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IDENTIFICATION OF MAIZE AND WEED USING MACHINE LEARNING MODEL IMPLEMENTED VIA YOLO v5

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ABSTRACT
Weeds are an unwelcomeguest at farmlands, as they are undesired plants that manage to thrive in conditions that are not conducive to their growth. These weeds compete with crops for essential resources such as sunlight, water, and carbon dioxide. Therefore, it is imperative to make a deliberate effort to eliminate weeds from agricultural land. Maize is a staple food in many countries and serves as a primary source of carbohydrates. It is versatile, being used for human consumption, animal feed, and industrial applications. Weeds are one of the major obstacles faced in crop production. Weeds compete with plants for nutrients, space and sunlight, affecting the quality of crop yield. This paper aims to use machine learning to train a model to identify weeds and maize plants on the farmland. This research focuses on implementing a real-time detection system using the YOLOv5 (You Only Look Once version 5) deep learning model. The Machine learning model was developed using a training set of about 3000 images of maize plants obtained from the farmland. The obtained data were annotated via makesense.ai and the labelled dataset was divided into training and testing sets. An overall accuracy of over 90 per cent was achieved with the implemented model and a mAP value of 0.95, demonstrating the efficacy of our approach for identifying and differentiating a maize plant from the weeds. Further integration of the model into a drone or unmanned ground vehicle is hereby recommended.

Keywords: Agriculture, computer vision, machine learning, weed, YOLO v5

INTRODUCTION
Maize, also known as corn (*Zea mays*) is one of the most cultivated crops globally. It acts as a staple food and a primary ingredient in livestock feed, it is also an essential element in various industrial products.It possesses the most extensive genetic variability among all the major cereal grains (Echkoff & Paulsen, 1996). Most times, maize can be consumed directly, either in the roasted or boiled formand is a fundamental dietary component for over two hundred million people (Du Plessis, 2003). The maize crop and weeds are in intense competition for nutrients, space, light, and water, all of which are essential for their respective growth and development (Sharma & Rayamajhi, 2022; Rajcan & Swanton, 2001).Weeds are plants that grow in locations and seasons where they are undesired, particularly amid cultivated crops or ornamental plants. (Sharma & Rayamajhi, 2022). Weeds pose a significant challenge to crop cultivation, leading to substantial reductions in maize yield across global production systems (Mhlanga *et al.*, 2016). Maize is at a high risk of infestation by weeds due to its slow rate of growth during the starting stages, which can last up to forty days after sowing (Shrinivas, 2016). Maize production canbe hindered by a variety of living factors such as insects, pests, predators, and weeds and non-living factors such as drought, salinity, and heat, with weeds being particularly significant in restricting crop yield (Sharma &Rayamajhi, 2022). Reports have shown an estimated global loss in total maize production as a result of weed action to be around 37 per cent (Sharma &Rayamajhi, 2022). Hence, the need to effectively eliminate weeds in the cultivation of maize cannot be overemphasized as maize is a major source of food globally.
Liebman *et al*. (2001) explained that plants classified as agricultural weeds are particularly adept at thriving in disturbed yet potentially fertile locations, and can persist in large numbers despite facing repeated disturbances. Organic growers often struggle with weed control as a major hindrance in their farming practices (Abouziena & Haggag, 2016). Weed management involves techniques and approaches aimed at regulating and reducing weed populations. Every measure is designed to hinder the growth and spread of weeds, either directly or indirectly, while also facilitating the successful growth of the desired crop (Pontes *et al*., 2022; Knezevic *et al*., 2019).
The customary approach to weed control in agriculture, which relies on manual labour and extensive herbicide application, is associated with notable issues such as resource inefficiency and environmental degradation. The indiscriminate use of herbicides not only results in increased operational costs but also gives rise to ecological concerns, posing a threat to biodiversity (Otorkpa, 2017; Liu & Bruch, 2020). The intersection of agricultural technology and environmental sustainability has prompted the exploration of innovative solutions for weed management in modern farming practices. Among these advancements, the integration of weed identification with technologies such as artificial intelligence (AI), machine learning, and image identification has emerged as a promising

frontier. Wu *et al.* (2023) used YOLOv4 for small target weed-detection. This paper examines the application of machine learning to identify weeds on the farmland using YOLOv5. This dynamic solution can be implemented into robotic systems to automate the weeding process to improve crop yield and the quality of maize to be produced.

