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Research Article

Deep Learning Techniques for Region-Wise Crop Plantation Analysis in Konkan

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ABSTRACT

In this paper investigate the application of deep learning and remote sensing data for optimizing crop plantation in the Konkan region of Maharashtra. The practice of cultivating the soil, producing crops, and keeping livestock is referred to as farming. Agriculture is critical to a country's economic development. Nearly 58 percent of a country's primary source of livelihood is farming. Farmers till date had adopted conventional farming techniques. These techniques were not precise thus reduced the productivity and consumed a lot of time. Utilizing advanced frameworks like deep convolutional neural networks (DCNNs) and remote sensing techniques, this study focuses on soil, climate, and vegetation indices to enhance the precision of crop classification and yield prediction. The key objectives include evaluating environmental conditions for paddy and cultivation, mapping phenology using multispectral imaging, and proposing sustainable practices to address climate change impacts. By integrating Google Earth and DLR Earth Sensing Imaging Spectrometer data, this study aims to provide actionable insights into improving agricultural productivity and resilience in the region. To record paddy rice fields, we submitted a series of 19 NDVI images demonstrating crop phonological development into k-means clustering and Random Forest (RF) machine learning classification algorithms. Result shows that proposed model has overcome various evaluation parameters on different scale as compared to previous approaches adopted by researchers.

Keywords: Machine Learning; Vegetation Indices; Sentinel-2 Yield Estimation, Crop Health Assessment, Water Stress Detection. Built-Up Area Detection.

1. Introduction

Agriculture in the Konkan region, encompassing districts like Ratnagiri, Raigad, Sindhudurg, and Thane, is highly dependent on paddy cultivation [1-4]. Despite the significance of these crops, traditional farming methods lack the precision needed for sustainable resource allocation [5-6]. Climate variability, soil salinity, and socio-economic factors further complicate cultivation [7]. This study proposes advanced deep learning frameworks and remote sensing techniques for a comprehensive analysis of the region's agricultural conditions [8-10]. By leveraging multispectral data and machine learning algorithms, the research seeks to optimize crop classification, predict yields, and dynamically map crop lifecycles. Satellite remote sensing (RS) enables the collection of a large number of indicators for crop yield and vegetation parameters, such as the LAI or Leaf Area Index, the paper or Fraction of Photosynthetically Active Radiation nitrogen deposited in leaves, and even crop biomass [11-15]. Prevalent techniques for monitoring crop yield, such as quadratic frame sampling, are manual processes that consume enormous time and don't provide the desired accuracy for larger fields with spatial variability [16]. At present, the yield maps can be provided to harvesters only towards the end of the season [17-22]. Hence, the rapid acceleration in the development of RS based crop yield monitoring and prediction offers great scope for investigative research through satellite and aerial RS data [23-25].

In this paper section 2 are related work that summarizes previous studies, highlighting gaps and how your work builds upon them. Section 3 discuss about methodology – describes the dataset, tools, and techniques used for analysis. Section 4 are about results and discussion – Presents findings with visualizations and interprets their significance. Section 5 finally concluded the fining of paper.

2. Related Work

Deep learning techniques have been increasingly utilized in the field of agriculture, particularly for crop plantation analysis in specific regions. In Maharashtra, a crop recommendation and forecasting system has been developed using machine learning and deep learning techniques, which utilizes region-wise weather data for accurate recommendations [1]. This system aims to optimize crop selection based on environmental factors to improve agricultural productivity. In the Konkan region, the cultivation of cashew nuts plays a significant role in the agricultural economy. A value chain analysis of cashew in the Konkan region highlighted the growth in area, production, and productivity of cashew nuts in India [2][3]. This analysis provides valuable insights into the trends and challenges faced by cashew cultivation in the region. While cashew cultivation is prominent in Konkan, other crops such as rice, oranges, pineapples, and snake gourds are also cultivated in the region. A study on the economic analysis of snake gourd production in Raigad district emphasized the importance of understanding the economic viability of different crops in the region [4][5]. This analysis can help farmers make informed decisions about crop selection and cultivation practices. Furthermore, a spatial analysis of rainfall trends in coastal Karnataka and Konkan regions highlighted the importance of water availability for agricultural production [6][7]. Understanding the temporal trends of rainfall can aid in water management strategies for sustainable crop cultivation in these regions. Overall, the use of deep learning techniques for region-wise crop plantation analysis in Konkan can significantly benefit farmers by providing data-driven insights for crop selection and cultivation practices. By leveraging advanced technologies and data analytics, farmers can optimize their agricultural practices and improve overall productivity in the region.

