Deep Learning Approach for Classification of Horticulture Plantations using Very High-Resolution Satellite Images

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Abstract

Regular assessment of orchards plays a crucial role in horticulture management and decision-making, particularly in diverse regions with varying terrain and environmental conditions. The fusion of cutting-edge remote sensing technology and advanced deep learning (DL) techniques has emerged as a potential solution for mapping and monitoring of plantation crops. This study focuses on use of deep learning for semantic segmentation of horticulture plantations, using very high-resolution satellite data (VHRS). Two DL architectures namely DeeplabV3 and U-Net were applied for the Semantic segmentation of mango orchards in Srinivasapura test site, Karnataka and apple orchards in Shopian test site, Jammu & Kashmir. VHRS image of 0.7m spatial resolution were used for generation of training samples. DeeplabV3 and U-net with Resnet101 as backbone architecture available in the ArcGIS Pro package, were trained with 94 and 118 labeled samples generated for training DL models. The analysis indicated that DeepLabV3 out-performed U-Net for classification of both apple and mango orchards. In Shopian test site, DeepLabV3 architecture showed better accuracy of 94.5% in comparison to U-Net model (88.6%) mainly due to more homogenous apple orchards. In Srinivasapura test site, the model accuracy was 80.3% and 79.3% for DeeplabV3 and U-Net, respectively for classification of mango plantations. The lower accuracy for mango plantations is mainly attributed to heterogeneity due to higher spacing, density and age category requiring more training samples catering to the diversity. The study demonstrated the use of DL models for improved assessment of plantation crops using VHRS data. In the future work, generation of scalable DL model shall be considered by incorporating large no. of annotated training samples from diverse agroforestry land use systems for mapping and monitoring of plantation crops across the country.

Keywords VHRS, Semantic Segmentation, Deep Learning, DeeplabV3, U-net, Accuracy

Introduction

Horticulture plays a role, in the industry as it involves the cultivation of fruits, vegetables and ornamental plants. Many countries, including India, rely on crops like apples and mangoes for a portion of their farming income (Choudhary et.al ,2021). However accurately classifying and identifying these crops using methods can be quite difficult due, to the characteristics of the plants and their varying appearances. There have been significant developments in deep learning and the use of very high-resolution satellite (VHRS) data. These advancements hold promise in enhancing the precision of crop classification and detection. Deep learning models are capable of comprehending features from extensive datasets enabling them to make reliable predictions for various types of crops. VHRS data provides insights, into crops, including their spectral characteristics and spatial distribution. This information can be effectively utilized to enhance the accuracy of crop classification and detection. In our study, our goal is to investigate how deep learning can be used with VHRS data to classify and detect apple and mango horticulture plantations. We will examine studies on deep learning methods in horticultural research and evaluate the effectiveness of various deep learning models for crop classification. The findings of this study will have implications for precise classification using emerging AI technologies like DL to enhance inventory of plantations and provide valuable insights.

Deep learning is a subset of machine learning that involves the use of artificial neural networks to learn from large datasets and make predictions or decisions based on that learning(Osco et al., 2021). A study proposed a TL-ResUNet segmentation model for land use/land cover classification in satellite imagery(Safarov et al., 2022). The model achieved high accuracy in agricultural field segmentation, which can be used to monitor crop growth and yield estimation. Deep learning techniques have been utilized for the classification of agricultural crops using unmanned aerial vehicle (UAV) imagery(Bouguettaya et al., 2022). These techniques can accurately identify and classify different crop types, leading to more efficient crop management practices. Deep learning models have been used for object detection and image segmentation in earth observation data(Shahi et al., 2023). These models can accurately segment and classify land use and cover types, including agricultural fields. Overall, deep learning is a powerful tool in the field of image classification and feature detection using aerial and satellite imagery(Indolia et al., 2018,Hoeser & Kuenzer, 2020). Utilizing deep learning techniques and remote sensing data together can improve crop management practices, increase crop yields, and optimize agricultural and horticultural processes.

