Classification and Phenological Stage Monitoring of Grape Crop using Sentinel-1 and Sentinel-2 Time Series and Deep Learning Techniques

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Abstract

The demand for food production is increasing rapidly with a surge in the population. To cope with this increasing food demand, precise agricultural management is essential. The existing techniques involve extensive field surveys for agricultural land discrimination. To minimize the man-hour efforts and time required by these techniques, automated techniques for precise crop type mapping and monitoring have been used. These techniques utilize satellite imagery and advanced machine learning techniques for crop type mapping and monitoring. However, the performance of such techniques is affected by factors such as fragmented land parcels, seasonal variability, and inconsistent field-level observations. To overcome these issues, this study attempts to classify grape and non-grape crops and monitor their phenological stages in the study area in Pune district, India, using Sentinel-2 satellite imagery and deep learning (DL) segmentation techniques: U-Net and DeepLabV3. Further, Sentinel-1C SAR imagery (VV and VH polarization) for the years 2016 to 2024 was utilized to train and evaluate a long short-term memory network (LSTM) model with an aim to analyze the temporal behavior of the grape crop from pruning to harvesting stage with emphasis on growth stages like leaf set, fruit set, and ripening. The experimental results demonstrate that U-Net outperforms DeepLabV3 (F1-score: 0.96; mAP: 0.95) in grape crop classification. The LSTM model showed performance (F1-score 0.82) for phenological stage identification. This study can help agricultural stakeholders in effective and large-scale crop discrimination with minimum human intervention. It has the potential to reveal grape distribution and development stages in a faster time.

1. Introduction

Indian agriculture mainly depends on weather patterns, especially where rainfall timing or irrigation methods play a crucial role in crop productivity (Government of India, 2021). Grape (*Vitis Vinifera*) is a major horticultural crop with higher monetary benefits. It is widely cultivated in Nashik, Pune, Sangli, and Solapur districts in Maharashtra, India. In the Pune district, Baramati and Indapur talukas are known for higher grape crop yields (Shah et al., 2024). However, grape growers in the region suffer from lower crop yields due to factors such as uncertain weather conditions, water stress, pests, and diseases. This necessitates monitoring the grape crop growth during its phenological stages, which is essential to ensure good yield and quality (Report of ICAR-NRCG, 2020). Currently, most farmers rely on traditional practices like field visits and visual inspections, which are time-consuming, labour-intensive, and not feasible for real-time or large-scale monitoring (Shah et al., 2023). Satellite-based remote sensing has opened up new avenues for monitoring agricultural practices. It provides consistent, large-scale data that can be accessed frequently across all weather conditions. Sentinel-1, which captures Synthetic Aperture Radar (SAR) imagery in vertical transmit vertical receive (VV) and vertical transmit horizontal receive (VH) polarisations, can be used effectively to detect the crop structure and moisture levels even during cloudy days due to the penetrating ability of SAR. On the other hand, Sentinel-2 offers multispectral optical imagery that is useful for calculating vegetation indices and is a reliable measure of plant health. These datasets enable all-weather, season-round crop monitoring (Veloso et al., 2017). Deep learning (DL) has been used widely to classify crops and detect their growth stages using satellite imagery in recent years. Studies have shown that models such as convolutional neural networks (CNNs), long short-term memory networks (LSTMs), and hybrid models that use CNN-LSTMs outperformed traditional methods. Rudiyanto et al. (2019) used Sentinel-1 in Google Earth Engine (GEE) to monitor rice growth, while Ferrant et al. (2019) combined Sentinel data with machine learning (ML) to track drought-affected crops. Recent research by Teixeira et al. (2023) highlights the improved accuracy of deep learning models in capturing spatial and temporal patterns. Advances like semantic segmentation (Gao et al., 2023) and NAS-based models (Slimani et al., 2024) now make real-time crop monitoring more achievable and accurate. Inspired by these recent advancements and drawbacks of traditional methods for crop monitoring, this study attempts to classify grape and non-grape crops and monitor their phenological stages in the study area in Pune district, India, using Sentinel-2 satellite imagery and DL segmentation techniques: U-Net and DeepLabV3. Further, the temporal behavior of the grape crop from pruning to the harvesting stage, with emphasis on growth stages like leaf set, fruit set, and ripening, was assessed using Sentinel-1 imagery and the LSTM technique.

