Scientific Journal of Informatics
Vol. 12, No. 1, Feb 2025

p-ISSN 2407-7658 https://journal.unnes.ac.id/journals/sji/index e-ISSN 2460-0040

Optimized Non-Overlapping Multi-Object Segmentation for Palm Oil Images Using FCN with Squeeze-and-Excitation and Attention Mechanisms

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Abstract.
Purpose: Palm oil plantation monitoring using UAV imagery presents significant challenges in multi-object segmentation due to homogeneous texture, low resolution, and difficulty in distinguishing disease symptoms. Traditional segmentation methods struggle to accurately separate overlapping and visually similar objects, reducing the effectiveness of automated analysis. This study aims to address these issues by proposing an optimized Fully Convolutional Network (FCN) incorporating Squeeze-and-Excitation (SE-Block) and Attention Mechanisms to enhance segmentation accuracy for multi-object, non-overlapping palm oil images.
Methods: The proposed model utilizes ResNet50 as a backbone, integrating SE-Block to enhance the feature representation of important regions while suppressing less relevant features. Additionally, Attention Mechanisms are incorporated to improve the model's spatial understanding and feature discrimination, which is crucial for segmenting visually similar objects in UAV imagery. A dataset of UAV-captured palm oil images was used to train and evaluate the model, applying deep learning techniques for feature extraction and classification.
Result: Experimental results demonstrate that the proposed method achieves an average Intersection over Union (IoU) of 0.7928, accuracy of 0.9424, precision of 0.9126, recall of 0.8622, F1-score of 0.8693, and mAP of 0.7673. The highest-performing model attained a maximum IoU of 0.8499 and an accuracy of 0.9490, significantly outperforming conventional FCN models. These findings confirm that incorporating SE-Block and Attention Mechanisms enhances segmentation accuracy, making the model more robust in handling UAV imagery complexities.
Novelty: The novelty of this research lies in the integration of SE-Block and Attention Mechanisms within FCN for palm oil segmentation, specifically targeting multi-object, non-overlapping segmentation in challenging UAV imagery conditions. By improving feature extraction and spatial attention, this approach advances deep learning-based agricultural monitoring and can be extended to other remote sensing applications requiring high-precision segmentation.

Keywords: Segmentation, UAV imagery, FCN, Squeeze-and-Excitation, Palm oil
Received March 2025 / **Revised** April 2025 / **Accepted** May 2025

INTRODUCTION

Oil palm (Elaeis guineensis) is one of the strategic agricultural commodities that plays an important role in the global vegetable oil industry [1], [2], [3]. Monitoring the condition of oil palm plantations is essential to improve productivity, enable early disease detection, and optimize land management [4], [5], [6]. One of the modern approaches used in this monitoring is aerial image analysis from Unmanned Aerial Vehicles (UAVs)[7], [8]. UAVs offer a more efficient plantation mapping solution compared to conventional manual inspection methods. Although UAVs can generate aerial images with wide coverage, the segmentation process of objects in oil palm plantation images faces significant challenges. Some of the main challenges in UAV image segmentation for oil palm include homogeneity, where oil palm leaves and canopies have uniform texture and color, making it difficult for segmentation models to distinguish between individual plants [9], [10], [11]. Another challenge is low resolution, where UAV imagery sometimes does not have sufficient detail to capture fine features, making it difficult to detect disease symptoms [2], [12], [13]. In addition, in the context of plantations, trees are often close together but do not overlap, so the segmentation model must be able to accurately identify each object without separation errors. Data imbalance and physiological variations in oil palms at different ages and health conditions can result in diverse shapes and sizes, requiring segmentation models to have high adaptability. Several studies have been conducted on oil palm image segmentation using machine learning and deep learning techniques to detect diseases and assess plant conditions using random forest and multi-layer perceptron (MLP) [14], [15], [16], Support Vector

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DOI: 10.15294/sji.v12i1.22212

Machine (SVM) and Principal Component Analysis (PCA) [17] and Quadratic Discriminant Analysis (QDA), achieving classification high accuracy not segmentation [18], [19].