Materials and Methods

Study Areas: Shopian district is located in the southern part of the Kashmir Valley in the Indian-administered Kashmir region. The district has an area of 30,741.6 hectares and is situated at an altitude of 2,057 m (6,749 ft) above sea level. The soil type in the district is mostly loamy and sandy loam. The average annual rainfall is 1,200 mm. The temperature ranges from -7°C in winter to 30°C in summer. The major agricultural practices in Shopian are apple cultivation, walnut cultivation, and saffron cultivation.

Srinivaspur taluk is located in the Kolar district of Karnataka, India. It is located at 13.33° N 78.22° E. It has an average elevation of 819 meters (2,687 ft) above sea level. The taluk has an area of 860 square kilometres. The soil type in the taluk is mostly red loam. The average annual rainfall is 750 mm. The temperature ranges from 15°C in winter to 35°C in summer. Mango is a major plantation crop in Srinivaspur taluk. The taluk is known for its Alphonso mangoes, which are considered to be some of the best in the world. Other varieties of mangoes grown in the taluk include Totapuri, Kesar, and Neelam.

Data used: The Data used in the study are VHRS images of Kompsat 3A satellite Images. There are two sensors onboard KOMPSAT-3A, the AEISS-A (Advanced Electronic Image Scanning System-A) high-resolution optical imager, and IIP (Infrared Imaging Payload), an

MWIR (Medium-wave Infrared) single channel imager. The spatial resolution of the images is 0.7m.

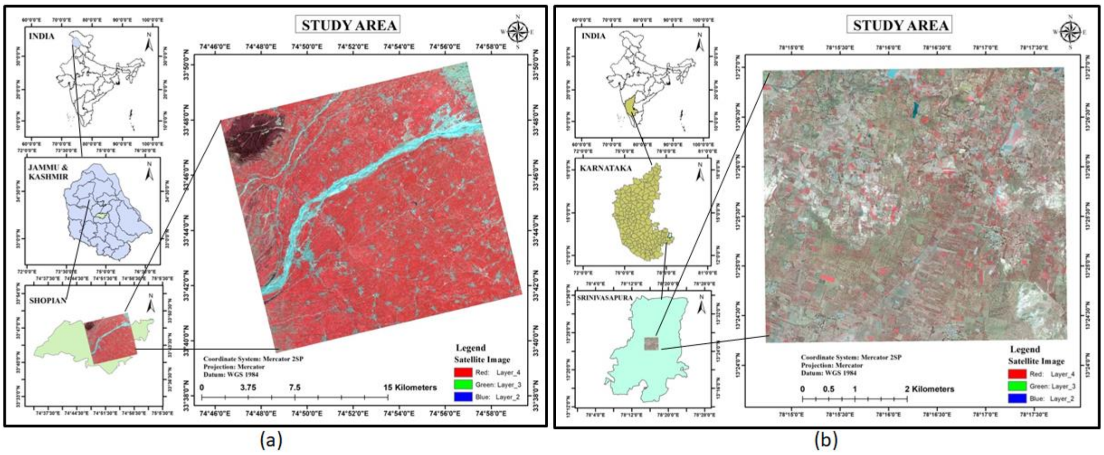


Fig. 1 (a) Shopian study area map. (b) Srinivasapura study area map.

Methodology: Methodology applied for the current study is presented in the figure2. it is divided into 3 steps a) Generation of labelled training samples b) Training the Deep Learning Models and c) Inferencing.