2. Study Area

The study region identified for this research involves Baramati and Indapur talukas in the southeastern part of Pune district, Maharashtra, India (Figure 1). Geographically, Baramati lies between 18.15°N-18.50°N latitude and 74.50°E -74.95°E longitude, while Indapur spans 17.95°N to 18.25°N latitude and 74.35°E to 75.05°E longitude. Covering a combined area of around 3,700 square kilometres, these talukas form an important agricultural belt in the region.

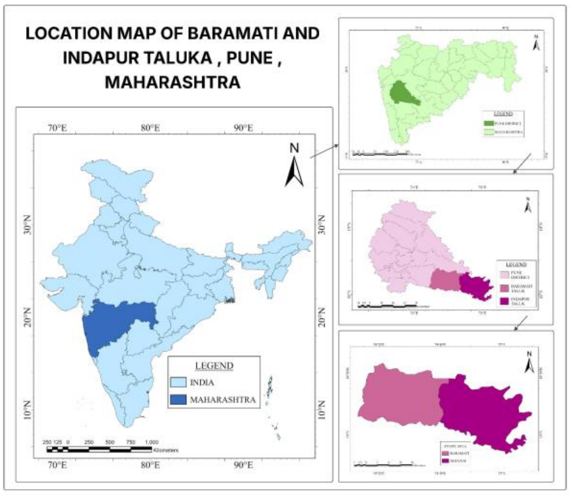

Figure 1. Location Map of Study Area

The area lies in the rain shadow zone of the Western Ghats, at an average elevation of 550–580 meters above sea level. The climate is semi-arid, marked by high temperature variations, low humidity, and limited rainfall. Three distinct seasons: summer (March–May), monsoon (June–September), and winter (October–February) define the agricultural calendar. Annual rainfall ranges from 500 to 700 mm, mostly received during the southwest monsoon, although its distribution varies significantly yearly. (Indian Meteorological Department (IMD), Pune; Directorate of Economics and Statistics, Government of Maharashtra Agro Climatic Reports, 2014–2024). Despite low rainfall, agriculture thrives here due to fertile black cotton and loamy soils, supported by canal irrigation from the Nira and Ujjani dams under the Krishna-Bhima irrigation project. This makes the region ideal for grape cultivation and other high-value crops. Grapes are a major commercial crop in the study area, booming between August and January through key stages like leaf set, fruit set, and ripening. However, climate change, erratic monsoons, and water stress threaten productivity. Traditional field monitoring is slow and limited. Integrating Sentinel-1 SAR and Sentinel-2 NDVI imagery with deep learning enables the timely and accurate detection of crop stages, supporting precision farming across large agricultural areas.

3. Methodology

The study aims to develop a near-real-time deep learning based grape monitoring system using multi-source geospatial and climatic data. The workflow involved data collection, image preprocessing, training sample generation, model training, and accuracy assessment using ArcGIS Pro 3.3 and Python (Figure 2).

3.1 Study Area Selection

Baramati and Indapur talukas in Pune were selected due to their high grape cultivation and availability of historical agro-climatic data.

3.2 Data Collection

Satellite Data:

- Sentinel-1 SAR (VV/VH) for canopy structure and moisture.
- Sentinel-2 MSI for NDVI (Band 8 & Band 4).

Monthly composites (Aug–Jan) from 2016–2024 were created in GEE, merged into NDVI + VV/VH raster stacks for classification.

Climatic Data:

Rainfall, temperature, and soil moisture (2016–2024 were sourced from IMD and NASA POWER and used as inputs for time-series prediction.

