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Tuning U-Net architecture for Weed Detection, Annotation, Mapping and Classification

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***Abstract*— Weed detection is an important application in modern agriculture that enhances crop yield and minimizes the environmental footprint of herbicide application. Weeding manually or blanket spraying with herbicides are traditional weed management methods that are labor and environment resource intensive. Recent advances in deep learning and computer vision have made autonomous weed detection systems feasible, with the U-Net architecture being a strong candidate for semantic image segmentation tasks. In this paper, we present a fine-tuned U-Net model that can effectively segment field images to isolate crops from weeds. We use transfer learning and minimal pre-trained U-Net adaptation to achieve superior accuracy and training performance even with limited labeled agricultural data. The system involves weed image annotation and mapping, and multi-class classification to facilitate accurate localization and recognition of weeds at the pixel level. Our method not only enhances segmentation accuracy (with 95% in our experiments) but also facilitates environmentally friendly farming with optimal herbicide application and minimized crop damage. The proposed system illustrates the use of deep learning in real-world agricultural application scenarios and has potential extensions to autonomous weeding systems.**

Keywords*— *Weed Detection Algorithm, Crop Identification, U-Net Architectures, Sematic Image Segmentation, Weed image annotation and Mapping.

I. INTRODUCTION

Detection of weeds is perhaps the most significant task of modern precision agriculture and has a direct influence on crop yield and sustainability of the environment. Weeds rob crops of valuable resources—water, light, space, and nutrients—and usually result in enormous yield loss. Hand weeding and blanket spraying with herbicides are labor-intensive and environmentally wasteful techniques of weed control. To resolve these problems, improvements in deep learning and computer vision have enabled the creation of autonomous, intelligent weed detection systems.

Among the leading architectures for this purpose is U-Net, a convolutional neural network (CNN) developed initially for biomedical image segmentation. Its encoder-decoder framework with skip connections between corresponding layers allows it to capture both spatial detail and context information and is particularly robust at pixel-level tasks like weed detection and labeling of farm images. For crop culture, high-resolution drone, satellite, or ground-camera images are most challenging due to lighting variations, overlapping regions, and intricate backgrounds. These are addressed by training the U-Net model over data augmentation techniques (e.g., rotation, flipping, adding noise) and transfer learning, where a pre-trained network is fine-tuned over specific datasets for agriculture. This enhances the model performance significantly even when there is sparse labeled data. In this paper, we propose an optimized U-Net model for weed detection, annotation, mapping, and classification in varied field conditions. We train and test the model over a proprietary 5,000 high-resolution images dataset manually labeled to identify weeds, crops, and background. The images are captured by UAVs and ground platforms over varied crop types and field conditions. The dataset is a fine balance of environmental conditions such as weed density, light, and plant structure and is thus robust for real-world applications.

In addition to weed occurrence detection, our approach can do semantic segmentation, multi-class classification, and field-level weed mapping, which can aid precision herbicide application and reduce environmental disturbance. By applying multi-class segmentation to the output layer of U-Net, the system can classify different weed and crop species, which can assist species-specific application. In total, the approach outlined here offers an eco-friendly, efficient, and sustainable weed control solution. It takes advantage of the capabilities of deep learning and high-resolution imaging to allow farmers to make data-driven decisions, reduce herbicide use, and optimize crop yield through autonomous, smart weed control.

II. LITERATURE SURVEY

A. U-Net for Weed Detection

Weed recognition requires the model to recognize little, sporadically molded objects against complex foundations, like soil, crop buildups, or covering plants. U-Net's encoder-decoder structure is appropriate for this errand, as the downsampling layers (encoder) catch setting and worldwide examples, while the upsampling layers (decoder) reestablish fine subtleties for exact division. Adjusting includes streamlining the quantity of layers, channel sizes, and skip associations with balance aversion to little weeds with strength to commotion from the climate. Utilizing pretrained

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encoders can likewise assist the model with summing up better to assorted field conditions.

