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Analysis and Detection of Maize Seed Quality Using Lightweight Models

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***Abstract*— Agriculture is one of the fastest-growing industries in India, but providing quality food to its large population remains a serious concern. Seed quality is of central importance to crop productivity, as low-quality seeds tend to result in decreased yields, higher production costs, and food insecurity. To address this issue, solve, this study proposes a real-time lightweight maize seed quality inspection system based on state-of-the-art You Only Look Once (YOLO) object detection models, including YOLOv5s6, YOLOv9, YOLOv11, and an Improved YOLOv8 (I-YOLOv8). The system distinguishes maize seeds into four classes—Pure, Discolored, Silk Cut, and Broken—based on a custom-labeled dataset of 2,128 images. By capitalizing on augmented small-object detection and better localization, the models were tested on important performance measures such as precision, recall, and mean Average Precision (mAP). The outcome of this comparison indicates that YOLOv5s offers the best trade-off between precision (72.0%) and mAP (76.7%), whereas I-YOLOv8 and YOLOv9 excel in terms of detection speed. This study highlights the accuracy-versus. efficiency trade-offs and presents timely insights for selecting the most appropriate YOLO model to ensure real-time maize seed quality detection. The envisioned system helps enhance seed quality evaluation, thereby ensuring sustainable agricultural practices and enhancing food security.**

Keywords—detection, analysis, yolov5, yolov8, yolo 11, maize.

I.INTRODUCTION

Maize, also known as corn, is a fundamental crop that has enormous economic and nutritional importance worldwide, particularly in developing nations such as India where agriculture is a leading industry. The rising population and demand for food security have made seed quality a central issue in cultivation.Seed quality is directly proportional to improved germination rates, enhanced crop yield, and resource utilization.

Traditional seed quality assessment procedures include visual examination, purity analysis, and germination testing. Although useful on small scales, these methods are time consuming, labour intensive, and extremely skill-dependent, and thus not adaptable for large-scale or real-time field applications. They are also susceptible to variability owing to human subjectivity and fatigue. The increasing demand for automation and accuracy in agriculture has led to research on machine vision and deep learning methods for crop and seed inspection.

Current developments in deep learning, especially object detection algorithms, have made it possible to achieve highly effective image-based classification systems deployed in real time. Among these models ,the You Only Look Once (YOLO) models stand out because of their high-speed and accurate object detection capabilities even on low end devices. Several authors have attempted to explore lightweight variants of YOLO for Maize quality inspection tasks. Maize (Zea mays L.) is one of the globe's major cereal crops, more prized for its high nutritional value and economic importance [1]. The seed quality of maize determines optimal germination, crop establishment, and general agricultural production. During harvest, post-harvest operations, and storage, seeds are exposed various types of damage, such as physical fractures, infection with mildew, and infestation by insects [2]. Planting deteriorated or poor-quality seeds not only decreases the chances of germination but also leads to wasteful use of land and labour, thus causing a decrease in yield and economic losses [3]. Therefore, it is important to ensure the use of healthy seeds to maintain agricultural efficiency and sustainability.

Conventional seed quality testing methods generally involve physical, chemical, or empirical testing methods. Although effective in controlled environments, they tend to be cumbersome, time-consuming, and subject to subjective variability, which restricts their adoption in large-scale agricultural production [4]. In light of these constraints, advances in machine vision and deep learning have opened new avenues for automating and enhancing seed-quality inspection. Machine vision facilitates quick, non-destructive, and impartial assessments of seed characteristics, whereas deep

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learning models exhibit robust capabilities in feature extraction and classification [5].Among the cutting-edge deep learning architectures, the You Only Look Once (YOLO)series of object detection algorithms has been a dominant force in real-time visual inspection. The YOLO models achieved high detection accuracy and speed, rendering them suitable for deployment in agricultural applications. Earlier research has effectively used YOLO and its variants, YOLOv5, YOLOv7, and YOLOv8,in a variety of agricultural applications, such as disease identification, broken kernel detection, and quality classification of maize seeds [6]–[9].

