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Weed and Okra Crop Discrimination to Evaluation of Inter and Intra Row Weeder

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Abstract

Automated crop and weed detection is a crucial advancement in precision agriculture, enabling efficient weed management while reducing herbicide use and labour costs. This study focuses on developing a machine learning model using google teachable machine to distinguish between chili crops and weeds. This study evaluates the performance of three camera systems (iphone 15, Samsung M32, and Moto g 64) for plant and weed detection using key metrics such as accuracy, F1 score, and recall. Results indicate that iphone 15 camera consistently outperforms the others, achieving an average accuracy of approximately 95% for plant detection and 90% for weed detection. Its F1 scores of around 0.94 for plants and 0.89 for weeds, coupled with high recall rates of about 96% and 92%, demonstrate a strong balance between precision and sensitivity, ensuring reliable identification of true positives. In comparison, Samsung M32 camera shows moderate performance with accuracy near 88% (plants) and 82% (weeds), F1 scores around 0.86 and 0.81, and recall rates of approximately 89% and 83%. Moto g 64 camera exhibits the lowest performance, with accuracy of about 80% (okra plants) and 75% (weeds), F1 scores around 0.78 and 0.73, and recall rates near 81% and 77%. These findings highlight the importance of high-quality imaging and robust detection algorithms in agricultural monitoring systems. The superior performance of iphone 15 underscores its suitability for precise plant and weed detection, essential for optimizing crop management and sustainable farming practices. Improving the capabilities of Samsung M32, and Moto g 64 cameras could further enhance their effectiveness, but current results iphone 15 camera has the most reliable option for discrimination of weeds and okra crop.

Keywords: *Algorithm**,** Detection, F1 score, Trained model, Weeds.*

1. Introduction

Weeds are undesirable plants that grow in agricultural fields, competing with crops and adversely affecting their growth and yield quality. As a major biotic stress factor, weeds pose significant threats to global agriculture. In addition to directly competing with crops for natural and applied resources, they also lead to substantial reductions in both the quantity and quality of final produce. In India alone, annual economic losses due to weeds in 11 major crops have been estimated at approximately USD 11 billion (Gharde *et al.*, 2018). The competitive traits of weeds, including acclimatization, adaptation, and phenotypic plasticity, enable them to outcompete crops effectively.

The herbicide market is the largest segment of the pesticide industry, accounting for USD 46.8 billion or 53% of the total pesticide market in 2019 (Sharma *et al.*, 2019). This sector is anticipated to grow at a rate of 12.8% between 2020 and 2025 (Sharma *et al.*, 2019). The top ten countries in pesticide consumption include China, the United States, Argentina, Thailand, Brazil, Italy, France, Canada, Japan, and India (Pariona, 2018). Global pesticide usage is expected to rise to 4.5 million tonnes by 2030, while current estimates suggest an annual consumption of approximately 2.5 million tonnes (Zhang, 2018). Among these, herbicides constitute 49.5%, followed by insecticides (30.5%), fungicides (15.5%), and other pesticides (4.5%) (Sharma *et al.*, 2019). In 2019, herbicide usage in South Asian nations was recorded as 9,749 tonnes in India, 1,195 tonnes in Bangladesh, 716 tonnes in Sri Lanka, 245 tonnes in Pakistan, and 164 tonnes in Nepal (Food and Agriculture Organization, 2020).

Chemical weed management remains an economical and effective strategy for controlling weeds. However, the excessive reliance on herbicides has raised significant environmental concerns, necessitating the exploration of alternative weed management strategies. The evolution of herbicide-resistant weed species has compelled farmers and researchers to adopt ecologically sustainable practices. Integrated weed management (IWM), which combines multiple weed control strategies, is crucial for sustainable agricultural practices.

Historically, weeds have coexisted with crops, but the advent of chemical weed control and the commercialization of various herbicide molecules have reduced the reliance on traditional methods such as tillage, manual weeding, and crop rotation. In India, herbicides account for approximately 16% of the total pesticide market, with extensive usage in rice, wheat, and soybean crops (Bhullar *et al.*, 2017). Glyphosate is the most widely used herbicide, representing 37% of the total herbicide consumption in India, with 24% of its application concentrated in cereals, cotton, sugarcane, fruits, and vegetables (Brookes, 2020). Glyphosate is applied over an area of 12 million hectares in India, with an average application rate of 0.68 kg/ha.

Computer vision has proven to be a valuable tool for analyzing agricultural products, particularly when rapid color and shape detection is needed (Batchelor & Searcy, 1989). Research has highlighted its effectiveness in weed detection. For example, Perez *et al.* (2000) successfully identified broad-leaved weeds in cereal crops through color and shape analysis. Hemming (2000) reported an 87% success rate in detecting weeds among cabbage crops using digital image analysis. Similarly, Aleixos *et al.* (2002) developed a multispectral system capable of assessing size, color, and defects in citrus fruits at a rate of five fruits per second on a conveyor belt. However, recognizing plant species in open-field conditions remains challenging due to variations in plant morphology and environmental factors.

