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Improved Real-Time Weed Detection and Assessment Framework Using an Enhanced YOLOv8n Model

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Abstract- Weed detection and management remain major challenges in modern agriculture, as weeds The identification and control of weeds in agriculture has been a major issue to modern agriculture, since the weeds compete with crops over crucial resources, and lower yield in case they are not well controlled. Manual weeding, manual application of herbicides are traditional techniques that are expensive but unsustainable to the environment. This research experiment suggests a new design with a real-time weed detector and assessor, based on a revised version of You Only Look Once 8 nano (YOLOv8n) model, trained with a Dual Attention Network (DAN) as the backbone and a refined Feature Pyramid Network (FPN) as the neck. An ensemble dataset was generated based on 10,000 images of rice farms sampled in Ihuokpara, Enugu, Nigeria and was augmented with publicly available datasets of Roboflow. Improved YOLOv8n was trained to detect various species of weeds in diverse conditions and combined with a Weed Severity Index (WSI) algorithm to measure the growth of weed in respect with the farm area. The experimental data proved that the improved YOLOv8n model had 96% detection probability, 100% accuracy, 99% recall, and F1-score of 92%, which are much better than the traditional models. It was found that the DAN allowed better spatial and channel attention and the enhanced FPN allowed good multi-scale feature extraction, which guaranteed a good detection even in case of occlusion and variable weed sizes. The WSI model categorized severity of weed into low, moderate, and high levels of severity as an intervention to take action. The suggested system was also confirmed by means of the software implementation and is expected to be deployed on Unmanned Aerial Vehicles (UAVs) having Simple Mail Transfer Protocol (SMTP)-capable farmer notifications. The framework further develops the field of precision agriculture through deep learning, transfer learning, and automated severity assessment, thereby lowering the number of herbicides applied to the crop, increasing its yield, and enhancing the environmental sustainability of farm management methods.

Keywords: Smart Agriculture; Weed Detection; YOLOv8n; Dual Attention Network; Feature Pyramid Network

I. INTRODUCTION

Weed detection and management are critical components of smart agriculture, a farming approach that leverages advanced technologies to optimize crop production and resource use. As shown in Figure 1 where there is farm with weed and one without, weeds keep competing with crops for nutrients, water, and sunlight, can significantly reduce agricultural yields if not properly controlled. Traditional methods of weed management, such as manual weeding and the use of chemical herbicides are not only labor-intensive and costly but also pose environmental risks. As the agricultural sector faces the dual challenges of feeding a growing global population and ensuring sustainability, smart agriculture solutions like automated weed detection and management systems have become increasingly vital (Mckay *et al.*, 2024).

In smart agriculture, weed detection systems often rely on advanced image processing techniques and machine learning algorithms to identify and classify weeds in real-time. These systems use sensors, drones, or ground-based cameras to capture images of crop fields, which are then analyzed by algorithms, typically powered by deep learning models (Gallo *et al.*, 2023). These models are trained on large datasets of labeled images, enabling them to accurately distinguish between crops and weeds. The precision offered by these technologies allows for targeted weed control, reducing the need for blanket application of herbicides and minimizing environmental impact (Lan *et al.*, 2021).

Today, pre-trained models have evolved as a promising tool to solve weed detection problems in real-time. Several literatures has engaged algorithms such as You Only Look Once version 8 (YOLOv8) in Guo *et al.* (2024a), which were trained for real-time detection of weed in rice farms. Lan *et al.* (2021) trained two improved pre-trained models of MobileNet-V2-Unet and FFB-BiSeNetV2. The former was tailored towards improving speed of weed detection, while the latter later focused on improved accuracy of recognition. Gallo *et al.* (2023) also considered YOLOV3 and V7 for real-time classification of weed in smart agriculture, while Mckay *et al.* (2024) considered the Residual Network (ResNet) series of 18, 34, and also Visual Geometry Group with 16layers(VGG-16) for weed classification. While these studies have recorded high accuracy in the classification of weed in a farm, there is weakness in their reliability to correctly define weed. This is because these models are evaluated based on their ability to detect individual weeds without a comprehensive assessment of the overall weed population on the farm, which has resulted in misrepresentation of weed situations. According to Zimdadh (2018), a farm cannot be 100% weed-free throughout the cultivation lifespan; however, an accurate assessment of the population of weed with respect to the size of the farm is needed to present a reliable model for the classification of weed, and to achieve this, this research presents a real-time model for the detection of weed using a transfer learning algorithm and an unmanned area vehicle in smart agriculture. The major proposed contribution of the work is to develop a model that can accurately detect weed in a farm and then serve as input to another algorithm that computes the percentage of weed population with respect to the farm size. This model will be integrated to formulate a reinforced solution for real-time weed classification in smart agriculture and will be deployed in a drone for remote sensing and classification of weed in Nigeria.