Convolutional neural network (CNN)-based object detection models are an important aspect of image-based classification, with the YOLO family being particularly renowned for speed-accuracy trade-off in real-time applications [10]. In contrast to methods such as R-CNN and Fast R-CNN, which are plagued by delays caused by multi-stage processing, YOLO reformulates detection as a problem of regression to allow bounding box and class probability prediction in parallel [11]. Fast R-CNN and Mask R-CNN provide more accurate and segmentation-driven enhancements but are still computationally intensive [11], [12]. In farm use, YOLO has proven to be better performing for applications such as corn disease detection and seed defect identification [11]. More recent releases, including YOLOv4 and YOLOv5, and their lightweight counterparts, such as YOLOv4-tiny and YOLOv5s, have gained popularity owing to their well-optimized balance between efficiency and accuracy [12].

The aim of the present study is to close this deficit by designing and testing a system that uses and compares several YOLO variants namely, YOLOv5s6, YOLOv9, YOLOv11, and an enhanced YOLOv8 (I-YOLOv8), on a labelled maize seed image dataset. The system grades seeds into four quality categories: pure, discoloured, silk cut, and broken.

The performance was assessed using key evaluation metrics, such as precision, recall, and mean Average Precision (mAP), identify the most effective model for real-world deployment. By leveraging deep learning and lightweight architecture design, this study provides an efficient solution for automating maize seed quality inspection, supporting agricultural productivity, reducing losses, and contributing to food security through scalable and sustainable technology.

II.MATERIALS AND METHODS

The proposed system is a real-time, lightweight system for detecting maize seed quality using multiple variations of the You Only Look Once(YOLO) deep learning technique. The system classifies maize seeds into four classes: broken ,pure, discoloured, and silk-cut. It is based on mainstream models such as YOLOv5 and YOLOv6 and includes upgraded versions such as YOLOv5s6, YOLOv5x6, YOLOv9, YOLOv11, and an upgraded Improved YOLOv8 (I-YOLOv8). The I-YOLOv8 model incorporates architectural improvements designed to enhance feature extraction, localization accuracy, and computational efficiency. All models were trained on a specially annotated dataset with 2,128 images of maize seeds, with uniform preprocessing steps performed to maintain equality in the input data. Training was performed by testing each model using standard object detection metrics such as Precision, Recall, and mean Average Precision (mAP). The major aim of this framework is to find a detection model that is optimal in terms of the balance between accuracy and computational expense, such that it is best suited for deployment in edge computing environments in agricultural applications.

Figure 1. system architecture.

Prior studies have empirically proven the efficacy of YOLO-based models for seed defect classification and detection tasks [2]. Based on these improvements, the developed system was designed to provide a high-throughput, high-speed, and efficient solution for real-world maize-seed quality inspection under actual field conditions.

Figure 1 depicts the architecture of the proposed detection system, which begins with the collection and annotation of a maize seed dataset. Image preprocessing and augmentation were applied to raw images to enhance data diversity and model generalization. The augmented data were used to train different YOLO model variants, namely YOLOv5, YOLOv6, YOLOv5s6, YOLOv5x6, YOLOv8, I-YOLOv8, YOLOv9, and YOLOv11. Every trained model was tested according to specified performance metrics, and their outcomes were compared on the basis of visualizations, such as bar charts, to determine the best architecture for deployment.

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A. DATASET DESCRIPTION

This experiment used a dataset of 2,128 high-quality maize-seed images, which were systematically acquired and manually labelled into four types, as indicated in Figure 1: (a) broken maize, meaning the kernels are physically broken; (b) pure maize, meaning seeds are intact and ready to be used; (c) discoloured maize, meaning seeds that have undergone color changes due to several factors; and (d) silk-cut maize, meaning kernels are cut half-way or have been damaged by remaining silk. Each image was meticulously checked to maintain label consistency and data accuracy across all four classes. The dataset represents a wide variety of visual features induced by both physical and biological damage, which is necessary for training accurate and robust object-detection models.