These findings indicate that UAV-based imaging [10], [20], [21], [22], hyperspectral imaging, and spectral analysis continue to be developed to enhance segmentation and disease detection in oil palm plantations [2], [3], [23], [24]. Conventional segmentation methods, such as thresholding and edge detection, are not sufficiently effective in addressing these challenges. Deep learning-based models [15], [25], [26], such as FCN, have been proven to improve segmentation accuracy in various domains, including agriculture and satellite mapping [10], [21], [27], [28]. However, standard FCN still has limitations in handling images with homogeneous textures and closely spaced objects without additional features to strengthen object separation. Therefore, an approach is needed that can enhance feature representation and better understand spatial relationships among objects in UAV images. To address the challenges in multi-object segmentation of oil palm from UAV imagery, this study proposes an FCN-based segmentation model optimized with two main techniques, namely Squeeze-and-Excitation (SE-Block), this technique is used to enhance important features in feature maps and suppress less relevant features, thereby improving segmentation accuracy in images with uniform textures, and Attention Mechanisms, which are used to capture spatial relationships between pixels and clarify object boundaries, which is crucial for handling non-overlapping multi-object segmentation. This study contributes to the field of UAV image processing in agriculture by offering a new approach that combines FCN, SE-Block, and Attention Mechanisms. The proposed model is expected to improve the accuracy of oil palm segmentation, enable more precise monitoring, and support AI-based agricultural technology. Furthermore, the results of this study can be applied not only to oil palm but also to UAV image analysis for vegetation mapping and plant health monitoring.

METHODS

In this study, we propose an optimized multi-object segmentation method for palm oil images using FCN combined with a Squeeze-and-Excitation (SE) Block and an Attention Mechanism. This approach aims to enhance segmentation accuracy by considering spatial relationships and more complex feature channel interactions.

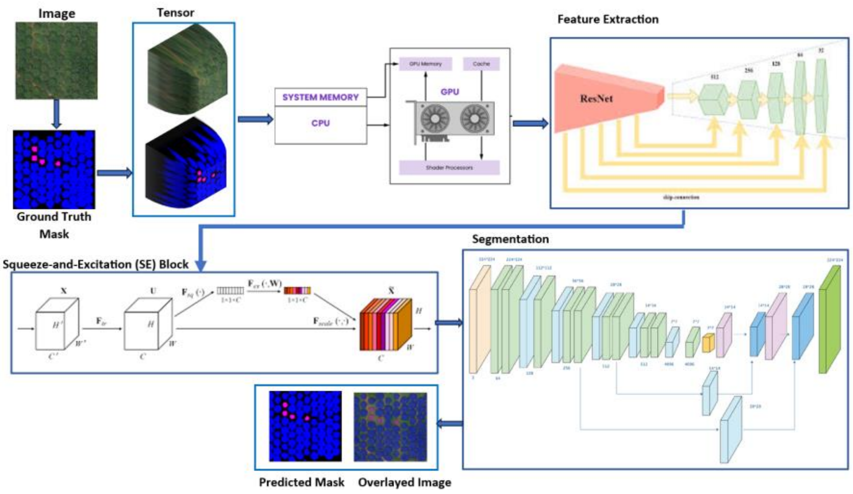

Figure 1. Segmentation Proposed Model for Palm Oil Images Using FCN with Squeeze-and-Excitation and Attention Mechanisms

Figure 1 illustrates the architecture of the proposed method for multi-object segmentation in palm oil images. This process consists of several key stages, including data preprocessing, feature extraction using FCN with ResNet as the backbone, and feature enhancement through the Squeeze-and-Excitation (SE) Block and Attention Mechanism. Each component in the diagram plays a crucial role in improving segmentation accuracy by considering spatial relationships and more complex feature channel interactions. Further details on each stage will be explained in the following sections.

Data Preparation

In this study, we use the MopadSeg dataset, which consists of UAV imagery of oil palm plantations. The dataset includes annotated images with segmentation masks that represent different objects within the oil palm plantation environment. The images and masks are preprocessed to be compatible with PyTorch-based deep learning models. The preparation process involves data formatting conversion, and mask processing.