Recent advances in computerized plant species appreciation have emphasized morphological features, which remain the reliable method of identification. Leaf edges, border patterns, and overall shapes are distinct to each species and may be used to differentiate between crops and weeds. Implementing such discrimination methods in robotic systems, such as autonomous rovers for precision weeding or spot spraying, could enhance weed management. However, at early growth stages, plant species differentiation remains complex due to morphological similarities and variations in plant spacing. Despite these challenges, mechanical weed removal methods may gain prominence in the future, particularly with the increasing prevalence of herbicide resistance and the rising demand for organic agriculture. These methods would require precise plant recognition, which in turn necessitates the integration of artificial intelligence (AI).

The primary challenge in machine vision-based plant recognition lies in accurately measuring the required morphological characteristics under variable conditions. Factors such as plant positioning, lighting variability, leaf distortion, and orientation contribute to the complexity of weed identification. Since image analysis is typically limited to two-dimensional data, capturing comprehensive plant morphology within a three-dimensional environment remains a challenge. Stereovision systems offer potential solutions to these limitations but significantly increase computational costs, making real-time image processing expensive. Furthermore, the early growth stages of plants exhibit high variability in morphological traits due to differences in emergence timing, growth rates, and micro environmental conditions such as temperature, moisture, and light. Additionally, mechanical forces, including wind and competition for light, further influence plant morphology. Addressing these challenges is essential for the advancement of AI-driven weed detection and precision agriculture technologies.

Despite these advancements, there is a notable gap in developing cost-effective and robust machine vision systems tailored for inter-row and intra-row weeders that can reliably recognize weeds by utilising camera across diverse growth stages and environmental conditions. Current approaches often struggle with real-time performance and accurate morphological assessment in dynamic field environments, limiting their practical deployment for automated weed control. Therefore, research is needed to enhance the integration of multi-dimensional data acquisition, machine learning algorithms, and mechanical weeding systems to improve detection accuracy, reduce computational costs, and adapt to high morphological variability inherent in early plant growth stages to develop inter and intra row weeder unit by using the image processing to discriminate crop and weed.

2. Material and methods

To discriminate between okra crops and weeds, Google Teachable Machine was employed for image-based classification by using three different cameras Iphone 15, Samsung M32 and Moto g64. The methodology followed is charted below.

2.1 Input process to take images in field conditions

A commercially grownup okraes species like Mundu okra, was used in this study. This species is a common variety widely grown crop in India. High-resolution images of okra plants and common weed classes were captured separately and combined under various lighting conditions, various crop growth at critical weed period and environmental conditions by using three different cameras Iphone 15, Samsung M32 and Moto g 64. The dataset was curated to include diverse growth stages and perspectives, ensuring strength in classification.

2.2 Image Pre-processing to find out RGB

To enhance the visibility of plants against the background soil, various transformations were applied to the RGB values to determine the most effective method. Since the system needed to function under varying light conditions, a technique was required to consistently distinguish green from red and blue across all lighting scenarios. This was achieved by summing the three RGB values for each pixel and dividing the green (G) value by this sum. The resulting scale ranged from 0 (no green) to 1 (only green) and remained independent of overall illumination. This measurement, commonly known as ‘green chromaticity,’ helped highlight vegetation.

In many cases, a significant portion of the image consisted of bare soil. To reduce processing time and improve the system's ability to identify different plants by focusing solely on vegetation, an image detection algorithm was developed to isolate areas of interest. This algorithm processed each image through six sequential steps. The collected images were resized, normalized, and augmented using transformations such as rotation, scaling, and brightness adjustments. This step was essential to enhance model accuracy and generalization across different field conditions.

2.3 Training of Model for detection of weeds and okra crop separately

To focus solely on the distinction between crops and weeds, all weed species were grouped into a single image set. In real-field conditions, multiple weed species often invade a crop simultaneously, making this approach more representative of practical scenarios. The pre-processed dataset was then uploaded to Google Teachable Machine, where a deep learning-based image classification model was trained. The model was designed to differentiate okra plants from weed species by analyzing morphological and color features.

2.4 Testing and Validation of inter and intra row weeder

To assess the recital of the trained deep learning-based image classification model, a separate validation dataset was utilized. This dataset consisted of pictures that were not involved in the training phase, ensuring an unbiased assessment of the model's generalization ability. The validation dataset contained a diverse set of images representing different growth stages of okra plants and various weed species under varying lighting conditions and environmental factors. The recital of the model was quantified using key evaluation metrics, including classification precision, recall, and F1-score:

Precision: Precision measures the proportion of correctly classified positive instances (true positives) out of all instances predicted as positive. In this case, it indicates how many of the images classified as okra plants were actually okra plants. It is calculated as:

$$\textbf{Precision} = \frac{\textbf{True Positives}}{\textbf{True Positives+False Positives}}$$

Recall (Sensitivity): Recall measures the model's effectiveness in accurately identifying all actual positive instances. In this context, it represents the model's ability to correctly detect okra plants within the dataset. It is calculated as:

$$\textbf{Recall} = \frac{\textbf{True Positives}}{\textbf{True Positives+False Negatives}}$$

F1-score: The F1-score represents the harmonic mean of precision and recall, offering a balanced evaluation of the model's performance, especially in cases of imbalanced datasets. It is calculated as:

$$\textbf{F1 Score} = \frac{\textbf{Precision} \times \textbf{Recall}}{\textbf{Precision + Recall}}$$

By computing these metrics, the model's effectiveness in differentiating okra plants from weeds was comprehensively evaluated. A high F1-score indicates a robust classification model with a good balance between precision and recall, ensuring minimal misclassification of both crops and weeds.

