Automated Farm Ponds Detection using Satellite Imagery and Deep Learning: Insights from Kadwanchi Village, Maharashtra

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(Received on 24 January 2024, in final form on 29 April, 2024)

***DOI**: https://doi.org/10.58825/jog.2025.19.1.220*

Abstract: Farm ponds play a crucial role in rainwater harvesting and irrigation, making their accurate detection essential for effective water resource management. This study explores the application of deep learning models for detecting farm ponds in Kadwanchi village, Maharashtra, where water scarcity challenges agricultural productivity. The Feature Classifier emerged as the most accurate model, achieving a perfect precision score of 1.0, a recall of 0.863, and an F1 score of 0.927, detecting 296 farm ponds. U-Net (Universal Network) also performed well, with an F1 score of 0.873. At the same time, Mask R-CNN (Mask Region-based Convolutional Neural Network) and DeepLabV3+ (Deep Convolutional Neural Network for Semantic Image Segmentation) showed more moderate results. These findings can assist government agencies in making data-driven decisions about water resource management and promoting sustainable agriculture in water-scarce regions. Future research could focus on hybrid models and larger datasets to improve farm pond detection accuracy.

Keywords: Farm Ponds, Deep Learning, Remote Sensing, Kadwanchi

1. Introduction

The availability and management of water resources play a pivotal role in sustaining agricultural productivity, particularly in water-scarce, rain-red regions. Farm ponds are crucial for capturing and storing rainwater, providing a reliable irrigation source for crops during dry periods (Reddy et al., 2022). The efficient management of these ponds can significantly enhance agricultural resilience, reduce water wastage, and improve food security (Kaur et al. 2024; Qadir et al., 2003). Efficient management of farm ponds also presents challenges in accurately mapping their area and volume, which is critical for understanding water storage capacity and usage. One major issue is the *lack of accurate topographical data* during farm pond construction, leading to incorrect pond volume and surface area estimation. Farmers may overestimate the pond's storage capacity without precise measurements, affecting water management practices (Liu et al., 2024). Another challenge is *siltation*, which reduces the actual volume of the pond and makes it difficult to track changes in pond capacity over time. Accurate volume estimation requires regular surveys and desiltation efforts to maintain the designed storage capacity (Straffelini et al, 2021). Moreover, *inconsistent methodologies* for measuring the area and volume of farm ponds further complicate management efforts. Different approaches to estimating pond dimensions, such as manual surveys or satellite-based mapping, can yield varied results, affecting water storage calculations (Béchet, 2018). Finally, the *limited use of advanced technologies* like satellite data, LiDAR, and UAVs (Unmanned Aerial Vehicles) for precise mapping can further challenge the accurate assessment of pond area and volume. Farmers often lack access to such technologies, relying on less accurate manual methods (Dhillon & Moncur, 2023).

The National Geospatial Policy (NGP) and Remote Sensing Policy of India significantly promote using advanced geospatial and satellite technologies for various applications such as agriculture, urban planning, and disaster management. With increased access to high-resolution imagery, these developments are driving innovation and sustainable growth. In recent years, further advancements in deep learning have opened new avenues for automating the detection of farm ponds from satellite imagery. Deep learning models, such as U-Net, Mask RCNN, DeepLabV3+, and Feature Classifier, have shown promise in various applications, including image segmentation and object detection (Attri et al., 2023; Ahmadkhani, 2025). These models leverage convolution neural networks (CNNs) to learn intricate patterns from data, accurately identifying and classifying various ground objects/features (He et al., 2017). Their application in agricultural settings can enhance the precision of farm pond detection, thus facilitating better management and planning of water resources (Kamilaris & Prenafeta-Boldú, 2018)

This study bridges the gap between conventional qualitative methods of assessing farm pond benefits and modern technological advancements for precise, quantitative measurements. By comparing the performance of various deep learning models, this research aims to identify the most effective approach for farm pond detection, which is essential for optimizing water resource management in rainfed regions.