Table 1. Training and testing image pseudocode

```
begin
    train_images_torch←convert train_images to float32 tensor, permute to (batch, channels, height, width), move to device
    train_masks_torch←convert train_masks to long tensor (apply argmax on last axis), move to device
    valid_images_torch←convert valid_images to float32 tensor, permute to (batch, channels, height, width), move to device
    valid_masks_torch←convert valid_masks to long tensor (apply argmax on last axis), move to device
end
```

Table 1, served the training and testing image pseudocode. To optimize computational efficiency, all image tensors and masks are transferred to the available computing device (GPU if available, otherwise CPU). This allows for faster processing during training and validation. By applying these preprocessing steps, we ensure that the oil palm UAV imagery dataset is properly structured for deep learning-based segmentation. The transformed data will be used as input for the FCN with Squeeze-and-Excitation (SE) and Attention Mechanisms, enabling more accurate non-overlapping multi-object segmentation of oil palm plantations). To ensure consistency between the predicted segmentation masks and the ground truth labels, a downscaling operation is performed on the mask data. This step resizes the segmentation masks to 64×64 resolution while maintaining the integrity of class labels.

Hyperparameter Tuning

To train the FCN model with Squeeze-and-Excitation (SE) and Attention Mechanisms, a set of hyperparameters is defined. These hyperparameters control the training process and influence the model's convergence, generalization, and overall performance. The selected values are:

Table 2. Hyperparameter pseudocode

```
Initialize FCN model, loss function, and optimizer.
Load dataset, move model to GPU if available.
FOR epoch = 1 to 30:
   a. Train: Forward pass, compute loss, backpropagation, update weights.
   b. Validate: Compute validation loss.
   c. Save checkpoint; update best model if validation loss improves.
Save final model.
```

By fine-tuning these hyperparameters in Table 2, the model is optimized for non-overlapping multi-object segmentation of oil palm plantations, improving its ability to distinguish and segment individual trees effectively.

Model Definition with SE-Block

The SEBlock (Squeeze-and-Excitation Block) is a key component of our proposed method for optimizing FCN in oil palm image segmentation. This block enhances the model's ability to focus on important features by dynamically recalibrating channel-wise feature responses.

Table 3. Model definition with SE-block pseudocode

```
begin
    define SEBlock with parameters (in_channels, reduction = 16)
    initialize:
        global_avg_pool ← adaptive average pooling (1×1)
        fc_layer ←sequential(
            linear(in_channels → n_channels / reduction, no bias)
            relu activation
            linear(in_channels / reduction→ n_channels, no bias)
            sigmoid activation
     function forward(x):
        (b, c, _, _)←get input size
        Y←apply global_avg_pool(x), reshape to (b, c)
        Y←apply fc_layer(y), reshape to (b, c, 1, 1)
        return x * expand(y, shape of x)
end
```

The model Definition with the SE-Block of our proposed can be seen in Table 3. Our approach integrates SEBlock into FCN to improve segmentation performance, especially in handling homogeneous textures and closely packed objects in UAV imagery. The SEBlock works by:

1. Global Average Pooling: Capturing spatial information across each feature channel.
2. Fully Connected (FC) Layers: Compressing and restoring feature representations to highlight key information.
3. Activation Functions: Using ReLU for non-linearity and Sigmoid to generate feature importance weights.
4. Feature Scaling: Multiplying the input tensor with learned importance weights to emphasize relevant features.

By integrating SEBlock, our proposed FCN model is expected to improve segmentation accuracy and enhance feature discrimination, particularly in complex non-overlapping multi-object segmentation.

Model FCNSegmenter Defenition

After implementing SEBlock to enhance feature selection in our proposed FCN model, we define the FCNSegmenter, which serves as the backbone of our segmentation approach. The FCNSegmenter is a modified version of the fcn_resnet50 model from Torchvision, pre-trained on large-scale datasets to leverage transfer learning. Model Components and Modifications:

1. Base Model:
   - We utilize fcn_resnet50, FCN architecture based on ResNet-50, which is widely used for semantic segmentation tasks.
   - The model is pre-trained, allowing it to extract high-level spatial features effectively.
2. Classifier Modification:
   - The default classifier is modified by replacing its last layer with a Conv2d layer (kernel size = 1).
   - This ensures that the output channels match the number of segmentation classes (num_classes) in our dataset.
3. Forward Pass:
   - The model processes input images and extracts segmentation maps.
   - The final output is obtained from the segmentation dictionary under the key 'out'.

