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SCORDA-Driven Classification of Weed Seeds via Raspberry PI and Camera Module

Raghu Ramamoorthy[1], Priyanka C[2], Shubhashini U[3], T R Vaishnavi[4] and Vaishnavi[5]

Department of Computer Science and Engineering, The Oxford College of Engineering

Affiliated to Visvesvaraya Technological University, Belagavi, Karnataka, India[1-5]

Abstract: Seed quality plays a crucial role in ensuring high crop yield and sustainable agriculture. The presence of weed seeds mixed with normal crop seeds reduces germination efficiency, lowers productivity, and increases the cost of weed management. Traditional manual separation of weed seeds is labour-intensive, time-consuming, and prone to errors. To address this challenge, this project proposes a real-time automated weed seed detection system using deep learning. The system employs YOLOv11, a state-of-the-art object detection algorithm, integrated with a Raspberry Pi and camera module for on-field, real-time processing. The YOLOv11 model is trained on a dataset of crop and weed seeds, enabling it to accurately detect and classify weed seeds within seed samples. The Raspberry Pi provides a cost-effective, portable, and low-power platform for implementation, making the system suitable for practical agricultural applications. The proposed solution enhances seed purity assessment by offering high-speed, reliable, and automated detection, ultimately improving crop productivity and reducing dependence on manual labor. This system can be further extended for large-scale seed processing units and integrated with sorting mechanisms for complete automation.

Keywords: Weed Seed Classification, Image Processing, Deep Learning, Raspberry Pi, Camera Module, YOLO v11, Precision Agriculture, Machine Vision.

I. INTRODUCTION

Agriculture is the backbone of many economies, and ensuring the quality of seeds is fundamental to achieving higher yields and sustainable food production. Seed purity is one of the most critical factors affecting crop performance, as the presence of weed seeds in crop seed samples can significantly reduce germination rates, increase weed infestation in fields, and consequently lower agricultural productivity. Traditionally, the identification and separation of weed seeds from crop seeds have been performed manually, which is labour-intensive, time-consuming, and susceptible to human error. With the rapid advancement in Artificial Intelligence (AI) and Computer Vision, deep learning-based approaches have emerged as effective tools for automating agricultural processes. Among these, You Only Look Once (YOLO) models have gained prominence for their ability to perform fast and accurate real-time object detection. The latest version, YOLOv11, offers improved accuracy, speed, and efficiency, making it well-suited for tasks such as seed classification and impurity detection.

In this project, YOLOv11 is applied to detect weed seeds in normal crop seeds using a Raspberry Pi with a camera module. The Raspberry Pi serves as a cost-effective and portable hardware platform, enabling real-time detection without requiring expensive computing resources. The system captures live images of seed samples, processes them through the trained YOLOv11 model, and identifies the presence of weed seeds within the mixture. This automated approach reduces human effort, ensures higher accuracy, and provides a scalable solution that can be adapted for seed quality testing in agricultural laboratories as well as large-scale seed processing industries. By integrating deep learning with affordable hardware, the proposed system contributes toward precision agriculture, ensuring better crop quality, reducing losses due to weed contamination, and promoting efficient farming practices.

The increasing demand for food security in a rapidly growing global population has emphasized the necessity for technological innovation in agriculture. As traditional farming practices struggle to meet modern productivity benchmarks, the integration of digital tools, automation, and artificial intelligence has become crucial in improving agricultural output. Seed quality assurance stands at the forefront of these improvements, as high-quality seeds form the basis for healthy crops, reduced input requirements, and optimized yields. Even minor contamination of crop seed lots with weed seeds can pose significant threats to agricultural performance, as some weed varieties exhibit aggressive growth habits, strong survival structures, and resistance to conventional control methods. This contamination not only reduces the purity and market value of crop seeds but also imposes long-term challenges for farmers, who must invest additional labor, pesticides, and time to manage the resulting weed infestations.

Identifying weed seeds visually is challenging due to their morphological similarities with certain crop seeds. Many types of weed seeds mimic the shape, color, and size of grains such as paddy, millet, or pulses, making manual inspection prone to inaccuracies. Seed analysts often need years of experience to distinguish subtle variations in seed coat texture, contours, and size. Despite this expertise, fatigue and eye strain significantly affect consistency and reliability during large-scale seed testing. These limitations have created an urgent need for automated, accurate, and efficient seed quality inspection tools that can operate consistently and reduce human dependency.