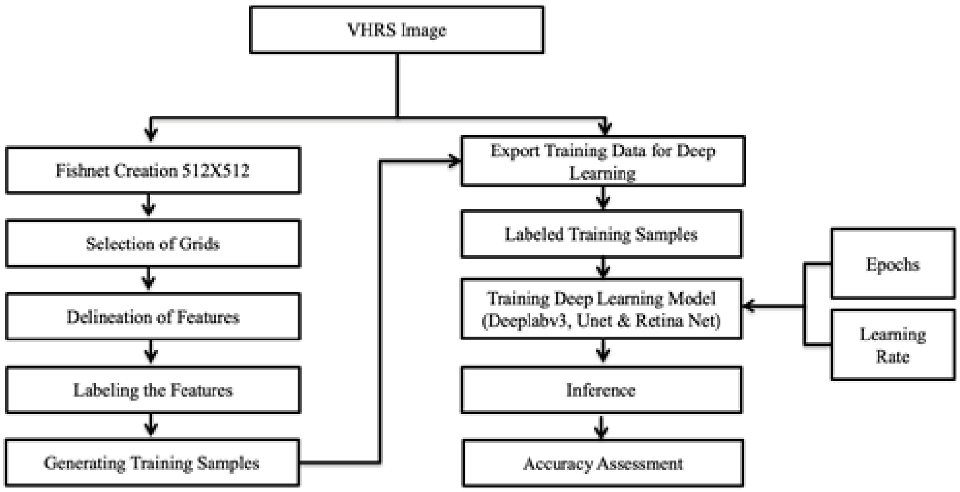


Fig. 6 Methodology flowchart.

Generation of labelled training samples: Generation of labelled training samples includes creating fishnet, and selection of grids which depict the variability of the target orchards. Selected grids are vectorised using visual interpretation techniques and labelled accordingly. Vectorised samples were then converted to image chips format.

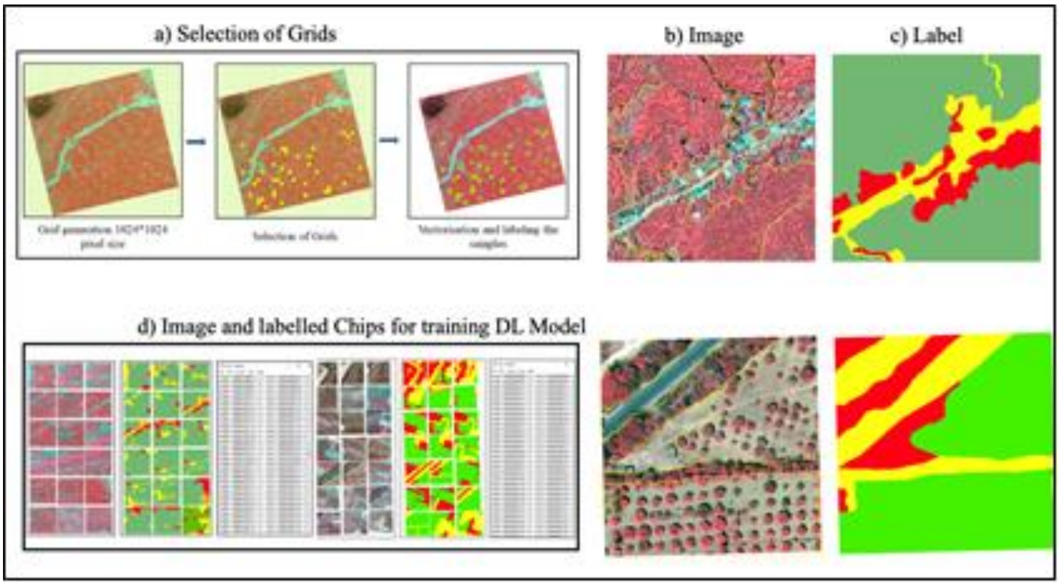


Fig. 3 94 Images of 512*512-pixel size for Apple Orchards 118 images of 256*256-pixel size for Mango Orchards.

Training the deep learning model: DL architectures DeeplabV3 and U-Net are trained and Resnet101 is used as backbone model for training. The model parameters used are in the Table1.