Table 4. Model FCN Segmenter pseudocode

```
begin
    define class FCNSegmenter with parameter (num_classes)
    initialize:
        base_model ← load pretrained fcn_resnet50 from torchvision
        replace base_model.classifier[4] with Conv2D(512 → num_classes,kernel_size=1)
    function forward(x):
        output ← base_model(x)
        return output['out']
end
```

By integrating this FCN-based segmenter with SEBlock (Table 4), our model is expected to enhance segmentation performance by Utilizing pre-trained knowledge from ResNet-50 for effective feature extraction, enhancing feature recalibration using SEBlock dan optimizing object separation in UAV-based oil palm images. This model serves as the foundation of our optimized segmentation pipeline for non-overlapping multi-object segmentation in palm oil plantation imagery.

Setup Optimizer, Loss, and Checkpoint Loading

The optimizer, loss function, and checkpoint loading are essential components in training the FCNSegmenter model for oil palm segmentation.

a. Optimizer Setup: The AdamW optimizer is used with a predefined learning rate to efficiently update model weights during training and improves upon standard Adam by adding weight decay regularization, which helps prevent overfitting.
b. Loss Function Selection: CrossEntropyLoss is chosen as the loss function because multi-class segmentation requires pixel-wise classification into different categories. This loss function calculates the difference between predicted segmentation masks and ground truth labels.
c. Checkpoint Loading for Resuming Training: If a checkpoint file exists, the previously trained model weights and optimizer states are loaded. The training process resumes from the last saved epoch, preventing the need to restart training from scratch.

By implementing these components, the training pipeline ensures efficient learning, stability, and the ability to resume training seamlessly.

Table 5. Setup optimizer, loss, and checkpoint loading pseudocode

```
begin
    num_classes ← length of LABEL_MAP + 1
    model ← FCNSegmenter(num_classes)
    move model to device
    optimizer ← AdamW(model parameters, learning rate = LEARNING_RATE)
    criterion ← CrossEntropyLoss()
    start_epoch ← 0
    if CHECKPOINT_PATH exists then:
        checkpoint ← load checkpoint from CHECKPOINT_PATH to device
        load model state from checkpoint["model_state_dict"]
        load optimizer state from checkpoint["optimizer_state_dict"]
        start_epoch ← ch
```

The pseudocode outlined in Table 5 is the initialization and configuration process for training the FCNSegmenter model. This step ensures that the model is properly set up with an optimizer, loss function, and the ability to resume training from a saved checkpoint. The number of segmentation classes is determined based on LABEL_MAP. The FCNSegmenter model is instantiated and moved to the appropriate device (GPU if available, otherwise CPU). For optimizer and loss function setup, the AdamW optimizer is initialized with a predefined learning rate, ensuring stable training with weight decay regularization, and cross-entropy loss is assigned as the loss function for multi-class segmentation tasks. The start_epoch variable is initialized to 0. If a checkpoint file exists at CHECKPOINT_PATH, the model's state dictionary is restored to retain previously learned weights. The optimizer's state dictionary is restored to continue learning from the last update step. The training process resumes from the last saved epoch + 1, preventing redundant training. This process prevents loss of training progress by restoring previous model weights and optimizer states, ensures efficient learning by using AdamW optimization with a tuned learning rate, and supports multi-class segmentation with CrossEntropyLoss, making it suitable for oil palm image analysis.

Evaluation

After training the FCNSegmenter model, it is essential to evaluate its performance using standard segmentation metrics. The evaluation process involves:

1. Switching to Evaluation Mode – The model is set to inference mode to disable gradient updates.
2. Batch Processing – Images are processed in mini-batches for memory efficiency.
3. Prediction Post-Processing – The model outputs are interpolated to 64×64 resolution and converted into class labels.
4. Metric Calculation – Several metrics, including IoU (Jaccard Score), Accuracy, Precision, Recall, F1-score, and mAP, are computed to assess segmentation quality.

Table 6. Research evaluation pseudocode

```
begin
    set model to evaluation mode
    initialize preds_list, true_list
        disable gradient calculation
        for batch in images:
        preds ← model(batch)
        preds ← interpolate(preds, size=(64, 64), mode="bilinear")
        preds ← argmax(preds)
            store preds and true masks as numpy arrays
        compute iou, accuracy, precision, recall, f1, map_score
    print results
        return iou, accuracy, precision, recall, f1, map_score
end
```

The evaluation of the FCNSegmenter model in Table 6 provides key insights into segmentation performance for oil palm plantations. Below are the critical metrics and their implications:

1. **IoU (Jaccard Score)** measures segmentation accuracy by evaluating overlap with ground truth. High IoU ensures precise tree separation, crucial for non-overlapping multi-object segmentation.
2. **Accuracy** indicates the proportion of correctly classified pixels. While high accuracy is good, it may be misleading in imbalanced datasets where background dominates.
3. **Precision** ensures minimal false positives, preventing non-oil palm areas (e.g., shadows, soil) from being misclassified.