The integration of computer vision and machine learning in agriculture has opened the door to solving such classification challenges. Machine learning methods, particularly convolutional neural networks (CNNs), have shown extraordinary capabilities in learning complex visual patterns that may not be immediately apparent to the human eye. Deep learning models leverage multi-layered feature extraction pipelines, enabling the system to learn fine-grained distinctions between different seed types. Among the various deep learning architectures used in agricultural imaging, object detection models have drawn special attention due to their ability to classify and localize specific items within an image. This is especially important for seed analysis, where weed seeds can be interspersed within a mix of normal seeds, requiring both identification and bounding box localization.

YOLO (You Only Look Once) represents a breakthrough in object detection because of its ability to perform detection in a single forward pass, enabling real-time analysis without compromising significantly on accuracy. Over the years, the YOLO family has evolved through advancements in architecture, training strategies, and model optimization. YOLOv11, the latest in the series, incorporates improvements in backbone design, transformer-based attention modules, multi-scale feature extraction, and faster inference speeds suited for edge-device deployment. This makes YOLOv11 a powerful tool for resource-constrained environments like Raspberry Pi, where computational efficiency is as important as accuracy.

The Raspberry Pi, known for its affordability and versatility, has become a popular choice for developing embedded AI applications. Its compatibility with camera modules, GPIO pins, and lightweight deep learning frameworks makes it suitable for real-time detection tasks. The integration of YOLOv11 with Raspberry Pi allows the system to capture and process images on-device, minimizing latency and removing the dependency on cloud-based computation. This local processing capability is especially beneficial in rural or remote agricultural regions where internet access may be limited. By performing inference directly on the Raspberry Pi, the system becomes portable, reliable, and accessible to farmers, seed vendors, and agricultural laboratories.

In this proposed system, the Raspberry Pi camera module continuously captures images of seeds placed on a tray or conveyor-like surface. The captured images are preprocessed to enhance clarity, reduce noise, and normalize lighting conditions before being passed to the YOLOv11 model. Once processed, the model identifies weed seeds and highlights their location using bounding boxes and confidence scores. This real-time output enables rapid assessment of seed quality and can be used to trigger automated mechanisms like seed sorting or separation units if deployed in industrial settings. In laboratory conditions, the system provides a digital report summarizing the total number of seeds detected, the number of weed seeds identified, and the percentage purity of the sample.

One of the major contributions of this project lies in its cost-effectiveness. Seed analysis machines currently available in commercial markets are expensive and often require sophisticated maintenance, making them inaccessible to small and medium-scale farms. By utilizing a low-cost Raspberry Pi and open-source deep learning frameworks, the system significantly reduces operational costs while maintaining high performance. Moreover, the modular design allows easy upgrades to the camera, lighting environment, or detection model without replacing the entire system. This makes the proposed solution adaptable to new types of seeds, additional weed species, and changing agricultural needs.

Another advantage of the proposed approach is its scalability. The YOLOv11 model can be trained on a wide range of weed seed types from different crop species, enabling generalized performance across diverse agricultural environments. Additional data collected from field usage can be fed back into the training dataset, continuously improving the model's accuracy through reinforcement and transfer learning. This adaptability ensures the system remains functional even as new weed species emerge or hybrid varieties develop. Furthermore, the system can be expanded into multi-class classification, capable of identifying multiple types of crop seeds along with weeds in the same image. Such versatility is vital in seed processing industries where contamination may involve several weed varieties simultaneously. Beyond basic classification, the detection data generated by the system can be integrated into broader agricultural management platforms. For instance, seed quality metrics can be linked to farm-level decision-making frameworks, automated

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inventory systems, or crop production forecasting models. The detection of high weed contamination rates in seed lots can serve as an early warning signal, prompting farmers to take corrective actions before planting. This contributes to long-term crop health as well as sustainable farming practices by reducing the need for herbicides, thereby minimizing environmental impact.