II. THE PROPOSED SYSTEM

The proposed system for the detection of weed in smart agriculture will be made of several components which include data collection, data preparation, development of new data model, an improved YOLOv8n, Dual Attention Network (DAN) model, improved Feature Pyramid Network (FPN), training of the model, testing and validation, experimental testing and validation of result. The proposed system block diagram was presented in the Figure 1;

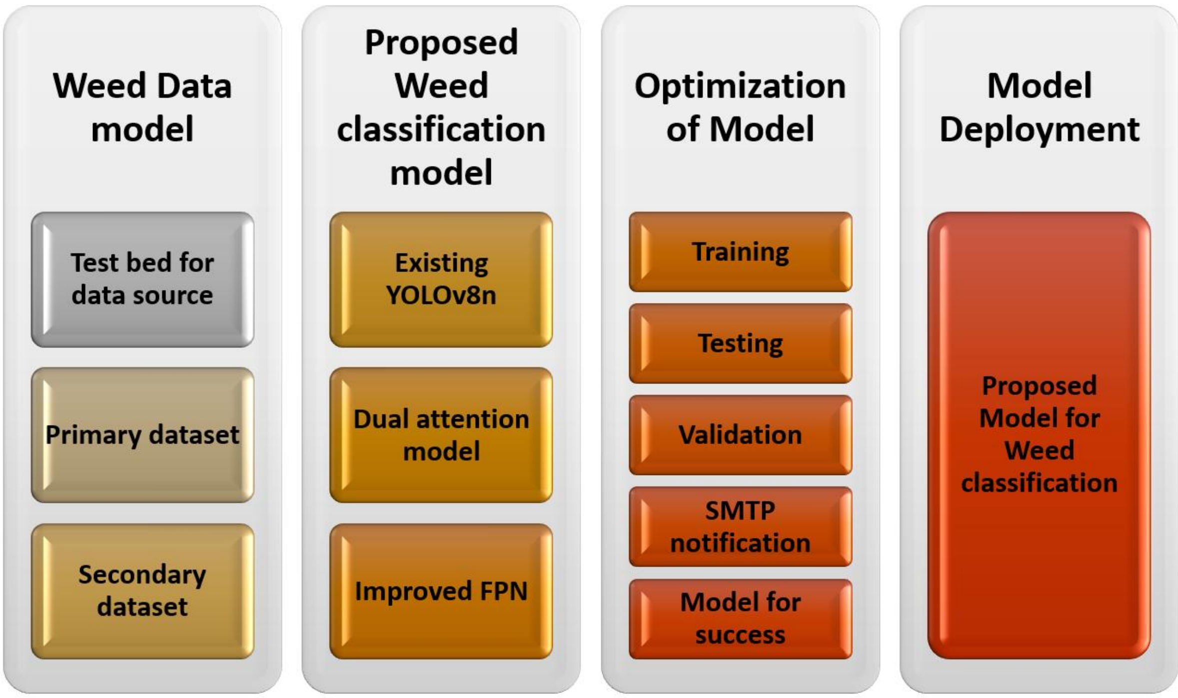

Figure 1: Block diagram of the proposed system

The Figure 1 presents the block diagram of the proposed weed classification model. First data was collected from a testbed at Ihuokpara, Enugu, Nigeria, and then used to form the primary dataset. Secondly already existing dataset of rice weed was collected from Robowflow repository and then applied with the primary dataset to form the new data model. In the next module, existing YOLOv-8n was be adopted, and then the backbone got improved with DAN while the neck was improved with modified Feature Pyramid Network (FPN). Collectively the models were integrated to form the newYOLOv-8n. In addition, an optimization algorithm was developed which computes the population of weed with respect to the farm size to determine if the farm has weed situation or not. The model of YOLOv-8n improved

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was trained with the dataset of weeds and then generated the model which serves as input to the optimization algorithm for the classification of weed in the farm. To notify the farmer of the results, the SMTP algorithm was used which employed email approach to notify users of weed situation in the farm.

This was achieved with an adopted existing YOLOv-8. This YOLOv-8 is made of four sections which are the focus layer, the backbone, neck and head. The backbone is made of spatial pyramid pooling function which is responsible for feature extraction; however, the fixed pooling size and filter sized make it not able to facilitate multi-scale feature extraction process which is an issue as it might affect correct classification of weed in rice farm. In addition, the inability for multiscale feature extraction limits the model ability to address issues of same object occlusion problem. To solve this problem, the DAN Model was adopted. The DAN was developed as an attention mechanism with adaptive filters, batch normalization layers and different convolutional sizes to formulate an adaptive mechanism for improved multi-scale extraction. In addition, to improve multi-scale feature identification, the FPN was improved by adding additional Pyramid Attention Network (PAN) for improved feature identification. Collectively, the models were integrated as the new YOLOv-8n model. To address issues of false, negative and misrepresentation of weed, an algorithm was developed which used the input of the classification output to compute the population of weed in the farm. Collectively this presents the model for the classification of weed in smart agriculture.

