Research Article

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Implementing Innovative Weed Detection Techniques for Environmental Sustainability

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ABSTRACT

Agriculture, supporting over half of India's population, grapples with the challenge of weed control. Current methods applied in plantation crops lack efficiency and pose environmental and health risks. This paper advocates a paradigm shift, emphasizing the critical need for effective weed detection using cluttered unmanned aerial vehicle (UAV) images. The research methodology integrates image processing, Mask R-Convolutional Neural Networks (R-CNN), and Internet of Things (IoT). A dataset of 200 UAV images was subjected to a thorough preprocessing. In the initial phase, weeds and crops were identified with precision employing an UAV-tailored Mask R-CNN with instance segmentation. This was found to surpass traditional methods in terms of communication between the model and the agricultural environment. For timely decision-making, real-time data were collected using IoT. Average Precision (AP) values reveal high accuracy, notably 89.1% for weeds, 88.9% for crops, and an overall precision of 89.4%. The Mask R-CNN network segments and classifies images, marking weed zones communicated to farmers via Raspberry Pi with a GSM module, enabling real-time alerts and informed decision-making for efficient weed control. This holistic approach, providing object classifications, detailed bounding boxes, and masks, addresses weed control challenges, highlighting the transformative potential of advanced technologies in agriculture.

Keywords: Agriculture; Weed control; Mask R-CNN; UAV images; IoT integration; Precision.

1. INTRODUCTION

Innovative techniques offer a sustainable solution to reduce greenhouse gas emissions while safeguarding environmental and human health. Traditional methods, which rely on chemical herbicides, often result in the overuse of machinery, leading to higher carbon emissions from fuel consumption (Leo *et al.* 2023; Krishnamoorthi *et al.* 2023; Kannan *et al.* 2024; Mohanrajhu *et al.* 2024). Agriculture, an ancient and indispensable profession, has evolved over millennia with the integration of various technologies, including artificial intelligence (AI), to enhance productivity and efficiency while mitigating negative environmental impacts. Currently, farmers are confronted with a major obstacle: a substantial decrease in agricultural productivity caused by the presence of weeds.

Research indicates that the presence of weed plants might reduce crop productivity by around 50% (Abouziena and Haggag, 2016; LeCun *et al.* 1998), leading to significant negative impacts on the economy. The use of herbicides is a cost-effective approach; however, it carries the risk of contaminating crop plants, posing potential health hazards. On the other hand, AI-driven robotic solutions, while effective, come with a higher price tag. Nevertheless, they eliminate the need for human labour and circumvent health risks associated with herbicides. In this dynamic landscape, the adoption of AI in agriculture has become prevalent. The deployment of AI technologies not only addresses the challenge of weed infestations but also aligns with the broader objective of sustainable and eco-friendly farming practices (Gatys *et al.* 2015). The ongoing integration of AI in agriculture signifies a strategic shift towards precision farming, where targeted and efficient solutions are employed to optimize crop yield without compromising environmental safety. The dual considerations of economic viability and environmental sustainability underscore the importance of striking a balance between traditional and cutting-edge approaches in agriculture. As the agricultural sector continues to embrace AI, there is a promising avenue for the development of innovative, cost-effective, and environmentally conscious solutions that can revolutionize weed control and contribute to the overall advancement of agriculture in the modern era (He *et al.*, 2017).