2. Study Area

In the Maharashtra state of India, Kadwanchi hamlet (19°53' N latitude and longitude 76°00' E) is situated in the Jalna district's Jalna tehsil and falls under the GP 33 watershed of Godavari Watershed in Maharashtra, India (Parab, 2018) (Figure 1). The region is known for its semi-arid tropical climate with an average temperature of 25℃ to 40 ℃, marked by scorching summers with drying winds, dry winters, and annual rainfall of about 700mm to 800mm. Thus, the region is vulnerable to droughts because of the significant year-to-year fluctuation that impacts agricultural output and water availability. This village was selected for the study because it is renowned for its 'Kadwanchi Model' of water conservation, which was adopted by the local community through farm pond construction as a key water conservation strategy. These farm ponds were primarily constructed as part of the watershed development programs during the 1990s and early 2000s, particularly under the Integrated Watershed Development Programme (IWDP), a key initiative of the Ministry of Rural Development, Government of India, and the Drought Prone Areas Programme (DPAP). Subsequently, after 2005-06, MGNREGA played a significant role in supporting the renovation of these farm ponds, mainly through desilting activities (Babu, 2022). Most of these farm ponds are relatively large, with dimensions of 20x20 meters and a depth of 3 meters, designed to meet the water needs for agricultural purposes.

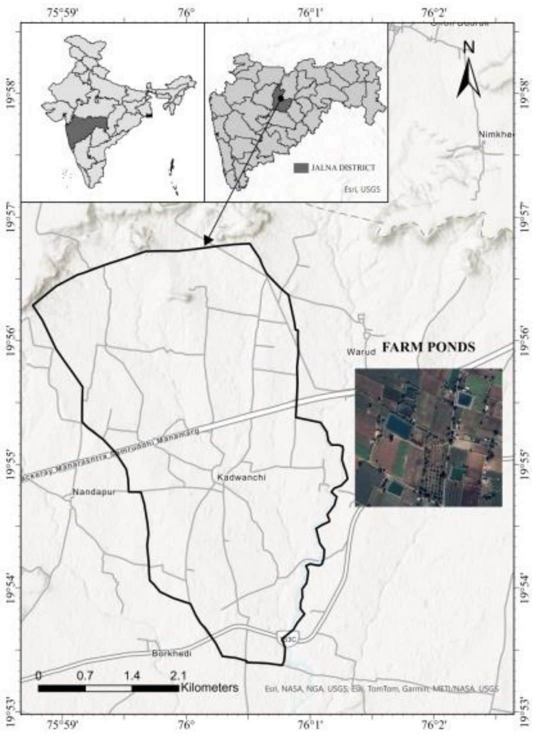

Figure 1. Study area location

3. Methodology

3.1. Data Used

Open access freely available ResourceSat-1 satellite, Linear Imaging Self Scanning Sensor (LISS) IV data acquired on 27 October 2023; accessible from the Indian Space Research Organisation (ISRO) Bhoonidhi portal (https://bhoonidhi.nrsc.gov.in/) is the primary data source for this study. It offers a spatial resolution of 5.8 meters. It comprises three bands (Band 02, Band 03, and Band 04) whose Spectral resolutions are 0.52-0.59 µm, 0.62-0.68 µm, and 0.77-0.86 µm, respectively. The use of LISS-4 data for delineating farm ponds in Kadwanchi is justified, particularly when considering the Minimum Mapping Unit (MMU). With a spatial resolution of 5.8 meters, LISS-4 data offers a sufficiently high level of detail to accurately identify and delineate farm ponds that are typically around 20 m x20m in size. The MMU refers to the smallest mappable area that can be reliably identified, generally considered to be about 3×3 pixels for LISS-4, translating to approximately 300 m². Given that most farm ponds in Kadwanchi are around 400 m² (20m × 20m), they are larger than the MMU and thus can be distinctly captured and delineated.

3.2. Training Samples

This study employed an unsupervised classification technique using K-means clustering in ERDAS Imagine 2023 to generate training samples for identifying farm ponds. As an unsupervised learning approach, K-means clustering proves to be a robust method for generating training datasets in remote sensing applications, particularly for features like farm ponds. The satellite image was initially classified into 36 default clusters, each representing a unique spectral signature corresponding to various land use/land cover (LULC) categories. Clusters associated with water bodies were visually interpreted and manually merged to form a single "farm pond" class, while the remaining clusters were grouped under a general "others" category. By clustering pixels with similar spectral properties, the technique simplifies high-resolution imagery into meaningful segments, enabling the detection of water bodies based on their distinct spectral signatures. These identified clusters serve as valuable positive samples for training deep learning models. The method significantly reduces dependency on manually labeled data and minimizes the effort required for sample preparation, making it both cost-effective and scalable. Additionally, K-means enhances the efficiency and accuracy of subsequent deep learning-based classification tasks by focusing on spectrally relevant regions. Three hundred twenty-threeFor further spatial analysis, farm ponds were delineated and exported to ArcGIS Pro 3.3.