Weed management is important for modern agriculture to improve crop yield and prevent quality losses caused by weeds competing with plants for essential resources. Traditional weed control methods, including manual removal and chemical herbicide application, are labour-intensive, time-consuming, and potentially harmful to both the environment and the farmer. Machine Learning can be used to analyze images and sensor data to accurately detect and identify weeds, supporting precision agriculture practices. This approach can optimize weed control, reducing herbicide usage and labour costs.

Wang *et al.* (2007) used two optical weed sensors, along with their control modules (comprising a central control module, a global positioning system unit, and a spray-control module) to design an embedded system for weed elimination. Upon conducting tests in two wheat fields, the system exhibited an accuracy rate slightly exceeding 70 per cent. However, the system's reliability is compromised by a 30% failure rate, suggesting that 3 out of every 10 crops could potentially be misclassified.

Dasgupta *et al*. (2020) reported an integrated wireless network, IoT devices, and AI methodologies to provide agricultural crop suggestions to farmers by considering variables such as temperature, annual precipitation, total land size, crop growth history, and other available resources. Additionally, the identification of undesirable plants in crops, specifically weed detection, is executed using a drone equipped with frame-capturing capabilities and deep-learning techniques. The utilization of the Naïve Bayes algorithm for crop recommendation, based on multiple factors detected by WSN sensor nodes, has yielded an accuracy rate of 89.29%.

Mazzia *et al*. (2020) implemented a real-time embedded solution, inspired by "Edge AI," to detect apples using the YOLOv3-tiny algorithm on several embedded platforms, including Raspberry Pi 3 B+, Intel Movidius Neural Computing Stick (NCS), Nvidia's Jetson Nano, and Jetson AGX Xavier. The training dataset was compiled from images taken during a field survey in a northern Italian apple orchard, while the testing dataset included filtered images from a popular Google dataset featuring apples in various scenes. The study successfully adapted the YOLOv3-tiny architecture for small object detection and demonstrated that the customized model could be deployed on cost-effective and energy-efficient embedded hardware without compromising mean average detection accuracy.

Venkataraju *et al*. (2023) utilized advanced learning techniques to differentiate weed from imagery. They explored the application of five state-of-the-art deep neural networks, namely VGG16, ResNet-50, Inception-V3, Inception-ResNet-V2, and mobile-V2. The study encompassed the utilization of multiple experimental settings and combinations of datasets. Notably, a comprehensive weed-crop dataset was created by amalgamating several smaller datasets, thereby addressing class imbalance through data augmentation. The results indicated that VGG16 demonstrated superior performance on a small-scale dataset, while ResNet-50 outperformed other deep networks on the larger combined dataset.

MATERIALS AND METHODS

Developing the model

Developing the machine-learning model involved several key steps: data collection, data annotation, training, testing, and result analysis as shown in Figure 1. First, a large and relevant dataset was gathered, as its quality and quantity significantly impact the model's performance. Next, the dataset was accurately labelled to ensure the model had the correct outputs to learn from. The annotated dataset is then divided into training and validation sets. The training set is used to teach the model by adjusting its parameters to minimize errors. The trained model's performance was evaluated using a separate test set to gauge its accuracy and generalizability. Finally, the model's performance analysiswas based on metrics, such as accuracy, precision, recall, and F1 score, and further adjustments were made as needed to achieve the desired criteria for deployment.