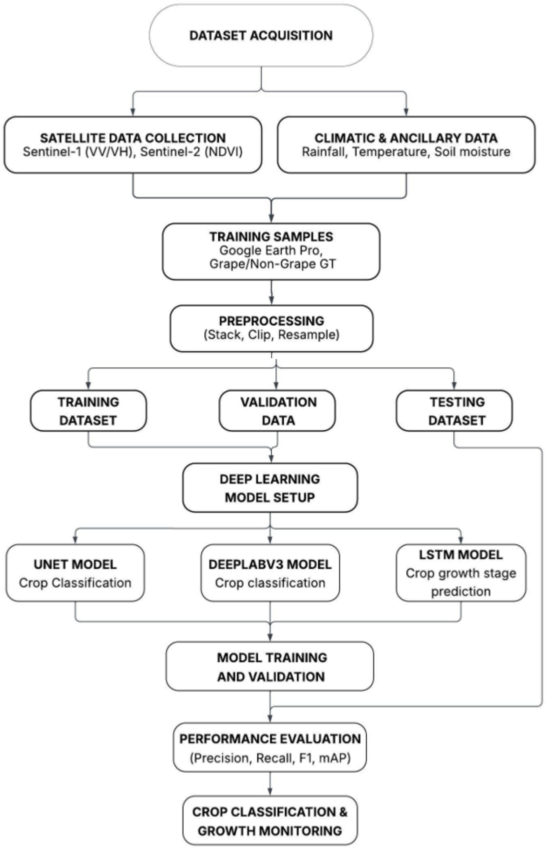

Figure 2. Methodology

3.3 Training Sample Creation

450 labelled polygons (grape/non-grape) were digitised in Google Earth Pro. These were converted to image-label pairs and time-series CSVs for training U-Net, DeepLabV3, and LSTM models.

3.4 Image Processing

Annual NDVI and SAR composites were stacked and clipped to the AOI. Climatic CSVs were temporally aligned with image timestamps.

3.5 Model Training

The potential of deep learning architectures: U-Net and DeepLabV3 was assessed for the grape crop classification, while the LSTM model was used for phenological growth stage monitoring.

U-Net Model

The U-Net model, a convolutional neural network (CNN) designed explicitly for image segmentation (Ronneberger et al., 2015), was employed to classify grape and non-grape fields. Its U-shaped architecture consists of an encoder for feature extraction and a decoder for spatial localisation, with skip connections that preserve context and fine spatial details. This makes it ideal for high-resolution satellite imagery where pixel-level classification is essential. This study applied U-Net to multi-temporal raster composites combining Sentinel-1 SAR (VV/VH) and Sentinel-2 NDVI data from 2016 to 2024. A total of 553 training tiles (64×64 pixels, stride 32) were generated. The model was trained for 50 epochs using a ResNet-34 backbone, enabling it to learn spatial patterns and rapidly segment grape fields effectively.

DeepLabV3 Model

The DeepLabV3 model (Ghosh et al., 2021), known for high-precision semantic segmentation, was applied in this study to classify grape and non-grape fields using stacked Sentinel-1 SAR (VV/VH) and Sentinel-2 NDVI data from 2016 to 2024. Using atrous (dilated) convolutions and Atrous Spatial Pyramid Pooling (ASPP) enables the model to capture fine spatial details and multiscale contextual features, which are crucial for detecting small, fragmented farm plots. A total of 1166 tiles (32×32 pixels, stride 16) were used to train the model with a ResNet-101 backbone, enhancing its feature extraction capability. The model aimed to accurately delineate crop boundaries and improve classification in diverse agricultural settings.

LSTM Model

The Long Short-Term Memory (LSTM) network (Gers et al., 2000), a specialised type of recurrent neural network (RNN), is well-suited for modelling sequential data. Its memory cells and gated architecture help capture temporal dependencies, making it ideal for tracking crop phenology over time.

This study applied the LSTM model to classify grape growth stages—Leaf Set, Fruit Set, and Maturity/Harvest—across the 2016–2024 period. It used multivariate time-series inputs including Sentinel-2 NDVI, Sentinel-1 VV/VH, and agro-climatic variables (rainfall, soil moisture, and temperature) for each year's growing season (August to January).

Each sample was structured as a 3D array with dimensions *(samples, time steps, features)* — specifically *(468, 9, 5)*. Time steps represented monthly data (August–April), and five features per month captured the spectral and climatic conditions. Labels were assigned as follows:

- 1 = Leaf Set (Aug–Sep)
- 2 = Fruit Set (Oct–Nov)
- 3 = Maturity/Harvest (Dec–Jan)

Out of 469 digitised points, 468 were successfully processed. The dataset was split into 80% training (374 samples) and 20% testing (94 samples) for model development and evaluation.