3.3. Applying Models

Next, the 'Export Data for Deep Learning' tool exported training samples in a format compatible with deep learning models such as U-Net and DeepLabV3+. To enhance model accuracy and robustness (Mohan et al., 2025), the 'Label Objects for Deep Learning' technique was employed to annotate segmented objects, generating additional training datasets systematically. Approximately 70% of the data was used for training, derived from satellite imagery, while the remaining 30% was set aside for testing. This division enabled a comprehensive model performance evaluation, facilitating accurate farm pond detection and mapping across diverse geographic regions. Four deep learning models were employed for pixel-level segmentation and object classification on satellite imagery (Table 1). The first model, U-Net, is a U-shaped convolutional neural network with an encoder-decoder structure, effective for detailed segmentation tasks. It was used with a ResNet-34 backbone, a tile size of 64×64 pixels, a stride of 32×32 pixels, and trained on 553 images. The second model, Mask R-CNN, is an extension of Faster R-CNN with an added branch for segmentation mask prediction, enabling precise object detection and segmentation. It was configured with a ResNet-50 backbone, a tile size of 128×128 pixels, a stride of 64×64 pixels, and trained on 282 images. The third model, DeepLabV3+, designed for semantic segmentation, integrates an encoder-decoder structure with dilated convolutions to enhance boundary accuracy.

This model was implemented using a ResNet-34 backbone, with a tile size of 32×32 pixels, a stride of 16×16 pixels, and trained on 1,166 images. The final model, Feature Classifier, is a CNN-based model that classifies features within satellite images into predefined categories. It utilized a ResNet-34 backbone, a tile size of 128×128 pixels, a stride of 64×64 pixels, and was trained on 325 images. The reason behind using different window sizes is that the same window size across different models gave significant variations in accuracy, indicating sub-optimal performance. This variability suggested that the window size alone could not capture the necessary spatial context or details for accurate farm pond detection. The model-specific window size was obtained by iteratively identifying the optimal size, which allowed striking a balance between capturing detailed features (like the shape and size of the ponds) and the surrounding context (such as vegetation and field boundaries). This adjustment helped improve model performance, and within the best performing window sizes, we could determine which model outperformed the others for the specific objective of detecting farm ponds. Thus, each model was chosen and configured based on its strengths to address specific requirements of high-resolution remote sensing applications. The training was conducted over 20 epochs, with a validation loss of 30%, indicating an optimized balance between learning and generalization for all four models.

The final step involved the accuracy evaluation, which was performed using the **'Compute Accuracy for Object Detection'** tool in ArcGIS Pro, which calculated key performance metrics, including **Precision**, **Recall**, and the **F1 Score** (Sholahuddin et al., 2023). These metrics collectively provided a robust assessment of the model's performance, ensuring reliable and accurate classification of objects within the dataset.

- Recall = $\frac{True\ Positives\ (TP)}{True\ Positives\ (TP)+False\ Negatives\ (FN)}$
  Recall measures the model's ability to identify all relevant instances (positive cases) correctly.
- Precision = $\frac{True\ Positives\ (TP)}{True\ Positives\ (TP)+False\ Positives\ (FP)}$
  Precision measures how many of the predicted positive cases were correct.
- F1 score = 2 X $\frac{Precision\ X\ Recall}{Precision+Recall}$

It is useful when Precision and Recall are equally essential or when there is a need for a balanced measure.

4. Results

The results of the performance evaluation of the deep learning models, with a focus on training-validation loss trends and the accuracy of farm pond detection, assessed through comparisons between ground truth data and model predictions in the study area, are as follows:

4.1. U-NETMODEL

The application of the U-Net model in our study shows significant decreases in the training loss with each batch, indicating that the model is improving its predictions (Figure 2). Similarly, the validation loss, which starts lower than the training loss, gradually decreases over time and levels off. The close alignment of the training and validation loss curves suggests that the model does not overfit but generalizes well to unseen data. Both loss curves flatten at nearly the same point, demonstrating that the model has reached an optimal balance between learning from the training set (Srinivasulu et al., 2025) and retaining its ability to generalize to new data. The U-Net model achieved a final precision of 0.955, confirming its high accuracy in detecting and segmenting farm ponds in the study area. The comparison of ground truth and model projections for farm ponds in the study area highlights the model's ability to accurately detect and locate farm ponds using satellite imagery (Figure 3)

4.2. MASK R-CNN MODEL

The comparison of the model's projections for farm ponds in the Kadwanchi region with the ground truth is shown in Figure 4. The training and validation loss of the MASK R-CNN model as a function of batch processing shows relatively high losses in the initial stages of training, both due to fine-tuning of the model's parameters (Figure 5). Although the validation loss begins at a lower value than the training loss, it also decreases quickly, likely due to the model's initial state or the validation data's characteristics. Both losses decline as training progresses but eventually flatten out when the model performs optimally. By 400 batches, the training and validation losses stabilized, indicating that the model has achieved a balance. The close alignment of the two-loss curves demonstrates that the model was well-trained, with good learning in the early stages and no signs of overfitting. It also confirms the model's ability to generalize effectively. The close agreement between the predicted results and the ground truth confirms the algorithm's ability to reliably detect farm ponds in their proper locations. Finally, the model achieved an accuracy of 0.932, highlighting its high predictive capability and readiness for practical application.