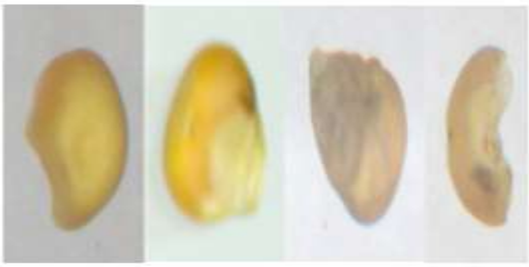

Figure 2. Maize seeds with four different health conditions.

All images were standardized according to the dimensions and colour channels to ensure uniformity and smooth integration into YOLO-based frameworks. These well-annotated and thoroughly curated datasets are vital for boosting research and the application of deep learning methods in maize seed quality inspection, as highlighted in earlier studies on defect classification and machine-based seed inspection [2].

B. Pre-Processing:

Pre-processing is an important process for the preparation of image data for deep learning models, making it consistent, accurate, and compatible. Pre-processing comprises methods such as image resizing, normalization, and conversion of formats to correspond to the input requirements of detection architectures. Efficient preprocessing improves model performance, minimizes training errors, and is required for reliable feature extraction and real-time classification tasks [2].

I. Image Processing: Image processing starts by translating seed images to blob objects appropriate for deep learning model consumption. The image was resized to a uniform dimension and then converted from BGR to RGB format to maintain colore consistency. Bounding boxes and class labels were set based on the seed conditions: pure, broken, silk cut or discolored. These annotations were formatted and saved as NumPy arrays to enable seamless handling during the training process. The processed data were then fed into pre-trained YOLO models, and their network architecture and output layers were retrieved to fine-tune them. Image masking and normalization also ais in object localization and enhance detection accuracy. This organized processing pipeline follows standard practices for maize seed surface defect detection models [2].

II. Data Augmentation:

To enhance the generalization of the model and avoid overfitting, data augmentation methods are used on the maize seed dataset. Geometric transformations, such as random rotation, flipping, scaling, and cropping, along with brightness and contrast modifications, are some of the processes involved. By mimicking various visual and environmental conditions, augmented images introduce controlled variability without changing the original class labels.

This makes YOLO-based models capable of accurately detecting seed defects under different lighting, orientations, and texture conditions. Augmentation expands the effective size of the dataset, allowing the network to learn more resilient features and depend less on limited original examples. Research on the detection of broken corn highlights the critical role of augmentation in improving real-time detection accuracy and robustness.

III. ALGORITHMS

YOLOv5: YOLOv5 is a popular object detection model recognized for its excellent trade-off between accuracy and speed, and is best for real-time maize seed quality inspection. YOLOv5 is capable of detecting different seed defects such as surface cracks and fungal spots accurately with mosaic augmentation features and anchor box learning features. Its variants such as the lightweight YOLOv5s6 are best for edge devices, while its variant YOLOv5x6 provides increased precision for laboratory inspection. Its flexibility renders the YOLOv5 family extremely versatile for real-time and scalable agricultural application. Easy deployment and training are enabled by its modularity, whereas fast performance is facilitated through GPU acceleration even with large datasets.YOLOv5 is a solid baseline for seed defect detection.

YOLO v5x6: YOLO v5x6, a larger sibling of YOLO v5, has deeper layers and attention mechanisms to improve fine-feature extraction. It excels at detecting fine problems, such as minute mildew or infestation-induced damage in maize seeds. Although resource-hungry, it is useful for top-end quality control scenarios that involve granular classification.