Table 1 *Model Parameters.*

		Apple orchards		**Mango orchards**	
S. No	**Parameter**		**Value**		
1	Epoch	20	20	20	20
2	Model type	DEEPLAB	U-Net	DEEPLAB	U-Net
3	Batch Size	8	8	8	8
4	Learning rate	0.0008318	0.0001	0.0008318	0.0001
5	backbone Model	RESNET101	RESNET101	RESNET101	RESNET101
6	Validation %	10	10	10	10

Brief of DL Models Used:

DeeplabV3: Deeplabv3 is a type of CNN model designed by Google for the semantic segmentation of images. It uses atrous convolutions to extract dense features from an image. It also has an encoder and decoder The encoder is a convolutional neural network that extracts features from the input image, while the decoder up-samples the feature maps to produce the final segmentation map(Chen et al., 2017).

U-Net: U-Net is a deep learning architecture specifically used for semantic segmentation i.e., pixel classification. It was developed for biomedical image segmentation by (Ronneberger et al., 2015) which was considered an advanced version of Fully convolution networks for image segmentation developed by (Long et al., 2014). As the name suggests U-Net is a definite architecture with the shape of which has three main segments namely the encoder, bridge and the decoder. Since it is based on convolutional layers, all the blocks represented are made up of convolution layers followed by activation and pooling layers(Gholamalinezhad & Khosravi, 2020).

Resnet: The Residual Blocks idea was created to address the issue of the vanishing/exploding gradient with increasing layers. The skip connection bypasses some levels in between to link-layer activations to subsequent layers. This creates a leftover block. These leftover blocks are stacked to create ResNet. ResNet is a deep neural network architecture that can have hundreds of layers. ResNet has achieved state-of-the-art performance on a variety of computer vision tasks, including image classification, object detection, and semantic segmentation(He et al.,2015).

All the above-mentioned models are used in current study with ArcGIS Pro package spatial analyst tools.

Evaluation Metrics: In deep learning, precision, recall, and F1 score are evaluation metrics used primarily for classification tasks. These metrics help assess the performance of a neural network in distinguishing between different classes.

Precision: Precision is a metric that measures the accuracy of positive predictions made by the model. Specifically, it calculates the ratio of true positives (TP) to the sum of true positives and false positives (FP).

Formula: Precision = TP / (TP + FP).

Recall: Recall (also known as sensitivity or true positive rate) measures the ability of the model to correctly identify all instances of the positive class. It is calculated as the ratio of true positives to the sum of true positives and false negatives (FN).

Formula: Recall = TP / (TP + FN)

F1 Score: The F1 score is the harmonic mean of precision and recall. It provides a single metric that balances both precision and recall.

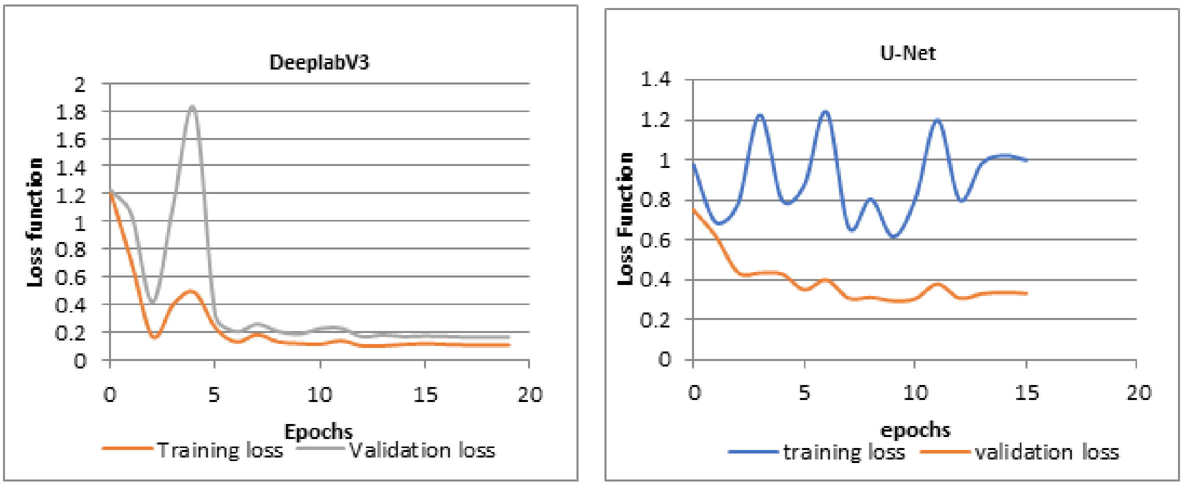
Formula: F1 Score = 2 * (Precision * Recall) / (Precision + Recall)

