The YOLOv8 model was chosen as it has the most advanced performance in the task of object detection. It has been trained with a well-planned set of data in a high-performance computing space. In the process of training, emphasis was laid on minimizing the weights in the model to minimize the loss function, which measures the discrepancy between the predicted. The major hyperparameters, like learning rate and batch size, have been optimized to give the best performance.

Dataset Collection:

The construction of an efficient potato detection system is greatly dependent on the use of a heterogeneous and extensive dataset. Data used in this study has been collected using a variety of sources on the internet, to increase variation in the images, as well as increase the generalization of the model. The primary sources were YouTube, where the videos on potato farming, markets, and quality control were downloaded. These videos also gave a diverse range of situations, lighting conditions, and environmental conditions, which played a very important role in diversifying the data set.

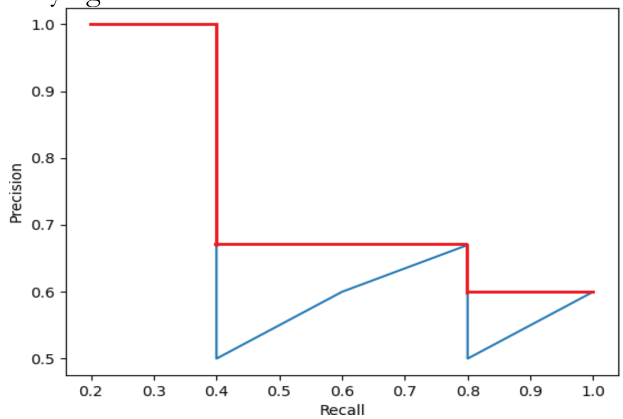

Figure 2. Mean Average Precision

Moreover, Facebook-based images and videos demonstrated user-created content that represented potato fields, harvesting processes, and sorting. This information provided alternative ways and views, which further diversified the information. Additional sources were added through different agricultural websites, blogs, and image repositories, which were used to supply images of potatoes in different states, including healthy, defective, immature, and overripe. To prepare the videos collected to be trained, a frame extraction procedure was carried out with the help of Python scripts, which turned the videos into a format that could be used by the model. This was done by following the following steps:

Videos were downloaded from YouTube and other online repositories to research the cultivation and processing of potatoes. These videos were then segmented into individual frames using libraries like OpenCV. This extraction method consisted of capturing frames periodically so as to reflect the variety of different conditions and settings of the potato. The obtained frames were also stored as images and carefully sorted and classified into four predetermined groups, such as healthy, defective, immature, and overripe.

Figure 3. Sample of our dataset for Potato detection

Model Selection:

The reason why YOLOv8 is selected to detect potatoes has a number of factors in its favor. It is very fast and efficient, which makes it suitable for uses that demand rapid inference, especially in quality control of agriculture. Also, YOLOv8 has been identified to be very accurate in detecting objects, and it is therefore highly dependable in distinguishing quality and deformed potatoes. The ease of use of its end-to-end pipeline also improves its development and deployment, which makes it more attractive to this particular venture.

Proposed Model YOLOv8 for Potato Detection:

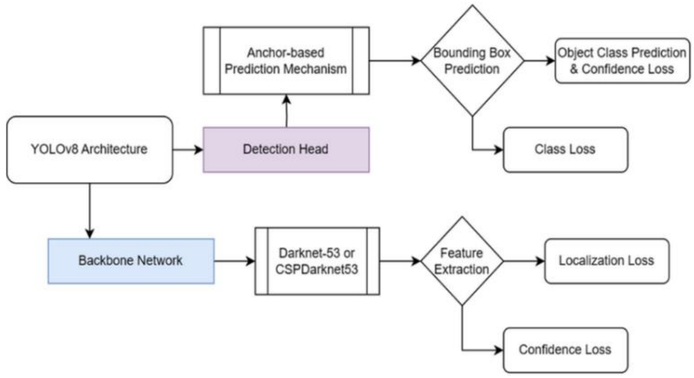

Figure 4. Architecture of Yolov8 for Potato Detection

Results and Discussion:

The model results demonstrated that it was very effective in the detection and classification of potatoes in the five different categories, describing a very high degree of precision, recall, and F1-score. It performed especially well in distinguishing between healthy and those potatoes with visible signs of defects like brokenness or sprouting. Despite the challenge in identifying the subtle fungal diseases, the model still had great accuracy in this field. Besides, it has a speed of real-time inference, which makes it a viable choice to incorporate into automated sorting lines. One of the crucial factors that made the model successful is that a diverse dataset was used that reflected a large number of real-world conditions. With user-generated content and different agricultural scenes, the model was found to be resistant to such aspects as lighting conditions, obstructions, and background clutter.