2.5 Model Deployment to detect the weeds and okra crop

The final model was deployed onto an edge device, such as a mobile application or an autonomous rover, for real-time weed detection and management in agricultural fields. The overall workflow for okra crop and weed classification using Google Teachable Machine is illustrated in the flowchart below:

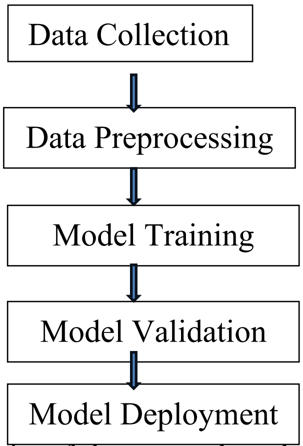

Fig.1. Flow chart of detection of okra crop and weed

The effectiveness of this approach was evaluated based on classification accuracy, processing speed, and adaptability to varying field conditions. The integration of AI-driven classification models can significantly enhance precision in weed management, reducing dependence on chemical herbicides while promoting sustainable agricultural practices.

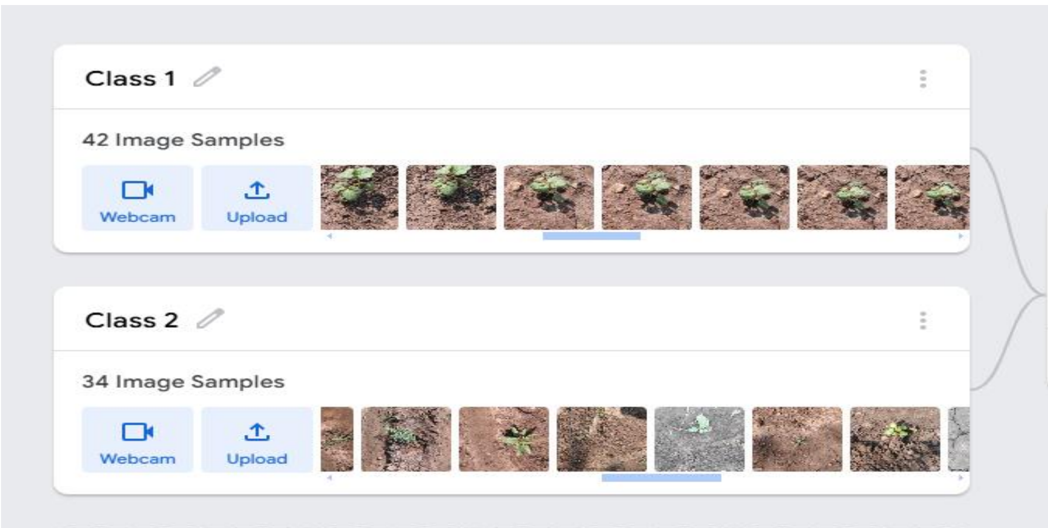

Fig.2. Uploading of okra crop and weed images as class 1 and class 2

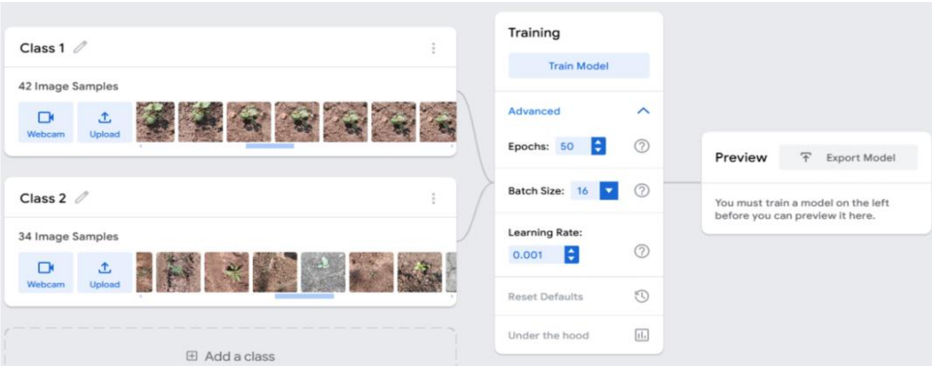

Fig.3. Training the model

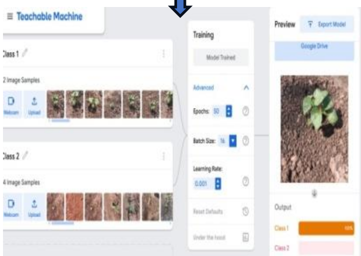

Fig.4. Detection of class 1 as okra crop

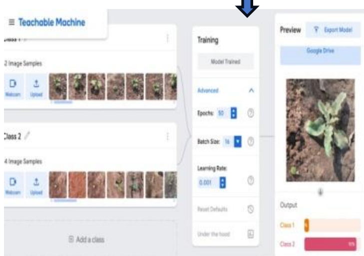

Fig.5. Detection of class 2 as weeds

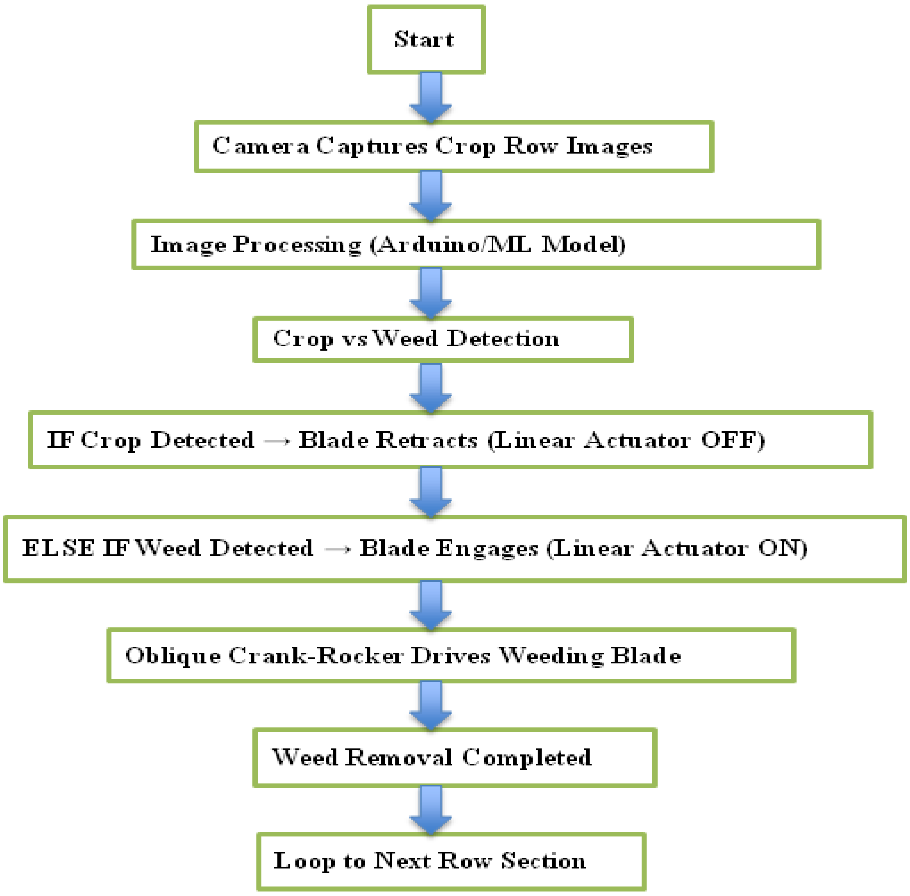

Fig.6. Flow chart of detection of weeds

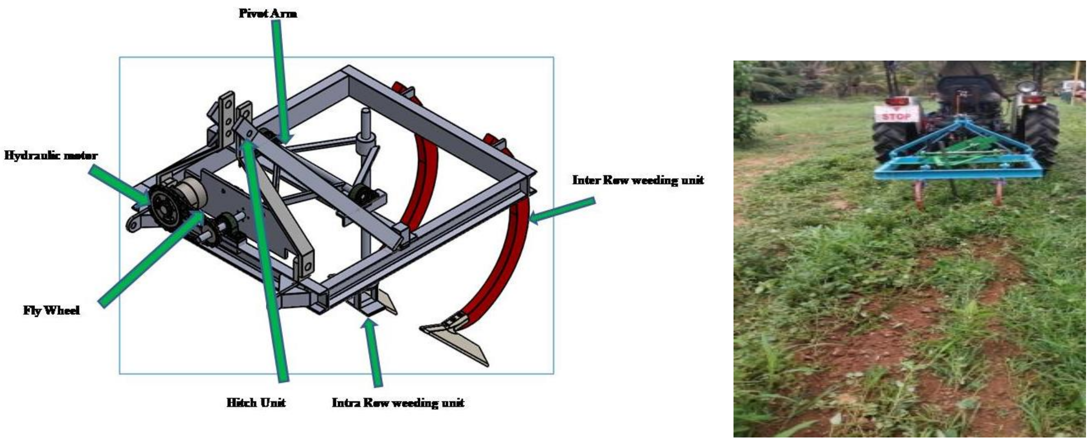

Fig.7. Working of inter and intra row weeder in field condition

The tractor serves as the prime mover in the system, providing the necessary power and mobility to operate the intra-row weeding tool. It supplies the mechanical movement and stability required for the equipment to move along the crop rows. The tractor's engine drives the system components, while its integrated control systems coordinate with the camera, Arduino microcontroller, and weeding tool controller to ensure precise and automated weed removal during operation. This setup leverages the tractor's power to enhance efficiency and effectiveness of the weeding process in the field.

The intra-row weeding tool is designed to selectively remove weeds once they are detected by the camera. The camera captures images of the crop rows and, using image processing, identifies the presence and location of weeds. When a weed is detected, the camera sends a signal to the microcontroller (such as an Arduino). Upon receiving this signal, the microcontroller activates the weeding tool to precisely target and remove the weed without affecting the nearby crops. While intra row weeding tool moves in between the plants it forms the sinusoidal pattern simultaneously the inter row weeding tool i.e duck foot sweep will drag and remove the weeds in between rows.