Results and Discussion

Models for semantic segmentation of apple and mango orchards have been trained using training data. DeeplabV3 and U-net architectures were trained utilising ResNet101 as the backbone model for both orchards.

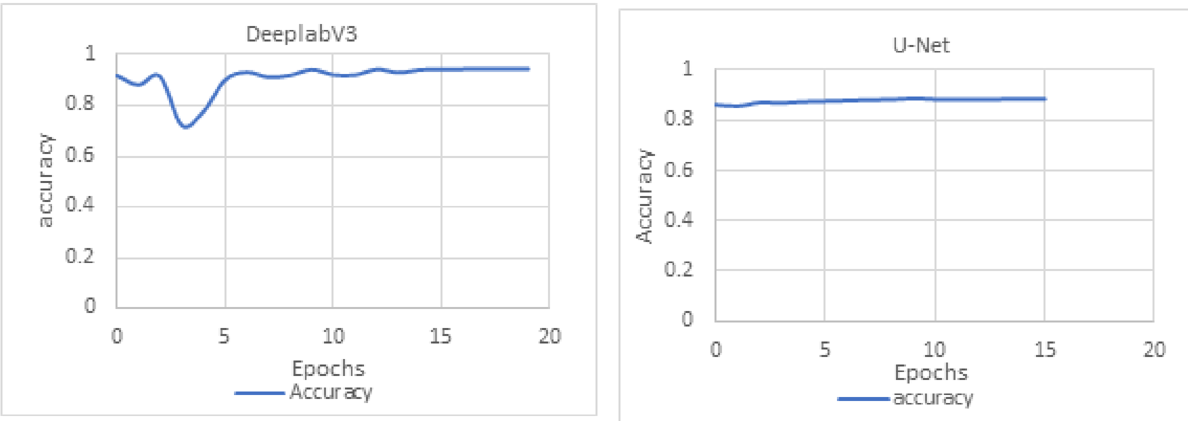
Semantic segmentation-based classification for Apple orchards: The training log of apple DL model displays the training and validation loss values for a neural network over multiple epochs. Fig. 4 shows that deeplabv3 performs better without any overfitting than the U-Net for apple orchards. The accuracy of deeplabv3 is better than that of U-Net. The Higher accuracy is due to homogeneous nature of apple orchards found in the test sites.

Semantic segmentation-based classification for Mango orchards: The training log of Mango DL Model for Mango Orchards shows similar trend in loss-function without any overfitting both models performed similar giving similar accuracy of 79% for Deeplabv3 and 80% for U-Net. The lower accuracy of the model is due to spacing of trees in mango orchards, density, age of trees etc.



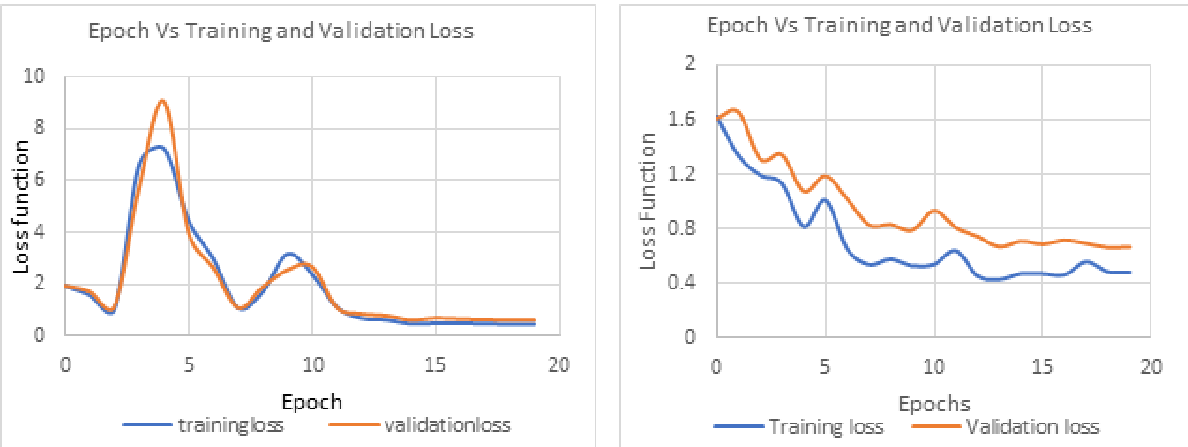
(a) (b)