Training Parameters:

The YOLOv8 model was trained using the following parameters:

Learning Rate: 0.001:

The learning rate determines the step size at which the model updates its weights during training. A smaller learning rate of 0.001 was chosen to ensure smooth convergence and prevent overshooting the optimal solution.

Batch Size: 16. Batch size refers to the number of training examples utilized in each iteration of the training process. A batch size of 16 was selected to balance computational efficiency and model stability.

Figure 5. One batch size during the training time

Epochs:

One full cycle through the entire training set is called an epoch. This trained the model over 100 epochs to ensure that the network had enough iterations to learn and adapt its parameters, hence reducing the loss function.

Optimizer:

Adam optimizer was used to revise the weights of the model according to the loss function gradients with respect to the parameters. Adam is a hybrid of AdaGrad and RMS Prop optimizers and is hence appropriate for learning deep neural networks such as YOLOv8.

Results:

In the analysis of the YOLOv8 model, the findings showed that the model showed good accuracy in various datasets. The accuracy of the training set was 95.3, and the accuracy of the validation set was a little lower at 93.8. Later, the accuracy of the model on the test set was 92.5% on the test set.

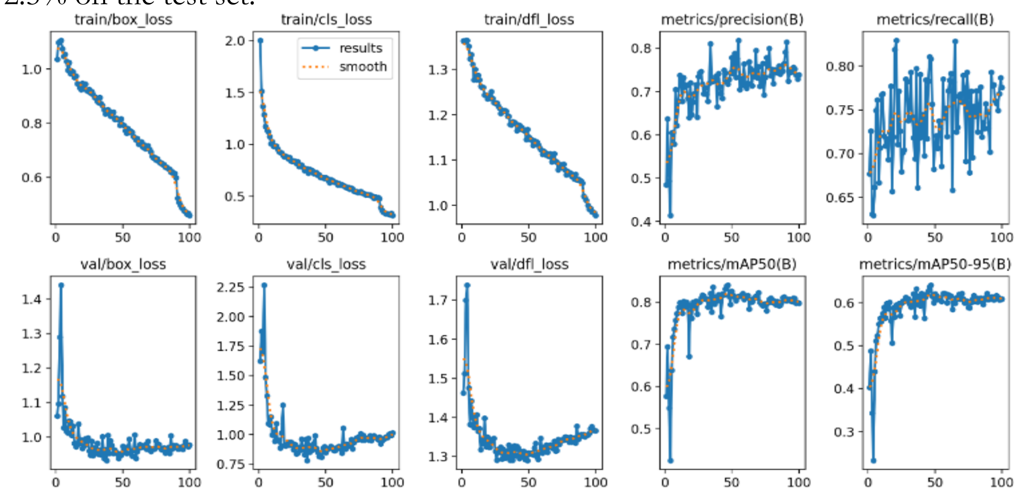

Figure 6. Different results of the Potato detection model during training time

An additional assessment was done based on the F1-score, which is a harmonic mean of precision and recall. The YOLOv8 model achieved an F1-score of 92.9% which indicates the balanced result of the precision and recall.