2. SURVEYING THE LANDSCAPE OF RELEVANT

In recent years, a plethora of deep learning models has been introduced to tackle object recognition tasks, showcasing their versatility across various domains. However, the agricultural sector poses unique challenges, especially in object recognition tasks where differentiating between weed and crop plants becomes intricate due to shared characteristics such as colour, texture, fill, and size (Yu *et al*. 2019a; Yu, *et al*. 2019b; Ferreira *et al*. 2017). Although numerous public datasets are available for species identification and disease prediction at the leaf level (Mallah *et al.* 2013; Huang *et al*. 2020; Chouhan *et al*. 2020; Mohanty *et al.* 2016), the shift to real-time applications necessitates datasets at the plant level (Olsen *et al*. 2019). Existing datasets often concentrate on diseased crop identification, with limited attention to weeds growing amidst the crops. For instance, the Deep Weeds dataset, while addressing weed species native to northern Australia, primarily serves classification tasks and lacks information about plant localization. Moreover, the role of lighting conditions in agricultural tasks is paramount, and many datasets are confined to a single lighting condition (Lameski *et al.* 2017). The Carrot-Weed dataset stands out by offering images under diverse lighting conditions, albeit restricted to carrot plants. However, the challenge persists in datasets like Plant Phenotyping and Plant Seedling, where the background consists of soil or stones rather than other plants (Minervini *et al.* 2016; Giselsson *et al.* 2017; Sudars *et al*. 2020). Recently advanced object detection has enabled collaboration between agriculture and deep learning, resulting in precision agriculture (Wang *et al*. 2019; Bakhshipour and Jafari, 2018). Convolutional Neural Networks (CNNs) can detect weeds in turf grass, ryegrass, and soybeans, making them a useful weed management tool. Besides supervised models, unsupervised models with minimal tagging can detect weeds. These advancements underscore the dynamic nature of the field and its potential to revolutionize weed detection and management strategies in agriculture (Ghazali *et al*. 2008). They introduced an innovative method to improve the accuracy of a computerised weed control system by employing machine vision. Their research is centred around creating a real-time system for removing unwanted plants in oil palm fields. The system has been developed to utilise image processing techniques in order to accurately detect and classify different types of weeds, with a particular focus on distinguishing between slender and bulky weeds. Kargar and Shirzadifar (2013) introduced an Automated Weed Detection System and Intelligent Herbicide Sprayer Robot specifically designed for maize fields. This study focuses on implementing an automated plantation system that utilises identification technology to recognise fruits and vegetables in the plantation. It then applies herbicides specifically to areas afflicted by weeds. The approach for Weed Recognition, as presented by Siddiqi *et al.* (2009), utilises the Erosion and Dilation Segmentation Algorithm. The system employs a CCD camera placed at a 45°-inclination and positioned 4 m above the ground, directly in front of the tractor and the sequential operations of Erosion and Dilation to categorise two distinct weed types - broad and narrow. The Quadratic Polynomial and Region of Interest (ROI) Techniques were utilised by Ishak *et al*. (2007) to develop a weed detecting technique. The authors investigated a curve detection technique that relies on the quadratic polynomial method and incorporates the utilisation of the ROI method. It is frequently employed to extract features for image tasks like classification. Burgos *et al.* (2010) presented a real-time system for analysing images to distinguish between crops and weeds in maize fields.

The survey highlights the growing significance of deep learning models in addressing complex challenges within the agricultural sector, particularly in the context of weed detection. Despite the shared characteristics between weed and crop plants, recent advancements, exemplified by various studies, demonstrate the potential of leveraging CNNs and innovative image processing techniques. However, existing datasets, often focus on diseased crops or lacking plant-level localization, underscore the need for more comprehensive and diverse data sources. The surveyed studies showcase a promising trajectory towards more accurate, efficient, and sustainable weed detection and management practices, emphasizing the dynamic nature of this field and its transformative potential for agriculture.

3. METHODOLOGICAL FRAMEWORK FOR WEED DETECTION

The research methodology initiates with a meticulous dataset collection, encompassing 200 unmanned aerial vehicle (UAV) images set against cluttered backgrounds, where weeds and crops serve as the focal points for segmentation and detection. To standardize this dataset, the images, initially sized at 9000 × 6000 pixels, undergo a preprocessing phase involving resizing to 800 × 600 pixels and normalization, enhancing overall quality. This foundational dataset forms the basis for the incorporation of Internet of Things (IoT) concepts into the research framework. In the first stage, weeds and crops are identified using a Mask R-Convolutional Neural Network (R-CNN) with instance segmentation. This advanced method is tailored to identify and categorise weeds and crops in photos taken by an UAV.