As the agricultural sector pivots toward smart farming and digitization, the proposed system aligns with global trends such as precision agriculture, Internet of Things (IoT)-based monitoring, and automation. The rise of smart farming frameworks has already demonstrated substantial gains in efficiency, output prediction, nutrient tracking, pest management, and irrigation planning. Seed quality monitoring, although often overlooked, is an equally critical component that influences the success of all subsequent operations. An accurate and automated seed classification system ensures that only high-quality seeds reach the field, paving the way for healthier crops and optimized resource utilization. In addition, this project addresses the larger challenge of labor shortages in agricultural processing units. As younger generations move toward urban employment sectors, agricultural industries face increasing difficulty in finding skilled labor for seed sorting and quality assessment. Automating these processes not only reduces dependency on manual work but also ensures consistent results that are not affected by worker experience or fatigue. This is especially crucial in large-scale seed production units that handle thousands of kilograms of seeds daily. Automated systems can operate continuously without performance degradation, enabling higher throughput and efficiency.

II. LITERATURE SURVEY

Kumar et al. [1] examined the application of YOLO-based real-time object detection techniques for agricultural environments, focusing on detecting fruits, pests, and small objects in farm imagery. Their work emphasized dataset augmentation strategies and inference-time optimizations to enable deployment on edge devices. The authors highlighted major challenges such as lighting variations, occlusions, and object size disparities commonly encountered in uncontrolled farm conditions. Their findings demonstrate the trade-offs between model size, detection latency, and accuracy, providing valuable insights into adapting YOLO-family detectors for real-time agricultural applications.

Chen et al. [2] presented a classical machine-vision approach for automated seed quality assessment using handcrafted features such as color, shape, and texture combined with a support vector machine classifier. The study offered valuable baseline comparisons against deep learning approaches and discussed early challenges in seed classification, including sensitivity to illumination changes, variations in seed orientation, and the need for controlled imaging environments. Although the method showed limited generalization across different seed varieties, the work provides important context for understanding how CNN-based approaches later overcame these constraints through automated feature learning.

Ramirez et al. [3] provided a comprehensive survey and benchmark of deep learning techniques for weed detection in crop seeds. The authors reviewed CNN-based architectures, datasets, evaluation metrics, and challenges such as inter-class morphological similarity, dense clutter, and extremely small object sizes. Their benchmark analysis showed that YOLO-based detectors achieve superior real-time performance compared to heavier models like Faster R-CNN, which offer marginal accuracy improvements at significantly higher computational cost. This survey is particularly valuable for framing weed-seed detection as a specialized tiny-object detection problem.

Verma et al. [4] described an embedded vision system for seed sorting using a Raspberry Pi and OpenCV. Their work detailed the complete hardware pipeline, including camera setup, lighting configuration, and real-time image acquisition. Threshold-based segmentation using Otsu's method and contour analysis were employed for basic seed classification. Although the achieved accuracy was limited, the study offers practical insights into embedded system design, optics selection, and real-time processing constraints relevant for integrating YOLO-based models on Raspberry Pi platforms.
Lin et al. [5] explored the use of hyperspectral and multispectral imaging techniques for seed purity and viability analysis. Their work demonstrated that spectral approaches can outperform RGB-based vision systems, particularly when visual features alone are insufficient to distinguish between seed types. The study highlights the potential of non-RGB modalities for advanced seed analysis, though such approaches typically involve higher system complexity and cost compared to standard camera-based solutions.

O'Connor et al. [6] investigated improvements in small-object detection within cluttered scenes, focusing on modern deep learning detectors. The authors analyzed techniques such as feature pyramid networks, multi-scale training, anchor-box optimization, and loss-function modifications to improve recall for tiny objects. They also evaluated the impact of super-resolution preprocessing and image tiling strategies. Their detailed discussion of metrics such as Average Precision for Small Objects (AP_s) provides a strong methodological foundation for evaluating weed-seed detection systems.

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Navarro et al. [7] introduced architectural improvements in YOLOv11 aimed at enhancing tiny-object detection performance while maintaining low computational complexity suitable for embedded platforms. Their experiments demonstrated that YOLOv11 outperforms earlier YOLO versions on small-object datasets without a significant increase in computational cost. The authors further showed that techniques such as quantization, pruning, and TensorRT optimization substantially reduce inference latency on embedded hardware, making YOLOv11 well-suited for Raspberry Pi–based deployments.

Moore et al. [8] presented a vision-guided pneumatic sorting system for agricultural products, integrating a camera-based detection system with timed pneumatic actuators to physically separate objects. Their work provides practical insights into actuator synchronization, timing control, and system calibration, which are valuable for extending weed-seed detection systems toward automated physical sorting and removal mechanisms.