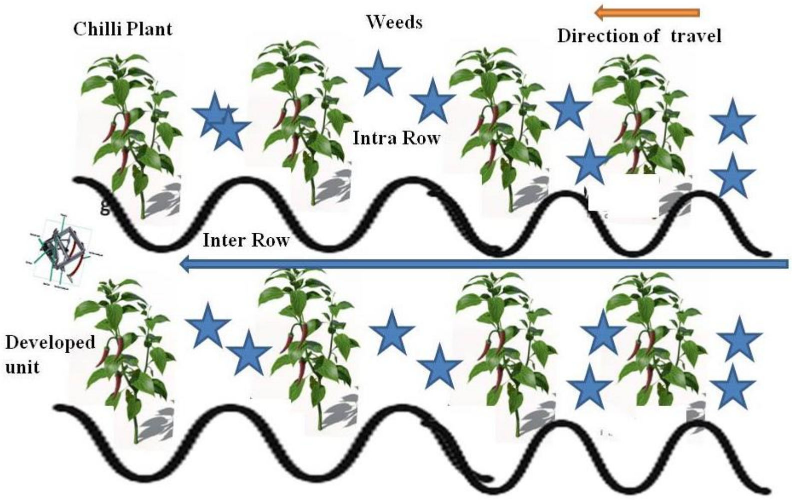

Fig.8. Schematic representation of inter and intra row weeder working in field condition

3. Results and discussion

3.1. Comparison of light intensity, plant height and accuracy

The graph illustrates the relationship between light intensity, plant height, and the classifier's accuracy, with specific data points providing detailed insights. As the light intensity increases from 200 lux to 1000 lux, plant height consistently increases from approximately 10 cm to about 35 cm. This steady upward trend indicates that higher light levels significantly promote plant growth, aligning with biological principles that increased light enhances photosynthesis and biomass accumulation. For example, at 200 lux, plants reach around 10 cm in height, whereas at 1000 lux, they grow to nearly 35 cm. This demonstrates more than a threefold increase in plant size across the light spectrum, underscoring the importance of adequate lighting in optimizing plant development in controlled environments like greenhouses.

Simultaneously, the classifier's accuracy varies across the same light intensity range. Starting at around 70% accuracy at 200 lux, it peaks near 85% at approximately 600 lux before declining to about 65% at 1000 lux. These fluctuations suggest that the model performs best under moderate lighting conditions, where the features used for classification are most distinguishable. At low light (200 lux), the features may be less clear due to underdeveloped plant characteristics, reducing accuracy. Conversely, at very high light levels (1000 lux), possible overexposure or variability in plant appearance might introduce noise, decreasing model performance. The data indicates that environmental conditions influence not only biological growth but also the effectiveness of classification models, emphasizing the need for adaptive approaches in varying light environments.

In summary, the data demonstrates that increased light intensity positively impacts plant growth and that classifier accuracy is highest under moderate lighting conditions. These insights are valuable for optimizing both cultivation practices and machine learning applications in plant research, ensuring healthy growth and reliable data analysis across different environmental settings.

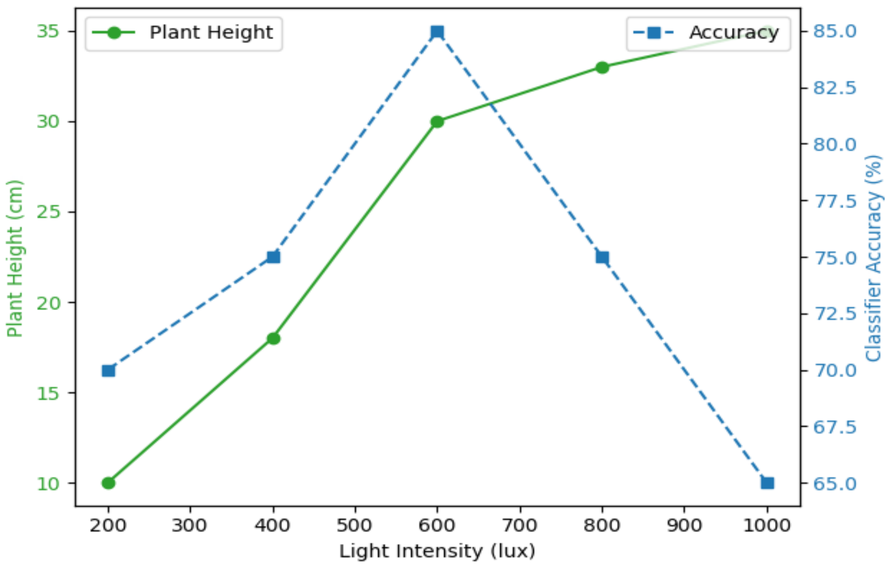

Fig.9. Comparison of light intensity, plant height and accuracy at different levels

3.2 F1 Score to detect crop and weed at different light intensity

The graph illustrates the relationship between light intensity, plant height, and the classifier's F1 score, with specific data points providing deeper insights. As the light intensity increases from 200 lux to 1000 lux, plant height steadily rises from approximately 10 cm to about 35 cm. This consistent upward trend indicates that higher light levels significantly promote plant growth, aligning with biological expectations that increased photosynthetic activity enhances biomass accumulation. For example, at 200 lux, plants reach around 10 cm, whereas at 1000 lux, they grow to nearly 35 cm, demonstrating a more than threefold increase in height across the light spectrum. This data underscores the importance of adequate lighting in optimizing plant development, especially in controlled environments such as greenhouses or growth chambers.