Table 1. Details of the Model parameters

Model	Metadata	Backbone	Tile size (Pixels)	Stride Size	Images
U-Net	Classified Tiles	ResNet34	64x64	32x32	553
MaskRCNN	RCNN Masks	ResNet50	128x128	64x64	282
DeepLabV3+	Classified Tiles	ResNet34	32x32	16x16	1166
Feature Classifier	Multi-labeled Tiles	ResNet34	128×128	64×64	325

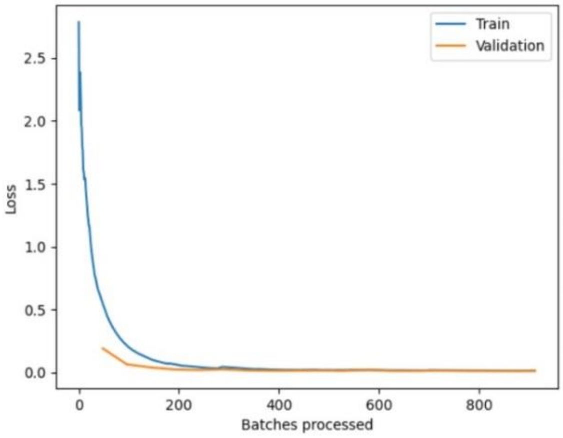

Figure 2. U-Net Model Training and Validation Loss Graph

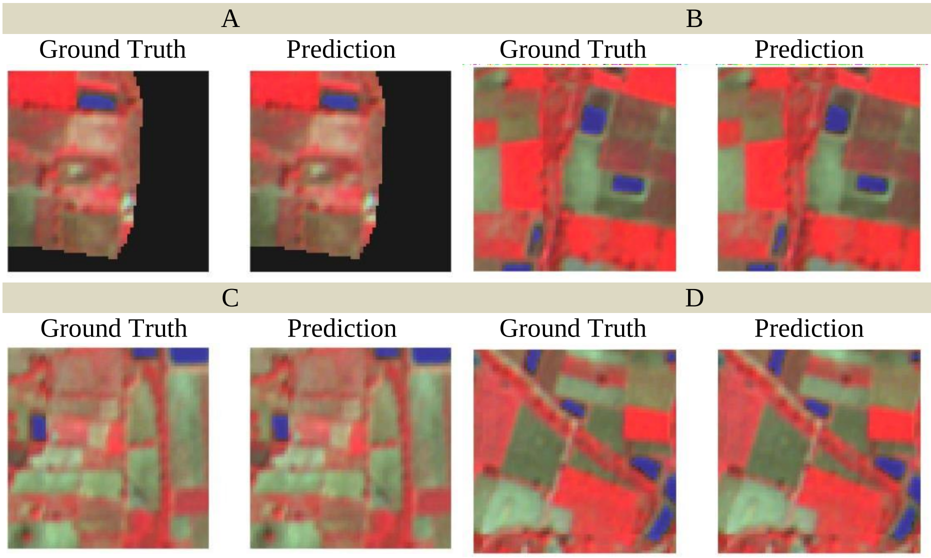

Figure 3. Ground Truth/Predictions of the U-Net Model

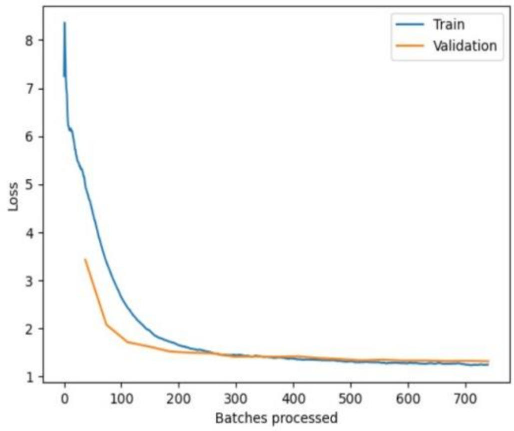

Figure 4. Mask R-CNN Model Training and Validation Loss Graph

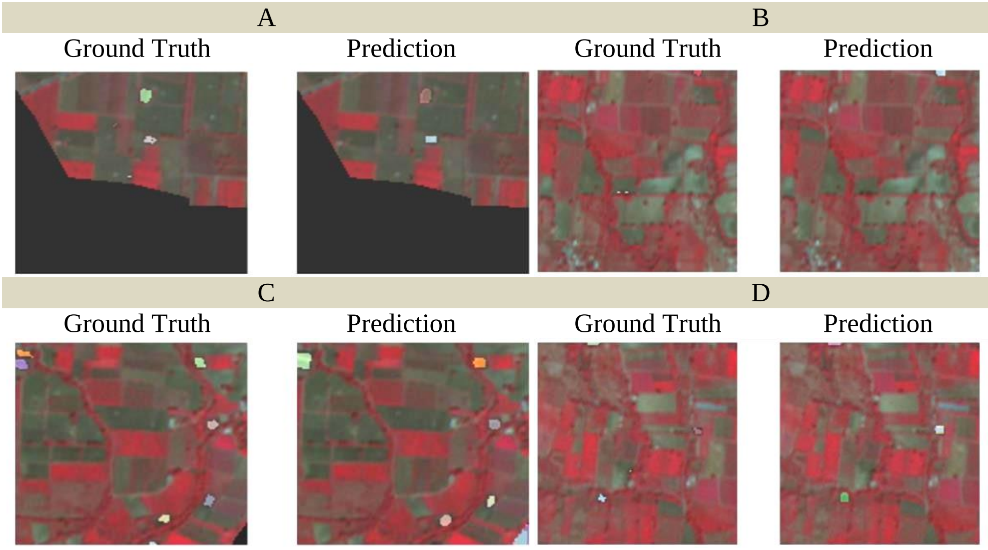

Figure 5. Ground Truth/Predictions of Mask RCNN Mode

4.3. DEEPLABV3+ MODEL

The training and validation loss curves for the DeepLabV3+ model are shown in Figure 6. In the initial stages of training, both the training (blue curve) and validation (orange curve) sets exhibit higher loss values. The training loss drops sharply as the model learns to reduce errors in the training set. However, the higher validation loss suggests the model initially struggles to generalize to unseen data (Leon, 2024). Around the 200th batch, the curves converge, indicating that the model has stabilized. While the validation loss fluctuates less than the training loss, hinting at possible overfitting, this effect is minimal. Notably, there is a slight increase in validation loss around the 1,000th batch, but it remains low, and there is no clear evidence of significant overfitting. Overall, the loss curves demonstrate that the model is well-trained, though there is potential for further optimization through regularization or early stopping techniques to achieve even better results. Figure 7 provides a comparative analysis of the model's predictions and the ground truth for farm ponds in the Kadwanchi region. The strong alignment between the predicted results and the ground truth (Yin et al., 2025) confirms that the algorithm can reliably detect farm ponds at their actual locations with high precision. The final precision achieved by the model was 0.939.

Table 2 show an overall comparison of different models in detecting the farm ponds in terms of visualization and the values of farm pond detection using different models as applied in the Kadwanchi.

4.4. FEATURE CLASSIFIER MODEL

The training and validation loss of the Feature Classifier model are presented in Figure 8. The x-axis represents the number of batches, while the y-axis shows the loss values. The blue line, representing the training loss, starts above 1.0 and steadily decreases as training progresses, indicating that the model is successfully learning and improving its performance on the training set. The validation loss, represented by the orange line, is initially very high and exhibits frequent oscillations during the early stages of training. These oscillations suggest instability in the model's performance on the validation dataset at the beginning. However, the validation loss drops sharply later and stabilizes at values close to zero, reflecting improved generalization on unseen data. The overall loss curves demonstrate that the model is training effectively, with both training and validation losses decreasing and converging over time. This behavior reflects error minimization and potential improvements in the model's feature classification accuracy. The final accuracy of 1.0 suggests that the model performs exceptionally well for real-world applications. Figure 9 compares the model's predictions with the ground truth of farm ponds in the Kadwanchi region, highlighting the model's strong capability in accurately identifying farm ponds.