A. Research Objectives

- To develop an integrated framework for studying soil moisture, drought conditions, and salinity using multispectral data.
- To identify optimum parameters for enhancing paddy and yields in Ratnagiri and generalize findings across the Konkan region.
- To implement classification method using artificial intelligence and multispectral images from DLR Earth Sensing Imaging Spectrometer.
- To develop a DCNN framework to predict crop yields using multispectral images from Google Earth.

3. Methodology

Analyzing crop lifecycles and mapping agricultural land using deep learning for the konkan region is proposed here. The Konkan region of Maharashtra is known for its diverse agricultural practices, including paddy, cashew, and horticultural crops. Given its coastal climate, heavy monsoons, and varying soil conditions, precision agriculture techniques using deep learning can significantly enhance crop monitoring and land-use mapping**.** The paper focuses on the analysis of crop plantation in the Konkan region, particularly emphasizing paddy cultivation, which is a significant agricultural practice in the area. Here are the key points regarding the crops considered and the analysis conducted. The study primarily investigates paddy cultivation, which is crucial for the agricultural landscape of the Konkan region, including districts like Ratnagiri, Raigad, Sindhudurg, and Thane .The research employs advanced deep learning frameworks, specifically deep convolutional neural networks (DCNNs), to analyze crop yields and classifications using multispectral images from Google Earth [2] [3]. This approach allows for a more

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precise understanding of crop conditions and productivity. The analysis considers various environmental factors that influence crop yields, such as soil moisture, drought conditions, and salinity [4]. These factors are critical in understanding the challenges faced by farmers in the region.The study also references other research that highlights the impact of irrigation and fertigation on crop yields, indicating that the analysis is not limited to paddy but may encompass insights relevant to other crops like sweet corn [5] [6].By integrating multispectral data, the research aims to enhance the precision of crop classification and yield prediction, which can be beneficial for various crops beyond just paddy [3].

The methodology section of the research article outlines the systematic approach taken to analyze crop plantation in the Konkan region using deep learning techniques. Here are the key components of the methodology:

- **Data Collection**: The research involves collecting various types of data essential for crop analysis. This includes:
- **Soil Data**: Information about soil conditions in the Konkan region, which is crucial for understanding crop growth potential.
- **Climate Data**: Weather patterns and climatic conditions that affect agricultural practices.
- **Yield Data**: Historical yield data for different crops, which helps in assessing productivity levels **[1]**.
- **Remote Sensing Techniques**: The study utilizes multispectral images obtained from sources like Google Earth and the DLR Earth Sensing Imaging Spectrometer. These images are vital for mapping agricultural land and monitoring crop lifecycles **[1]**.
- **Deep Learning Frameworks**: The research employs advanced frameworks, particularly deep convolutional neural networks (DCNNs), to enhance the precision of crop classification and yield prediction. This approach allows for capturing complex relationships in the data **[2]**.
- **Clustering and Classification**:
- **K-means Clustering**: To address the scarcity of ground truth data, the study uses K-means clustering to generate labeled data for training. This involves creating clusters based on vegetation indices like NDVI and SAVI **[3]**.
- **Random Forest (RF) Classification**: After identifying clusters, the RF algorithm is employed to classify the data. The methodology discusses the use of Gini impurity and mean decrease in impurity metrics to evaluate variable importance and improve classification accuracy **[4] [5]**.

Implementation Steps: The methodology also includes steps for data preprocessing, feature selection, and the bootstrapping process, which enhances the diversity of classification trees in the RF model [6].