3.6 Model Evaluation

Model performance was evaluated using Precision, Recall, F1-Score (Powers, 2011), and mAP (Everingham et al., 2010). These metrics helped validate classification accuracy and stage prediction reliability.

4. Results and Discussions

In the section below, the performance of each model is discussed along with its learning curves and classification maps.

4.1 Results of the U-Net Model

Figure 3 shows the training and validation loss curves of the U-Net model. Initially, the model began with a training loss of 1.0781 and a validation loss of 0.2371. Both losses rapidly decreased within the first few epochs, reaching 0.0282 (training) and 0.0332 (validation) by the end of training. The close alignment of both curves throughout suggests minimal overfitting and strong generalisation.

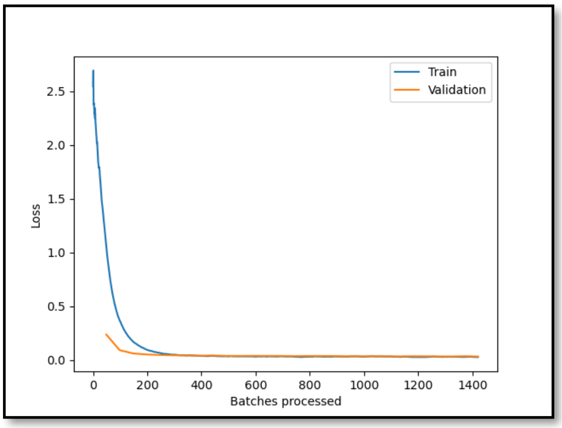

Figure 3. U-Net Model Training and Validation Loss

The model reported validation accuracy of 99.34% with a precision of 0.955, a recall of 0.968, and an F1-score of 0.961 for grape and non-grape crop classification.

These results confirm the model's accuracy in distinguishing grape and non-grape fields from Sentinel-1 and Sentinel-2 composites.

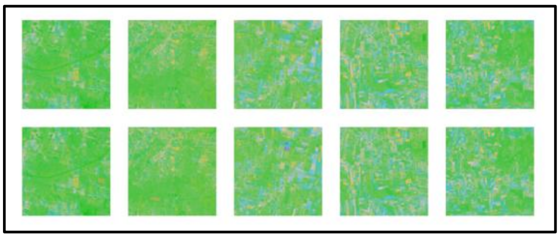

Figure 4. Actual Vs. Predictions of U-Net Model (Yellow showing Grape crop, Green showing Non-Grape Crop)

Figure 4 visually compares ground truth (left) and U-Net model predictions (right) for selected samples. The predicted segmentation closely aligns with manually labelled grape plots, accurately preserving field shapes and sizes, even in fragmented landscapes. Minor misclassifications are minimal, showing consistent performance across test areas. These visual results, supported by a precision of 0.955, highlight the model's effectiveness for real-time grape crop mapping, aiding timely irrigation, disease control, and harvesting decisions.

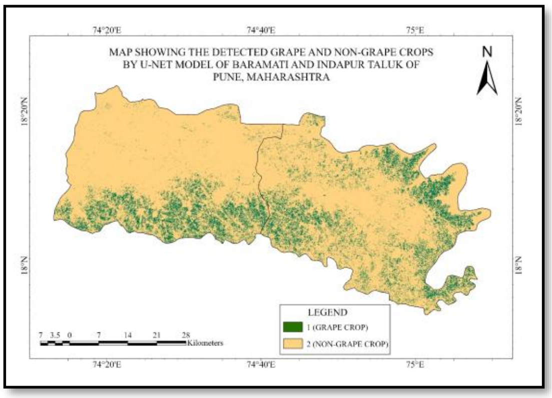

Figure 4. Grape Classification Map by U-Net Model

The classification map (Figure 4) produced by the U-Net model illustrates the spatial extent of grape and non-grape areas within the Pune district study area. Green areas represent grape cultivation, while yellow-beige indicates non-grape fields. It is observed that grape cultivation is densely concentrated in the southern and eastern parts of Baramati and Indapur, as shown by clustered green patches. In contrast, the western and central regions appear primarily non-grape or fallow land.
The model effectively captures field-level patterns, even in fragmented agricultural settings, making the map valuable for targeted vineyard management, irrigation planning, and resource allocation.