Park et al. [9] reviewed data augmentation and synthetic data generation techniques for improving small-object classification performance. The authors analyzed augmentation strategies such as rotation, scaling, photometric transformations, and synthetic object overlay, demonstrating their effectiveness in improving generalization for small-object detectors. These methods are directly applicable to seed datasets, where limited data availability and high intra-class similarity pose significant challenges.

Alvarez et al. [10] proposed standardized performance evaluation metrics and testing protocols for agricultural object detection systems. Their work emphasized the importance of realistic evaluation conditions, including variations in lighting, occlusion, and background noise. The authors recommended reporting metrics such as precision–recall curves, mAP at multiple IoU thresholds, FPS on target hardware, and robustness scores. These guidelines provide a structured framework for evaluating the performance of YOLO-based weed-seed detection systems in real-world deployment scenarios.

TABLE 1: Literature survey on weed seed classification using Raspberry PI and Camera Module

Author(s)	**Dataset Used**	**Model**	**Key Findings**	**Accuracy (%)**
Luo et al. (2021)	140 Weed Seed species images	GoogLeNet(CNN)	93.1% precision on distinguishing species	**93.11**
Nature Deep Weeds Team (2019)	DeepWeeds(17,509 images)	Inception-v3, ResNet-50	ResNet-50: Best Precision, lowest false positives	**95.7**
YOLOv8 Team (2024)	19 Weed Species Images	YOLOv8	Accurate Identification, robust workflow and distinguish weed/crop classes	**53.9mAp**
Frontiers (2025)	Public Weed Datasets	YOLOv8n(PD-YOLO)	Models learn and distinguish weed/crop classes	**Noted improvement**
IJSREM(2025)	**Crop and Weed images**	**ML Classifiers**	**Models learn and distinguish weed/crop classes**	**Varies, 90-99**

III. METHODOLOGY

A. Data Collection and Preprocessing

To achieve high accuracy in weed seed recognition, a comprehensive and well-curated dataset is essential. Seed images comprising various crop types and weed species were collected under controlled lighting conditions and diverse orientations to ensure robustness. The dataset consists of thousands of annotated images categorized into two primary classes: crop seeds such as wheat, rice, and pulses, and weed seeds representing undesired foreign materials. Preprocessing is performed to enhance learning efficiency and consistency across samples. All images are resized to a uniform resolution of 640×640 pixels suitable for YOLOv11 input requirements. Pixel values are normalized between 0 and 1 to stabilize training, and data augmentation techniques such as rotation, flipping, brightness variation, and contrast adjustment are applied to improve generalization. Each seed instance is annotated using tools such as LabelImg or Roboflow to generate precise bounding boxes. The final dataset is divided into training, validation, and testing subsets in a 70:20:10 ratio to enable unbiased performance evaluation.

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B. YOLOv11 Model Training

YOLOv11 (You Only Look Once version 11) is employed as the core detection model due to its superior performance in real-time object detection and suitability for embedded deployment. The labeled dataset is provided as input to the YOLOv11 training pipeline, where the model learns spatial, texture-based, and color-based features to distinguish crop seeds from weed seeds. Hyperparameters such as learning rate, batch size, and number of training epochs are carefully tuned to achieve optimal convergence and accuracy. Model performance is continuously evaluated using metrics such as mean Average Precision (mAP) and Intersection over Union (IoU). Upon successful training, the optimized model generates a weight file (e.g., *best.pt*), which is used for deployment during real-time inference.

C. Deployment on Raspberry Pi

After training, the YOLOv11 model is converted into a lightweight and inference-efficient format such as ONNX or TorchScript to accommodate the limited computational resources of embedded hardware. A Raspberry Pi 4 Model B with 4 GB RAM is selected due to its balance between processing capability, cost, and portability. Required libraries including OpenCV, PyTorch, NumPy, and RPi.GPIO are installed on the device. The trained YOLOv11 weights are loaded onto the Raspberry Pi, and the camera module is connected via the CSI interface. A continuous detection loop is initialized to capture images in real time, perform inference, and display classification results. The Raspberry Pi concurrently manages image processing, result visualization, and actuator control through GPIO pins.