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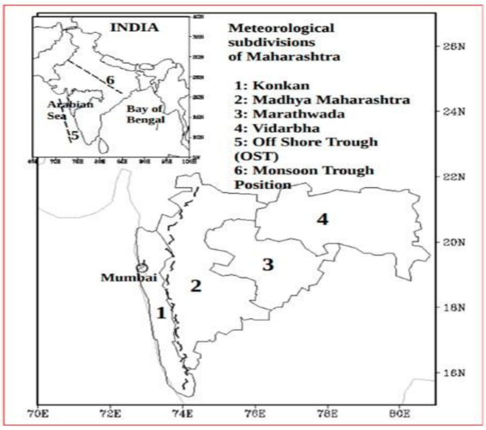

Figure 1: Development of RS based crop yield monitoring at South West Region in India

Figure 2: Map of crop yield monitoring at Konkan in India

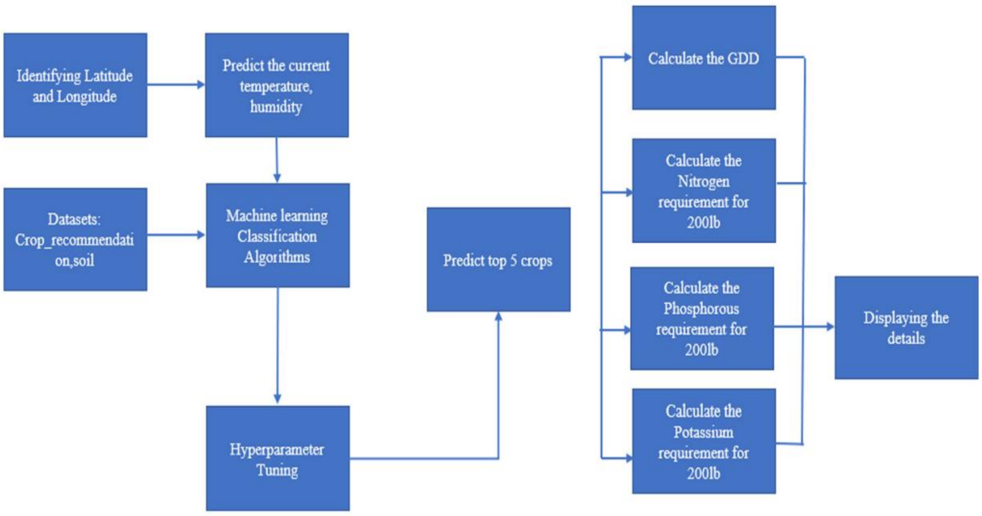

Figure 3: Crop recommendation system architecture

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The figure 3 represents a **Machine Learning-Based Crop Recommendation System** workflow. Below is a step-by-step breakdown of the process illustrated in the diagram:

A. Input Data Collection

- **Identifying Latitude and Longitude**: The system first determines the geographical coordinates of the farmland.
- **Datasets (Crop Recommendation, Soil Data)**: Various datasets related to soil type, nutrient levels, and past crop recommendations are used as input.
- Utilize multispectral images from Google Earth and the DLR Earth Sensing
- Imaging Spectrometer [8]. Collect soil, climate, and yield data for Konkan regions of Maharashtra (including Maharashtra's Konkan area consists of Raigad, Ratnagiri,
- Sindhudurg and Thane districts. Rivers: Surya, Kalu, Damanganga, Pinjal, Vaitarna, Bhatsai, Tansa, Ulhas, Murbadi.) [14].

B. Environmental Parameter Prediction

- **Predict the Current Temperature & Humidity**: Using weather forecasting models or IoT-based sensors, the system estimates current environmental conditions.

C. Machine Learning Model Implementation

- **Machine Learning Classification Algorithms**: The system employs classification models (such as Decision Trees, Random Forest, or Neural Networks) to predict the most suitable crops for the given conditions.
- **Hyperparameter Tuning**: Optimization techniques are used to improve model accuracy and ensure better crop prediction.