2.1 Data Collection

Images of various rice weeds were captured manually using high-resolution cameras at different times of the day to reflect varied lighting conditions. Each image was focused on capturing clear, close-up views of the weeds as they appeared within the rice fields. Figures 2 - 4 presents the testbed where data were collected considering different species of rice weeds.

Figure 2: Rice Flatsedge

Figure 3: Barnyard grass

Figure 4: Blistering ammannia

Figure 2 and 4 presents the different classes of weed collected from the farm. The size of the data captured is 320320 resolutions. The total number of images captured is 10,000 as the sample size. Figure 5 presents the actual rice farm without weeds.

Figure 5: Rice farm without weeds

The collected images were labeled and annotated using the Roboflow tool, which allowed for efficient bounding box generation and class assignment for each weed type. After annotation, the image data, along with corresponding metadata such as image paths, weed types, annotation coordinates, and timestamps, were systematically stored in a SQLite database. This structured storage enabled seamless integration with the deep learning model and allowed for efficient retrieval during training, validation, and real-time inference processes.

2.2 Dual Attention Network (DAN) and Improved Feature Pyramid Network (FPN) Models

Optimizing YOLOv8n with a DAN and an improved FPN is essential for enhancing rice weed detection, where accuracy, scale sensitivity, and feature discrimination are critical. Rice fields often contain complex backgrounds, varying weed sizes, and occlusions, making it difficult for standard models to differentiate between rice plants and diverse weed species. Integrating DAN enables the model to focus more effectively on relevant spatial and channel features, enhancing its ability to distinguish subtle differences between crops and weeds. Meanwhile, an improved FPN enhances multi-scale feature fusion by more accurately preserving fine-grained details and contextual information across different layers, which is crucial for detecting small or partially hidden weeds. Together, these enhancements address YOLOv8's limitations in feature refinement and scale variation, leading to improved precision and robustness in real-world rice field environments. Figure 6 presents the flowchart of the DAN.