The integration of IoT principles improves the approach by facilitating smooth communication between the Mask R-CNN model and the agricultural setting. Well-placed sensors and actuators facilitate real-time data collection, augmenting the system's responsiveness. This innovative approach successfully mitigates the limitations of traditional methods. Diverging from pixel-wise comparisons inherent in traditional methods, the Mask R-CNN identifies and segments objects by creating masks that precisely delineate the contours of the target classes. The integration of IoT contributes to real-time decision-making, ensuring prompt responses to identified weed infestations. The holistic methodology aims to present a comprehensive perspective on the combined impact of instance segmentation, mask creation, and IoT integration, providing a more precise and efficient solution for detecting and localizing weeds and crops in UAV images. This advanced technique emerges as a promising alternative, particularly in scenarios where traditional methods fall short due to processing time and accuracy constraints. The culmination of the methodology results in an output that not only includes object classifications but also encompasses detailed bounding boxes and masks for each identified instance. Rigorous validation and testing on separate datasets evaluate the model's generalization capabilities. The research utilises criteria such as mean Average Precision (mAP), precision, recall, and F1 score to provide a thorough performance evaluation of the suggested method in comparison to previous methodologies. This approach represents a refined and accurate solution, overcoming the limitations associated with template matching in the detection and localization of target objects within cluttered UAV images.

Proposed method shown in Fig.1 represents an advanced and intricate approach to the detection and recognition of weeds and crops in UAV images.

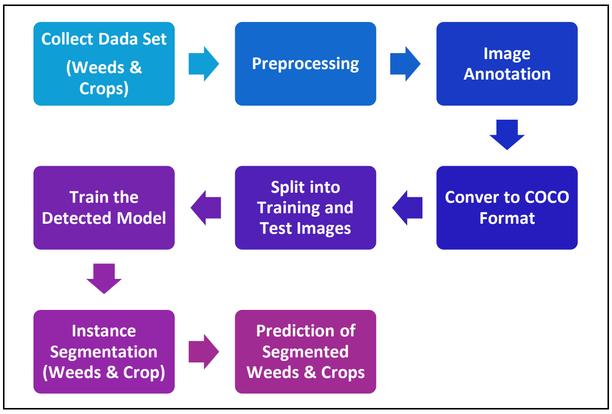

Fig. 1: Advanced weeds and crops detection methodology

The Mask R-CNN network conducts the categorization of every segment in an image, assigning them into categories of either crops or weeds. Upon identifying a segment as a weed, the associated area in the original image is tagged, thus indicating it as a zone containing weeds. Afterwards, the image with clearly indicated weed areas is sent to farmers *via* email using a Raspberry Pi that has a GSM module. This communication technique enables farmers to receive visual notifications regarding the existence of weeds in their fields, assisting them in making prompt and well-informed decisions for efficient crop management.

3.1 Weeds and Crops Detection with Image Processing and Mask R-CNN

3.1.1 Object Detection with Convolutional Neural Networks

Convolutional Neural Networks have significantly transformed computer vision by excelling in tasks such as picture classification, segmentation, and object detection. These networks draw inspiration from the human visual system, utilize convolutional layers to extract hierarchical characteristics from input images, starting from edges and advancing to more intricate shapes. The typical CNN architecture shown in Fig. 2 includes convolutional, pooling, and fully connected layers, with deep layers capturing abstract patterns. In object detection, CNNs generate feature maps, recognizing edges and textures to identify complex structures. Deep Convolutional Neural Networks (DCNNs) enhance CNN capabilities with deeper architectures, learning intricate representations. These neural networks excel in simultaneous localization and classification, and their transfer learning ability, utilizing pre-trained models, is advantageous for limited datasets. Convolutional Neural Networks are a fundamental tool in object detection. They automatically learn hierarchical representations from data, making them highly effective for identifying and classifying objects. By combining convolutional operations with deep learning and transfer learning techniques, CNNs excel in various computer vision applications, enhancing accuracy and efficiency.