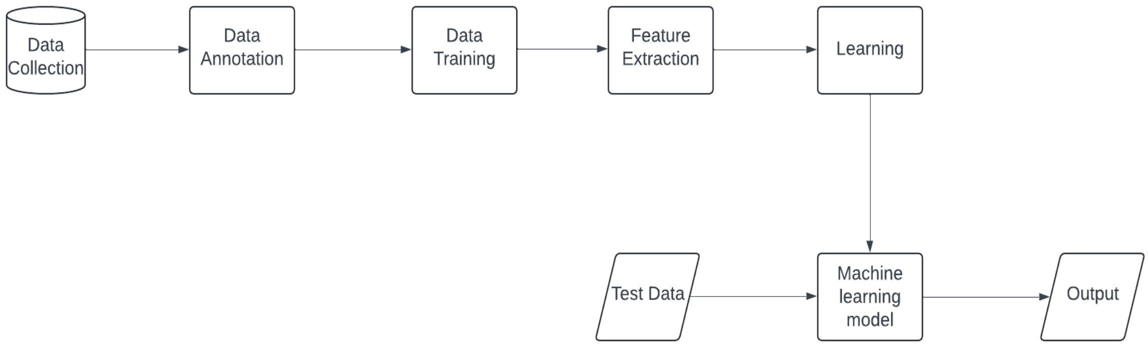

Figure 1: Block diagram of the machine learning model

Figure 2: Some of the collected image dataset

Data collection

Over 3000 high-resolution images, some of which are shown in Figure 2, were collected at the Federal University of Agriculture, Abeokuta maize plantation. The images were snapped using a 32MB resolution camera of a mobile device. All the images were collected and grouped into four folders for ease of annotation. The collected images were field dynamic as the images contained maize plants and weeds surrounding the maize plants.

Data annotation

The collected data were annotated using makesense.ai online object detection platform. Data annotation involves drawing bounding boxes around each object in the image. Two classes were created namely “maize” and “weed” and each bounding box is classified to the appropriate class that the labelled object belongs to as shown in Figure 3.

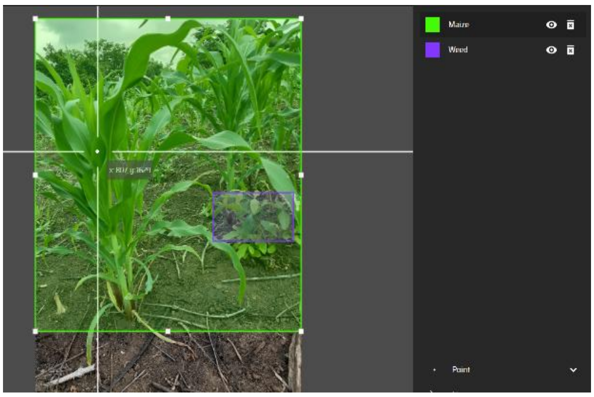

Figure 3: Annotation using makesense.ai suite

Model training

Training the YOLOv5 model encompasses several steps. First, the labelled dataset is divided into training and validation sets. The training set is used to optimize the model's parameters, while the validation set assesses its performance. The training process involves using transfer learning and fine-tuning techniques to utilize pre-trained weights and adapt them to the maize disease detection task. The training employs a loss function that integrates localization loss, objectless loss, and classification loss. These elements ensure the model accurately identifies disease regions, assigns high confidence scores to correct detections, and correctly classifies the diseases. The model undergoes training for multiple epochs, with hyperparameters such as learning rate, batch size, and momentum carefully adjusted to achieve optimal performance. The labelled image of the maize plants and the weed in their bounding boxes is shown in Figure 4 after the completion of the training model.