4.2 Results of DeepLabV3 Model

Figure 5 displays the training and validation loss trends for the DeepLabV3 model. Initially, both losses were high, reflecting early learning stages. As training progressed, losses declined steadily, with the validation loss stabilising at 0.0315 around the 300th batch, indicating strong convergence and generalisation.

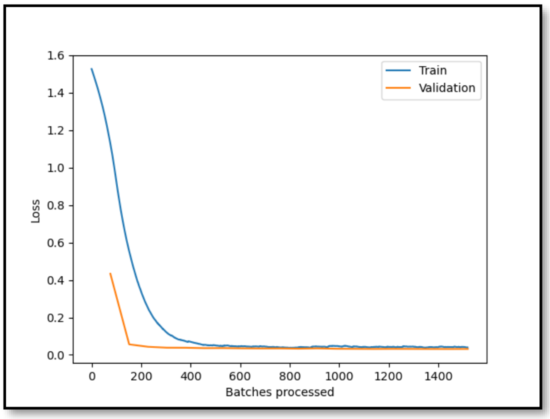

Figure 5. DeepLabV3+ Model Training and Validation Loss

The close alignment of the training and validation curves suggests no overfitting. The model consistently performed well across different regions and years.
The model reported validation accuracy of 93.30% with a recall of 0.91, and an F1-score of 0.92 for grape and non-grape crop classification with mAP of 0.96.

These results demonstrate DeepLabV3's robustness for accurate vineyard segmentation and its suitability for real-time agricultural monitoring systems.

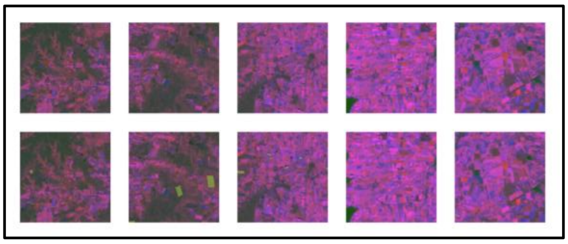

Figure 6. Actual Vs. Predictions of DeepLabV3+ Model (Red showing Grape crop, Pink or Violet showing Non-Grape crop)

Figure 6 presents a side-by-side comparison of ground truth and DeepLabV3 predictions for multiple test samples. Each pair—derived from Sentinel-1 SAR and Sentinel-2 NDVI composites—shows vineyard (grape) and non-vineyard areas across different locations and seasons. The model demonstrates strong alignment with ground truth, accurately capturing fine-scale vineyard plots and maintaining spatial consistency even in fragmented or mixed-field environments. Boundary localisation is precise, with low false positives.

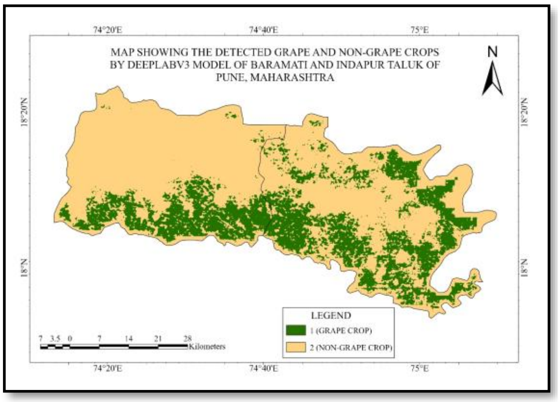

Figure 7. Grape Classification Map by DeepLabV3 Model

The classification map (Figure 7) generated by the DeepLabV3 model shows the spatial extent of grape (green) and non-grape (beige) fields across the study area. Compared to the U-Net output, this map reveals a denser and more continuous distribution of grape cultivation, particularly in the southern, south-eastern, and eastern parts.
DeepLabV3 effectively captures acceptable field boundaries, even in fragmented or densely planted zones, offering refined segmentation ideal for precision viticulture and regional crop management.