Region-Based Convolutional Neural Networks (RCNNs) are a significant leap in object detection, tackling the precise identification and localization of objects within images. The innovative approach involves using selective search to generate Regions of Interest (ROIs), allowing independent assessment by convolutional networks for each ROI. This method revolutionizes object detection by classifying distinct image regions into suggested classes. Selective search, a pivotal component, iteratively merges adjacent regions based on cues like color, texture, and intensity. This process creates a diverse set of ROIs, forming a comprehensive pool of potential objects of interest within the image. Each ROI undergoes independent processing by the convolutional network, extracting features for precise object recognition. The RCNN architecture, initially designed for image detection, has paved the way for subsequent advancements, including Mask R-CNN, by combining convolutional neural networks with region-based strategies. In practical implementation, a Python script employs RCNN for inference. Selective search determines regions to be classified, and RCNN evaluates and classifies these regions, yielding detailed results with detected objects, their classes, and bounding box coordinates. This integration of selective search and RCNN provides a robust framework for accurate object localization and classification

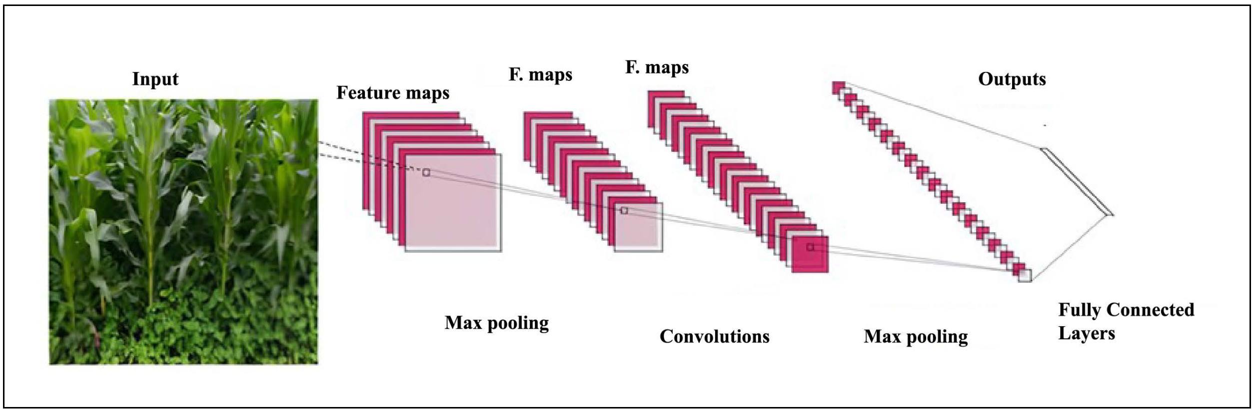

Fig. 2: Object detection with convolutional neural networks

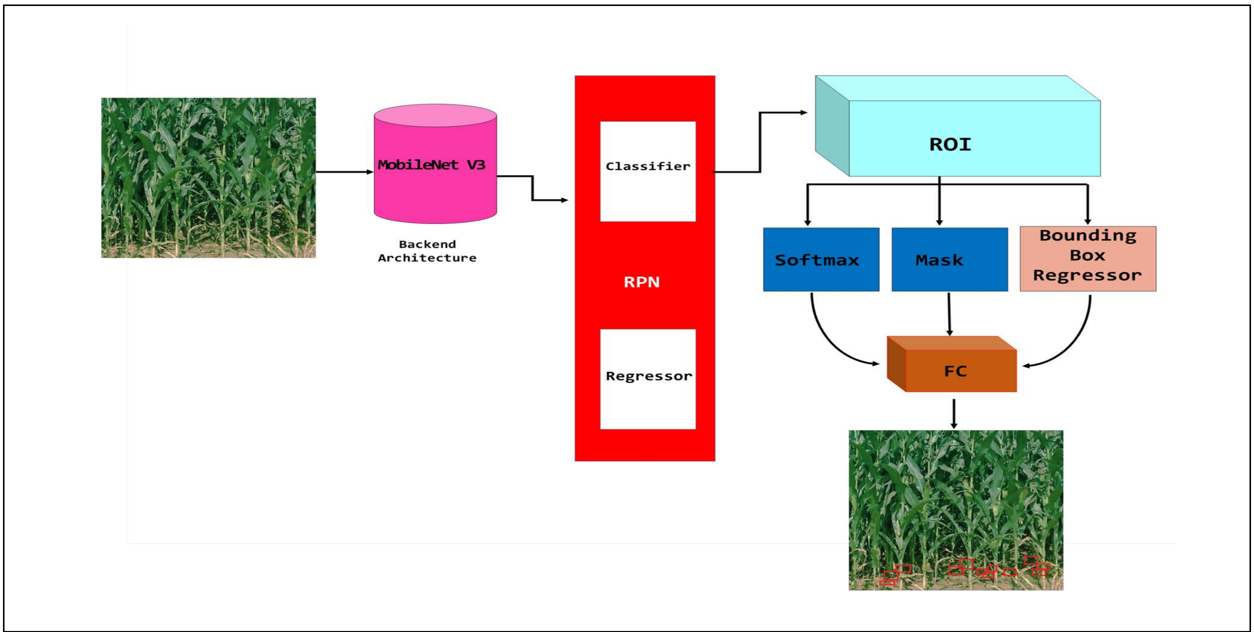

Fig. 3: Proposed Mask R-CNN

3.1.2 Advancement to Mask R-CNN in Object Detection

The architectural paradigm of R-CNN shown in Fig. 3 holds significant prominence in the domain of computer vision, specifically tailored for object detection tasks. Initially devised for proposing regions of interest and subsequent independent classification, R-CNN encountered drawbacks pertaining to operational speed and the absence of end-to-end training capabilities. The evolutionary stride culminating in Mask R-CNN sought to overcome these limitations, introducing a transformative attribute—instance segmentation. In contrast to conventional object detection methodologies, Mask R-CNN achieves pixel-level precision in outlining object boundaries through the generation of segmentation masks. Mask R-CNN distinguishes itself by concurrently executing three fundamental tasks: object detection, classification, and instance segmentation. While preserving the region proposal mechanism inherent in RCNN, Mask R-CNN extends this by predicting segmentation masks for each