AN INTELLIGENT DEEP LEARNING-BASED MODEL FOR WEED DETECTION AND CLASSIFICATION USING YOLOV8N

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ABSTRACT

The weed invasion is one of the most severe challenges to sustainable rice production, which diminishes crop production and over depends on herbicides, which usually result in environmental degradation and appearance of herbicides-resistant species of weeds. Precision agriculture requires early and accurate detection of weeds, which have limitations on their accuracy of detection, false alarms in cases of background occlusion, and differences in the appearance of the weed across farm settings. This paper will suggest a smart deep learning model that detects and classifies weeds based on the YOLOv8n architecture created within the Extreme Programming (XP) approach. The testbed was a case study rice farm in Ndibinagu-Uzam, Ihuokpara, Enugu State, Nigeria. A total of 10,000 annotated images of the most common species was collected as rice weed, specifically barnyard grass, rice flatsedge, and blistering ammannia in different lighting and field conditions. The labels were given to the images with the help of Roboflow and were organized in a SQLite database to train and validate the model. Using this data, the YOLOv8n transfer learning model was trained, and its performance was measured according to such standard metrics as accuracy, precision, recall, and F1-score. The experimental findings have shown that the proposed model has achieved a total accuracy of 94.6%, precision of 92.8%, recall of 93.5% and F1-score of 93.1% indicating that the proposed model is robust when detecting small objects and minimizing false alarms due to overlapping and occlusion. The results indicate that the system can effectively be used as a dependable decision support tool in real time monitoring of weeds, lessening herbicide addiction, and enhancing rice harvest in small-scale farms. The paper concludes that a solution of deep learning with locally gathered agricultural data is context-specific to sustainable management of weeds, and further efforts will involve real-time Simple Mail Transfer Protocol (SMTP) and aerial implementation to implement this solution in large scale.

Keywords: Weed Detection; Rice Farming; YOLOv8; Deep Learning; Computer Vision; Real-time, SMTP

1. INTRODUCTION

"Farming is a profession of hope." This timeless quote captures the essence of agriculture, where the farmer's toil is deeply intertwined with the sustainability of life itself through crop production. Since time immemorial, one major threat to the sustainability of crop production is weed (Qu *et al.*, 2024). Undoubtedly, weed plays a role in the eco-system; however, in the context of crop production, Rosle *et al.* (2021) revealed that weed has significant economic consequences as it has continued to affect the volume of global food production negatively. Weeds have strong adaptability to environments and often compete with crops for nutrients and space, thus resulting to a decline in the quantity of crop yield (Guo *et al.*, 2024a). To solve these problems, herbicides have resonated as one of the traditional approaches to combating weed on the farm.

According to the United Nations Food and Agriculture Organization (FAO, 2021), from the year 1990 to 2019, Asia has used 805,412 tons of herbicides to control weed, Europe has used 179,799 tons, Oceania has used 23,309 tons, Americas used 593,619 tons, and Africa has used 21,117 tons of herbicides to control weed. However, Rosle *et al.* (2021) revealed that the too much application of herbicides has made weeds in recent time resistant and hence necessitates a strategic means for weed control.

One noticeable crop that has suffered the impact of weed over time is rice, which is available all over the world (Aznan *et al.*, 2021). Weed impacts overall rice yield and can be managed through early detection (Dadashzadeh *et al.*, 2020). Early detection of weeds, according to Oerka (2006), Wu *et al.* (2021) and Aznan *et al.* (2021) has the capacity to prevent the loss of crop yield by about 34% and, in addition, can reduce the impact of disease and pests.

At present, several computer vision algorithms have been developed in the scientific community for the early detection of weed using various techniques, such as machine learning-based computer vision (Dadashzadeh *et al.*,

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2020). A remote sensing approach for weed detection was investigated by Rosle *et al.* (2021), while Qu *et al.* (2024) and Lan *et al.* (2021) investigated the impact of deep learning algorithms for weed detection. Despite the success of this literature for early weed detection, several limitations were identified, which include the need for increased weed detection accuracy with semantic intelligence, false alarm due to issues of background occlusion and overlapping behavior of weed, variability in weed behavior, and uncertainty due to the unpredictable nature of weeds in the farm. On that note, this study an intelligent model is presented for accurately detecting 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.

