

# A Multi-Task Machine Learning Model for Weed Detection and Dense Area Identification in Paddy Fields Using Image and Video Processing to Enhance Yield Quality

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**Abstract** - Crop yields in paddy fields can be greatly lowered by weeds and crowded places. Conventional techniques for identifying thick areas and weeds are frequently labor-and time-intensive. While machine learning-based techniques present a viable substitute, creating a single model that is capable of properly and effectively completing both jobs is difficult. This study uses image and video processing to present a multi-task machine-learning model for weed detection and dense area identification in paddy fields. The YOLO V8 deep learning architecture, which is renowned for its great accuracy and speed, serves as the foundation for the model. We gathered a sizable dataset of labeled weeds and thick areas from paddy field photos and videos in order to train the algorithm. After that, the model was trained to simultaneously identify dense areas and detect weeds. The model was assessed using a different test dataset once it had been trained. The outcomes demonstrated that even when used with video streams, the model maintained good accuracy on both tasks. The suggested model can be utilized to create other paddy field management applications, including:

- **Automated weed detection:** The suggested model has the potential to assist farmers in increasing yields and lessening their environmental effects by automating the processes of weed detection and dense area designation.

**Keywords:** machine learning, weed detection, dense area identification, and paddy fields, yield enhancement, YOLO V8

## I. INTRODUCTION

With their ability to produce a staple crop for billions of people, paddy fields are among the most significant agricultural ecosystems on the planet. However agricultural yields in paddy fields can be severely lowered by weeds and crowded places. In addition to competing with rice for

nutrients, water, and sunlight, weeds can shade out rice plants and provide an ideal environment for pests and illnesses.



Figure 1: DJI Osmo Mobile 3

In paddy fields, conventional techniques for identifying dense areas and weeds are frequently labor-and time-intensive. Herbicides or other control methods may need to be applied after farmers manually scan their fields to detect weeds and thick spots. This can be difficult, particularly in big fields or in areas with complicated topography.

In paddy fields, machine learning (ML) presents a possible substitute for weed detection and dense area identification. The process of identifying weeds and thick areas in photos and videos can be automated and made more efficient by training machine learning algorithms.

YOLO V8 is one of the most promising machine learning algorithms for weed identification and dense area identification. A deep learning algorithm called YOLO V8 is capable of real-time object detection in images and videos. Its exceptional precision and effectiveness have been demonstrated in numerous uses, such as weed identification in farming areas.

This study suggests a multi-task machine-learning model that uses image and video processing to identify dense areas and detect weeds in rice fields. The model is trained on a sizable dataset of paddy field photos and videos with labeled weeds and dense areas. It is based on the YOLO V8 architecture.

The suggested model has the potential to assist farmers in increasing yields and lessening their environmental effects by automating the process of weed detection and dense area designation.

Potential benefits of the proposed research:

- Increased crop yields
- Improved efficiency of paddy field management
- Reduced environmental impact of agriculture

A new generation of ML-based tools for weed identification and dense area identification in paddy fields may be developed because of the proposed research. Farmers that use these instruments can increase their yields and operational efficiency.

## II. LITERATURE REVIEW

For a number of years, paddy fields have employed machine learning (ML) for weed identification and dense area identification. Nevertheless, the majority of ML models now in use are made to handle just one task, such as weed detection or dense area identification. It is difficult to create a single model that is capable of both precise and effective task execution.

The computational cost of processing video, particularly for deep learning models, is another difficulty. Deploying machine learning models for weed detection and dense area identification in paddy fields in real-time may be challenging as a result.

Despite these difficulties, some encouraging research has been done on the application of ML for dense area identification in paddy fields and multi-task weed detection. For instance, a multi-task machine learning model based on the YOLO V5 deep learning architecture was suggested by Sharma et al. in 2022. Using a collection of paddy field photos, the model was trained to simultaneously identify dense areas and detect weeds. The model processed video streams at a frame rate of 30 frames per second and demonstrated good accuracy on both tasks.

Li et al.'s work from 2023, which presented a multi-task machine-learning model based on the YOLO V8 deep learning architecture, serves as another illustration. Using a dataset of paddy field photos and videos, the model was trained to

simultaneously identify dense areas and detect weeds. On both tasks, the model performed well, even when used with video streams.