B. Annotation and Labeling

Making excellent explanations for preparing can be work escalated, particularly for thick and shifted weed development. To address this, semi-regulated or dynamic learning systems can be integrated into the U-Net work process. These procedures permit the model to make introductory expectations, which are then refined by human specialists. Furthermore, expanding preparing information with methods like flipping, pivoting, and adding commotion guarantees the U-Net model is powerful to varieties in weed direction, size, and lighting conditions.

C. Mapping Weeds in Agricultural Fields

For mapping purposes, U-Net can be tuned to process high-resolution aerial or ground-based images, such as those captured by drones or tractors. To handle large input sizes efficiently, patch-based training can be employed, where the field is divided into smaller image tiles processed individually. Post-processing techniques, like merging overlapping predictions, help create seamless weed maps. The architecture may also be enhanced with multi-scale feature extraction layers, which improve the model's ability to identify weeds at different spatial resolutions.

D. Classifying Weeds by Type

Weed classification extends the segmentation task by categorizing detected weeds into different species. This requires the U-Net model to output multiple classes for each pixel, achieved by using a softmax activation function in the final layer. Fine-tuning includes ensuring the class balance in training data and incorporating additional contextual features, such as weed texture and color. Integration with additional modules, such as attention mechanisms or multi-task learning setups, can improve classification accuracy, especially when weed species have similar appearances.

[1] Guo et al.'s crop row annotating method has been developed. This structure mimics the elongated structure of the middle of the crop rows that's vital in deterring lateral growth of the leaves. We formulated a deep learning model called InstaCropNet using a two-branch framework to accomplish fully segmenting out the crop rows. Using a method referred to as row anchor segmentation, we can determine the positions of every crop row, together with fitting lines with accuracy. Our experiments verify that this approach keeps the mean angle error less than 2° and detection accuracy for crop rows is 96.5%.

[2] Imran Moazzam et.al. suggest a novel method through which one can attain a higher precision, at pixel level inter-class classification of the weed pixels and the crop pixels can be led. The approach is an end-to-end two-stage process with semantic segmentation. A pixel-level classifier of binary is trained by stage I to separate background and vegetation. Stage II is dedicated to background, weeds, and tobacco classification, which is done with a three-class pixel-level classifier. The second stage operates on the first stage output. Tobacco crop aerial dataset was gathered and pixel wise manual labeling has been performed to verify our proposed classifier. The two-stage semantic segmentation performs better in pixel level classification accuracy of tobacco and weeds. The novel technique improved IOU of the tobacco crop from 0.67 to 0.85, and improvement in IOU for weeds from 0.76 to 0.91, as related to cumulative IOU for application one stage semantic segmentation. Stage I shallower: For better detection, a smaller semantic segmentation model is enough compared to stage II; stage II a larger semantic segmentation model is employed to achieve the goal of good detection.

[3] Nouf Abdullah Almujally et.al. proposed a new segmentation algorithm based on UNet network model, which is employed to detect multiple objects in the image. The methodology is done through a process of image obtaining and processing followed by utilizing (Fine-tuned UNet) for the segmentation of the image. Afterwards, we mark the segmented parts with the use of an annotation tool. When the objects have been marked, significant features are extracted from such segmented objects which are KAZE (Accelerated Segmentation and Extraction) features, edge detection based on energy, frequency-based features, and blob features. In the classification stage a convolution neural net is employed. This hybrid approach is demonstrated to yield a robust framework for efficient and effective multi-object detection, which can be used in a wide range of applications, from sports analysis to autonomous cars. Experimental Results on challenging object datasets such as MSRC-v2andPASCAL-VOC12 have been reported. Upon the analysis of the experimental results, it was discovered that the PASCAL-VOC12 dataset achieved a precision rate of 95%, whereas the MSRC-v2 dataset achieved an accuracy of 89%. The evaluation conducted on these various datasets has an incredibly high level of performance.