2. METHODOLOGY

The methodology used for this work is the extreme programming approach. In achieving this methodology, data was collected from the case study testbed at Ndibinagu-Uzam, Ihuokpara, Nkanu-East, Enugu, Nigeria and then applied to develop the new data model for weed detection. The data model was applied to train an improved deep learning model designed with YOLO-v8, and then generate the classification model for weed. The model will be evaluated experimentally at the test bed, and also with other data collected from a real rice farm.

2.1 Case Study Rice Farm

The case study rice farm is located at Ndibinagu-Uzam, Ihuokpara community, in Nkanu-East Local Government Area of Enugu State, Nigeria. The geographical coordinates of the farm are approximately 6.5530° N latitude and 7.6933° E longitude. This region is characterized by a tropical wet and dry climate, with distinct rainy and dry seasons, which supports rice cultivation. The farm spans several hectares and experiences seasonal challenges with weed infestation, particularly during the early and mid-growth stages of rice. The predominant weed types observed in this location include barnyard grass, rice flats edge, and blistering ammannia, which significantly reduce rice yield if not effectively managed. Figure 1 presents the location of the site in Google Map. This location was chosen due to its representative nature of smallholder rice farms in southeastern Nigeria, where farmers face common challenges in weed identification, timely assessment, and intervention. The case study serves as the operational base for testing and validating the proposed weed classification and real-time monitoring system using deep learning and SMTP technologies.

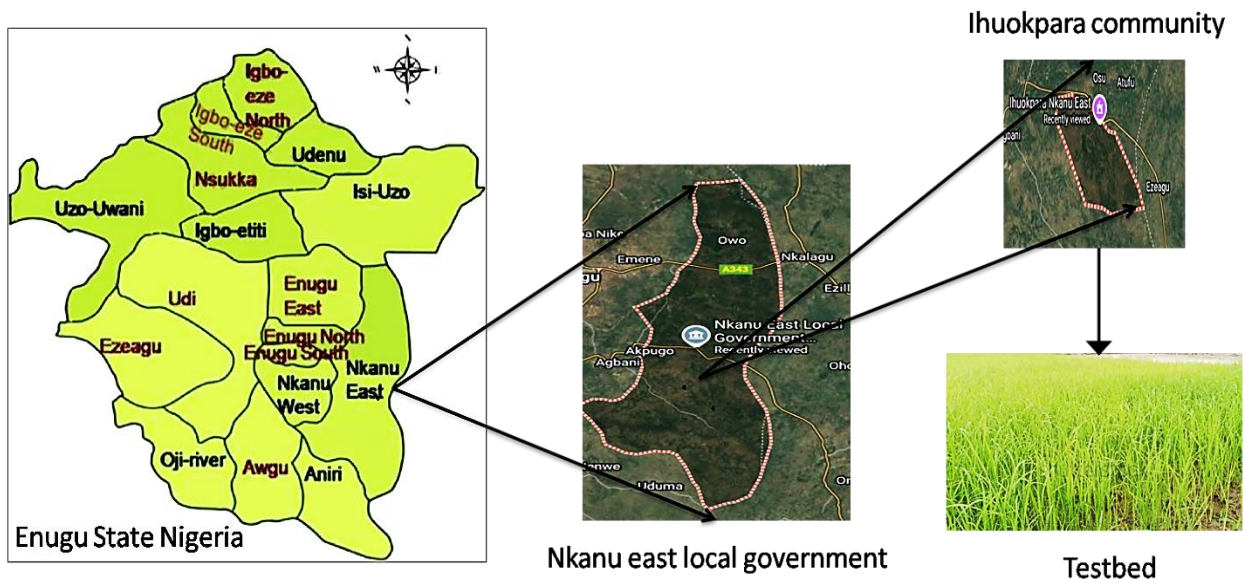

Figure 1: The Case Study Rice Farm

2.1.1 Experimental Setup

The experimental setup was designed to facilitate data collection of weeds from the testbed. The setup constitutes components such as high resolution camera, Hp laptop, and tripod stand. These devices were connected and then applied to capture data of weed from the farm. Figure 2 presents the setup.