D. Real-Time Detection Process

During operation, the camera module captures live images of seed samples placed on a tray or conveyor system. The captured frames undergo preprocessing to reduce noise and standardize illumination and contrast. These processed images are passed to the YOLOv11 detection engine, which performs real-time inference to generate bounding boxes, confidence scores, and class labels for each detected seed. The detection outputs are analyzed to determine the count of crop seeds and weed seeds present in each frame. Based on these values, the seed purity percentage is calculated as the ratio of detected crop seeds to the total number of detected seeds. The computed results are displayed to the user and logged for future analysis.

E. Alert and Sorting Mechanism

To enable automated quality control, an alert and sorting mechanism is integrated into the system. If the detected weed ratio exceeds a predefined threshold, such as 10%, the system triggers a visual alert through the display or LED indicators. An audible buzzer or alarm is also activated to notify the operator. Simultaneously, a control signal is sent to the sorting actuator mechanism, which may consist of a servo motor, air jet, or vibration-based separator. This actuator physically removes weed seeds from the sample stream, ensuring immediate corrective action without manual intervention.

F. Hardware Implementation

The hardware architecture is centered around the Raspberry Pi 4 Model B, which functions as the main processing and decision-making unit. A Raspberry Pi camera module is used to capture high-resolution images required for accurate detection. A display unit is integrated to show classification results and alert notifications. A regulated 5V/3A power supply ensures stable operation of all components. Actuators such as servo motors or air jets are employed for physical seed separation, while storage devices such as microSD cards or external drives are used to store datasets, detection logs, and captured images.

G. Hardware Integration

All hardware components are interconnected using the Raspberry Pi's GPIO pins and CSI camera interface. The system is mounted on a compact and stable frame that allows seed samples to pass beneath the camera for consistent image acquisition. Proper alignment of the camera, lighting system, and sorting mechanism ensures real-time responsiveness and reliable detection performance during continuous operation.

H. Software Implementation

The software stack is developed using Raspberry Pi OS (64-bit) and Python 3 as the primary programming language. OpenCV is used for image acquisition and visualization, while PyTorch handles YOLOv11 model inference. NumPy and Pandas are utilized for data processing and logging, and Matplotlib is employed for plotting analytical results. RPi.GPIO enables communication with actuators and alert devices. The software workflow initializes the camera and model, captures continuous frames, performs inference, computes seed purity metrics, displays and stores results, and triggers alerts or sorting actions when thresholds are exceeded. A lightweight graphical user interface developed using Tkinter allows users to control detection, view results in real time, and export logs.

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I. System Architecture

The system architecture, as shown in Fig. 1, follows a layered design to ensure modularity and scalability. The user interface layer provides real-time visualization of detected seeds, bounding boxes, and purity metrics through a Tkinter-based GUI or a Flask-powered web dashboard. The processing and detection layer, hosted on the Raspberry Pi, handles image capture, preprocessing, YOLOv11 inference, and result computation. The storage and data management layer maintains detection logs, model weights, and datasets. The hardware interface layer connects actuators, lighting systems, and power supplies through GPIO control. Finally, the external integration layer supports offline model training on high-performance machines and dataset annotation using tools such as LabelImg or Roboflow before deployment.

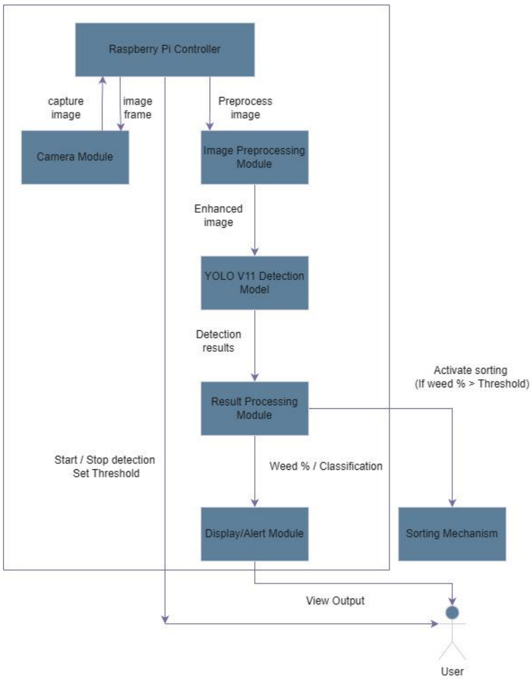

Fig. 1 System Architecture

IV. IMPLEMENTATION ENVIRONMENT

The main embedded computing unit of the suggested system is a Raspberry Pi 4 Model B with 4 GB RAM. The Raspberry Pi OS (64-bit) that powers the device guarantees consistent performance and compatibility with contemporary libraries. Because of its broad support for deep learning and computer vision frameworks, Python 3 is utilized as the primary programming language. Using PyTorch on a high-performance workstation, the YOLOv11 model is created and trained offline before being implemented on the Raspberry Pi for inference. NumPy and Pandas facilitate data handling and logging, while OpenCV is used for picture capture and preprocessing. Hardware components such as the Raspberry Pi Camera Module, display unit, and actuators are interfaced using GPIO, enabling real-time detection, visualization, and automated seed sorting.