Table 2. Model Accuracy

Model	Precision	Recall	F1 Score	Farm Ponds detected
U-Net	0.955	0.805	0.873	269
Mask RCNN	0.932	0.625	0.749	207
DeepLabV3+	0.939	0.700	0.801	228
Feature Classifier	1.0	0.863	0.927	296

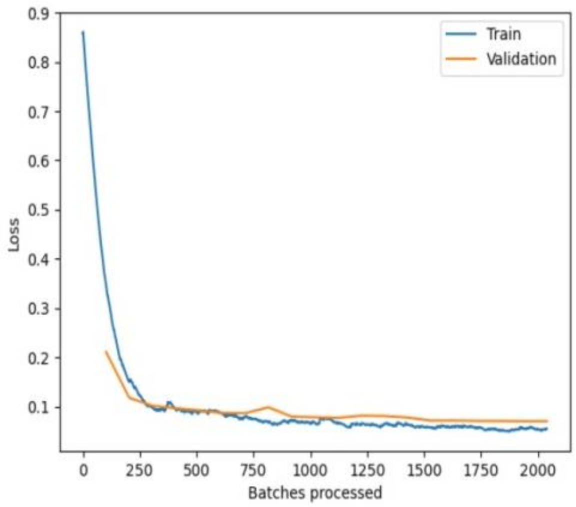

Figure 6. DeepLabV3+Model Training and Validation Loss Graph

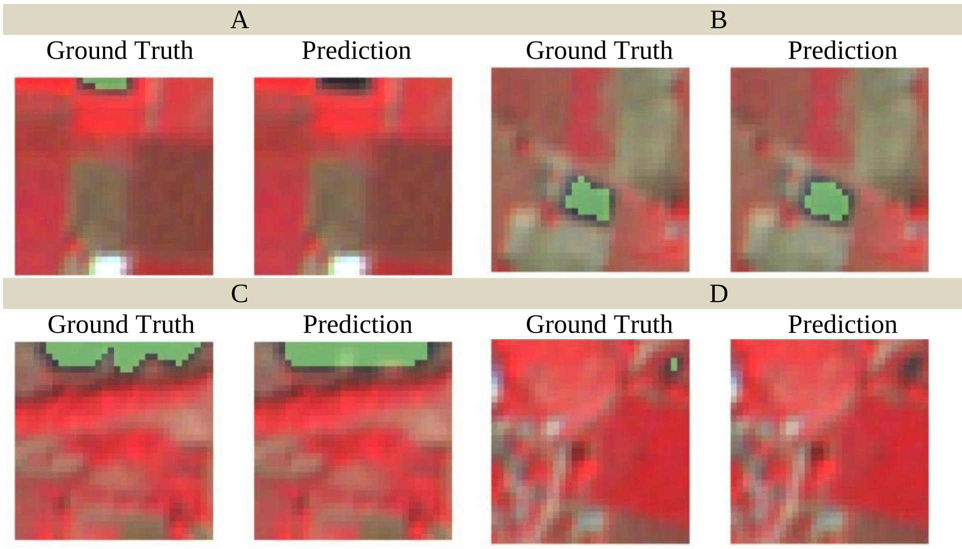

Figure 7. Ground Truth/Predictions of DeepLabV3+ Model

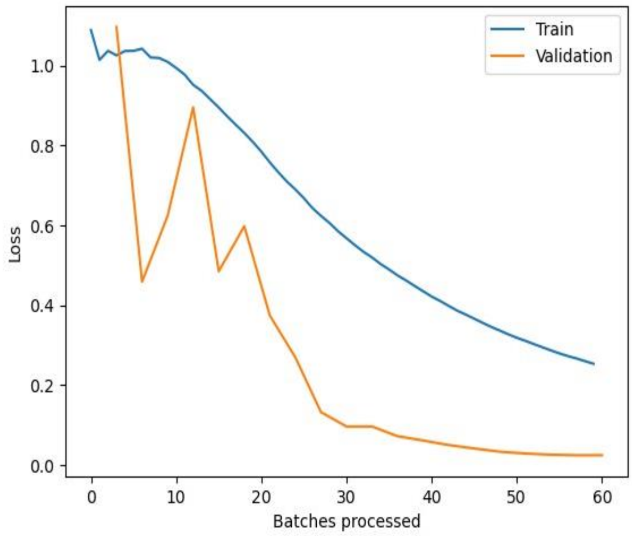

Figure 8. Feature Classifier Model Training and Validation Loss Graph

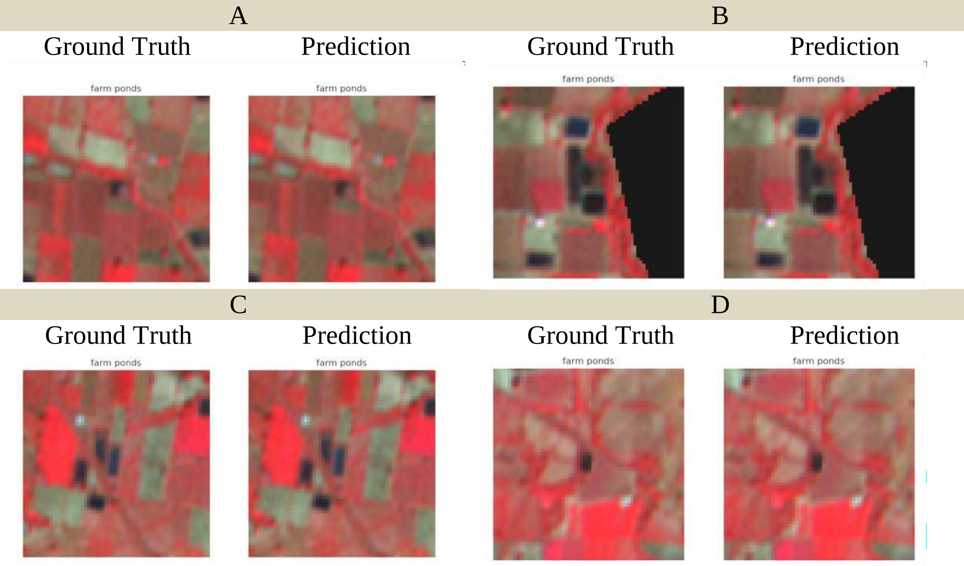

Figure 9. Ground Truth/Predictions of Feature Classifier Model

4.5. Model Validation

Table 3 presents the Confusion Matrix summarizing the performance of four models: u-Net, Mask RCNN, DeepLabV3+, and a Feature Classifier for detecting farm ponds using satellite imagery. The Feature Classifier showed the highest accuracy, with 296 farm ponds detected and a true positive (TP) count 279. It achieved perfect precision by avoiding false positives (FP = 0) and showed the lowest false negative (FN) value of 44, indicating its superior ability to identify farm ponds with minimal errors. U-Net identified 269 farm ponds, with a high true positive count of 257 and a relatively low FP of 12. However, its FN value of 63 highlights some missed detections. Mask RCNN detected the fewest farm ponds (207), with 193 true positives but the highest FN value of 121, reflecting a significant under-detection issue. DeepLabV3+ achieved a balanced performance with 228 detections, 214 true positives, and an FN value of 97, showing moderate effectiveness compared to the other models.