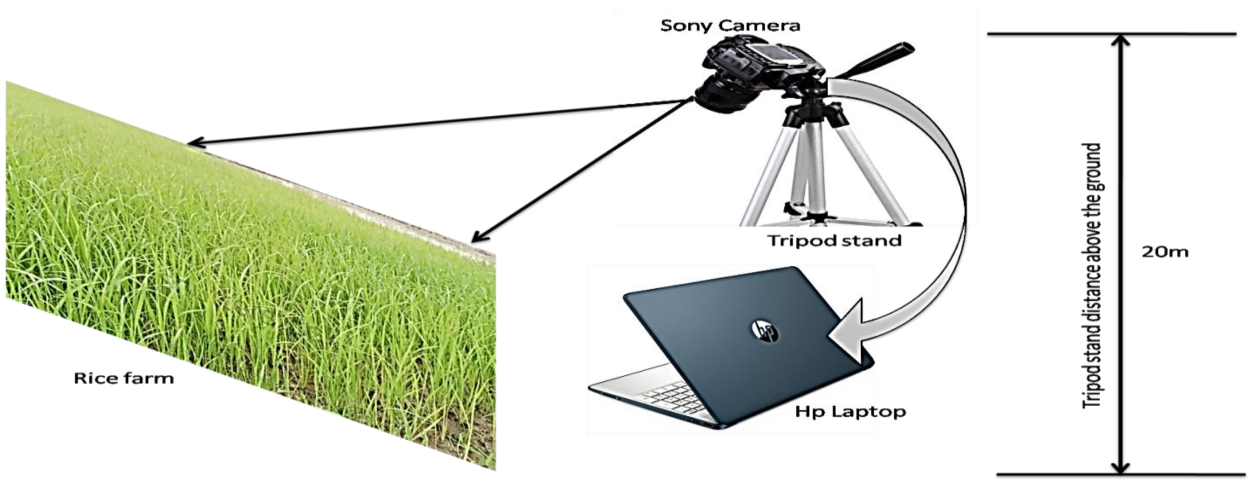

Figure 2: Experimental Setup

2.1.2 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 3 - 5 presents the testbed where data were collected considering different species of rice weeds.

Figure 3: Rice Flatsedge

Figure 4: Barnyard grass

Figure 5: Blistering ammannia

Figure 3 and 5 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 6 presents the actual rice farm without weeds.

Figure 6: 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 The Proposed Transfer Learning Model

The proposed transfer learning model for this work is the YOLOv8n. This is the smallest but very effective version of YOLOV8 which is a popular algorithm for object detection problem. This YOLOV8n is made of four main components which are the input layer which sizes the input data, backbone, neck and the output. The backbone is made of convolutional layers, C2F layers and Spatial Pyramid Pooling Function (SPPF) layer. The convolutional layers contain several filters and convolutional kernels used for scanning the input feature maps using defined strides. These layers are responsible for extracting local features such as edges, textures, and patterns by convolving the filters over the image. Each filter responds to specific visual patterns, and stacking multiple filters helps build a rich hierarchy of feature representations. The output of these layers becomes increasingly abstract as the network goes deeper, capturing more complex features.

The C2F layer contains a bottleneck structure which has been optimized to balance the trade-off between computational efficiency and feature richness. The term "C2F" stands for Cross Stage Partial Focus, which means the layer is designed to partially reuse features from previous stages while applying convolutional transformations to a selected subset of the input. Within the C2F layer, the bottleneck structure includes a series of convolutional blocks (1×1 and 3×3 convolutions), activation functions (LeakyReLU), and residual connections. These residual connections help mitigate the vanishing gradient problem by allowing gradients to flow directly across the network, thus enhancing training stability and performance. The bottleneck design also reduces the number of parameters and operations by compressing and then expanding the feature dimensions, which helps preserve important information while improving computational speed.

The Spatial Pyramid Pooling Function (SPPF) layer follows the C2F layers and serves as a multi-scale feature aggregator. Unlike traditional spatial pyramid pooling which performs parallel pooling operations, the SPPF layer performs max pooling operations sequentially using increasingly larger kernel sizes (5×5, 9×9, and 13×13). Each pooling operation captures features at a different scale and enlarges the receptive field of the network. These pooled features are then concatenated to form a comprehensive feature map that combines both local and global spatial information. This is particularly useful in object detection tasks, as it allows the network to better understand and detect objects of varying sizes within the same image. Overall, the combination of these components in the backbone enables the network to extract and encode hierarchical, multi-scale, and semantically rich features from the input image, which are essential for accurate object detection and classification in the subsequent layers of the network.