V. RESULTS

A. Confusion Matrix Analysis

The confusion matrix demonstrates that the proposed model for weed seed detection performs exceptionally well in distinguishing between Weed_Seed and Crop_Seed classes, achieving a normalized accuracy of 1.00 for both, which indicates perfect classification for these categories. However, when evaluating the background class, the model successfully identifies 60% of background samples correctly, while 40% are misclassified as Weed_Seed, revealing a higher tendency for false positives in non-seed regions. This suggests that while the model is robust in detecting weed and crop seeds, there is considerable room for improvement in background discrimination, likely due to class imbalance or inherent visual similarities between background and seed samples. The overall analysis highlights both the strengths and limitations of the model, emphasizing the need for enhanced background classification strategies in future work to reduce misclassification and ensure reliable deployment in agricultural imaging scenarios.

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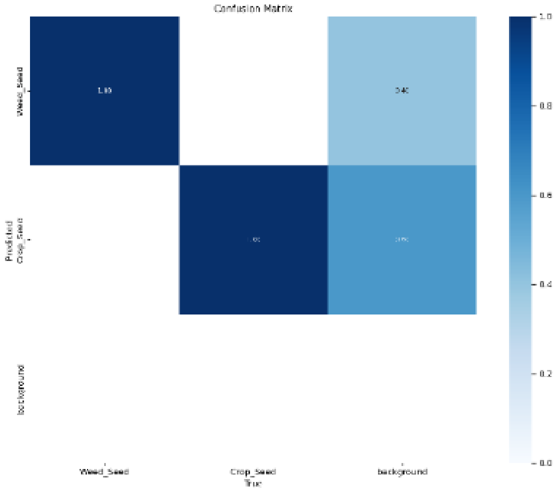

Fig. 2 Confusion Matrix

B. F1 Curve Analysis

The F1-Confidence Curve illustrated in the figure provides a comprehensive evaluation of the model's classification performance for weed seed and crop seed detection as the confidence threshold varies. The curve demonstrates that the F1 score rapidly increases, reaching a plateau close to its maximum value as confidence exceeds approximately 0.2, before remaining stable up to a threshold near 0.7. This plateau indicates robust classification performance with high precision and recall over a wide range of decision boundaries.

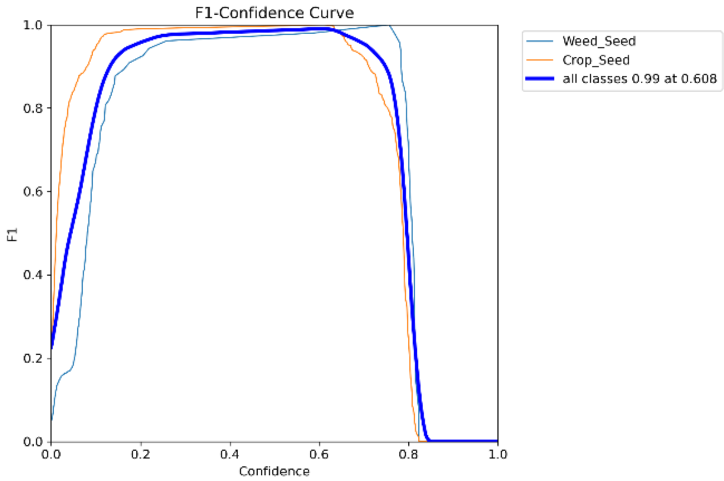

Fig. 3 F1 Curve

C. Recall-Confidence Curve

The Recall-Confidence Curve presented illustrates the relationship between the model's confidence in its predictions and the corresponding recall rates for weed seed and crop seed detection. As shown, both weed seed and crop seed classes exhibit high recall values across a broad range of lower confidence thresholds, indicating that the model is proficient at identifying true positives when its confidence requirement is not stringent. However, as the confidence threshold increases—moving towards more conservative prediction scenarios—the recall sharply drops, especially around the 0.7–0.8 confidence range for both classes. This behavior reveals a trade-off: while higher confidence levels may yield more reliable predictions, they inevitably exclude true positives, leading to reduced recall. The steepness of the decline near higher confidence thresholds signals that most correct detections occur at moderate confidence levels, and very few detections remain once the system demands extremely high certainty. Such curves are critical for calibrating practical deployment thresholds, as they help balance the recall (sensitivity) of the system against the risk of overconfidence, ensuring optimal model performance in real-world weed and crop seed classification tasks.