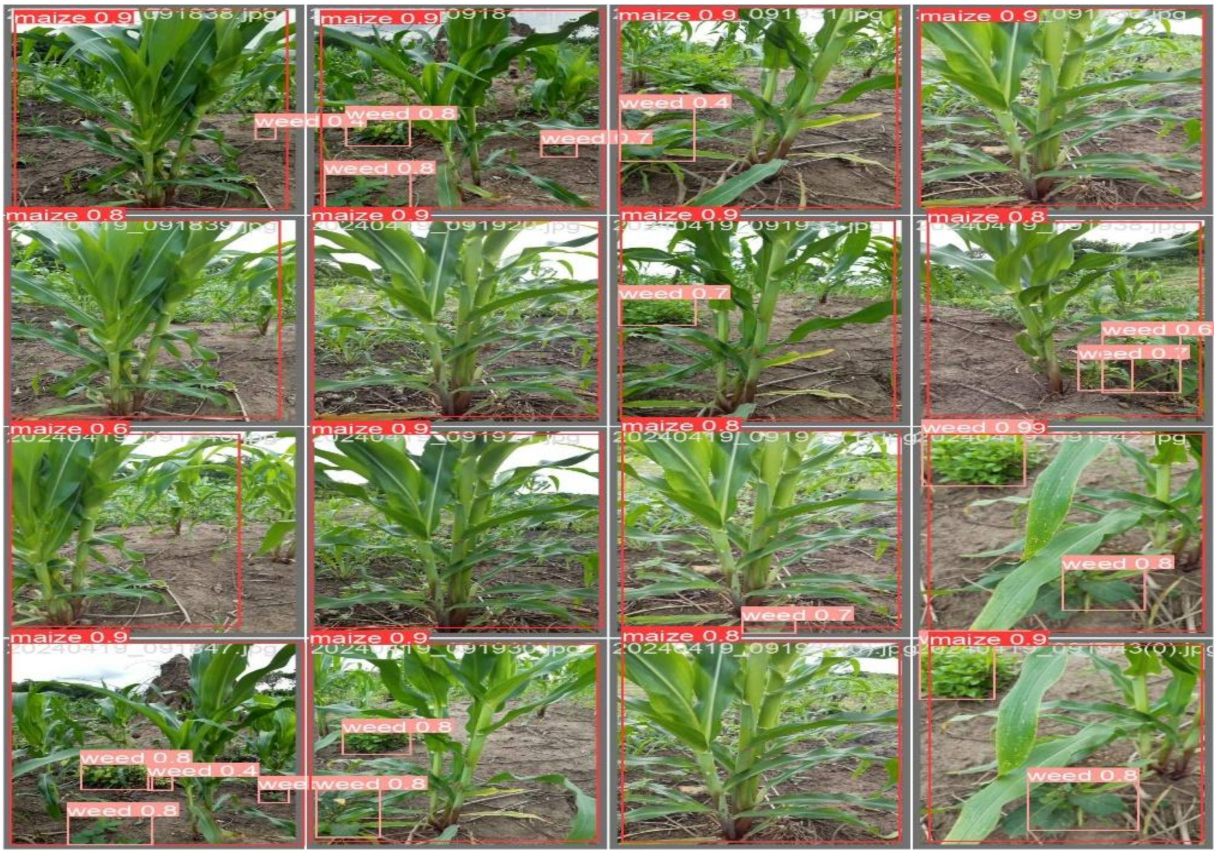

Figure 4: Labelled images showing the maize plants and weeds in their bounding boxes

TESTING AND RESULT

Training and validation loss curves

The training and validation dataset were tested using the model and the graph is shown in Figure 5, it can be seen from the graph that the Bounding Box Loss, decreased steadily, reaching a minimum value of 0.04, also the Objectness Loss was reduced to 0.028 while the Classification Loss converged to 0.15. It can also be deduced that a Precision of 1.00 was achieved at the final epoch.