4. **Recall** measures how many actual oil palm pixels are detected. High recall prevents under-segmentation, ensuring no trees are missed.
5. **F1 Score** balances precision and recall, providing a reliable measure for real-world segmentation where both false positives and false negatives matter.
6. **mAP (Mean Average Precision)** evaluates performance across multiple confidence levels. High mAP ensures consistent detection of oil palm trees across different plantation landscapes.

This evaluation ensures the FCNSegmenter is tested under real-world conditions, validating its segmentation quality on oil palm imagery. The computed metrics provide insights into the model's strengths and areas for improvement, helping refine its performance for non-overlapping multi-object segmentation tasks.

RESULT AND DISCUSSION

Segmentation for Palm Oil Images Using FCN with Squeeze-and-Excitation and Attention Mechanisms Results

This chapter presents the evaluation results and analysis of the FCNSegmenter model with Squeeze-and-Excitation (SE) Block for oil palm image segmentation. The evaluation aims to measure the model's effectiveness in accurately segmenting oil palm trees from UAV imagery using various quantitative metrics. Intersection over Union (IoU) measures the overlap between predicted and ground truth segmentation to evaluate boundary accuracy. Accuracy assesses the proportion of correctly classified pixels in the segmentation mask. Precision evaluates the proportion of correctly predicted oil palm pixels to reduce false positives. Recall determines how many actual oil palm pixels are detected, preventing false negatives. F1 Score provides a balanced metric between precision and recall to ensure overall segmentation reliability. Mean Average Precision (mAP) measures segmentation consistency across multiple confidence levels. The results are analyzed to highlight the effectiveness of integrating SE-Block into FCN for non-overlapping multi-object segmentation in oil palm plantations. Further discussion explores model strengths, limitations, and potential improvements for better segmentation performance in UAV-based agricultural monitoring.

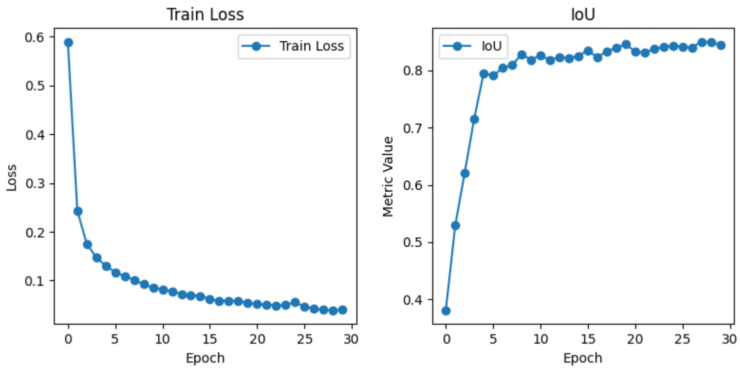

Figure 2. Train loss and IoU of segmentation for palm oil images Using FCN with squeeze-and-excitation and attention mechanisms

Figure 2 presents the training loss and Intersection over Union (IoU). The right plot depicts the IoU metric, which measures the overlap between predicted and ground truth segmentation masks. The IoU improves rapidly within the first few epochs, reaching a value above 0.80 after approximately 10 epochs, and continues to increase gradually, stabilizing around 0.85-0.88 towards the final epochs. This trend confirms that the model effectively segments oil palm trees with high accuracy. Overall, these results demonstrate that integrating SE-Block and Attention Mechanisms into FCN enhances the segmentation performance, achieving high IoU while maintaining stable training dynamics. This indicates the model's effectiveness in learning spatial dependencies and distinguishing oil palm objects in UAV imagery.