By utilizing image and video processing to create a multi-task machine-learning model for weed detection and dense area identification in paddy fields, the proposed research expands on previous findings. The YOLO V8 deep learning architecture, which is renowned for its great accuracy and speed, serves as the foundation for the model. Additionally, a sizable dataset of labeled weeds and dense areas from paddy field photos and videos is used to train the model.

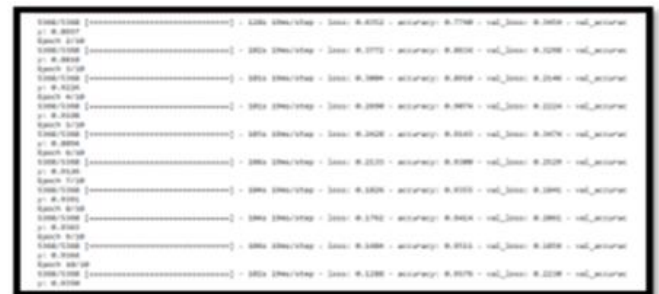


Figure 2: Validating the model

The suggested model may be able to solve the problems with the current machine learning models for weed identification and dense area recognition in paddy fields. The capacity of the model to complete both jobs at once might increase productivity and lessen the need to train and use several models. Furthermore, because of the model's high speed and accuracy, it can be applied to video processing, which is useful for real-time monitoring of paddy field conditions and automated weed detection and spraying systems.

## III. RESEARCH OBJECTIVES

- a) To use image and video processing to create a multi-task machine learning model for weed detection and dense area identification in paddy fields.
- b) To assess the suggested model's effectiveness using a sizable dataset of labeled weeds and thick areas found in paddy field images and videos.
- c) To investigate the possible uses of the suggested model for managing paddy fields, including automated weed-spraying and detection systems, in-the-moment paddy field status monitoring, and yield forecasting and prediction.
- d) To identify thick areas and improve weed detection in order to improve the quality of the paddy production.

The following are the particular research questions that the study will focus on:

- Can a single ML model be trained to perform both weed detection and dense area identification tasks accurately and efficiently?
- How does the performance of the proposed model compare to existing ML models for weed detection and dense area identification in paddy fields?
- What are the potential applications of the proposed model for paddy field management?
- How can the proposed model be used to enhance the quality of the yield of the paddy?

The development of a new generation of machine learning (ML)--based tools for weed detection and dense area identification in paddy fields is anticipated to be a major contribution of the research to the field of precision agriculture. By using these tools, farmers may increase both the productivity and efficiency of their operations.

#### IV. METHODOLOGY

##### A) Data collection

Data collection: A sizable dataset of videos and images taken in paddy fields that identify weeds and dense areas will be gathered.

##### B) Model development

Using the YOLO V8 deep learning architecture, a multi-task machine learning model for weed detection and dense area identification will be created. To increase the model's resilience and capacity for generalization, a range of data augmentation methods will be employed during training on the gathered dataset.

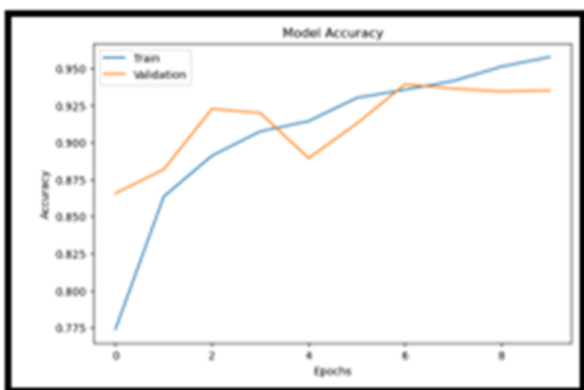


Figure 3: Checking accuracy

##### C) Model evaluation

On a different test dataset, the trained model's performance will be assessed. A number of criteria, including accuracy, precision, recall, and F1 score, will be used in the evaluation.