4.3 Results of LSTM Model

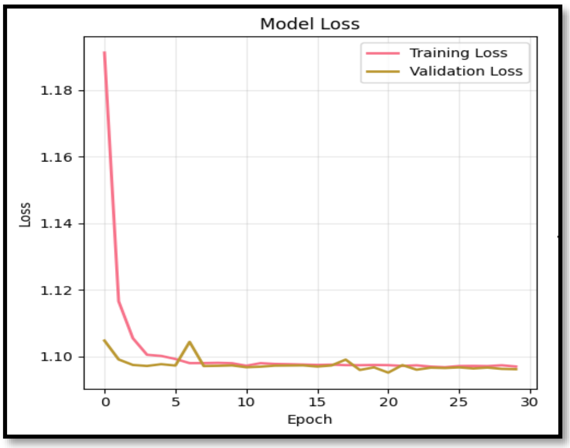

Figure 8. LSTM Model Training and Validation Loss

Figure 8 illustrates the training and validation loss curves across 30 epochs for the LSTM-based grape growth stage prediction model. The x-axis represents the epoch number, while the y-axis shows the loss values. The training loss (pink line) starts at 1.19, and the validation loss (golden-brown) begins slightly lower, near 1.10. A sharp decline is observed in the first five epochs, with both curves stabilising around 1.09, indicating effective early learning. From epoch five onward, the losses remain low and closely aligned, showing minimal overfitting and strong generalisation. This behaviour confirms the model's robust learning of temporal dynamics from combined NDVI, SAR, and climate data for accurate classification of grape crop stages: Leaf Set, Fruit Set, and Maturity/Harvest.

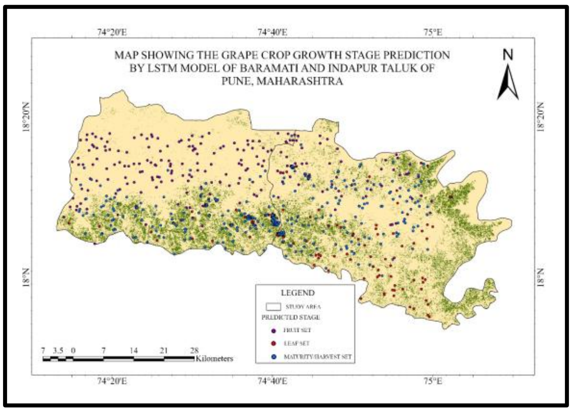

Figure 9. Phenological Growth Stage Prediction of Grape Crop by LSTM Model

Figure 9 presents spatial predictions of grape crop growth stages: Leaf Set**,** Fruit Set, and Maturity/Harvest, across the study area, generated by an LSTM model. Each point is colour-coded: green for Leaf Set, red for Fruit Set, and blue for Maturity/Harvest. The distribution highlights apparent spatial variations in phenological phases, reflecting diverse cultivation practices and climatic influences. Leaf Set dominates the southern regions, while Fruit Set and Maturity/Harvest are concentrated in the northern and central zones. These patterns offer valuable insights for precision irrigation scheduling, disease management, and harvesting operations. This demonstrates how deep learning combined with geospatial data can support real-time, site-specific decision-making in precision viticulture.

Figure 10 highlights an important aspect of grapevine growth stage analysis. The box plot compares NDVI values for the three key phenological stages: Leaf Set, Fruit Set, and Maturity/Harvest. As expected, Maturity/Harvest shows the highest NDVI values (around 0.7), indicating lush vegetation and fully developed canopies. Fruit Set comes next with moderate NDVI (around 0.6), while Leaf Set records the lowest values (around 0.4), reflecting early leaf development and limited canopy cover.