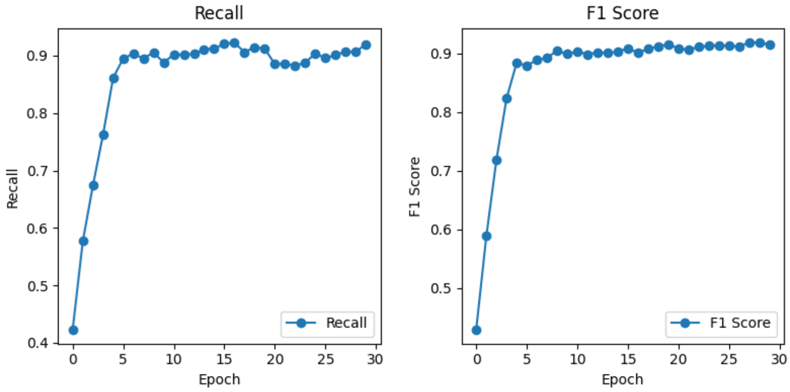

Figure 3. Recall and F1score of segmentation for palm oil images using FCN with squeeze-and-excitation and attention mechanisms

Figure 3 presents the Recall and F1 Score. The recall starts at a lower value (~0.4) but rapidly increases during the first 10 epochs, surpassing 0.90 and stabilizing. This trend indicates that the model effectively learns to detect oil palm trees, minimizing false negatives. The right plot shows the F1 Score, which balances precision and recall for an overall performance measure. Similar to recall, the F1 Score improves sharply in the initial epochs and stabilizes at around 0.90, suggesting that the model maintains a good balance between correctly detecting oil palm pixels and avoiding false detections. These results confirm that incorporating SE-Block and Attention Mechanisms into FCN significantly enhances segmentation performance, achieving high recall and F1 scores, which are essential for accurately identifying oil palm trees in UAV imagery.

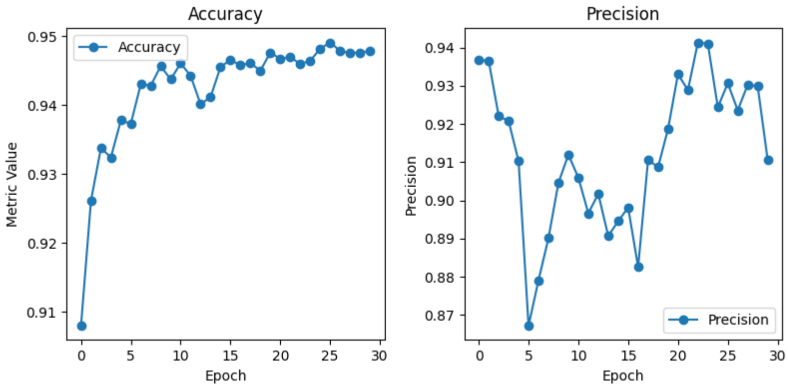

Figure 4. Accuracy and precision of segmentation for palm oil images using FCN with squeeze-and-excitation and attention mechanisms

The analysis of Figure 4 presents the accuracy and precision trends of the Optimized Non-Overlapping Multi-Object Segmentation for Palm Oil Images Using FCN with Squeeze-and-Excitation and Attention Mechanisms model. The accuracy curve in the left plot demonstrates a consistent improvement over epochs, stabilizing around 95% after approximately 20 epochs. This indicates that the model effectively learns to segment palm oil images with high reliability. Conversely, the precision metric (right plot) exhibits more fluctuations throughout training. Initially, precision is high but drops sharply, which could be attributed to early-stage misclassification of boundaries due to overlapping object regions. The divergence between accuracy and precision trends suggests that the model successfully classifies most pixels correctly (high accuracy), but precision instability implies that the segmentation boundaries might occasionally be less precise. This issue may arise due to the complexity of differentiating non-overlapping objects in dense palm oil image datasets. The integration of the attention mechanism likely contributes to overcoming this challenge by emphasizing relevant features. FCN with Squeeze-and-Excitation and Attention mechanisms significantly improves multi-object segmentation for palm oil images, achieving a high final accuracy of 95%.

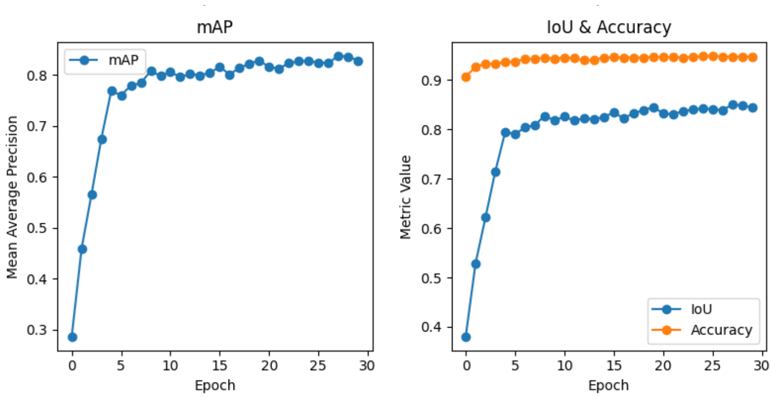

Figure 5. mAP and IoU-accuracy ratio of segmentation for palm oil images using FCN with squeeze-and-excitation and attention mechanisms