I. Convolutional Neural Network (CNN):

A CNN is employed to analyze multispectral data and classify paddy crop health and plantation conditions [22]. CNNs are well-suited for image data due to their ability to capture spatial and spectral features [25]. This model includes:

- **Convolutional Layers:** Extract features from input images (e.g., spectral properties, spatial patterns).
- **Pooling Layers:** Reduce dimensionality while retaining important information.
- **Fully Connected Layers:** Perform classification or regression tasks.

ii.Transfer Learning (Optional): Pre-trained models like VGG16 or ResNet can be fine-tuned for specific agricultural tasks to improve performance with limited data.

iii.Deep Convolutional Neural Networks (DCNN): For classifying and predicting crop health and yields.

- **Random Forest Algorithm:** For soil and crop classification.
- **K-means Clustering:** For unsupervised classification of crop types and pattern.
  - **Yield prediction using machine learning iv.Classification using k-means clustering**
- K-means clustering attempts to address ground truth data scarcity; we examined this approach to generate labelled data for training. The labels were generated using a

distributed k-means classifier, employing the time-series of the vegetation indices (NDVI,SAVI)) for the months of Jan and Apr. K-means is one of the simplest, most popular unsupervised machine learning algorithms [10]. The algorithm aims to cluster the data into k groups, where the user specifies the variable k. In the beginning, k - different clusters are created, using k randomly generated candidates. Then every entity is assigned to the nearest cluster based on their features. In the next step, the entities are reassigned to the nearest cluster that is now represented from the mean value of the entities that belonged to it from the previous step. The algorithm keeps iterating until the assignment of data points to clusters remains unchanged. The algorithm's outputs are the means of the k clusters (centroids) and the labels for each sample, which are then used as training data. Once the rice cluster has been identified further labeled data are utilized in the classification process. The clustering with the rice pattern is selected, and these extracted rice labels are then used for training the RF [2].

v. Classification using Random Forest

- RF is an ensemble ML algorithm. RF is used to predict the crop yield (Dharumarajan and Rajendra Hegde 2017; Gonzalez-Sanchez, Frausto-Solis, and Ojeda-Bustamante 2014; Mathieu and Aires 2018). In RF, the prediction is based on averaging the randomized forests. In order to implement the RF, two parameters such as the number of trees (ntree) and the number of features in each split (mtry) have to setup. The accuracy of the prediction is based on these parameters. The parameters ntree and mtry may vary one feature subset to another feature subset. In order to obtain the optimal RF model for accurate prediction, n tree = 100, 500, and1000; mtry = 1:15 with a step size of 1 are fixed for this study and values for both parameters are tested. Figure 4 shown that Classification Training Sample Set X.