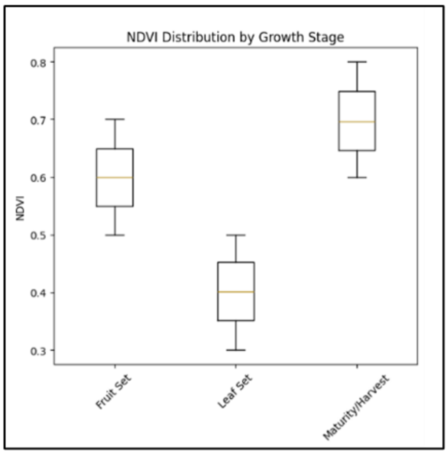

Figure 10. Distribution of NDVI by Growth Stage

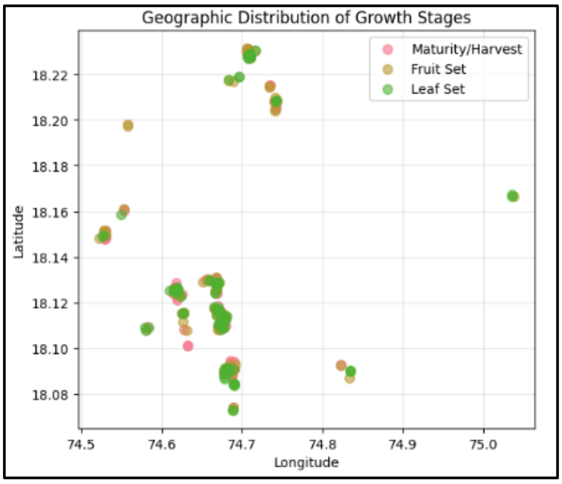

Figure 11. Geographic Distribution of Grape Crop Growth Stage

Figure 11 illustrates the geographical distribution of these growth stages across the study area. Each stage is colour-coded using point-based mapping: green for Leaf Set, orange for Fruit Set, and pink for Maturity/Harvest. The spatial pattern suggests that different parts of the region are in different growth stages, likely due to variations in climate, soil, and farming practices. This spatial insight is valuable for targeted interventions, helping farmers schedule irrigation, nutrient application, or harvests more precisely, ultimately improving productivity and resource efficiency.

The confusion matrix highlights the excellent classification capability of the LSTM model. It shows perfect accuracy for the Fruit Set stage, with all 85 instances correctly predicted. The Leaf Set stage also performs exceptionally well, with 84 out of 85 correct predictions and just one misclassified as Maturity/Harvest. For the Maturity/Harvest stage, 72 samples are correctly identified, while four are misclassified as Leaf Set, indicating minimal overlap between stages. Table 1 presents the classification performance of the model.

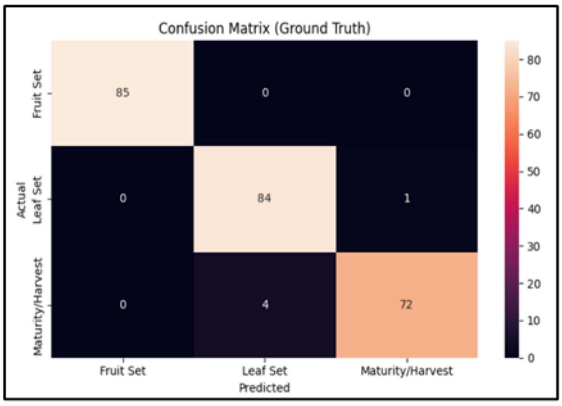

Figure 12. The Confusion Matrix for the Grape Crop Growth Stage Phases

Table 1. Classification Report of LSTM Model

Stage	Precision	Recall	F1-Score	Support
Fruit Set	1.00	1.00	1.00	17
Leaf Set	0.94	1.00	0.97	17
Maturity/ Harvest	1.00	0.94	0.97	16
Accuracy			0.98	50
Macro Avg	0.98	0.98	0.98	50
Weighted Avg	0.98	0.98	0.98	50

Predicted stage distribution:

- Leaf Set: 543 (43.6%)
- Maturity/Harvest: 368 (29.5%)
- Fruit Set: 335 (26.9%)

Table 2 illustrates the correct and incorrect classifications during various growth stages as predicted by the LSTM model.

Table 2- Class-wise Error Summary

Stage	Total Samples	Correct	Correct %	Misclassified	Miscass %
Fruit Set	85	72	84.71%	13	15.29%
Leaf Set	85	70	82.35%	15	17.65%
Maturity/Harvest	76	62	81.58%	14	18.42%

It presents the prediction performance of the LSTM model across three grape growth stages. The Fruit Set stage has the highest accuracy with 84.71% correct predictions, followed closely by Leaf Set (82.35%) and Maturity/Harvest (81.58%). Misclassification is lowest for Fruit Set (15.29%) and highest for Maturity/Harvest (18.42%), indicating that predictions become slightly less reliable in later stages. The model demonstrates good but slightly decreasing accuracy as the crop progresses through its growth cycle.