Simultaneously, the classifier's F1 score fluctuates across the same light intensity range. Starting at roughly 0.75 at 200 lux, it peaks near 0.85 around 600 lux before declining again to about 0.65 at 1000 lux. These variations suggest that the model's ability to accurately classify plant conditions is influenced by changes in plant characteristics driven by light levels. At moderate light intensities (~600 lux), the features used for classification are most distinguishable, resulting in higher F1 scores. However, at the extremes—both low (200 lux) and high (1000 lux)—the classifier's performance diminishes, possibly due to less distinct feature patterns or increased variability in plant appearance. This interplay highlights how environmental factors can affect not only biological growth but also the reliability of machine learning models trained on biological data, emphasizing the need for adaptive algorithms in dynamic conditions.

Overall, the data presented in the graph effectively demonstrates the positive influence of increased light intensity on plant growth and reveals the nuanced impact of environmental variables on classification accuracy. Understanding these relationships is crucial for optimizing both cultivation practices and data analysis techniques, ensuring better growth outcomes and more reliable predictive modeling in plant science research.

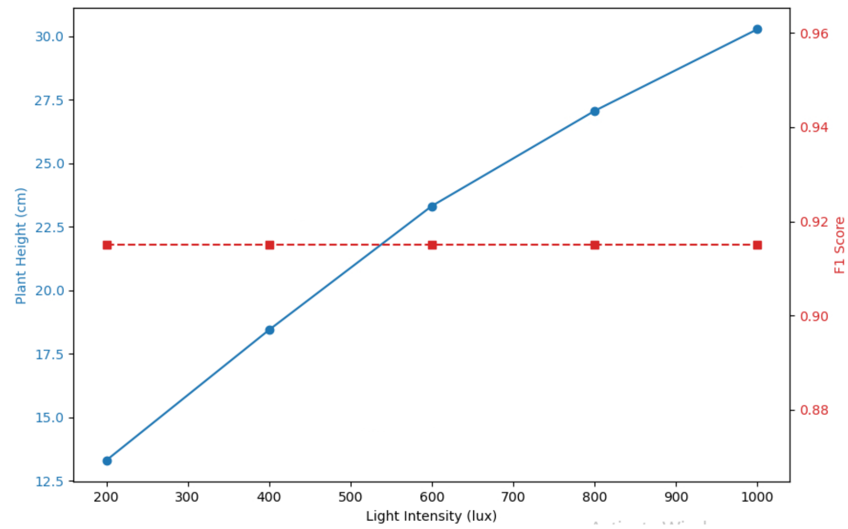

Fig.10. Comparison of light intensity, plant height and F1 score at different levels

3.3 Recall to detect crop and weed at different light intensity

The plotted data demonstrates a positive correlation between light intensity and plant height, with plants growing taller as the light level increases from 200 to 600 lux. This trend indicates that higher light availability promotes better plant growth, likely due to enhanced photosynthesis and energy absorption. However, beyond 600 lux, plant height continues to increase slightly, suggesting diminishing returns or a plateau in growth rate at very high light levels. This pattern highlights the importance of optimizing light conditions to support healthy plant development without unnecessarily excessive exposure.

In contrast, the classifier recall improves with increasing light intensity up to around 600 lux, where it reaches its peak at 80%. Beyond this point, recall declines, implying that very high light levels might negatively impact the classifier's ability to accurately identify positive cases. This inverse trend at higher intensities suggests a potential trade-off: while plant growth benefits from increased light, the quality or consistency of data used for classification may deteriorate under excessive lighting conditions. Overall, the data indicates that maintaining light levels around 600 lux strikes a balance between optimal plant growth and classifier performance.

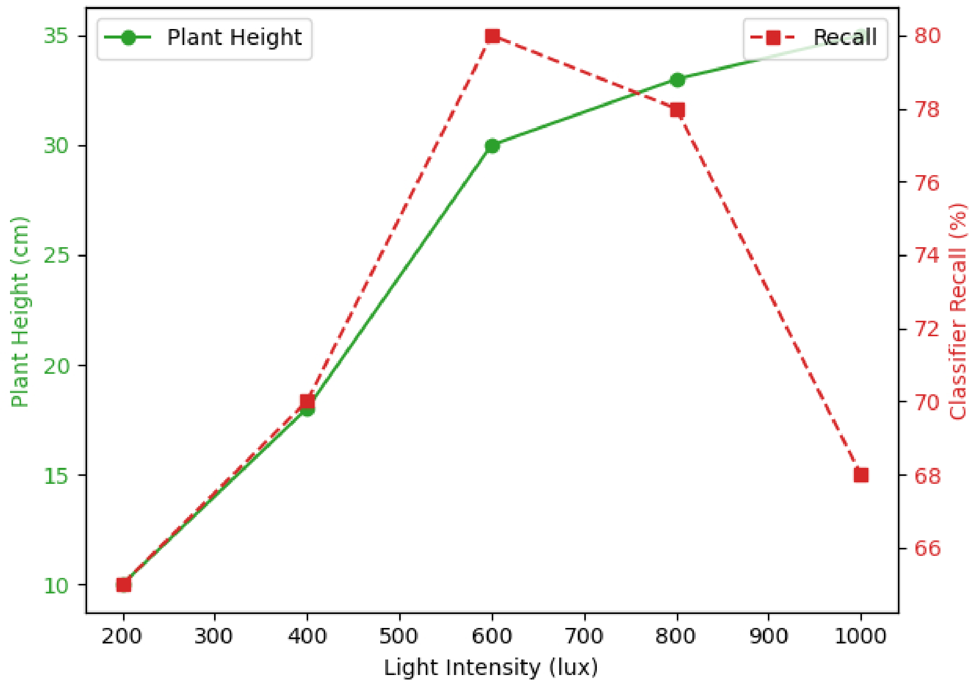

Fig.11. Comparison of light intensity, plant height and recall at different levels