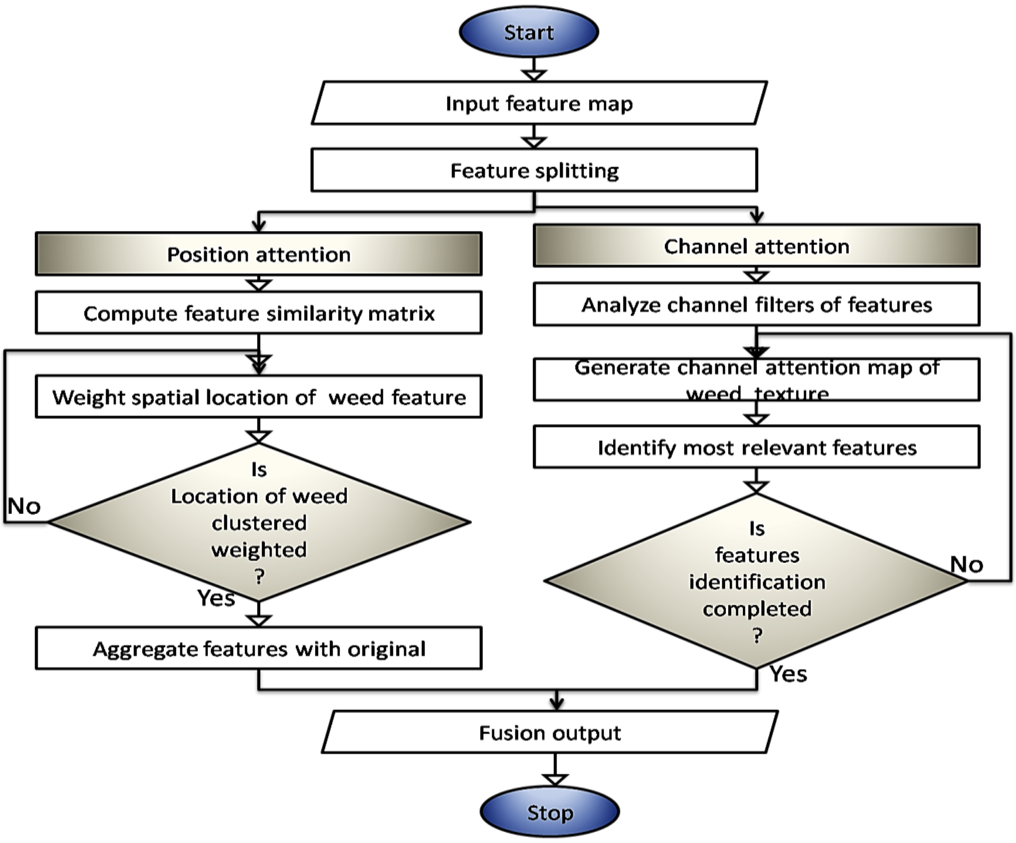

Figure 6: The Flowchart of the DAN

The flowchart in Figure 6 illustrates the functioning of the Dual Attention Network (DAN), beginning with the input feature map, which contains raw spatial and semantic information extracted from the previous layers of the detection network. This map is split into two attention paths: Position Attention and Channel Attention. In the Position Attention path, a feature similarity matrix is computed to determine the correlation between different spatial locations, enabling the network to weight the spatial location of weed features more effectively. A check is performed to ensure that clustered weed regions are properly weighted, after which the refined spatial features are aggregated with the original feature map. Meanwhile, the Channel Attention path begins by analyzing the channel filters, i.e., the various feature types (textures, edges, etc.) across the depth of the input. It then generates a channel attention map focusing on weed-related textures and identifies the most relevant feature channels for detection. A conditional check ensures that the channel-based feature identification is complete. Once both spatial and channel-wise attentions are refined, their outputs are fused together, producing an enriched fusion output that is better at localizing and identifying weeds in complex agricultural imagery.

2.3 Improved Feature Pyramid Network FOR YOLOv8n

The improved FPN is tailored towards maximizing feature identification from the backbone using weighted sum approach which better combines the feature maps from different layers, making it rich for better weed texture identification.

The features map dimension are reduced using eleven (11) convolutions, then upsampling is applied or higher feature identification, while downsampling is applied for shallow layer feature detection. Concatenation is applied using weighted sum to fusion all feature maps, ten normalization using thirty three (33) convolutions is applied to enhance the feature quality and return the output. The Improved FPN algorithms are presented as;

FPN Algorithm

1. *Start*
2. *Input features %% the multi-scale feature maps from backbone*
3. *Reduce channel dimensions using 1×1 convolutions.*
4. *Upsample higher-level feature maps*
5. *Downsample shallow layers*
6. *Concatenate features with weighted sum*
7. *Enhance features with 33 convolutional layers*

8. *Apply batch normalization*
9. *Smooth feature with 3×3 convolutions*
10. *Output enhanced multi-scale features for the detection head*

2.4 New Transfer Learning Model

The New transfer learning model integrated the DAN algorithm and the improved FPN algorithm into the backbone and the neck of the YOLOv8n as the improved model suitable for weed classification. Figure 7 presents the new YOLOv8n model.