YOLO v5s6: YOLO v5s6 is a lightweight model specifically optimized for low-resource settings. With lower depth and width, it achieves minimal computation overhead while maintaining detection accuracy. It is optimally suited for edge-based maize seed quality inspection where on-site, quick evaluation is essential. The model was optimized to possess productive throughput and robustness for realistic use in seed-screening systems.

YOLO v6: YOLO v6 is a contemporary object detection architecture for industrial accuracy and efficiency. It provides better backbone architecture and efficient training strategies that enhance inference speed and accuracy. Using YOLO v6, the maize seed quality detection study was able to effectively and accurately classify seeds into pure, broken, silk cut, and discoloured classes. For the detection of minor faults for different seed sizes, the model includes features such as better anchor-free mechanisms and decoupled head architecture. For real-time and scalable agricultural inspection systems, YOLO v6 works well even under challenging conditions with background clutter or irregular lighting.

Improved YOLO v8 (I-YOLO v8): Improved YOLO v8 (I-YOLO v8) is a modified version of YOLO v8 that has been optimized to detect minor or overlapping flaws in maize seeds more effectively. To increase the sensitivity to small fluctuations, this model incorporates improved feature fusion layers, additional attention mechanisms, and optimized training procedures. When it comes to seed examination, I-YOLO v8 works especially well at spotting small cracks, early stage mildew, or subtle discolorations that conventional detectors could miss. It offers greater detection precision while retaining real-time capabilities, making it ideal for meticulous agricultural quality control, where even minute flaws affect seed value[3][1].

YOLO v9: YOLO v9 is a next-generation object identification framework that improves spatial comprehension by introducing transformer-based modules and innovation convolutional techniques. It can better identify complicated or irregular seed faults because it captures long-range dependencies. YOLO v9 is an excellent tool for detecting the quality of maize seeds because it can analyse high-resolution photos and spot intricate damage, such as deep fractures or patterned insect effects. The multiscale learning technique used by the model improves its capacity to identify flaws in a range of seed sizes and orientations. YOLO v9 performs well in settings that require high defect classification accuracy and durability, even in loud or visually congested environments.

YOLO v11

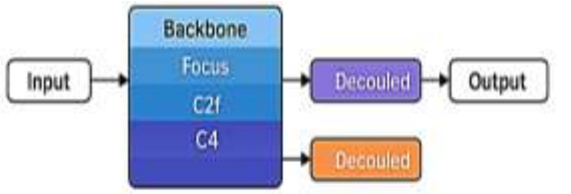

Figure 3 : YOLOv11 architecture.

Self-attention and convolutional neural networks were combined in the sophisticated object identification model YOLO v11 to improve contextual and spatial learning. Adaptive feature fusion, deep supervision, and effective transformers were used to detect minute details with low errors. When it comes to maize seed analysis, YOLO v11 enhances classification performance for visually comparable categories and minor abnormalities. Owing to its speed and high-resolution accuracy optimization, the model can be used for intricate, real-time inspection procedures. Owing to improved interpretability and consistency, YOLO v11 ensures dependable performance in automated agricultural quality systems across various seed damage types [12].

IV. RESULTS AND DISCUSSIONS

To measure the performance of the maize seed quality detection system, three main metrics were employed: Precision, Recall, and mean Average Precision (mAP). These measures offer quantitative insight into how well the YOLO models predict and locate maize seed defects. Precision is the ratio of true positive predictions to total predicted positives and is calculated as

$$\text{Precision} = \frac{\text{Relevant retrieved instances}}{\text{All } \textbf{retrieved} \text{ instances}}$$

where TP and FP stand for true positives and false positives, respectively. In the case of this study, high precision implies that when the system identifies a seed as faulty (e.g., discoloured, broken), it most of the time gets it right, minimizing the chances of eliminating good-quality seeds. Conversely, recall, captures the model's capacity to identify all actual faulty seeds. It is calculated as:

$$\text{Recall} = \frac{\text{Relevant retrieved instances}}{\text{All } \textbf{relevant} \text{ instances}}$$

where FN indicates false negatives. A high recall ensures that most of the faulty seeds are detected by the system, thus minimizing the possibility of poor-quality seeds being planted for cultivation. This is very important in agricultural use where failure of detection leads to huge loss in yield. Finally, the mean Average Precision (mAP) provides a complete