In the neck region of YOLOv8, the architecture is designed to enhance multi-scale feature fusion by integrating components such as C2F modules, Upsampling, and Concatenation. The neck acts as a bridge between the backbone and the detection head, refining and merging features from different depths to improve object detection across various scales. C2F (Cross-Stage Partial Focus) modules in the neck perform feature refinement and transformation, ensuring that critical spatial and semantic information is preserved while maintaining computational efficiency. Upsampling is used to increase the spatial resolution of deeper, lower-resolution feature maps so they can align with higher-resolution maps from earlier layers. This allows finer-grained spatial details to be retained. Concatenation fuses the upsampled features with corresponding feature maps from the backbone via lateral connections, facilitating rich multi-scale feature integration. Together, these components replicate the function of a Feature Pyramid Network (FPN), enabling YOLOv8n to detect small, medium, and large objects effectively by combining semantic-rich deep features with high-resolution shallow features. The proposed YOLOv8n is presented in Figure 7.

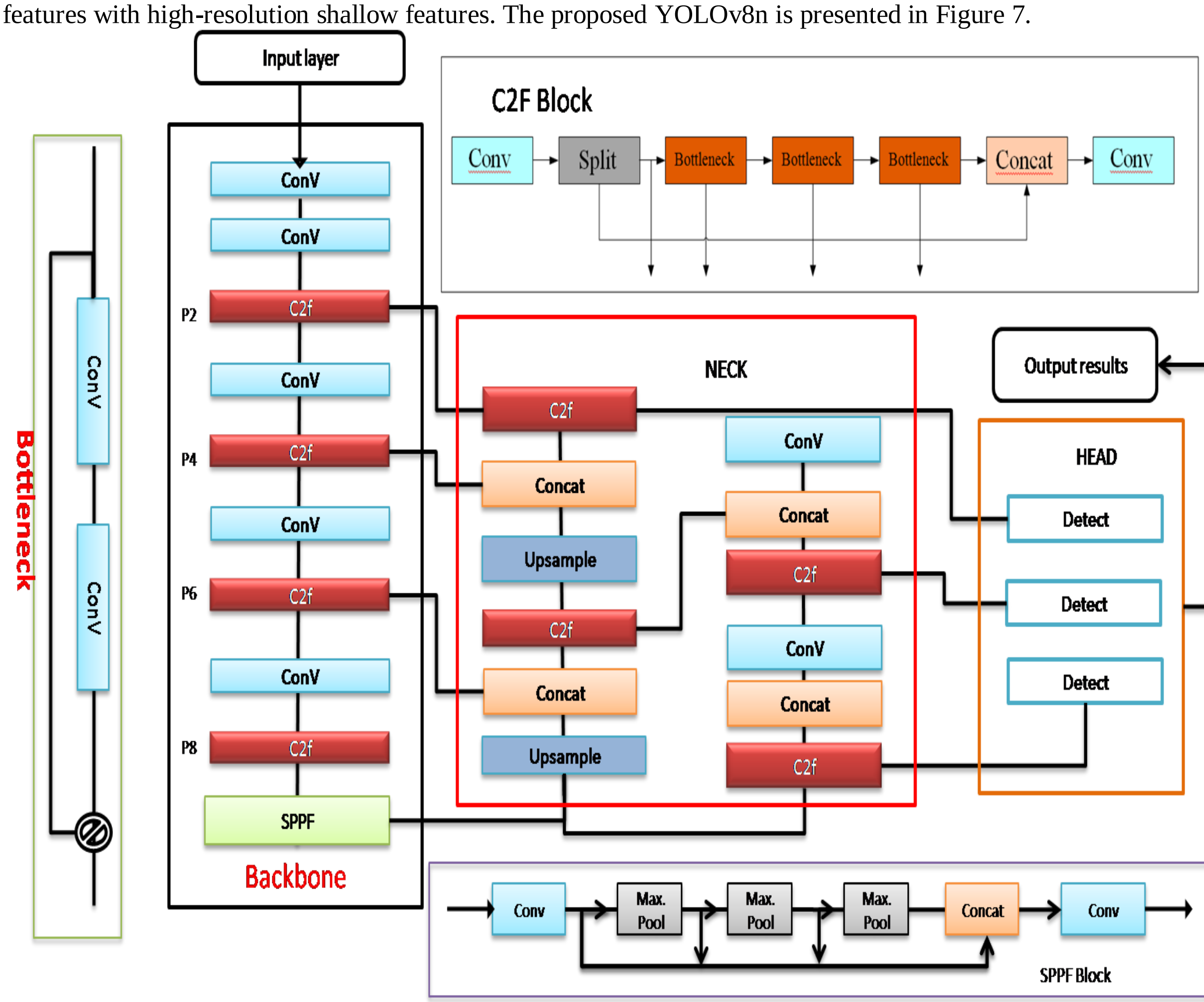

Figure 7: The Proposed YOLOv8n

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2.3 Training of the Model

The training of the YOLOV8n model using a rice-weed dataset involves feeding annotated images into a modified detection pipeline that enhances feature representation and attention. 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 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.