Figure 10 shows the Confusion Matrix of the four models- U-Net, Mask RCNN, DeepLabV3+, and Feature Classifier. Although the feature classification had the highest performance, U-Net and DeepLabV3+ presented a trade-off between precision and recall. At the same time, Mask RCNN showed a problem regarding sensitivity when detecting farm ponds. This means that the feature classifier would be the best model for detecting farm ponds for this study.

5. Discussions

Farm ponds are crucial in agricultural water management, particularly in regions of water scarcity. Their detection and monitoring are essential for effective irrigation planning and resource management, as they contribute significantly to optimizing water usage and enhancing crop productivity. With advances in satellite technology, detecting farm ponds from aerial imagery has become increasingly feasible. Satellite data provides a comprehensive view of the landscape, allowing for the identification of small water bodies like farm ponds that traditional ground surveys might miss. In this context, various deep learning models have been employed to enhance the accuracy of farm pond detection. We found that the Feature Classifier is the most effective model, achieving a perfect precision score of 1.0, a recall of 0.863, and an impressive F1 score of 0.927.

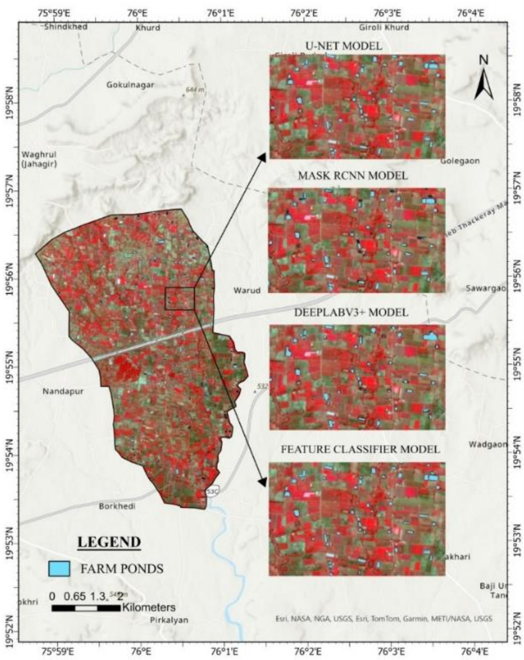

Figure 10: Farm Ponds Detection Using Different Models - Comparative Visualization