Fig. 4 (a) Apple Deeplab V3 Loss function. (b) Apple U-Net Loss function.



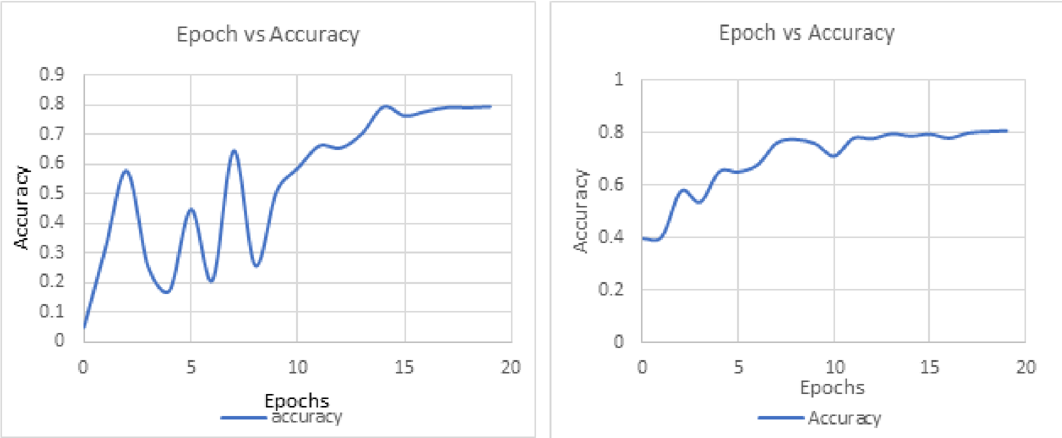
(a) (b)

Fig. 5 (a) Apple Deeplab V3 model accuracy. (b) Apple U-Net model accuracy.



(a) (b)

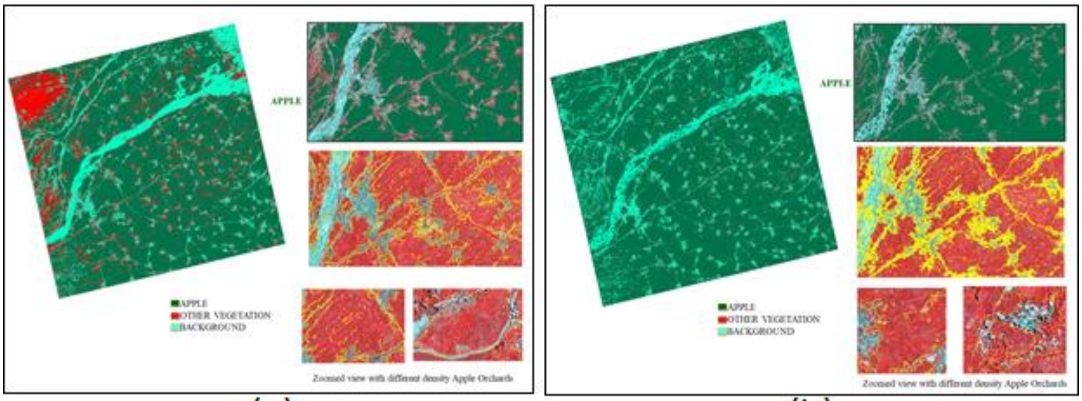
Fig. 6 (a) Mango Deeplab V3 Loss function. (b) Mango U-Net Loss function.