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evaluation by averaging the precision at different confidence levels for all classes of seeds. It is represented by:

$$\mathrm{mAP} = \frac{1}{N}\sum_{i=1}^{N} AP_i$$

where N is the number of classes and AP is the area under the precision-recall curve per class. In this study, mAP was the primary measure used to contrast the overall performance among a variety of various YOLO models (YOLOv5s6, YOLOv9, YOLOv11, and I-YOLOv8). This indicates that a high mAP value corresponds to the model's consistent and balanced capacity to accurately detect a various seed defects. Combined, these indicators informed the determination of the top-performing model—YOLOv5s6—to be deployed in real time, providing dependable, accurate, and efficient maize seed quality classification for farmers' use in enhancing crop yield and food safety. Based on the evaluation of various YOLO models for maize-seed quality classification, 400 test images with 408 labeled instances across four classes—broken, discolored, pure, and silkcut—were analyzed. Among the models, YOLO v8 achieved the fastest inference speed of 0.7 ms and the highest detection performance with a precision of 0.667, recall of 0.746, and mAP of 0.760, resulting in a normalized score of 0.724.

YOLOv5s closely followed with a score of 0.723, offering strong detection with lower computational demands. Considering both accuracy and speed, YOLO v8 and YOLO v9 are the most balanced and efficient models, whereas YOLOv5s is ideal for resource-constrained, real-time agricultural applications based on the dataset.

FIGURES AND TABLES

Tables -1

YOLO Model	Precision	Recall	mAP@50	mAP@50-95	Inference Time (ms)
YOLO v5s	0.720	0.682	0.767	–	–
YOLO v5s6	0.700	0.667	0.747	–	–
YOLO v5x6	0.578	0.606	0.628	–	–
YOLO v6	0.530	0.569	0.579	0.316	0.8
YOLO v8	0.667	0.746	0.760	0.409	0.7
Improved YOLO v8	0.587	0.626	0.631	0.343	0.7
YOLO v9	0.593	0.713	0.711	0.403	1.5
YOLO v11	0.556	0.648	0.634	0.340	0.8

Figure 4: Performance evolution of all YOLO versions.

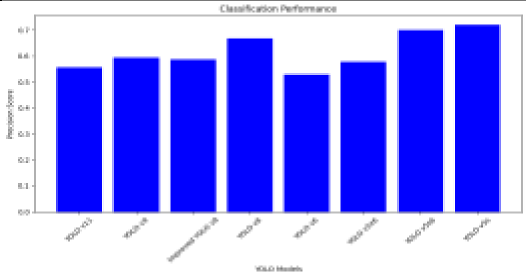

Figure 5: Precision score of YOLO version.

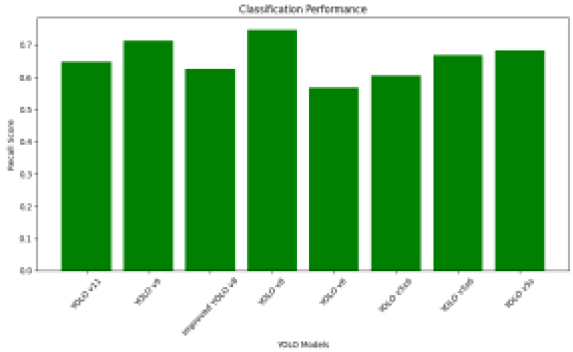

Figure 6: Recall score of YOLO version.