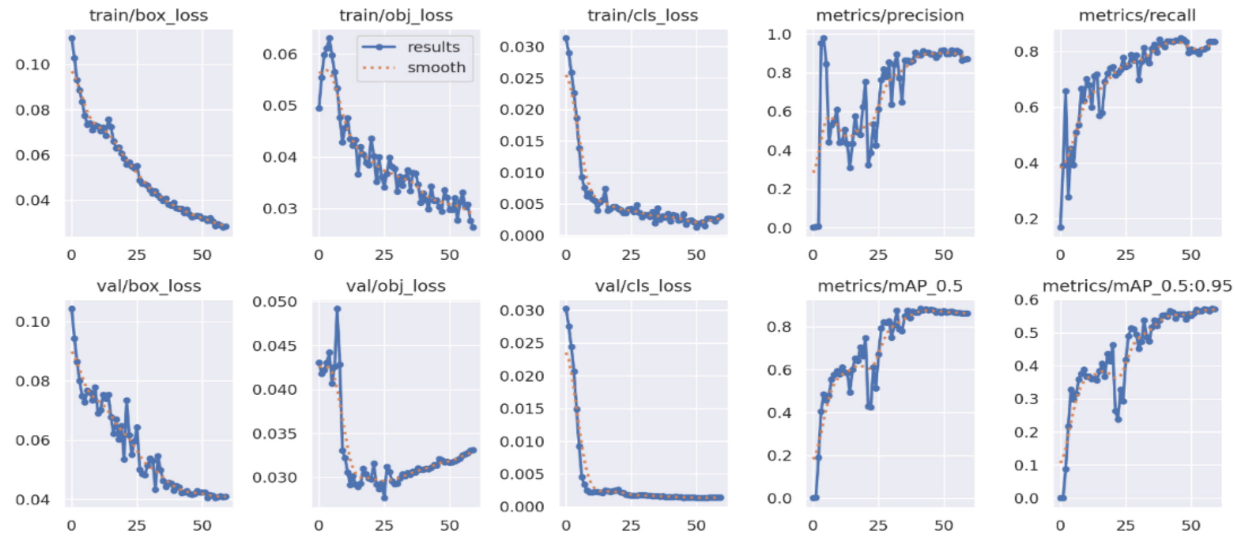

Figure 5: Training and validation loss curves

Confusion matrix

The confusion matrix (illustrated in Figure 6) provides a detailed examination of the real positive, false positive, false negative, and real negative rates for each class. It identifies particular areas where the model may have mis-classify maize plants and weeds.

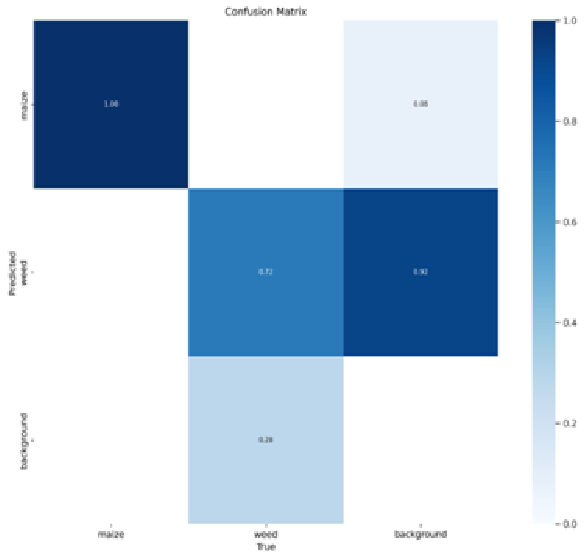

Figure 6: Confusion matrix

The Classes involved in the matrix are:

Maize: This represents areas in the image where maize plants are present.

Weed: This class indicates areas with weeds.

Background: Areas that are neither maize nor weed are considered as background or irrelevant in classification.

The model has a recall of 1.0 for the maize plant, indicating that all maize plants were correctly identified with no misclassification as either weed or background. This is an ideal performance for maize detection. The recall for weed detection is 0.72, which indicates that 72% of the weeds were correctly classified, but there is still a 28% error rate, where weeds were mistaken as background.

The model is very accurate at detecting maize (1.0 recall), showing that it can distinguish maize plants well from the surrounding environment. However, the performance in classifying weeds and background is less than ideal. A large portion of the background is misclassified as weed (92%), leading to an inflated weed count. This suggests that the features extracted by YOLOv5 for distinguishing between weeds and background are not robust enough, possibly due to similarities in colour or texture.