proposed region. This implies that, for every identified object, Mask R-CNN not only discerns the object's class but also furnishes a meticulous mask depicting the object's precise contours. The operational sequence involves the generation of region proposals utilizing selective search, individualized processing through convolutional layers for feature extraction, and three parallel pathways for object classification, bounding box regression, and segmentation mask generation. The pathway dedicated to segmentation masks employs supplementary convolutional and up sampling layers to generate a binary mask for each proposed region, encapsulating the instance segmentation of the corresponding object. The conclusive output encompasses class labels, bounding box coordinates, and intricate segmentation masks detailing the object's contours. The instance segmentation functionality embedded in Mask R-CNN proves to be particularly advantageous in scenarios characterized by object overlap or close alignment, thereby amplifying precision in localization and affording a nuanced comprehension of the spatial distribution of objects within a given image.

The Visual Geometry Group Image Annotator (VIA) is employed for annotating images in the development of computer vision algorithms, particularly object detection. User-friendly interface of VIA simplifies the process of labelling objects using polygons or bounding boxes. Following the process of annotation, images are stored in JSON format, providing flexibility and adaptability. Subsequently, the dataset is partitioned to facilitate efficient algorithm training and evaluation. The suggested approach aims to enhance the accuracy and precision of object detection in UAV images by integrating Mask R-CNN with instance segmentation. This approach prioritizes the efficient segregation of desired objects by utilizing anchor boxes, a crucial component in the process of object detection. In order to ensure compatibility with Mask R-CNN, tagged UAV images are transformed into the COCO (Common Objects in Context) format. This format is widely used to assess real-time object identification algorithms, facilitating smooth performance comparisons. Intersection over Union (IOU) is a crucial statistic used in object detection to evaluate the degree of overlap between predicted and real bounding boxes. The IOU bounding boxes play a crucial role in achieving precise detection during Mask R-CNN training. The model predicts categorization, bounding boxes, and masks at the same time, making the process of detecting objects in UAV images more efficient and precise.