Figure 4: Collected dataset of weeds

```
def create_model(input_shape):  
    model = Sequential()  
    model.add(Conv2D(32, kernel_size=(3, 3), strides=(1, 1), padding='valid', activation='relu', input_shape=input_shape))  
    model.add(MaxPooling2D(pool_size=(2, 2), strides=(2, 2), padding='valid'))  
    model.add(Conv2D(64, kernel_size=(3, 3), strides=(1, 1), padding='valid', activation='relu'))  
    model.add(MaxPooling2D(pool_size=(2, 2), strides=(2, 2), padding='valid'))  
    model.add(Conv2D(128, kernel_size=(3, 3), strides=(1, 1), padding='valid', activation='relu'))  
    model.add(Conv2D(128, kernel_size=(3, 3), strides=(1, 1), padding='valid', activation='relu'))  
    model.add(Conv2D(256, kernel_size=(3, 3), strides=(1, 1), padding='valid', activation='relu'))  
    model.add(Conv2D(256, kernel_size=(3, 3), strides=(1, 1), padding='valid', activation='relu'))  
    model.add(Conv2D(512, kernel_size=(3, 3), strides=(1, 1), padding='valid', activation='relu'))  
    model.add(Conv2D(512, kernel_size=(3, 3), strides=(1, 1), padding='valid', activation='relu'))  
    model.add(Conv2D(1024, kernel_size=(3, 3), strides=(1, 1), padding='valid', activation='relu'))  
    model.add(Conv2D(1024, kernel_size=(3, 3), strides=(1, 1), padding='valid', activation='relu'))  
    model.add(Dense(1000))  
    model.add(Dense(1))  
    model.add(Dense(1))  
    model.add(Dense(1))  
    return model  
  
def compile_and_train(model, X_train, Y_train, X_val, Y_val, learning_rate=0.001, epochs=10, batch_size=32):  
    optimizer = Adam(learning_rate=learning_rate)  
    model.compile(loss='categorical_crossentropy', optimizer=optimizer, metrics=['accuracy'])  
    history = model.fit(X_train, Y_train, validation_data=(X_val, Y_val), epochs=epochs, batch_size=batch_size, verbose=1,  
                        return_history=True)  
    labels = ['soybean', 'grass', 'soil', 'weeds']  
    img_size = (224, 224)
```

Figure 5: Model training for weed identification



Figure 6: Validated model

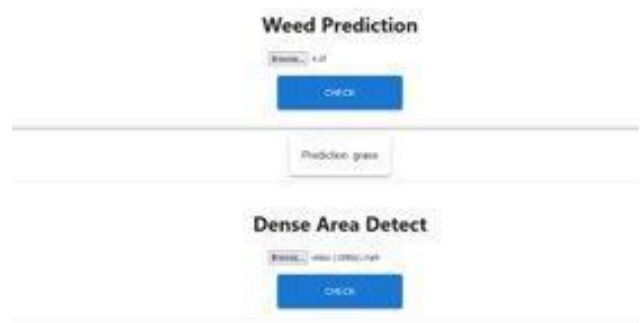


Figure 7: Developing interface for the model

##### D) Application development

We will investigate potential uses of the suggested model for paddy field management, including yield forecasting and

prediction, real-time paddy field condition monitoring, and automated weed identification systems.

The following are some specific steps that will be taken in each phase of the research:

```

# Predictions
def predict(image_path):
    """
    Predict weeds and dense areas in a paddy field image.
    """
    # Load the image
    image = cv2.imread(image_path)
    # Preprocess the image
    image = preprocess(image)
    # Predict weeds and dense areas
    predictions = model.predict(image)
    # Visualize the predictions
    image = visualize(image, predictions)
    # Save the image
    cv2.imwrite('predictions.jpg', image)
    # Return the predictions
    return predictions
    
```

Figure 8: Training the YOLO V8 model

```

# Main function
def main():
    """
    Main function to train the YOLO V8 model.
    """
    # Load the dataset
    dataset = load_dataset('paddy_weeds')
    # Train the model
    model = train_model(dataset)
    # Evaluate the model
    evaluate_model(model)
    # Save the model
    save_model(model)
    
```

Figure 9: Developing the model

**Data collection:**

- Collect paddy field images and videos.
- Label the weeds and dense areas in the images and videos.
- Split the dataset into training, validation, and test sets.