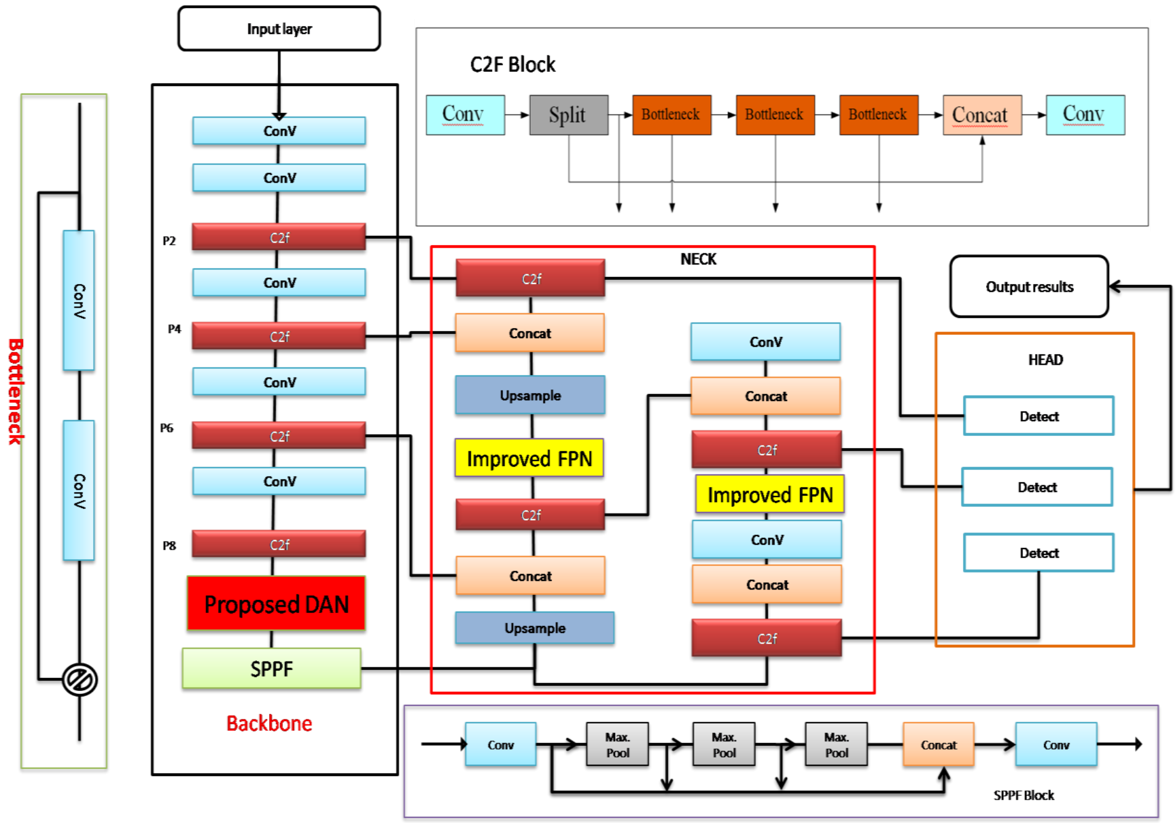

Figure 7: The Newly Enhanced YOLOv8n model

Figure 7 presents the architecture of the New YOLOv8n. In the diagram, the proposed DAN was connected before the SPPF, while the Improved FPN was connected in the two segments of the neck region. This interconnection process facilitates the optimized feature identification process, facilitating deep and shallows feature maps detection before the SPPF extraction process. In the Neck, the improved FPN facilitates fine multi-scale features which are normalized and enriched with diverse feature maps which characterized weed. This architecture made up the improved YOLOv8n for rice weed detection.

2.5 Training of the Model

The training of the new YOLOV8n model integrated with DAN and an Improved FPN using a rice-weed dataset involves feeding annotated images into a modified detection pipeline that enhances feature representation and attention. The Improved FPN strengthens multi-scale detection by adaptively fusing spatial-semantic features across scales, particularly improving small weed detection under complex backgrounds. Simultaneously, the DAN module refines spatial and channel attention, allowing the model to focus more precisely on discriminative weed patterns while suppressing background noise and irrelevant crops. During training, standard regularization was used to improve generalization, while the loss function, comprising objects of interest, classification, and localization terms are optimized using backpropagation. The enhanced model learns to distinguish visual differences between rice and various weed types, resulting in improved accuracy, robustness, and real-time performance across different field conditions.

2.6 Weed Assessment Model

The weed assessment model is designed to quantify and evaluate the severity of weed proliferation within rice fields, ensuring that intervention is triggered only when weed presence surpasses a critical threshold. The model operates by analyzing outputs from the enhanced YOLOv8n classifier, which detects and classifies weeds across an image. A mathematical formulation is used to assess the Weed Severity Index (WSI), which combines weed count, spatial coverage, and weed-to-crop ratio.

Let

- N_w= total number of weeds instances
- N_c is the number of rice crops instances detected
- A_w is the total area covered by the weed bounding boxes
- A_t is the total image area of the camera
- $D_w = \frac{N_w}{A_t}$ = weed density per unit area
- $R_{wc} = \frac{N_c}{A_t}$ = weed to crop ratio
- $C_w = \frac{A_w}{A_t} * 100$ which is the total area percentage covered by weed

$WSI = \alpha . D_w + \beta . R_{wc} + \gamma . C_w$ Equation(1)

Where $\alpha, \beta, \gamma \in [0,1]$ are weighting coefficients such that, $\alpha + \beta + \gamma = 1$, tuned based on field importance. The WSI threshold is categorized as;

Low $WSI < \varphi_1$

Moderate $\varphi_1 \leq WSI < \varphi_2$

High $WSI \geq \varphi_2$

Where φ_1 and φ_2 are threshold for weed severity.

Weed Assessment Algorithm

1. Start
2. Initialization of counter %% weed, crop and area
3. Loop through all detection
4. $for\ i\ in\ range(length\ of\ detections)$
5. $if\ detections[i]\ ==$ "$weed$":
6. $N_w \leftarrow N_w + 1$ %% detect all weeds
7. $A_w \leftarrow A_w + bounding\_boxes[i]$ %% detect all weed area
8. $else\ if\ detections[i]\ ==$ "$rice$":
9. $N_c \leftarrow N_c + 1$ %% detect all rice crops
10. Compute WSI
11. Classify weed level with decision base
12. Return output
13. End

2.7 System Implementation

The implementation of the rice weed detection and monitoring system is based on an intelligent, modular design that integrates deep learning, computer vision, and automated communication. It was developed with a focus on scalability, user accessibility, and real-time processing of field images to assess weed conditions and generate actionable feedback. The system runs on a client-server architecture, allowing users to interact with the application through a graphical user interface, while backend modules handle detection, assessment, and notifications. Below are the proposed system requirements necessary for effective implementation.

III. RESULT OF IMPROVED YOLOV-8N TRAINING

Training of the improved YOLOv8n was done using the prepared weed dataset. During the training process confusion matrix was used to evaluate the performance. Metric such as True Positive (TP), False Positive (FP), recall, precision and f1score were applied to evaluate the model performance. Figure 8 presents the confusion matrix. This normalized confusion matrix provides insights into how well the improved YOLOv8n performs in detecting weeds in rice fields, distinguishing between "Weeds" and "Background".