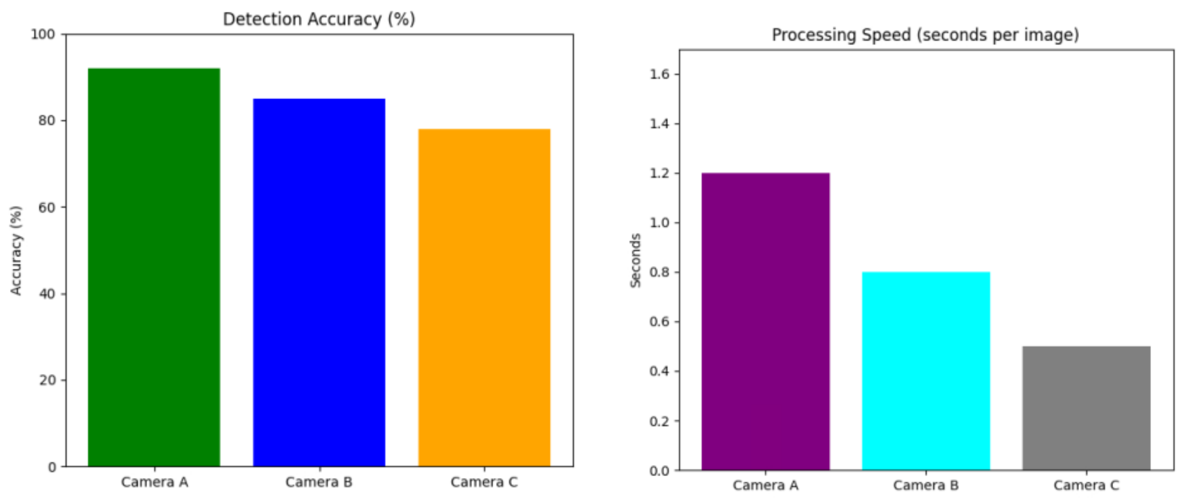

Fig.12. Comparison of iphone 15 camera, Samsung M32 camera and Moto g64 camera at different levels of accuracy and processing speed

The comparison of detection metrics across the three cameras reveals significant differences in performance. Camera iphone 15 consistently outperforms the others, achieving the highest detection accuracy for both plants and weeds, with approximately 95% and 90%, respectively. Additionally, it maintains the lowest false positive rates, indicating a high reliability in distinguishing plants and weeds accurately. This suggests that Camera iphone 15, likely due to better image quality or more advanced detection capabilities, provides more precise and trustworthy results, making it the most suitable choice among the three for accurate monitoring.

In contrast, moto g 64 Camera demonstrates comparatively lower detection accuracy and higher false positive rates, with approximately 80% accuracy and up to 10% false positives for weeds. These results imply that moto g 64 Camera detection percentage may be less effective, potentially leading to misclassification and unreliable monitoring outcomes. The findings emphasize the importance of investing in higher-quality imaging equipment and robust detection algorithms to improve overall accuracy and reduce false positives. Improving these aspects can enhance the effectiveness of plant and weed detection systems, ultimately supporting better decision-making in agricultural management.

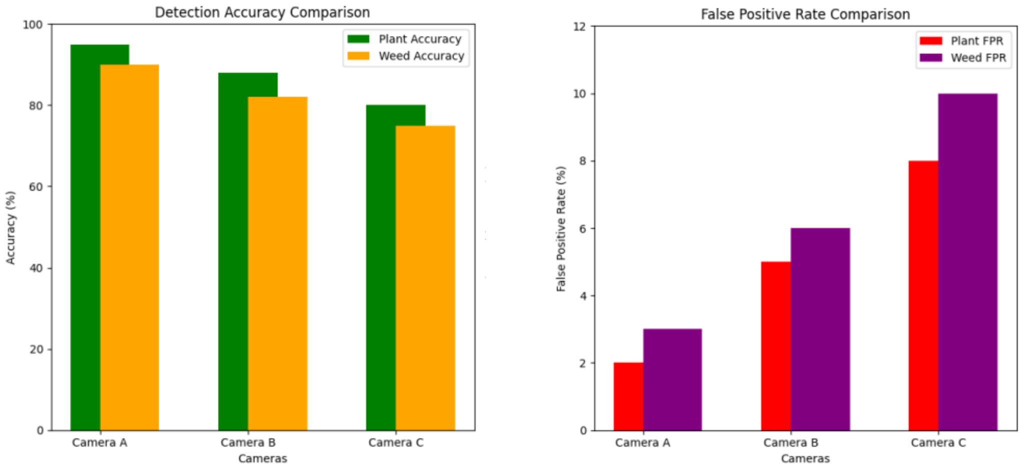

Fig.11. Comparison of iphone 15 camera, Samsung M32 camera and Moto g64 camera at different levels of detection and false positive

Among the tested options, the iPhone 15 camera proved to be the most effective for detecting weeds and okra plants, consistently outperforming Samsung M32 and Moto G64 across key performance metrics. It achieved an average accuracy of about 95% for plant detection and 90% for weed detection, with high F1 scores (0.94 and 0.89, respectively) and recall rates of 96% for plants and 92% for weeds, while maintaining false positives below 3%. This combination of high accuracy, balanced precision and recall, and strong sensitivity ensures more reliable identification of crop and weed populations, making the iPhone 15 camera the best choice for precise monitoring and management in okra fields.