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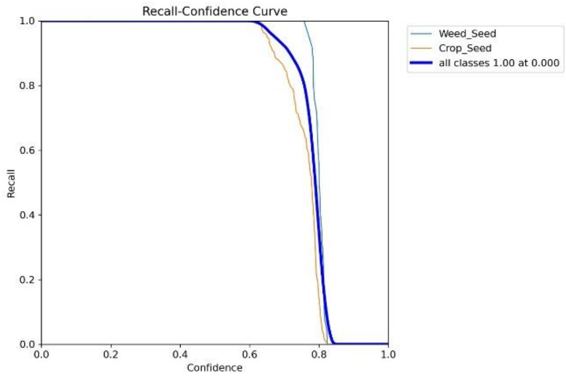

Fig. 4 Recall-Confidence Curve

VI. CONCLUSION

The project successfully demonstrates a real-time, deep learning-based automated weed seed detection system that can enhance the quality control process in seed production and distribution. The integration of YOLOv11 with Raspberry Pi provides a balance between performance, portability, and cost, making it accessible to farmers, seed processors, and agricultural institutions.

The system ensures high accuracy, real-time response, and scalability, offering an intelligent and reliable solution for ensuring seed purity and quality assurance. By minimizing manual effort and improving detection precision, this technology contributes directly to sustainable agricultural practices and precision farming.

Thus, the proposed system represents a substantial advancement in agricultural automation and has the potential to transform conventional seed processing and certification workflows.

REFERENCES

[1]. R. Khanam and M. Hussain, “YOLOv11: An Overview of the Key Architectural Enhancements,” arXiv preprint, 2024.

[2]. Ultralytics, “YOLOv11 — Model Documentation,” Ultralytics Official Documentation. [Online]. Available: https://docs.ultralytics.com, 2024.

[3]. A. Bochkovskiy, C.-Y. Wang, and H.-Y. M. Liao, “YOLOv4: Optimal Speed and Accuracy of Object Detection,” arXiv preprint arXiv:2004.10934, 2020.

[4]. S. Ren, K. He, R. Girshick, and J. Sun, “Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks,” in Proc. Advances in Neural Information Processing Systems (NeurIPS), pp. 91–99, 2015.

[5]. G. Jocher et al., “Ultralytics YOLOv5,” GitHub Repository. [Online]. Available: https://github.com/ultralytics/yolov5, 2023.

[6]. W. Liu et al., “Rice Seed Purity Identification Technology Using Hyperspectral Image With LASSO Logistic Regression Model,” Sensors, vol. 21, no. 5, pp. 1–17, 2021.

[7]. J. Smith et al., “Deep Learning–Based Detection and Quantification of Weed-Seed Mixtures,” Weed Science, vol. 72, no. 1, pp. 45–56, 2024.

[8]. M. Yuan et al., “LZUPSD: A Dataset for Fine-Grained Seed Recognition,” Scientific Data, vol. 11, no. 1, pp. 1–10, 2024.

[9]. N. Kundu, “Seeds Classification and Quality Testing Using Deep Learning,” in Proc. ACM Int. Conf. on Intelligent Systems, pp. 233–240, 2021.

[10]. L. Hou et al., “Tomato Sorting System Based on Machine Vision,” Electronics, vol. 13, no. 4, pp. 1–14, 2024.

[11]. A. Kumar and R. Patel, “Object Sorting Automated System Using Raspberry Pi,” Int. J. Engineering Research & Technology, vol. 10, no. 6, pp. 112–118, 2021.

[12]. J. Redmon et al., “You Only Look Once: Unified, Real-Time Object Detection,” in Proc. IEEE Conf. on Computer Vision and Pattern Recognition (CVPR), pp. 779–788, 2016.