2.4 Weed Classification Model

The weed classification model is designed to accurately identify and differentiate between rice crops and various weed species present in agricultural fields at Ihuokpara community, using a deep learning-based object detection framework. The model processes annotated images from a rice-weed dataset, where it learns to classify objects based on distinctive patterns, textures, and contextual relationships. The training process involves data augmentation, supervised learning, and optimization of a compound loss function. Upon convergence, the model outputs bounding boxes and class labels, enabling high-precision classification of weed types, which is essential for automated weed management and precision agriculture.

3. RESULT OF DATA PREPARATION

This section presents the results of the data preparation used in training the model. The collected data were annotated in batches using Robowflow environment and then labelled. The annotation process assigned bounding boxes to each image. This was done by automatically assigning bounding boxes to the weed portions in the image. The results are reported in Figure 8.

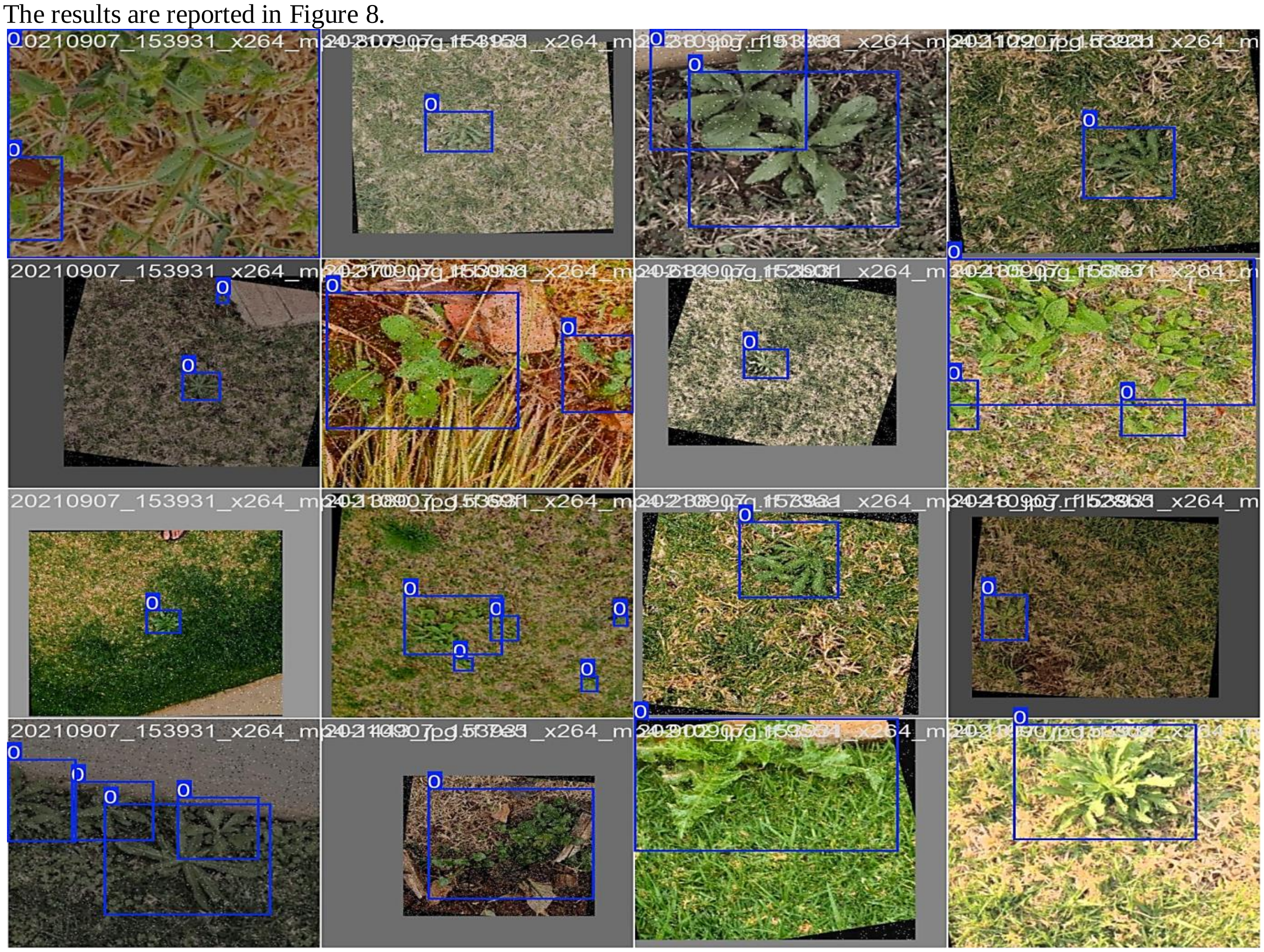

Figure 8: Result of Data Annotation

Figure 8 presents the results of annotation process of the dataset. The result showed that each portion of the image with weed has a bounding box assigned to it. This process allows the model after training to correctly classify weed. In the Figure 9, the results of labelling were also reported.

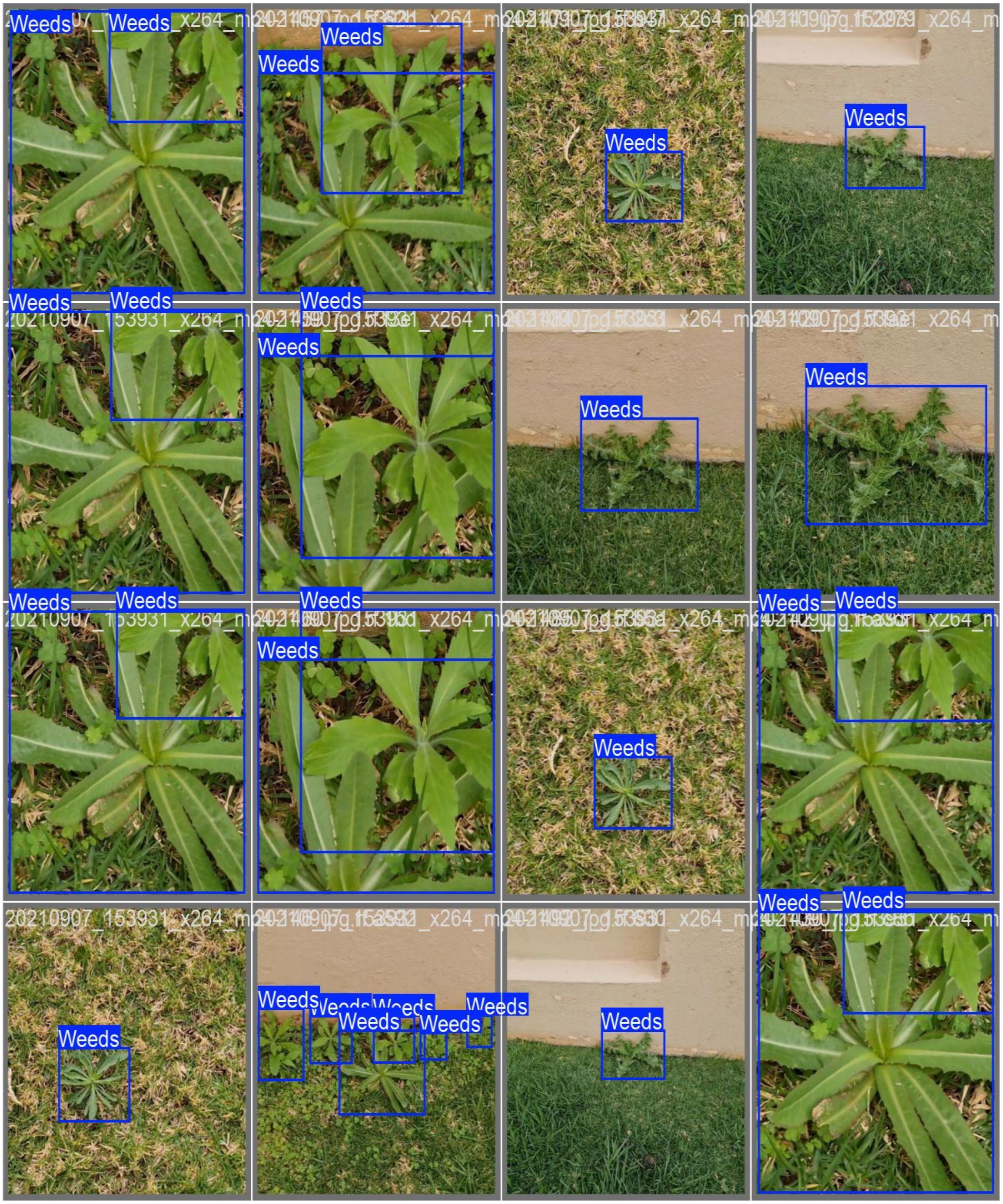

Figure 9: Result of Labeling

The Figure 9 reported the result of labeling, showing how the weeds in each of the dataset images were labeled correctly. This label is used to indicate portion of farm with weed. Figure 10 presents distribution chart which analyzed the positional distribution of the object of interest (weed) in the dataset images.