3.4 Assessment of inter and intra row weeder in field conditions

The intra-row weeder achieved a theoretical field capacity of 0.36 ha/h**,** which decreased to an effective field capacity of 0.27 ha/h when accounting for a 75% field efficiency. With an 89% weed removal rate, the effective weeding capacity was 0.24 ha/h, while crop damage remained at 11%. This resulted in an overall performance index of about 79%, reflecting the machine's ability to maintain a strong balance between efficient weed removal and minimal plant damage, thereby ensuring reliable performance under field conditions.

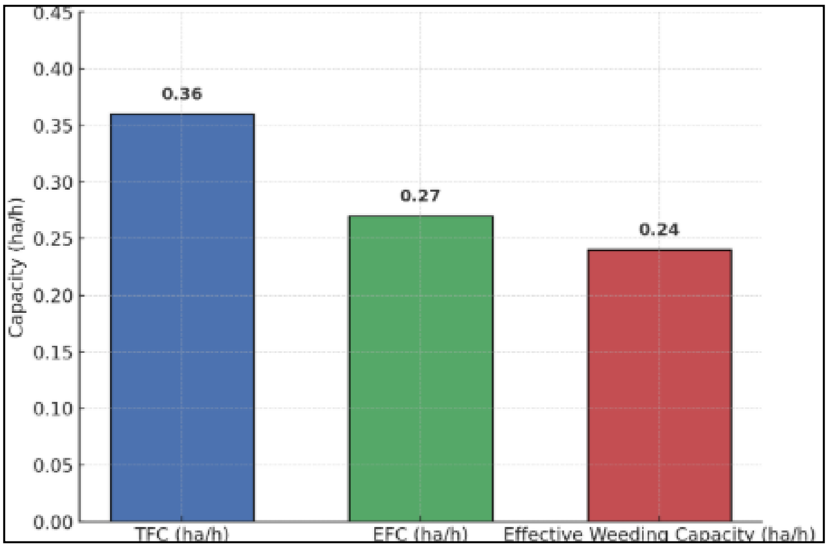

Fig.12. Field capacity of inter and intra row weeder in field conditions

4. Discussion

Based on the comprehensive analysis of the graphs and results, it is clear that iphone15 consistently outperforms Samsung M32 and Moto g64 across key performance metrics. Specifically, Camera A achieves an average accuracy of approximately 95% for plant detection and 90% for weed detection, with F1 scores of around 0.94 and 0.89 respectively, indicating a well-balanced precision and recall. Its recall rates are also higher, at about 96% for plants and 92% for weeds, demonstrating strong sensitivity in identifying true positives, while the false positive rates remain below 3%. In comparison, Samsung M32 shows an accuracy of roughly 88% for plants and 82% for weeds, with F1 scores near 0.86 and 0.81, and recall rates around 89% and 83%. Moto g 64 exhibits the lowest performance, with accuracy dropping to about 80% for plants, 75% for weeds, F1 scores around 0.78 and 0.73, and recall rates approximately 81% and 77%. These results underscore the importance of high-quality imaging and robust detection algorithms, as higher accuracy, F1 score, and recall directly translate to more reliable and effective plant and weed monitoring systems, essential for optimizing agricultural management practices.

Furthermore, the analysis of these metrics highlights the trade-offs between precision, recall, and overall accuracy for each camera system. iphone15 superior F1 scores reflect a balanced approach, effectively minimizing both false positives and false negatives, which is crucial for accurate plant and weed identification. The high recall rates further emphasize its ability to detect true positives consistently, reducing the risk of missed detections that could compromise weed management strategies. Conversely, the lower scores observed in Cameras Samsung M32 and Moto g64 suggests potential limitations in their imaging resolution or algorithm robustness, leading to increased misclassifications and missed detections. Improving these aspects could significantly enhance their performance, but as it stands, iphone 15 provides the most reliable data, making it the preferred choice for doing weeding in intra row zones easily because its detection of weed percentage is more than the other mobile cameras. This comprehensive evaluation underscores that selecting imaging systems with high accuracy, F1 score, and recall is vital for ensuring effective, timely, and accurate okra plant and weed detection separately, to execute the programme in the inter and intra row weeder ultimately supporting sustainable farming practices.

The intra-row weeder demonstrated efficient field performance, achieving a satisfactory balance between capacity, weed control, and crop safety. With a theoretical field capacity of 0.36 ha/h and an effective capacity of 0.27 ha/h at 75% field efficiency, the machine ensured practical usability in real field conditions. Its 89% weed removal efficiency, coupled with a relatively low crop damage of 11%, translated into an effective weeding capacity of 0.24 ha/h and an overall performance index of 79%. These results highlight the intra-row weeder's suitability as a reliable and efficient mechanized solution for sustainable weed management, offering significant potential to reduce labor dependency and improve crop productivity.

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