(a) (b)

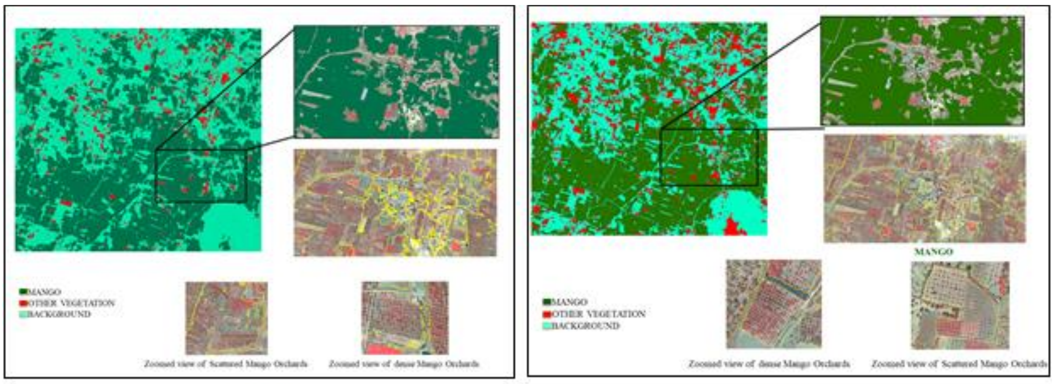
Fig. 7 (a) Mango Deeplab V3 model accuracy. (b) Magno U-Net model accuracy.

The inference output of the model shows that the deeplabv3 raster when converted to vector is smooth compared to U-Net in both the scenarios.



(a) (b)

Fig. 8 (a) Apple Deeplab V3 model inference. (b) Apple U-Net model inference.



(a) (b)

Fig. 9 (a) Magno Deeplab V3 model inference. (b) Mango U-Net model inference.

Review of the Models:

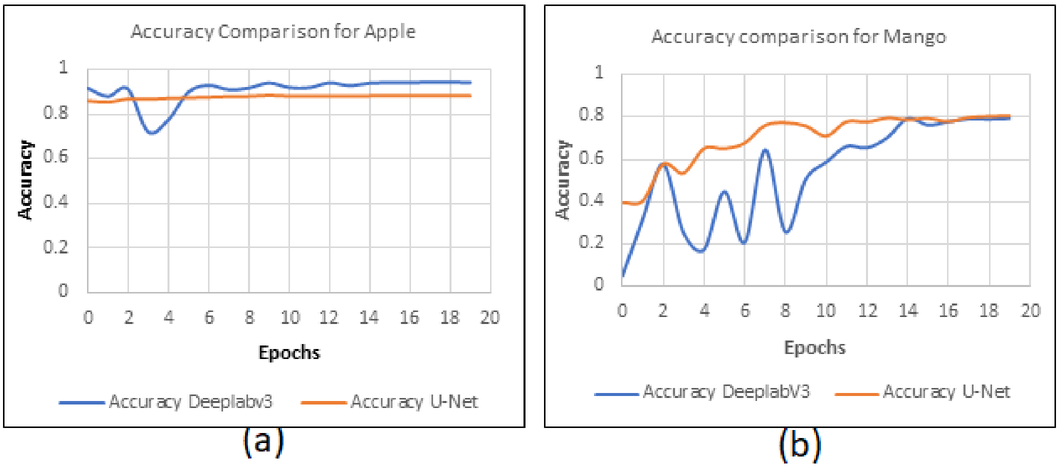


Fig. 9 (a) Accuracy Comparison of DeeplabV3 and U-net Model for Apple Orchards. (b) Accuracy Comparison of DeeplanV3 and U-Net Model for Mango Orchards.