3.1.3 Deep Learning Model MobileNetV3 in Mask R-CNN

The deep learning model used to integrate Mask R-CNN with instance segmentation greatly affects performance. The proposed study chose MobileNetV3 due to its reputation for handling complicated datasets. This model is ideal for real-time applications and low-resource environments because of its lightweight design and quick feature extraction. This design balances model accuracy and computational efficiency, achieving our goal of improving object recognition and precision in UAV photos while taking into account UAV computational constraints. The incorporation of MobileNetV3 is anticipated to contribute to improved speed and accuracy, addressing the specific challenges posed by instance segmentation in the context of UAV image analysis. This model represents a notable advancement in the realm of lightweight deep learning architectures, specifically tailored for efficient neural network inference on mobile and edge devices. Departing from its predecessors, MobileNetV1 and MobileNetV2, MobileNetV3 introduces innovative features and optimizations aimed at achieving a delicate balance between model accuracy and computational efficiency. A distinctive characteristic of MobileNetV3 is its utilization of inverted residual blocks. These blocks start with a lightweight linear bottleneck layer, followed by a depth-wise separable convolution layer, and conclude with a linear expansion layer. This inverted structure enables the capture of complex patterns while minimizing computational costs, making it well-suited for deployment in scenarios with resource constraints. Within each inverted residual block, MobileNetV3 incorporates a linear bottleneck layer, which contributes to enhanced feature representation by preventing the network from discarding valuable information. The hard sigmoid activation function and Parametric Rectified Linear Unit (PReLU) activation increase the model's non-linearity and expressive capability. The MobileNetV3 uses Squeeze-and-Excitation (SE) blocks to tune channel-wise feature responses during training to improve attention. This lets the network focus on more informative channels, improving performance. The MobileNetV3 has two sizes: Large and Small. The former is powerful and accurate, whereas the latter balances efficiency and performance for limited computational resources. The last layers use lightweight pooling instead of fully connected layers, decreasing model parameters and computing complexity. This model is a popular backbone network for computer vision tasks like image categorization and object recognition, especially in real-time applications when computational resources are limited. Its unique design and optimizations make it a versatile and effective solution for low-computational devices.

3.2 Role of Internet of Things in Enhanced UAV Weed Detection

The integration of the IoT within the research methodology represents a profound advancement in the realm of weeds and crop detection in UAV images. It serves as a transformative element by strategically placing sensors and actuators throughout the agricultural landscape. These IoT devices function as intelligent nodes, constantly collecting real-time data on various facets, including environmental conditions, crop health parameters, and potential weed infestations. The significance of this real-time data acquisition cannot be overstated, as it forms the foundation for an adaptive and responsive system. In practice, IoT facilitates seamless communication between the intricate Mask R-CNN model and the agricultural ecosystem. This interconnectedness ensures that the model is not solely reliant on static datasets but dynamically adjusts its responses based on the evolving conditions in the field.

The placement of sensors and actuators at strategic points contributes to a comprehensive understanding of the agricultural environment, capturing nuances that might be missed through static image analysis alone. The collected IoT data becomes a crucial component in the decision-making process of the Mask R-CNN model. By assimilating information on environmental changes, crop health fluctuations, and potential weed threats, the model gains a holistic perspective. This holistic approach empowers the system to make informed decisions in real-time. For instance, upon detecting a weed infestation, the system can trigger immediate responses, such as alert notifications, automated weeding equipment activation, or other predefined actions. The synergy between image processing and IoT in this methodology marks a paradigm shift in precision agriculture. The adaptability and responsiveness introduced by IoT not only enhance the accuracy of weed and crop detection but also pave the way for intelligent, data-driven agricultural practices.