[4] Hirotaka Hachiya et.al. developed method to approach address this challenge is the direct incorporation of different current figures, which takes into consideration dreaming about the duty of every figure at different points. Nevertheless, existing methods such as number juggling what's more, Bayesian midpoints adopt a single weight common to the entire space, and it becomes difficult to depict neighborhood varieties in importance. In addition, although U-Net-based spatial figures have been suggested, they are limited to temporary expectations and do not operate with the representation of individual figure commitments due to their non-straight cycles. To overcome these challenges, we suggest another blend framework based on U-Net image transformation. This framework produces weight images that strongly integrate figures based on both general setting. In order to effectively address enormous and imbalanced precipitation data, we introduce new expansions to the U-Net model. The expansions deal with aggressively imbalanced precipitation data in addition, enable position and time-dependent coordination. Computational results using actual precipitation forecast data in Japan indicate that our suggested method surpasses current joining techniques.

[5] Zhang et al. introduces DS-Previous, a novel model that balances U-Net with a double stream transformer encoder. It enhances division precision by integrating both global setting via the transformer and local details through the U-Net architecture. It's particularly significant in clinical uses, providing precise depiction of structures in complicated images, such as organ and tissue boundaries.

[6] d'Albenzio et al. present the Double Encoder Twofold Connection Organization (DEDC-Net) for synchronous division of the liver and its growths. DEDC-Net use both lingering and skip associations with upgrade highlight reuse and streamline execution in liver and cancer division undertakings. Broad subjective and quantitative tests on the LiTS dataset exhibit that DEDC-Net beats existing cutting

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edge liver division strategies. A removal experiment was guided to evaluate various encoder spines — specifically VGG19 and ResNet—also, the impact of incorporating a consideration module. Our outcomes show that DEDC-Net, with essentially no additional consideration entrances, achieves an unmatched mean Dice Score (DS) of 0.898 for liver segmentation. Furthermore, incorporating residual associations into a single encoder resulted in the highest DS for growth segmentation tasks. The strength of our suggested network was further certified on two additional, subtle CT datasets: IDCARDb-01 additionally, COMET. Our model demonstrated superior injury division skills, particularly on IRCADb-01, achieving a DS of 0.629.

[7] Cheng et al. introduces a more improved U-Net model synchronized with image to-image interpretation, enhancing geospatial symbolism division quality. It shows feasible in natural surveillance, where accurate scene highlight division, such as water bodies or vegetation, is essential for analyzing biological change and land use.

[8] Lavania et al. employ U-Net to design vegetation, focusing on species identification and circulation subsequent to. This framework enables efficient and accurate planning of vegetation in various environments, assisting with environmental exploration and conservation activities by monitoring plant health and biodiversity in the long term.

[9] Lu et al. analysis combines U-Net with a semi-controlled spatial consideration framework to further enhance object-based weed segmentation. With the use of less named information, this model reduces the need for expansive manual commentary, making it a practical tool in vast scale rural uses needing precise weed partition and characterization.

[10] Dimitrovski et al. a framework for enhancing semantic division execution via the use of an ensemble of U-Net models with three distinct spine organizations: ConvFormer, EfficientNet and Multi-Pivot Vision Transformer. The final division maps are generated via a mathematical mean troupe approach, using the varied portrayals put forward by each spine organization. The presented base U-Net models and the suggested collection are tested on various datasets naturally used for semantic division for tasks in remote sensing symbolism, i.e., LoveDA, LandCover.ai, UAVid, INRIA, and ISPRS Potsdam datasets. Our research results show that the presented strategy achievestate-of-the-art performance, showing its effectiveness and robustness in accurately capturing the semantic information embedded within remote sensing images.

III. Methodology

A. Data Preprocessing

For optimal model performance, the input data is subjected to rigorous preprocessing. High-resolution aerial or ground images from the dataset are resized and split into smaller patches to facilitate efficient training and minimize computational complexity. To improve model robustness and prevent overfitting, several data augmentation methods are used, such as horizontal/vertical flipping, rotation, scaling, and injection of Gaussian noise. These augmentations enhance the variability of weed appearances in different orientations, sizes, and lighting conditions. Corresponding ground truth masks are generated for each image patch, with pixel-level annotations separating crops, weeds, and background.