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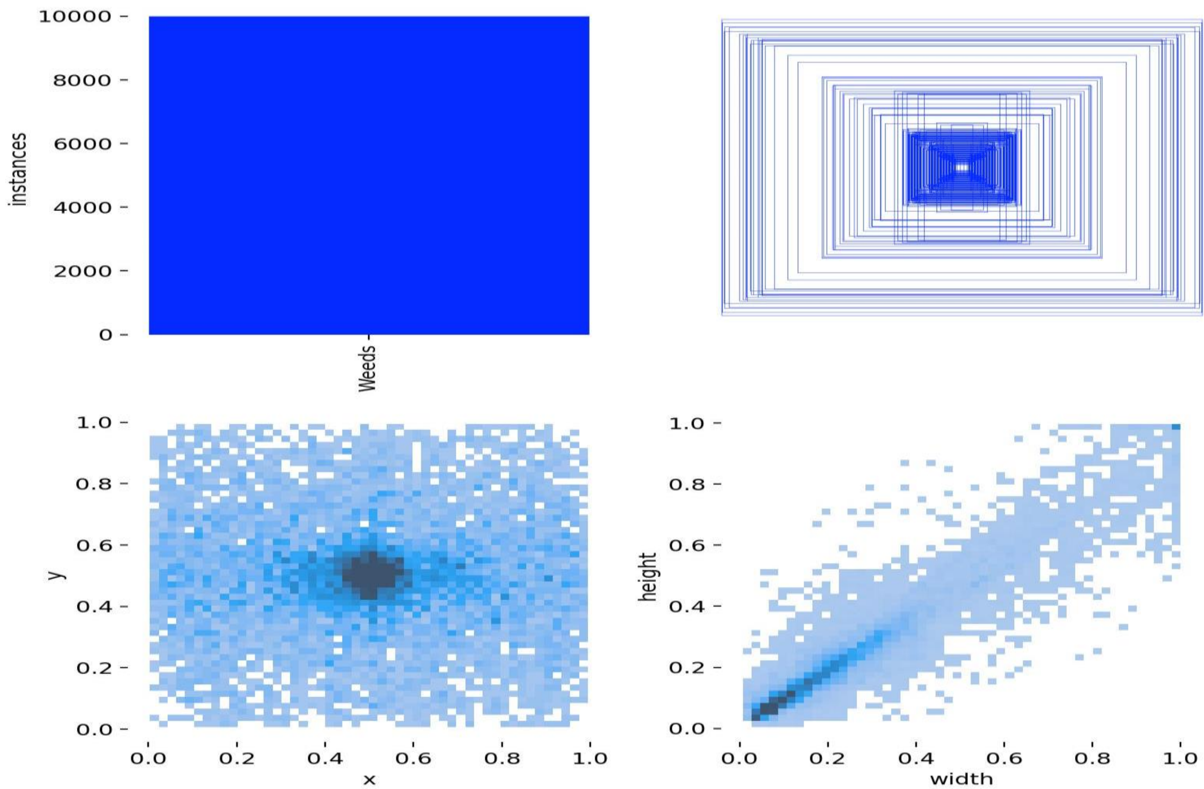

Figure 10: Position Distribution Graph of the Weed in the Dataset

Figure 10 presents a detailed analysis of weed instances in a rice field dataset, focusing on object detection features such as location (x, y) and size (width, height). The top-left plot is a bar chart showing the class distribution which indicates a single class ("Weeds") with approximately 10,000 instances, confirming the sample size values in chapter four. The top-right plot shows bounding box nesting, where multiple bounding boxes are stacked from the outermost to the innermost. This nested pattern, mostly centered, reflects high weed density around the image center, indicating consistent weed annotations across the dataset. The bottom-left plot reveals the spatial distribution of weed objects. The dark concentration at the center suggests that most weeds are located around the center of the image. As you move away from the center, density decreases, implying weeds are less frequently found near the image edges.