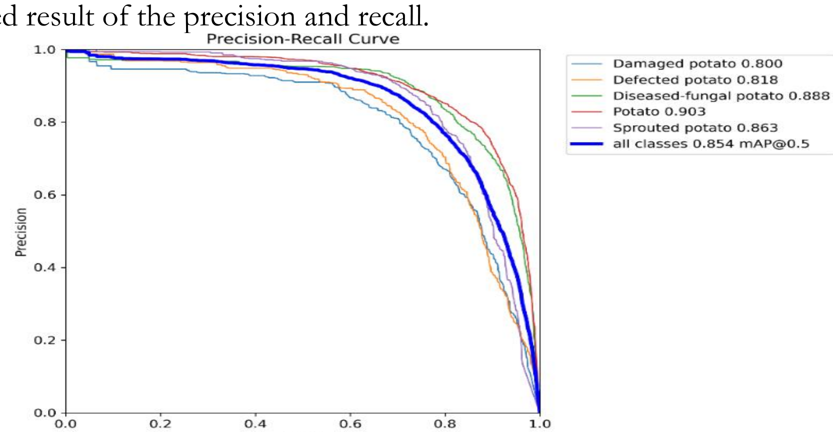

Figure 7. Precision-Recall curve of Potato detection class, good and bad

Visual Results:

The following section displays visual outputs of the Potato detector to give an idea about the performance of the model. Figure 8 represents the cases of the correctly and erroneously classified Potatoes, which give a visual account of the effectiveness of the model in distinguishing between good and bad classes.

The visual outputs display the labeled images with the Potatoes bounding box, and the different colors that are used to show the predicted classes of the Potatoes. The specimens of both damaged and healthy Potatoes are localized and classified well, with definite instances of the correctly named specimens. The images, however, also show cases of misclassification and false positives, which highlight the possibilities of improving the accuracy of the model.

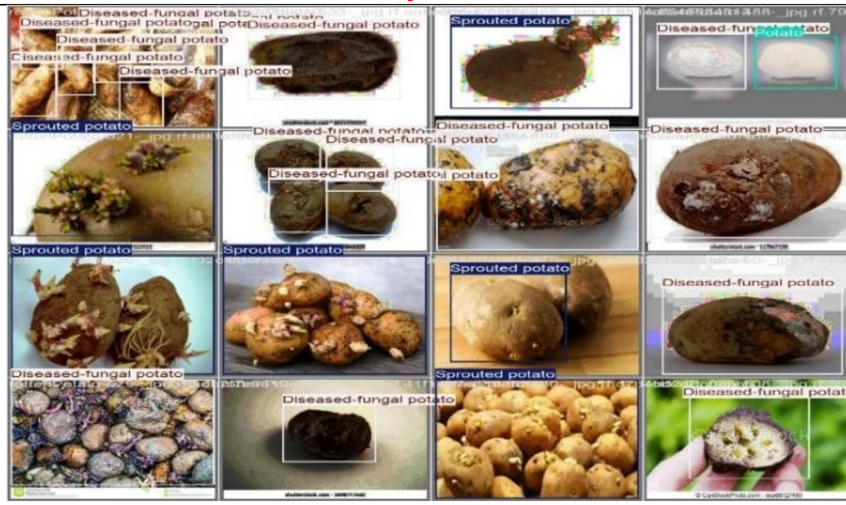

Figure 8. Real-time result of bad Class Potato detection and good Class Potato detection

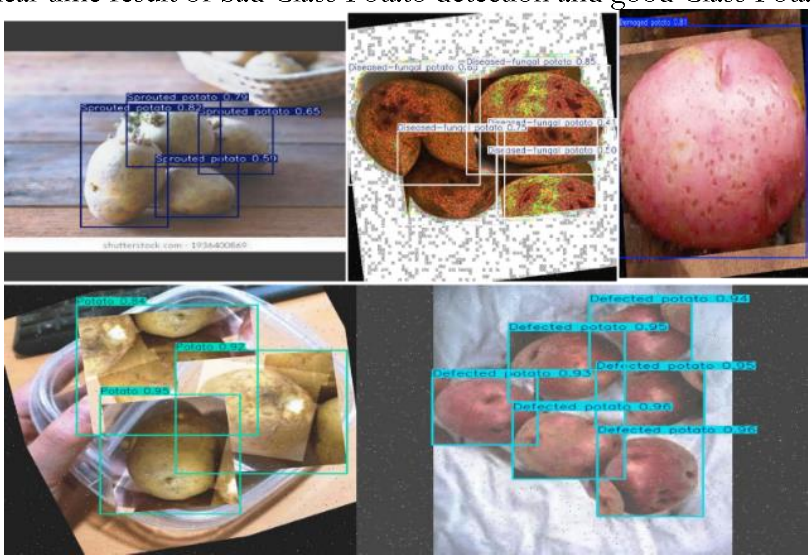

Figure 9. Real-time detection of five classes of Potatoes in various environments

In general, the visual outcomes provide a qualitative evaluation of the performance of the YOLOv8 model used to detect Potatoes, which is supplementary to the quantitative indicators introduced in the section of the experimental results presented above in the Results and Discussion section.