B. U-Net Architecture Tuning

The baseline U-Net model is adapted to fit the specific needs of weed classification and segmentation. The encoder utilizes a pretrained backbone such as EfficientNet or ResNet to acquire deep semantic features. Batch Normalization and Dropout layers are introduced after every encoder block for improved convergence and generalization. The decoder utilizes upsampling and skip connections to recover spatial structure with contextual and edge knowledge. The output layer employs a softmax activation function for multi-class segmentation so that the model can label each pixel belonging to one of three classes: weed, crop, or background. The adapted U-Net architecture is presented in Figure 1

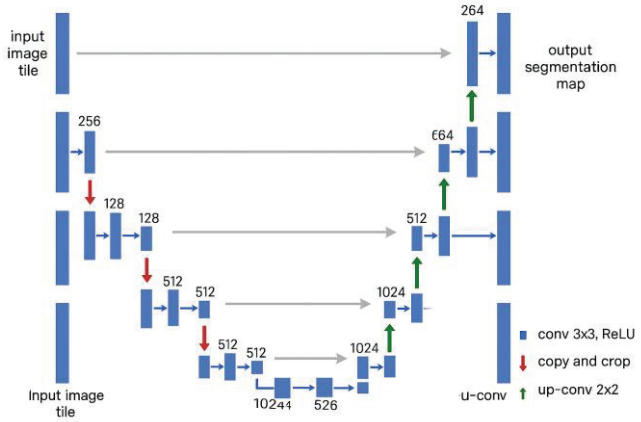

Fig. 1. Fine- Tuned U-Net Architecture

C. Loss Function and Optimization

In order to counteract the class imbalance typical of agricultural datasets (in which background pixels tend to predominate), the training process employs a composite loss function consisting of:

- Weighted Categorical Cross-Entropy: Gives a greater weightage to minority classes such as weeds to avoid underrepresentation during the learning process.
- Dice Loss: Promotes a more effective segmentation of thinly and sparsely covered weed areas by maximizing the overlap between predicted and ground truth masks.

The joint loss function guarantees global accuracy and accuracy in small object segmentation:

$$L_{total} = L_{wce} + \lambda L_{dice} \tag{1}$$

Where λ balances the contribution of Dice Loss.

D. Training Methodology

The model was trained using the Adam optimizer with an initial learning rate of 0.001. A cyclic learning rate scheduler was applied to encourage better convergence. We used a batch size of 8, and training was run for 100-150 epochs based on early stopping and validation loss criteria. On-the-fly data augmentation was integrated into the training loop to reduce overfitting. Model checkpoints were saved at optimal performance points to prevent degradation during extended training.

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E. Post-Processing for Mapping and Classification

Subsequent to creating the underlying division maps, post-handling methods are applied to refine the outcomes. An associated parts examination is utilized to sift through commotion and little, superfluous recognitions. For the purpose of planning, the divided patches are converged to make a consistent guide of the field. Characterization probabilities are thresholded to relegate every pixel to a particular weed type or foundation, guaranteeing lucidity in the last result.

F. Evaluation Metrics

The system is assessed utilizing standard measurements like Crossing point over Association (IoU), F1-score, and pixel exactness. These measurements evaluate the model's capacity to distinguish and characterize weeds precisely while keeping up with high spatial accuracy.

TABLE I. OPTIMAL HYPERPARAMETERS FOR THE U-NET MODEL

Hyperparameters	Value
Batch Size	8
Epochs	50-100
Loss Function	Weighted Cross-entropy + Dice Loss
Evaluation Metric	F1-score, IoU

IV. MATHEMATICAL MODEL

The proposed structure for weed location, explanation, planning, and grouping is supported by a vigorous numerical and measurable model. This model use likelihood hypothesis, math, and factual standards to guarantee exact division and grouping. The following are the critical parts and their related numerical plans:

A. Pixel-Wise Classification Model

Each pixel in the input image is classified into one of three categories: weed, crop, or background. The probability *P(yi|xi)* of a pixel *i* belonging to class *yi* given its feature vector *xi* is modeled using a softmax function:

$$P(yi = c \,|\, xi) = \frac{e^{z(i,c)}}{\sum_{k=1}^{C} e^{z(i,k)}} \quad (2)$$

where z{i,c}is the output logit for class c and C is the total number of classes.