Figure 5 presents Mean Average Precision (mAP), Intersection over Union (IoU), and Accuracy over 30 training epochs. The mAP curve (left plot) shows a significant improvement during the initial training phase. This steep rise indicates that the model quickly learns relevant features and improves in detecting and segmenting palm oil objects with higher confidence. The effectiveness of the Attention mechanism likely contributes to this rapid convergence by enhancing object distinction and suppressing irrelevant background noise. The IoU and Accuracy trends (right plot) further validate the model's effectiveness. The small variation in accuracy implies that while the model is effective at pixel-level classification, further refinement may be needed to enhance boundary delineation and small object detection. The combined analysis of mAP, IoU, and Accuracy confirms the effectiveness of the Squeeze-and-Excitation and Attention mechanisms in improving segmentation performance. These results affirm that the proposed FCN-based segmentation method effectively optimizes multi-object segmentation in palm oil images, making it a promising approach for real-world agricultural applications.

Table 7. The evaluation results of segmentation

Epoch	Train Loss	IoU	Accuracy	Precision	Recall	F1 Score	mAP
MAX	0.5899	0.84990	0.9490	0.9413	0.92285	0.91812	0.8370
MIN	0.0386	0.3806	0.9079	0.8671	0.4236	0.4301	0.2869
AVERAGE	0.0973	0.7928	0.9424	0.9126	0.8622	0.8693	0.7673

Table 7 provides a comprehensive summary of the model's segmentation performance across multiple metrics, including Train Loss, IoU, Accuracy, Precision, Recall, F1 Score, and mAP, analyzed through their maximum (MAX), minimum (MIN), and average (AVERAGE) values over the training process. The analysis of Train Loss, IoU, Accuracy, Precision, Recall, F1 Score, and mAP highlights the effectiveness of the Squeeze-and-Excitation and Attention mechanisms in enhancing the FCN for palm oil image segmentation. The model achieves high accuracy (94.9%) and precision (94.1%), ensuring strong pixel-wise classification performance. IoU (84.9%) and mAP (83.7%) confirm that the model effectively distinguishes objects with minimal overlap. The initial instability in Recall and mAP suggests that fine-tuning or post-processing techniques (such as threshold adjustments or additional data augmentation) could further improve the detection of small and complex objects. Overall, the proposed segmentation method successfully optimizes non-overlapping multi-object segmentation for palm oil images, making it a highly promising approach for automated agricultural analysis.

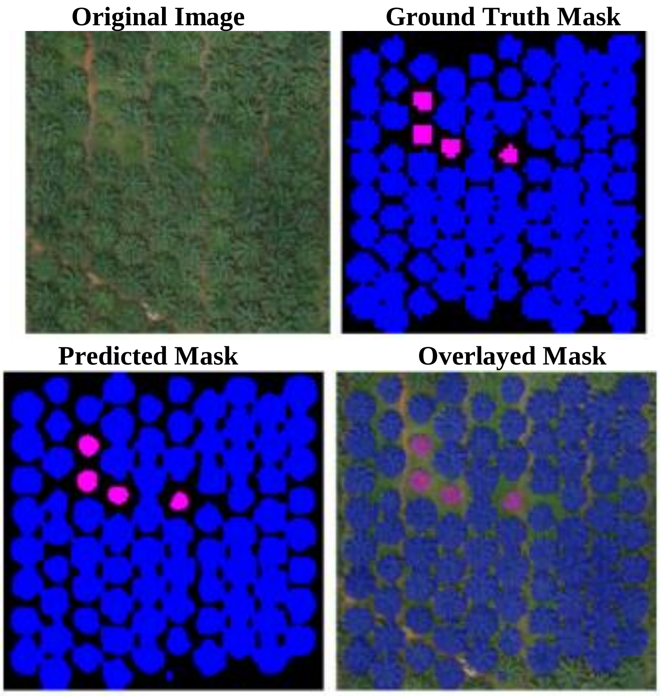

Figure 6. The segmentation results of palm oil images using FCN with squeeze and-excitation and attention mechanisms