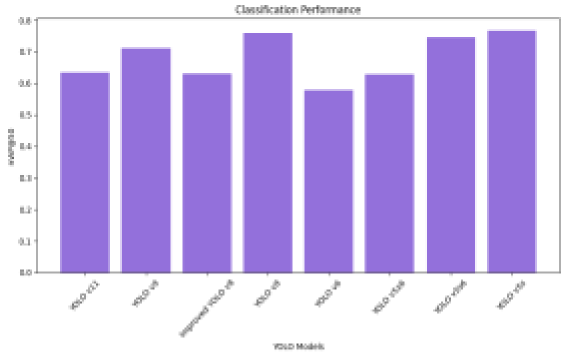

Figure 7: MAP score of YOLO version.

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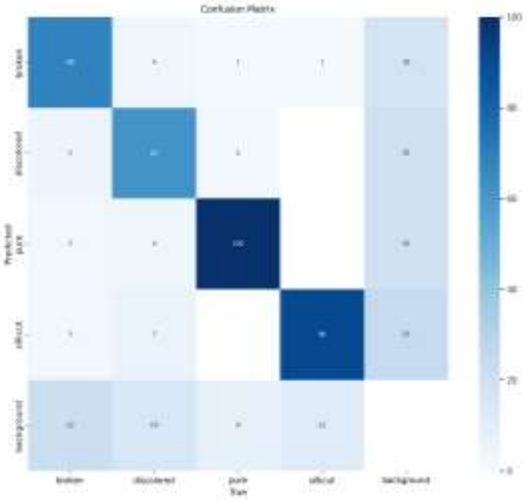

Figure 8: Confusion matrix with all classes.

The system is designed to automatically identify maize seed quality by grouping the seeds into four groups: pure, broken, discoloured, and silk-cut. After a seed image has been uploaded to the web application, the object detection model that has been trained handles the image and determines the seed quality by drawing bounding boxes with class labels and confidence scores ranging from 0 to 1.

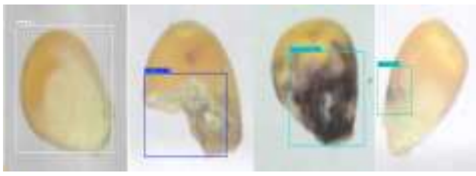

Figure 8: Detection images of all maize seed classes.

The detection performance is demonstrated in Figure 9, where (a) demonstrates the detection of the pure class with a precision of 0.74, representing seeds that are intact and suitable for consumption; (b) demonstrates the detection of the broken class with a precision of 0.73; (c) demonstrates the detection of the discoloured class with a precision of 0.95; and (d) demonstrates the detection of the silk-cut class with a precision of 0.78.

V. CONCLUSION

This study illustrates the efficacy of state-of-the-art YOLO object detection models for maize seed quality classification. The experimental findings emphasize that YOLOv8 was the overall best performer, providing maximum detection accuracy with the highest inference speed, rendering it extremely suitable for real-time agricultural applications. Similarly, YOLOv5s maintained a great balance between precision, recall, and MAP and proved to be a good choice in scenarios with limited resources. At inference time, YOLOv8 and YOLOv9 performed the best with an average detection speed of 0.7s, followed by YOLOv11 at 0.8s, further establishing their feasibility for real-time applications. Both YOLOv8 and its enhanced version, along with the other evaluated models, demonstrated high potential for the automation of quality assessment for maize seeds, thus enhancing sow accuracy, maximizing input use, and ensuring agricultural productivity. The fusion of these models into real-time quality inspection systems can be instrumental in digitizing agriculture, ensuring efficiency, sustainability, and food security in the long term.

The proposed maize-seed-quality detection system offers significant potential for future advancements. Integrating the model with mobile and embedded platforms can enable real-time, on-field assessment. Expanding the dataset with more seed types and environmental conditions, along with applying model optimization techniques such as pruning and quantization, will improve the performance of low-resource devices. Additionally, incorporating explainable AI can enhance interpretability and trust, making the system more reliable for agricultural experts.

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