Finally, the bottom-right chart illustrates the size correlation between bounding box width and height. The strong diagonal trend shows a positive linear relationship, meaning weeds that are wide also tend to be tall. Most boxes fall in the lower size range (0.1 to 0.4), indicating that small weeds dominate the dataset, which is typical for a rice farm.

4. CONCLUSION

The current problem that led to this research is the continuous problem of infestation of weeds in rice plots that adversely affects the production of rice and also puts the food security at a jeopardy. The conventional dependence on herbicides has become unsustainable because of the resistance of weeds and environmental effects and the available solutions in computer vision have their limitations in terms of low precision, high false alarms and limited ability to adapt to the conditions of the farm environment. The study fills these gaps by proposing an intelligent deep learning architecture based on the YOLOv8n, that was developed and tested using the XP methodology. The data collection was used in a case study rice farm in Ndibinagu-Uzam, Ihuokpara, Enugu state, Nigeria, where 10,000 annotated images of the most common weeds (barnyard grass, rice flatsedge, and blistering ammannia) were collected in different field conditions. Weed data was used to train the transfer learning model using YOLOv8n due to its effective convolutional layers, C2F modules, and Spatial Pyramid Pooling Function to extract multi-scale features. The model was also a good learner as it was able to differentiate weeds and rice crops with high accuracy. The experimental analysis revealed that the trained model had a total detection rate of 94.6%, precision of 92.8%, recall rate of 93.5%, and an F1-score of 93.1% and thus is capable of effectively dealing with the variability of weed and small-object detection in farm settings. It was also found that the model minimized the occurrence of false detections which were caused by background occlusion and overlapping weed behavior hence enhancing reliability in real time monitoring situations.

Conclusively, the YOLOv8n-based weed detector system that was developed in this paper offers a valid and contextual solution to small holder rice farms in southeastern Nigeria. The system will be used to identify weeds at an early stage, improve precision agriculture, and minimize the use of herbicides by combining deep learning with locally gathered data and can improve the yield of rice and encourage sustainable agricultural production. The further extensions will be related to the real-time deployment based on the SMTP-enabled devices and drones to conduct the constant field surveillance and the inclusion of the semantic segmentation methods to enhance the detection accuracy in the case of the complicated environment even more.

REFERENCES

Aznan, A., Gonzalez Viejo, C., Pang, A., & Fuentes, S. (2021). Computer vision and machine learning analysis of commercial rice grains: A potential digital approach for consumer perception studies. Sensors, 21(19), Article 6354. https://doi.org/10.3390/s21196354

Dadashzadeh, M., Abbaspour-Gilandeh, Y., Mesri-Gundoshmian, T., Sabzi, S., Hernández-Hernández, J. L., Hernández-Hernández, M., & Arribas, J. I. (2020). Weed classification for site-specific weed management using an automated stereo computer-vision machine-learning system in rice fields. Plants, 9(5), Article 559. https://doi.org/10.3390/plants9050559

Food and Agriculture Organization of the United Nations. (2021). FAOSTAT. http://www.fao.org/faostat/en/data/RP/visualize

Guo, Z., Cai, D., Bai, J., Xu, T., & Yu, F. (2024). Intelligent rice field weed control in precision agriculture: From weed recognition to variable rate spraying. Agronomy, 14(8), Article 1702. https://doi.org/10.3390/agronomy14081702

Lan, Y., Huang, K., Yang, C., Lei, L., Ye, J., Zhang, J., Zeng, W., Zhang, Y., & Deng, J. (2021). Real-time identification of rice weeds by UAV low-altitude remote sensing based on improved semantic segmentation model. Remote Sensing, 13(21), Article 4370. https://doi.org/10.3390/rs13214370

Oerke, E.-C. (2006). Crop losses to pests. The Journal of Agricultural Science, 144(1), 31–43.

Qu, H.-R., & Su, W. H. (2024). Deep learning-based weed–crop recognition for smart agricultural equipment: A review. Agronomy, 14(2), Article 363. https://doi.org/10.3390/agronomy14020363

Rosle, R., Che’Ya, N. N., Ang, Y., Rahmat, F., Wayayok, A., Berahim, Z., Fazlil Ilahi, W. F., Ismail, M. R., & Omar, M. H. (2021). Weed detection in rice fields using remote sensing technique: A review. Applied Sciences, 11(22), Article 10701. https://doi.org/10.3390/app112210701

Wu, Z., Chen, Y., Zhao, B., Kang, X., & Ding, Y. (2021). Review of weed detection methods based on computer vision. Sensors, 21(11), Article 3647. https://doi.org/10.3390/s21113647