4. RESULTS AND DISCUSSION

An Intel Xeon E5-2643v3 CPU at 3.40 GHz was used in the experiment because of its computing power and multicore capabilities needed for complicated deep learning applications. Our weed detection system had 64 GB of RAM to manage large datasets and deep neural networks. An NVIDIA Quadro M4000 GPU with 8 GB of video memory accelerated deep neural network training. Intel Xeon Toolkit 9.0, cuDNN V7.0, Python 3.5.2, TensorFlow GPU 1.8.0, and Keras were important frameworks. To optimize convergence and GPU parallelization, input images were organized into ten batches and trained with an epoch-wise learning rate of 0.01.

To address limitations in traditional method, the study proposes the adoption of Mask Region-based CNN as an advanced approach to target object detection. The MASK R-CNN model undergoes fine-tuning with specific parameters, including a learning rate of 0.003, 156 training epochs, and a batch size of 25. This parameter configuration enables the model to effectively discern various objects within the images. Quantitative assessment includes performance metrics such as accuracy for weeds, accuracy for crops, and mean average precision, presented in Table 1.

Table 1. Comparison of performance metrics

Models	Accuracy of Weed	Accuracy of Crop	mAP (%)
Mask R-CNN	88.3	86.7	83.5(m12)
	87.2	88.1	84.2(m19)
	89.6	87.8	87.3(m24)
	89.1	88.7	88.6(m43)
	86.5	88.9	88.1(m69)
	87.8	86.3	86.9(m95)

These metrics provide insights into the efficacy of MASK R-CNN model in precisely detecting and segmenting specified target objects. Results, grounded in the implementation process, highlight the model's capability to surmount limitations associated with traditional template matching, achieving heightened accuracy and efficiency in target object detection. Average Precision values are subsequently computed for weeds, crops, and overall accuracy, revealing notably high values of 89.1% for weeds, 88.9% for crops, and an impressive overall precision of 89.4% for the specific image under consideration.

The Mask R-CNN network is essential for segmenting images and categorizing each segment as crop or weed. An area indicated as a weed in the original image is delineated as a weed zone. A Raspberry Pi with a GSM module sends farmers an email alert with the changed image emphasizing weed regions after categorization. This intricate communication process not only enables farmers to visually discern the presence of weeds in their fields but also empowers them with additional details for informed decision-making. The real-time alerts facilitate timely interventions, aiding farmers in implementing effective crop management strategies based on the identified weed zones. This comprehensive system enhances the overall efficiency of weed control and contributes to optimized agricultural practices.

The above work is mentioned to be a proposed work. Sampling images has been considered only for the implementation of the validity of the proposed work.

5. CONCLUSION

The research methodology seamlessly integrates advanced technologies, including Image Processing, Mask R-CNN, and IoT, fostering efficient communication between the model and the agricultural environment. The process commences with a meticulous preprocessing of a substantial dataset comprising 200 UAV images. In the initial phase, a specialized UAV-tailored Mask R-CNN, incorporating instance segmentation, outperforms conventional methods by demonstrating exceptional precision in identifying both weeds and crops. The integration of IoT facilitates real-time data collection, ensuring timely decision-making for effective agricultural management. The evaluation of AP values reveals a remarkable accuracy level, with specific metrics such as 89.1% for weeds, 88.9% for crops, and a remarkable overall precision of 89.4%. The Mask R-CNN network not only segments and classifies images but also delineates weed zones. These identified zones are then communicated to farmers through a Raspberry Pi equipped with a GSM module, enabling real-time alerts and informed decision-making. Looking towards the future, the research opens avenues for further enhancement and exploration. A potential future scope involves the integration of machine learning algorithms to adaptively optimize the detection model based on evolving environmental conditions. Additionally, the incorporation of robotic systems for targeted herbicide application in weed-identified areas could further enhance the precision and efficiency of weed control measures. This forward-looking approach underscores the transformative potential of advanced technologies in agriculture, paving the way for sustainable and technologically-driven farming practices.

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CONFLICTS OF INTEREST

The authors declare that there is no conflict of interest.

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