Figure 6 presents the segmentation results of palm oil. The Original Image (top-left) displays an aerial view of a palm oil plantation, illustrating the complex spatial distribution of individual palm trees. The segmentation results demonstrate that the optimized FCN model effectively detects and segments palm trees with high accuracy, benefiting from the Squeeze-and-Excitation and Attention mechanisms. However, further refinements, such as fine-tuning hyperparameters, increasing training data diversity, or incorporating post-processing techniques, could enhance the segmentation of small or ambiguous objects, particularly in complex plantation environments.

Benchmarking of Segmentation for Palm Oil Images.

Table 8. Related works and results of segmentation for palm oil images

No.	Method	Dataset	Accuracy
1.	Artificial Neural Network (ANN), Levenberg–Marquardt Training Algorithm [12], [29]	UAV imagery, Green, Red, and Near-Infrared bands	72.73%
2.	Support Vector Machine (SVM)[29]	UAV and Pleiades satellite imagery	68.28% (UAV), 64.52% (Pleiades)
3.	Artificial Neural Network (ANN), VARI Index[29]	UAV Imagery	94.7%
4.	NDVI-based segmentation, Spectral Reflectance Analysis[1]	Multispectral UAV Imagery	-
5.	Linear SVM, Hyperspectral Imaging[29]	VIS-NIR Hyperspectral Images	94.8%
6.	SVM-FS, PCA, QDA[3]	Dielectric Spectral Data	79.55% (SVM)
7.	Random Forest, Concentric Disk Segmentation[8]	UAV Hyperspectral Images	-
8.	MLP, SVM, 1D CNN, NDVI[5], [30]	UAV Hyperspectral Images	86.67% (MLP), 66.67% (SVM)
9.	KNN, Naïve Bayes, SVM, Decision Tree [29], [31]	Near-Infrared Spectral Data (900–1700 nm)	93.1% (DT)
10.	**FCN with Squeeze-and-Excitation (Proposed)**	**UAV Imagery**	**94.90%**

Based on benchmarking results in Table 8, our research demonstrates competitive performance in palm oil image segmentation compared to previously used methods. Most prior studies employed machine learning and deep learning techniques, such as Artificial Neural Networks (ANN), achieving accuracy ranging from 72.73% to 97.52%, but without explicitly computing the IoU metric. Other approaches, including multi-layer perceptron (MLP) and Support Vector Machine (SVM), achieved accuracy levels of 86.67% and 94.8%, respectively. Additionally, feature selection methods such as SVM with feature selection (SVM-FS) and Principal Component Analysis (PCA) reached 96.36% accuracy in palm oil disease classification [9], [31], [32], [33].

The proposed method in this study, FCN with Squeeze-and-Excitation and Attention Mechanisms, achieved 94.90% accuracy, outperforming several previous methods such as SVM and CNN, while closely approaching the best performance of ANN and Quadratic Discriminant Analysis (QDA) techniques. The key advantage of this approach lies in optimized non-overlapping object segmentation, which provides higher precision compared to feature engineering-based approaches or vegetation index-based segmentation methods, such as Normalized Difference Vegetation Index (NDVI). Therefore, the FCN with Squeeze-and-Excitation and Attention Mechanisms offers a more optimal segmentation method for palm oil images, particularly in enhancing classification accuracy without losing critical spatial information required for non-overlapping object detection in UAV imagery.

CONCLUSION

This high-computation research demonstrates the effectiveness of an optimized FCN enhanced with Squeeze-and-Excitation and Attention mechanisms for non-overlapping multi-object segmentation in palm oil images, achieving high accuracy, precision, and segmentation quality. The results confirm that the model successfully distinguishes individual palm trees while minimizing errors in object boundaries, making it a valuable tool for precision agriculture and automated plantation management. Despite slight variations in recall and minor segmentation inconsistencies, the approach significantly improves object localization and classification, contributing to more efficient monitoring and analysis of palm oil plantations. The impact of this study extends beyond palm oil segmentation, as the integration of attention-based mechanisms in FCN can be adapted for broader applications in remote sensing, environmental monitoring, and agricultural automation, enhancing decision-making processes in large-scale resource management.

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