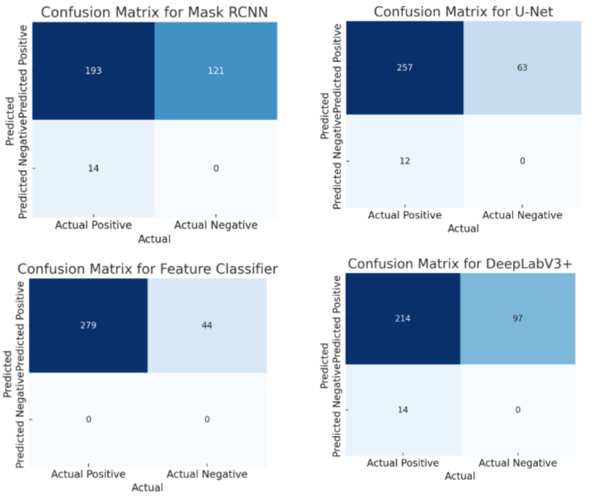

Figure 11: Confusion Matrix of the Models Used

Table 3. Confusion matrix comparison of farm pond detection models

Model	Farm Ponds Detected	True Positive	False Positive	False Negative
U-Net	269	257	12	63
Mask RCNN	207	193	14	121
DeepLab V3+	228	214	14	97
Feature Classifier	296	279	0	44

This exceptional performance demonstrates the model's ability to accurately identify nearly all relevant farm pond instances while avoiding false positives. Such accuracy is vital for agricultural stakeholders who rely on precise assessments of water resources for effective irrigation planning and management (Kamilaris, A., & Prenafeta-Boldú, 2018). Accurately identifying farm ponds allows farmers to optimize water usage, which is especially crucial in Maharashtra, where water scarcity significantly affects crop yields and livelihoods.

In contrast, the U-Net model also demonstrated robust performance, with a precision of 0.955 and a recall of 0.805, yielding an F1 score of 0.873. U-Net's performance highlights its strength in semantic segmentation tasks, as evidenced by its successful detection of 269 farm ponds. Previous studies have reported similar observations emphasizing the model's efficiency in delineating agricultural features from complex landscapes (Ronneberger et al., 2015). However, the U-Net model exhibited some limitations regarding missed detections, indicating that while it can capture a majority of ponds, it may not be as reliable in densely populated areas or where pond features are less distinct.

Conversely, the Mask RCNN model, despite achieving a commendable precision of 0.932, recorded a low recall of 0.625, resulting in an F1 score of 0.749. This disparity suggests that while Mask RCNN can accurately identify some farm ponds, it fails to capture many actual instances, which may lead to underreporting of available water resources (He et al., 2017). The challenges faced by Mask RCNN in detecting farm ponds may stem from the intricate features of satellite imagery in agricultural landscapes, which require sophisticated feature extraction capabilities. This observation is consistent with the findings of (Kamilaris & Prenafeta-Boldú, 2018), who noted that instance segmentation models can struggle with complex agricultural environments.

DeepLabV3+ offered a relatively balanced performance with a precision of 0.939 and a recall of 0.700, resulting in an F1 score of 0.801. This model detected 228 farm ponds, indicating its suitability for specific applications; however, its performance was not as strong as that of the Feature Classifier and U-Net models. The balanced metrics suggest that DeepLabV3+ could serve as a middle ground for applications requiring a trade-off between precision and recall (Chen et al., 2017). While it can effectively detect farm ponds, its limitations in capturing finer details in complex regions might hinder its utility in high-precision scenarios.

6. Conclusion

Deep learning methods applied to remote sensing data have significantly enhanced the ability to detect and monitor changes across large numbers of small water bodies, such as farm ponds, with high speed and consistency. These methods enable scalable, cost-effective, and timely assessments, which would be impractical through field surveys alone. Deep learning algorithms offer standardized analysis across vast landscapes and facilitate historical change detection using satellite archives. However, remote sensing–based detection complements rather than replaces field investigation. Ground truth validation remains essential to ensure the accuracy of remote observations, especially in heterogeneous and dynamic environments where sensor limitations or classification errors can occur. Thus, an integrated approach combining deep learning-based remote sensing with strategic field verification provides the most reliable pathway for monitoring and managing farm ponds over time.

Acknowledgment

The authors thank the Outreach Facility and National Remote Sensing Centre for providing the facilities under the student internship program to carry out this work.

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