Precision-confidence test

The precision-confidence curve plays a crucial role in assessing the performance of object detection models like YOLOv5, particularly in agricultural tasks such as maize-weed classification. This curve as shown in Figure 7 shows the relationship between precision (the ratio of correctly predicted positive observations to the total predicted positives) and confidence (the model's certainty in its predictions).

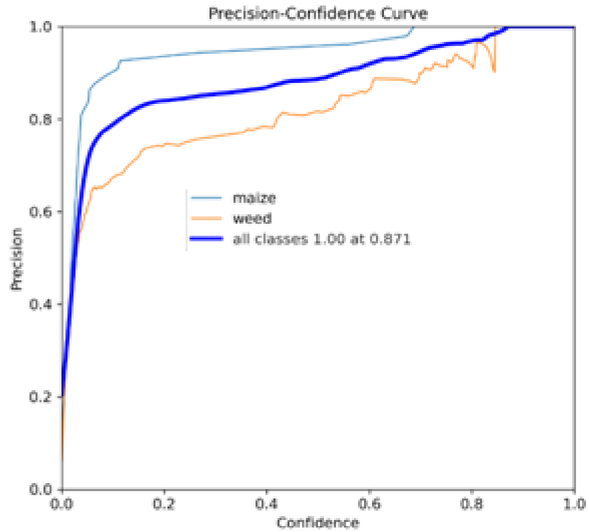

Figure 7: Precision-confidence graph

The precision curve for maize is near-perfect, showing that YOLOv5 performs exceptionally well in identifying maize even at lower confidence thresholds. This is typical in agricultural object detection when the object of interest (maize) has distinct and easily recognizable features such as structured rows and uniform colour, which contribute to the model's high precision. The precision for maize in this study remains at 1.0, indicating zero false positives at high confidence levels. This outcome aligns with the work by Wu *et al.* (2023), where YOLOv4 demonstrated near-perfect classification for high-contrast crops like maize. The distinct characteristics of maize plants enable the YOLOv5 model to make confident predictions without much ambiguity, as observed in the nearly vertical rise of the maize curve in the graph.

F1 score

The F1 score shown in Figure 8 is a performance metric in machine learning that combines precision and recall into a single measure. It is the harmonic mean of precision and recall. It gives an insight into the robustness of the model and offers a balanced evaluation. It is particularly useful in classification tasks where the distribution of classes is imbalanced or when the cost of false positives and false negatives is different. In the context of maize-weed classification using YOLOv5, the F1-Confidence curve helps in evaluating how well the model handles both classes under varying confidence thresholds.

The F1 curve for maize remains consistently high across a wide range of confidence levels. The curve shows an almost ideal behaviour, with the F1 score reaching close to 1.0 (perfect precision and recall) and remaining high between 0.2 and 0.8 confidence levels before dropping off sharply. This behaviour indicates that the YOLOv5 model is very effective at detecting maize plants, maintaining a strong balance between precision and recall across a broad spectrum of confidence thresholds. The curve representing weed detection shows a significantly lower F1 score compared to maize. It peaks around 0.7, with a noticeable drop in performance at confidence thresholds above 0.6. The lower F1 score for weeds can be attributed to several factors, including high variability in weed appearance, similarity to background elements, and possible class imbalance in the training data.