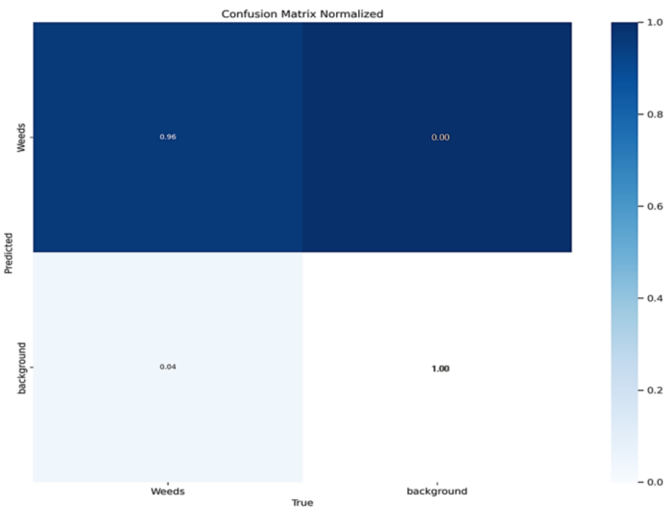

Figure 8: Confusion Matrix of the Weed Detection Model Training

Figure 8 presents the confusion matrix which measures the TP and FP of the model performance in weed detection. From the result, it was observed that the weed detection TP recorded 0.96 which implied that the model was able to classify weed from the dataset images with 96% accuracy. The results also recorded 0.04% FP. This implied that the model recorded error of 4% during the classification process, as it mistakenly classified the farm background without weed as weed. In addition, it correctly labels 100% of the background (non-weed areas) as "background," showing that the model can distinguish background of the farm from actual rice weeds. The reason for the high classification success was because the model trained was optimized with the application of improved FPN and DAN. Figure 9 presents the precision confidence score of the model performance in weed detection.

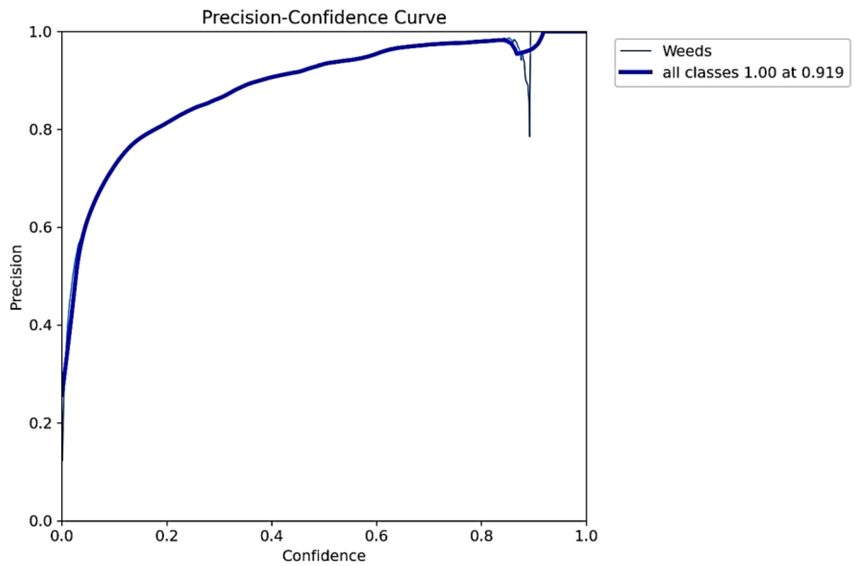

Figure 9: The Precision Confidence Graph

Precision measures the ability of the model in correctly classifying weed in the rice farm. In the results it was observed that the model recorded 1.00 as the precision results with a confidence value of 0.919. This result implied that the trained YOLOv8n model was able to correctly classify weed in the rice farm with 100% success rate, and 92% confidence that the classification was positive.

In the next results, the recall performance was evaluated. The recall measures the reliability of the model. It ensures that the plant classified as rice weed is actually rice weed. This is because there are tendencies where the model will detect other plants in the farm and mistakenly classify as weed. Figure 10 presents the recall graph.