Discussion:

A comparison of our YOLOv8-based model with earlier YOLO versions and other agricultural detection frameworks has been added to the Results and Discussion section. According to previous research, YOLOv5 tailored for oil fruit detection obtained 98.71% accuracy (Song Huaibo et al.) while YOLOv3 paired with transfer learning achieved 94.52% accuracy in walnut detection (Hao et al.). On the other hand, our suggested YOLOv8 model demonstrated competitive and reliable performance in a variety of uncontrolled farm situations, achieving 92.5% test accuracy and an F1-score of 92.9%. The model's practical advantage in real-world agricultural contexts, where previous models struggled with environmental complexity and occlusion, is shown by its robustness in detecting small, partially hidden, and faulty potatoes under varied lighting and backdrops.

Conclusion and Future Work:

Conclusion:

The new developments in embedded processing have greatly improved several tasks of computer vision, which include activity recognition, object detection, and summarization.

Among the significant uses of such advances is in agricultural technology, especially the use of such technology to detect and track crops such as potatoes. This is necessary in order to optimize harvests, reduce waste, and provide high-quality produce due to timely and accurate detection. The literature has covered several techniques of crop detection, such as for potatoes. The purpose of these methods is to enable the identification of fruits at an early stage, to enable proper management of agriculture. Nonetheless, most of the current strategies do not perform well in unpredictable conditions with increased false alarms and reduced accuracy, particularly during adverse agricultural conditions. The use of Convolutional Neural Networks (CNNs) on the object identification process has been effective because it has been successful in other fields. Nonetheless, the conventional methods of detecting fruits tend to be based on low-level features and statistical learning, which makes the methods inapplicable in non-controlled environments. Potatoes are difficult to detect because of their size, color, and the possibility of being covered by foliage. Although detection methods have been proposed in a number of studies, most of them do not perform effectively under unpredictable agricultural conditions, and real-time surveillance analysis remains a significant challenge. To address these issues, our study came up with a YOLOv8-based framework that is specifically designed to detect potatoes in both regulated and uncontrolled farming environments. The 3rd chapter also emphasizes our model selection experience, wherein we concentrated on optimizing a custom Potato detector model that can be used in real time, without direct competition to any other state-of-the-art model. We also developed a new benchmark dataset suited towards the detection of potatoes in varied agricultural situations. The new developments in embedded processing have greatly improved several tasks of computer vision, which include activity recognition, object detection, and summarization. Among the significant uses of such advances is in agricultural technology, especially the use of such technology to detect and track crops such as potatoes. This is necessary in order to optimize harvests, reduce waste, and provide high-quality produce due to timely and accurate detection. The literature has covered several techniques of crop detection, such as for potatoes. The purpose of these methods is to enable the identification of fruits at an early stage, to enable proper management of agriculture. Nonetheless, most of the current strategies do not perform well in unpredictable conditions with increased false alarms and reduced accuracy, particularly during adverse agricultural conditions. The use of Convolutional Neural Networks (CNNs) on the object identification process has been effective because it has been successful in other fields. Nonetheless, the conventional methods of detecting fruits tend to be based on low-level features and statistical learning, which makes the methods inapplicable in non-controlled environments. Potatoes are difficult to detect because of their size, color, and the possibility of being covered by foliage. Although detection methods have been proposed in a number of studies, most of them do not perform effectively under unpredictable agricultural conditions, and real-time surveillance analysis remains a significant challenge. To address these issues, our study came up with a YOLOv8-based framework that is specifically designed to detect potatoes in both regulated and uncontrolled farming environments. The Methodology also emphasizes our model selection experience, wherein we concentrated on optimizing a custom Potato detector model that can be used in real time, without direct competition to any other state-of-the-art model. We also developed a new benchmark dataset suited towards the detection of potatoes in varied agricultural situations.

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