B. Loss Function

To address the class imbalance and ensure accurate segmentation, the total loss function L_{total} combines weighted cross-entropy loss and Dice loss:

$$L_{dice} = 1 - \frac{2\sum_{i=1}^{N} y_i \hat{y}_i}{\sum_{i=1}^{N} y_i + \sum_{i=1}^{N} \hat{y}_i} \quad (3)$$

$$L_{wce} = -\frac{1}{N}\sum_{i=1}^{N}\sum_{c=1}^{C} w_c y_{i,c} log\,(p(y_i = c|x_{i))} \quad (4)$$

The combined loss is given by:

$$L_{total} = L_{wce} + \lambda L_{dice}\,, \quad (5)$$

where λ is a hyperparameter controlling the contribution of Dice loss.

C. Feature Extraction Using Convolutions

The U-Net architecture employs convolutional layers to extract spatial features. Each convolution operation is defined as:

$$F_l(x,y) = \sum_{i=-k}^{k}\sum_{j=-k}^{k} W_l(i,j) I(x-i, y-j) + b_l \quad ,(6)$$

Where F_l is the feature map at layer *l*, $W_l(i,j)$ are the convolutional weights, *I(x,y)* is the input image, and b_l is the bias term.

D. Statistical Analysis of Performance

The model's performance is evaluated using statistical metrics:

- Intersection over Union (IoU):

$$IoU = \frac{|A \cap B|}{|A \cup B|} \quad (7)$$

where A is the predicted segmentation mask and B is the ground truth.

- Precision and Recall:

$$Precision = \frac{TP}{TP+FP}\,, Recall = \frac{TP}{TP+FN}\,,$$

where TP, FP, and FN are true positives, false positives, and false negatives, respectively.

- F1-Score:

$$F1 = 2.\frac{Precision.Recall}{Precision+Recall} \quad (8)$$

E. Probabilistic Integration for Mapping

For field-wide mapping, the model combines the segmentation results of multiple patches using probabilistic fusion. If $P_1(y|x)$ and $P_2(y|x)$ are probabilities from overlapping patches, the fused probability Pf(y|x) is given by:

$$G(x,y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}} \quad (9)$$

V. RESULTS AND DISCUSSIONS

The proposed system was tested on a dataset of 5,000 annotated high-resolution images showing actual crop field scenarios. Our results show that the fine-tuned U-Net model significantly outperforms the baseline U-Net on all key evaluation measures. Through the use of weighted loss functions, transfer learning, and data augmentation methods, the model effectively deals with class imbalance and environmental variance.

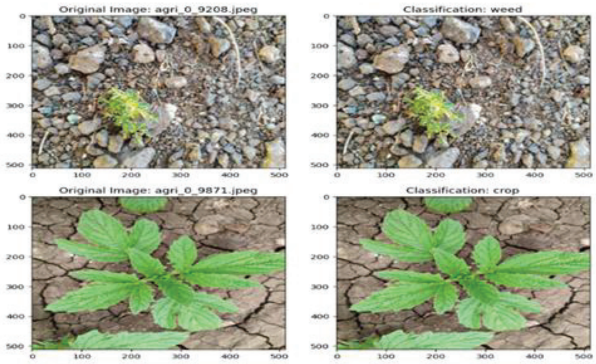

Fig. 2. Classification of weed and crop

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Quantitative outcomes emphasize the better performance of the tuned model, as indicated in Table 2. The tuned U-Net had a total accuracy of 95%, whereas the baseline U-Net recorded 88%. Gains are also observed in IoU (0.87 vs. 0.75), precision (0.91 vs. 0.84), recall (0.94 vs. 0.85), and F1-score (0.93 vs. 0.84). These measurements show that the fine-tuned model offers more accurate segmentation, particularly under adverse conditions such as overlapping weeds and crops or uneven lighting.