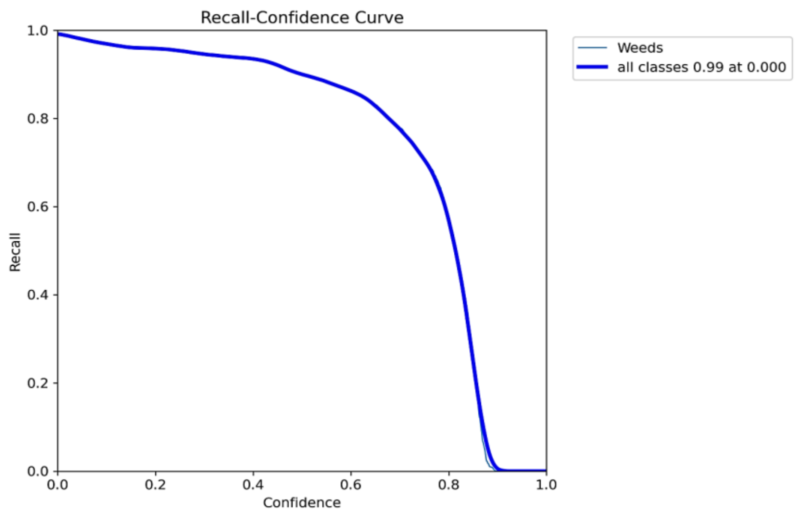

Figure 10: The Result of Recall

From the results in Figure 10, it was observed that the recall value for weed detection is 0.99. This result means that the model was able to correctly classify actual rice weed with 99% success rate. The reason was because the model utilizes the DAN which maximized feature extraction using a mix of channel and position attention mechanism to optimize feature map of weed extracted from the rice farm. In addition, the FPN which applied weighted attention to maximize multiscale feature identification was also a factor which results to the high classification success recorded for weed detection. Figure 11 presents f1-score of the model for the classification of weed in rice farm. This measures the relationship between precision and recall.

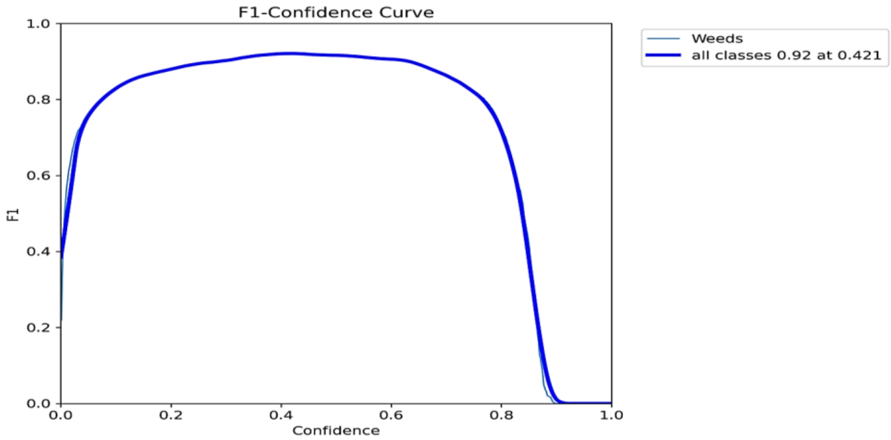

Figure 11: The F1-Score Confidence Score

Figure 11 presents the f1score of the model. This result measures the model performance in correctly classifying actual rice weed from the farm. From the results, the F1score reported 0.92 with 0.421 confidence score. The results implied that 92% success rate was recorded in the model performance in successfully classifying positively actual weed in rice farm. The confidence score for the classification performance is 42% which is ok, and implied that the trained weed classification model was not able to just classify weed in the rice farm correctly, but was able to classified actual rice weed as the object of interest.

3.1 Experimental Validation of the Model with software

This section presents the performance of the model when it was deployed as a software application and then tested as software. The software was developed to allow access to videos, real time data acquisition and images of practical farm settings with weed. Figure 12 presents the results of the software interface with the imported data of rice farm containing weed.

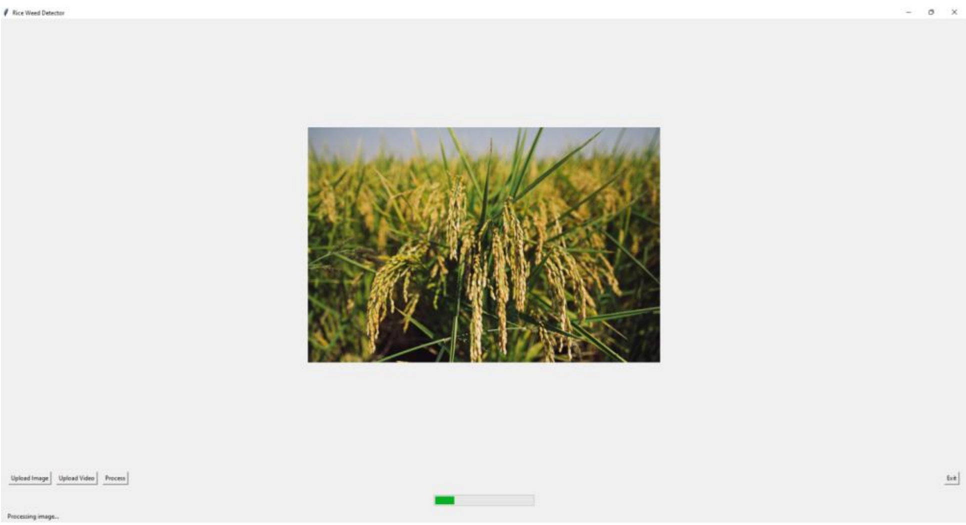

Figure 12: The Result of the Software Implementation

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Figure 12 presents the data upload result of the weed classification software. In the results, it was observed that test data was imported into the model. This data imported was identified by the trained YOLOv8n which utilized the DAN to maximize feature identification, then the neck which applied the improved FPN for multi scale feature identification of features of different dimensions. The features are used as input to classify weed in the farm and the outcome, then assessed by the weed assessment algorithm. The result was reported in Figure 13.