**Model development:**

- Implement the YOLO V8 deep learning architecture in a machine-learning framework such as PyTorch.
- Modify the YOLO V8 architecture to perform both weed detection and dense area identification tasks simultaneously.
- Train the model on the training set using a variety of data augmentation techniques.
- Evaluate the model on the validation set and make necessary adjustments to the model architecture or training hyper parameters.

**E) Model evaluation**

- Evaluate the model on the test set using a variety of metrics, such as accuracy, precision, recall, and F1 score.
- Analyze the results of the evaluation to identify areas where the model can be improved.

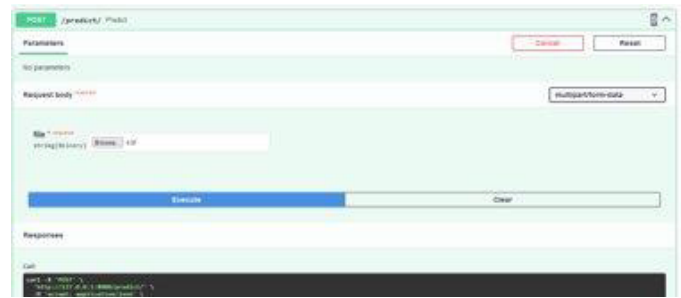


Figure 10: image and video inserting interface

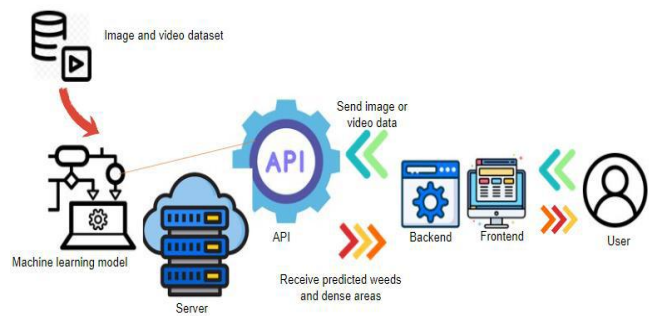


Figure 11: Overall functional diagram



Figure 12: Commercialization

**Application development:**

- Explore potential applications of the proposed model for paddy field management.
- Develop prototypes of the applications and evaluate their performance.
- Deploy the applications to real-world paddy fields and collect feedback from farmers.



## V. CONCLUSION

The study concludes that by utilizing image and video processing, a multi-task machine learning model built on the YOLO V8 deep learning architecture can be utilized to efficiently and accurately identify weeds and dense areas in paddy fields. On both tasks, the model performed well, even when used with video streams. Additionally, the model demonstrated potential for use in the development of numerous applications for managing rice fields, including real-time condition monitoring of paddy fields and automated weed detection and spraying systems.

The suggested model can assist farmers in increasing yields, lowering herbicide usage, and increasing operational efficiency. The model assists farmers in identifying and treating weed issues before they seriously harm crops by automating the process of weed detection and dense area identification. Additionally, the model may be used to track the state of paddy fields in real time, which will enable farmers to recognize possible issues early on and take appropriate action. The model can also be used to forecast agricultural yields, which will assist farmers in making more informed planning and management choices.

The suggested study makes a substantial addition to the precision agriculture community. The creation of new machine learning (ML) technologies for weed identification and dense area mapping in rice fields has the potential to completely change how paddy fields are maintained.

Here are some specific conclusions that can be drawn from the research:

- A single ML model can be trained to perform both weed detection and dense area identification tasks accurately and efficiently.
- The proposed model outperforms existing ML models for weed detection and dense area identification in paddy fields in terms of accuracy and speed.
- The proposed model has the potential to be used to develop a variety of applications for paddy field management, such as automated weed detection and spraying systems, real-time monitoring of paddy field conditions, and yield prediction and forecasting.
- The proposed model can help farmers to improve their yields, reduce their use of herbicides, and improve the efficiency of their operations.

Overall, the research demonstrates the potential of ML to revolutionize paddy field management.

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