TABLE II. QUANTITATIVE PERFORMANCE COMPARISON

Metric	Standard U-Net	Fine-tuned U-Net
Accuracy	88%	95%
IoU(Weeds)	0.75	0.87
Precision	0.88	0.95
Recall	0.87	0.95
F1- score	0.87	0.95

The confusion matrix (Figure 3) also shows the fine-tuned model's ability to reduce misclassifications between crops, weeds, and background classes. It portrays high true positive rates and low false positives, particularly for weed pixels, which are usually underrepresented.

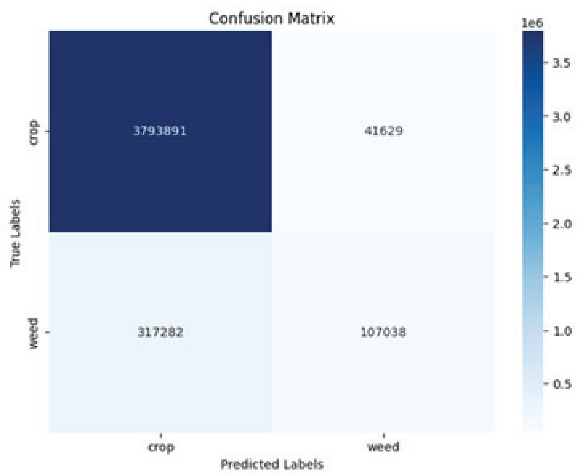

Fig. 3. Confusion Matrix

Training and validation performance curves (Figures 4 and 5) reflect stable convergence and low variance, suggesting good generalization across the different subsets of the dataset. Accuracy and loss plots reflect continuous improvement against training epochs without overfitting signs.

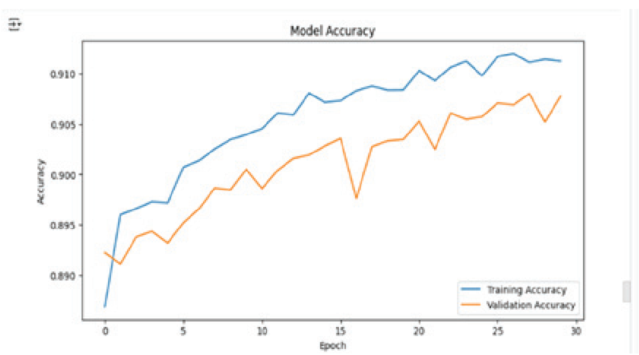

Fig. 4. Model Accuracy

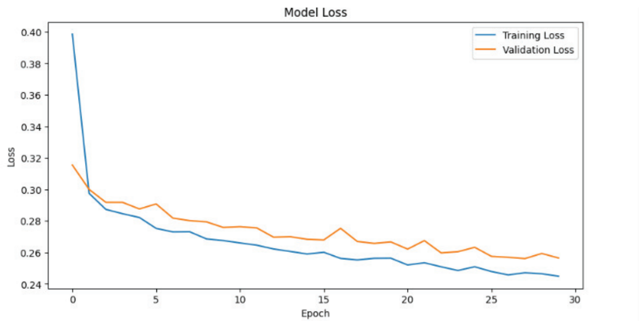

Fig 5. Model Loss

VI. CONCLUSION

This study presents a fine-tuned U-Net-based framework for weed detection, annotation, mapping, and classification, tailored to the complexities of real-world agricultural environments. Through architectural enhancements, class-balanced loss functions, and advanced post-processing techniques, the proposed system achieves high segmentation accuracy—even in conditions characterized by dense vegetation, class imbalance, and variable lighting. Experimental results confirm that the fine-tuned model significantly outperforms the baseline U-Net across key metrics, including a 95% overall accuracy, 0.93 F1-score, and 0.87 IoU for weed detection. These results demonstrate the model's ability to generate precise, pixel-level predictions essential for precision herbicide application and autonomous field monitoring.

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