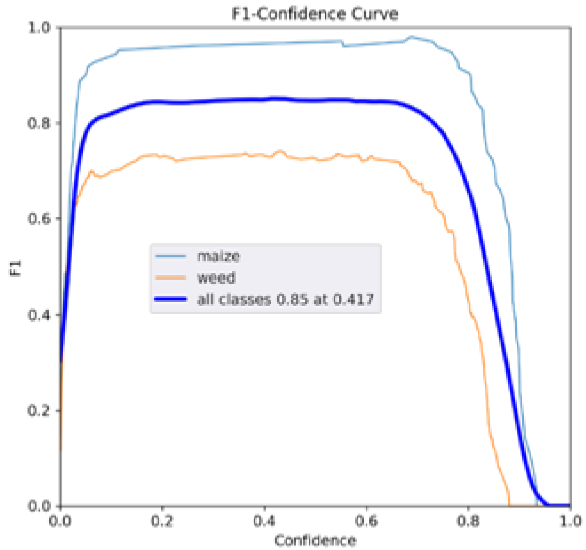

Figure 8: F1 score- confidence curve

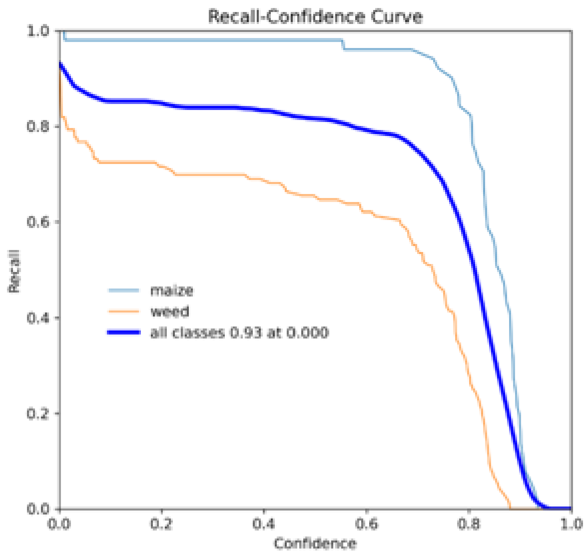

Figure 9: Graph showing the recall-confidence curve

Recall-confidence test

Recall, also known as sensitivity or real positive rate, evaluates the capacity of a model to accurately detect all pertinent instances in a dataset. It is calculated as the proportion of true positive predictions to the total of true positives and false negatives. A high recall value suggests that the model is proficient in capturing genuine positive instances, thereby reducing the occurrence of false negatives. The graph shown in Figure 9 indicates the recall-confidence interaction of the model after validation and testing.The maize classification curve maintains a high recall (above 0.8) up to a confidence threshold of around 0.85. This shows that YOLOv5 performs well in detecting maize at various confidence levels, achieving good results in identifying maize even at higher confidence levels. As confidence increases beyond 0.85, recall begins to drop sharply. This is expected because as the model becomes stricter (requires higher confidence to classify), it begins to miss some maize detections, reducing recall.

The weed curve shows a lower recall across the confidence spectrum compared to maize. Recall stays between 0.6 and 0.8 for most of the curve, indicating that the model is less effective in correctly identifying weeds compared to maize. The sharp drop in recall for weeds starts at a lower confidence threshold (~0.75) compared to maize. This indicates that the model's ability to correctly identify weeds diminishes quickly as confidence requirements increase. The All Classes curve represents the combined performance of the model across all classes (maize and weed). The curve shows that, in general, the model achieves an overall recall of 0.93 at a confidence threshold near 0, indicating that the model is highly sensitive in detecting both classes but may trade off precision at lower confidence levels. As confidence increases, this curve shows a steep drop-off in recall beyond 0.85, indicating that the model struggles to balance recall across classes at higher confidence levels.

CONCLUSION

The machine learning model was successfully designed to achieve the set objective of identification of weed and maize with over 90per cent accuracy. This was achieved by implementing a transfer learning algorithm which enables the model to recognize patterns in the training data set and then map it onto the validation dataset. The accuracy of this machine learning model can be enhanced by employing the use of aerial images. This is because hundreds of weeds can be associated with maize plants and this is due to factors such as temperature, soil condition, environmental humidity and pressure. Effective usage of machine learning can be integrated into hardware components to help enhance processes applied in weed control. The hardware can be integrated with autonomous spraying systems, robotic arms to uproot weeds or hammer-type actuators to crush weeds.

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