Discussion

This study explored how three deep learning models, U-Net, LSTM, and DeepLabV3, can be used together to monitor grape crops more effectively. Using satellite data from Sentinel-1 SAR and Sentinel-2 NDVI, along with agro-climatic records from 2016 to 2024, each model addressed a specific aspect of the monitoring process: U-Net helped with mapping the exact location of grape fields, LSTM tracked crop growth stages over time, and DeepLabV3 enhanced segmentation accuracy in complex agricultural areas.

The U-Net model performed exceptionally well in separating grape from non-grape fields. Its unique encoder-decoder design preserved important spatial details, which is crucial when working with high-resolution satellite images. With an F1-score of 96.1% and an mAP of 95.5%, it proved its strength in spatial segmentation. The alignment between training and validation losses also showed that the model didn't overfit and could generalise well across different seasons and field shapes.

The LSTM model was trained to identify grape growth stages—leaf set, fruit set, and maturity—by analysing monthly time-series data on NDVI, SAR, rainfall, temperature, and soil moisture. Although it didn't outperform the spatial models, it still showed decent accuracy with an F1-score of 80.4%. Some drop in performance may be due to seasonal noise in the climate data, but it still offered meaningful predictions that can guide decisions about irrigation or harvesting.

Among the three, DeepLabV3 stood out regarding accuracy and edge precision. Thanks to its advanced architecture that uses atrous convolutions and the ASPP module, it was able to capture even the most minor details of crop boundaries. With an F1-score of 92.08% and an mAP of 96.95%, it handled complex and fragmented field patterns remarkably well. The model's low validation loss confirmed its consistency, making it a strong candidate for real-world agricultural mapping and vineyard monitoring.

Compared to traditional machine learning methods like Random Forests or SVMs, which rely heavily on handcrafted features, the deep learning models used in this study showed significantly better accuracy, flexibility, and scalability. The combination of Sentinel-1 SAR and Sentinel-2 NDVI data played a key role in this improvement—SAR captured structural field characteristics, while NDVI reflected vegetation health.

The three deep learning models brought complementary strengths to the crop monitoring system: U-Net offered precise field-level segmentation, LSTM effectively tracked crop growth stages over time, and DeepLabV3 provided sharp boundary detection and strong generalisation across varied field types. This integrated approach creates a robust, scalable tool for precision agriculture, supporting timely decisions in vineyard management, yield forecasting, and sustainable resource use.

5. Conclusion

This study aimed to develop a near-real-time system for monitoring grape cultivation, using a combination of satellite imagery (Sentinel-1 SAR and Sentinel-2 NDVI) and climate data such as rainfall, temperature, and soil moisture. The goal of covering the years 2016 to 2024 was to map grape and non-grape fields while tracking key growth stages with greater accuracy and timeliness than traditional approaches.

Three deep learning models, U-Net, LSTM, and DeepLabV3+, were used to achieve this. Each model served a different purpose: U-Net was used for detailed field segmentation, LSTM was used to predict crop growth stages over time, and DeepLabV3+ was used for high-precision classification across varied landscapes. U-Net performed well in identifying field boundaries (F1-score: 96.1%), LSTM effectively captured growth stages like Leaf Set, Fruit Set, and Maturity (F1-score: 80.4%), and DeepLabV3+ provided excellent segmentation results, especially in fragmented fields (F1-score: 92.08%).

Compared to earlier machine learning methods that relied on handcrafted features, these models offered stronger performance, better scalability, and improved adaptability. By combining SAR and NDVI data, the system could leverage both structural and vegetation health information, leading to better decision-making tools for vineyard management.

Looking ahead, this framework can be enhanced by adding more advanced data sources like hyperspectral imagery or LiDAR, and by deploying it on cloud platforms for real-time monitoring. Overall, this approach holds real promise for making grape farming more data-driven, efficient, and sustainable, especially in India's rapidly evolving agricultural landscape.

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