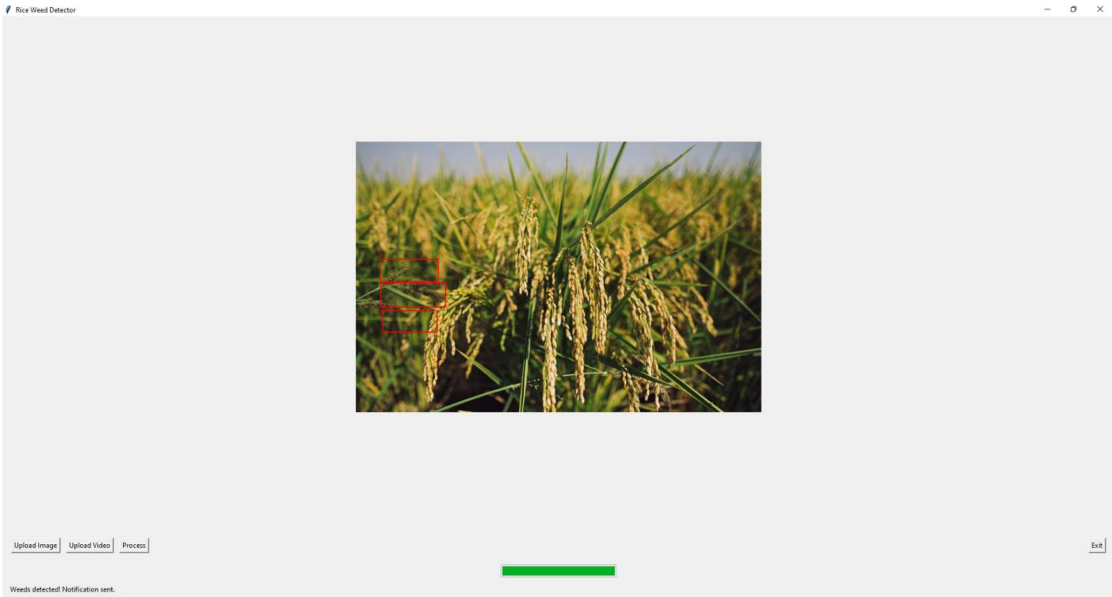

Figure 13: Result of the Weed Classification Software

Figure 13 presents the classification output of the deep model for rice weed detection. The results showed that the model was able to correctly classify the portion of the farm with high severity of weed.

CONCLUSION

The proposed paper came up with an improved weed detection and evaluation system that is specific to rice farms in Nigeria to overcome the weaknesses of the conventional weed management practices and previous machine learning systems. The proposed design enhanced the YOLOv8n model by incorporating a Dual Attention Network (DAN) into the backbone and an enhanced Feature Pyramid Network (FPN) into the neck that would allow extracting features at multiple scales and distinguish weeds and crops more effectively. On 10,000 high-resolution images of the fields that were taken at Ihuokpara, Enugu, and on pre-existing datasets of rice weed on Roboflow, a hybrid dataset was developed to ensure that the model was trained in various lighting types and diverse weed species.

The better version of YOLOv8n model made major performance improvements in training and validation. The model achieved a true positive detection rate of 96%, 100% precision and a 99% recall indicating that it has the capability of identifying rice weeds and reducing false positives and negatives. The F1-score was 92% as well, which is an affirmation that there existed a tradeoff between precision and recall. Weed Severity Index (WSI) model further enhanced the framework in quantifying the weed population compared to the farm size by categorized the severity as low, moderate or high. This is because of its dual ability to detect and determine the severity of the weed making the system more reliable to be used in the real world compared to the current models which detect single weeds.

To sum up, the incorporation of DAN and enhanced FPN into YOLOv8n resulted in a highly precise, real-time weed-detecting framework that could be used in the field of precision agriculture. The training of this model on unmanned aerial vehicles (UAVs), along with the SMTP-driven notification systems, will make sure that farmers are provided with the information about the weed condition and intervention in a timely manner. This work will help in making agricultural practices more sustainable as it will reduce excessive dependence on herbicides and enhance active farm management, therefore, enhancing crop yields and resource-using efficiency.

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