Table 2 Evaluation Score of both models for both Orchards.

	precision	recall	f1
Apple DeeplabV3	0.95	0.99	0.97
Apple U-Net	0.90	0.99	0.94
Mango DeeplabV3	0.84	0.93	0.88
Mango U-Net	0.83	0.94	0.89

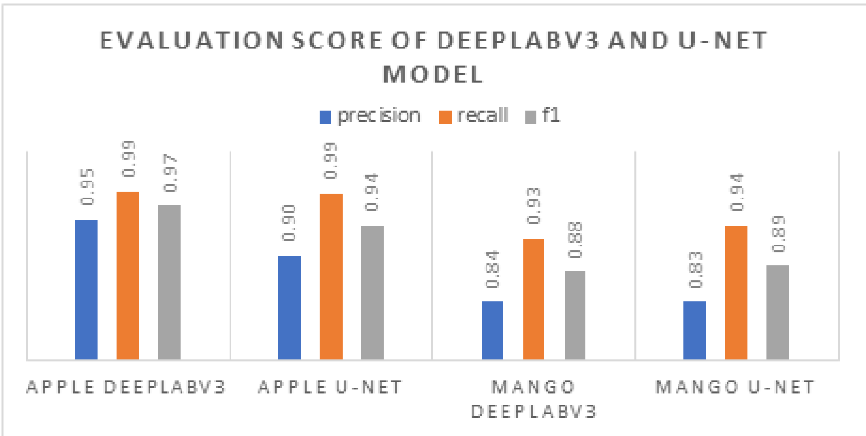


Fig. 10 Evaluation Score Chart.

Both "Apple DeeplabV3" and "Apple U-Net" models have high precision and recall scores, indicating that they are performing well on the task. "Apple DeeplabV3" has a slightly higher precision (0.95 vs. 0.90) but both have very high recall scores (0.99). Among the Mango models, "Mango U-Net" has slightly higher precision (0.83 vs. 0.84) and recall (0.94 vs. 0.93) compared to "Mango DeeplabV3". Apple DeeplabV3 seems to be the best model for classifying apples. It has the highest precision, recall, and F1-score among the Apple models, indicating that it performs well in both avoiding false positives and false negatives. For mango classification, "Mango U-Net" appears to be the better choice. It has a slightly higher precision, recall, and F1-score compared to "Mango DeeplabV3".

Conclusion

In conclusion, this study embarked on a comprehensive inventory and classification of horticulture plantations, leveraging Very High-Resolution Satellite (VHRS) data and employing advanced Deep Learning (DL) techniques. The primary objectives encompassed semantic segmentation-based classification of Apple and Mango Orchards and detailed comparison of DL models. The study areas, spanning Shopian district for apple orchards, Srinivasapura taluk for mango plantations, offered a rich and diverse dataset for analysis. The application of the Semantic Segmentation approach yielded notable results, with the Deeplabv3 model demonstrating an outstanding accuracy of 94.5% for apple orchards, surpassing the U-Net model's commendable accuracy (88%). Similarly, for mango orchards, the Deeplabv3 and U-Net models achieved a similar accuracy of 79% and 80% These findings underscore the potential of Deep Learning techniques, specifically Semantic Segmentation in accurately classifying and detecting horticulture plantations from VHRS data. The high accuracy levels achieved, particularly with the Deeplabv3 model, highlight its potential for practical applications in agricultural inventory and management. The comparative analysis of DL models provides invaluable insights into their respective strengths and areas of application, serving as a valuable resource for researchers and practitioners alike. The successful detection of various orchard types showcases the adaptability and versatility of the employed methodology. In essence, this study significantly contributes to the growing body of knowledge in the horticulture plantation inventory and classification. The demonstrated accuracy levels provide a robust foundation for future research endeavors. This research heralds a promising era in agriculture, where advanced technologies like Deep Learning and satellite data integration promise to revolutionize agricultural monitoring, ultimately leading to enhanced sustainability and productivity in horticulture plantations.

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