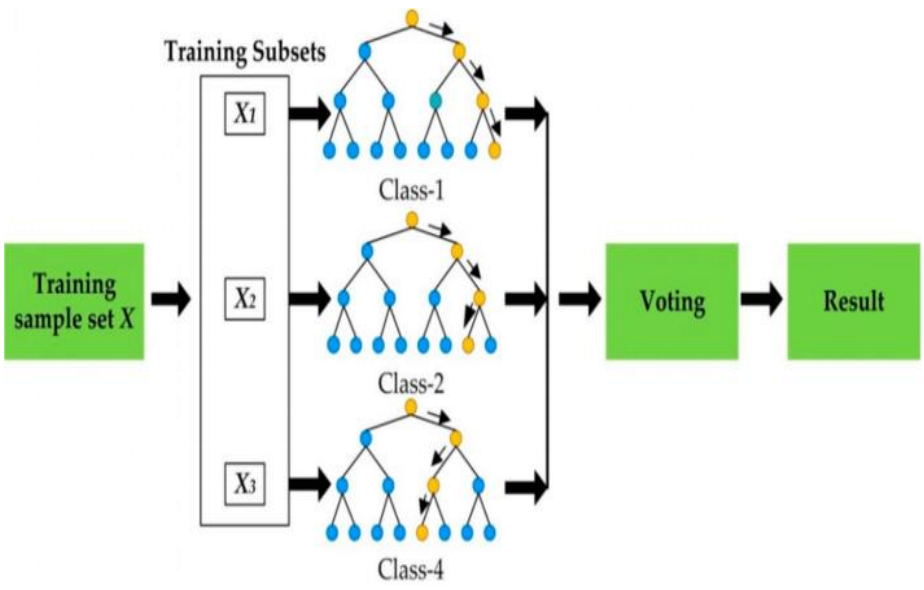

Figure 4: Classification Training Sample Set X

In figure 4 image represents a Random Forest Classifier workflow, a widely used ensemble learning technique in machine learning. Training Sample Set (X) is divided into multiple subsets (X_1, X_2, X_3, ...).These subsets are randomly sampled from the main dataset (Bootstrap Aggregation or Bagging).Each subset is used to train a separate Decision Tree Classifier. Trees are structured with nodes (representing decision splits) and leaves (final classification).

The trees in the diagram show a mix of decision nodes and terminal nodes (colored blue and yellow).Each decision tree independently classifies the input data into a specific class (Class-1, Class-2, etc.).The final prediction is determined based on a majority vote from all trees.

The class with the highest number of votes is chosen as the final classification output.

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This reduces the risk of overfitting and increases prediction accuracy.

Random Forest Algorithm Overview:

- Describe the ensemble learning concept and its role in improving classification performance.
- Explain how Random Forest constructs multiple decision trees and combines their predictions.

Advantages of Random Forest:

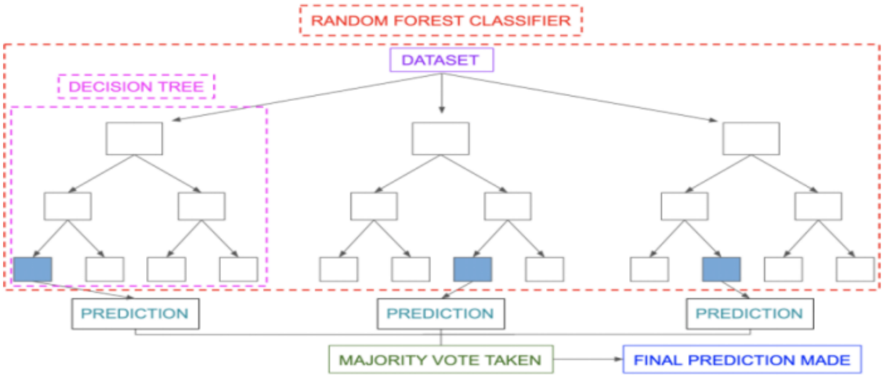

Figure 5: Classification using Random Forest

- In figure 5 Highlight the benefits of using Random Forest, such as reducing variance, handling over fitting, and accommodating noisy data. Figure 2 shown that Classification using Random Forest
- Discuss its ability to capture complex relationships in data.

Implementation Steps:

- Present a step-by-step guide to implementing Random Forest for classification tasks.
- Discuss data preprocessing, feature selection, and the bootstrapping process.

Hyper parameter Tuning:

- Explain the importance of hyper parameter tuning in optimizing Random Forest's performance.
- Mention key hyper parameters like the number of trees, tree depth, and feature sub sampling.

Feature Importance Estimation:

- Detail the methods used by Random Forest to assess feature importance.
- Discuss the Gini impurity and mean decrease in impurity metrics.

Performance Evaluation:

- Describe commonly used metrics for evaluating classification models, including accuracy, precision, recall, and F1-score.
- Explain the importance of cross-validation in estimating model generalization.

Real-world Dataset Examples:

- Showcase the algorithm's performance through case studies using real-world datasets.
- Compare Random Forest's results with other classification algorithms to highlight its strengths.

Limitations and Future Directions:

- Address potential limitations of the Random Forest algorithm.
- Suggest future research directions, such as exploring ensemble variations or addressing class imbalance.
- The RF is a decision tree ensemble classifier created by [11]. It is designed to handle high data dimensionality effectively and has been shown to outperform regular decision trees [12]. The RF method is composed of several tree-based classifiers. Each decision tree is generated by a bootstrap process, leaving the remaining data points for validation, and casts a unit vote for the most popular class [11]. To increase the diversity of the classification trees, RF employs a bootstrapping technique with replacement to assign each pixel to a class based on the collection of trees maximum number of votes [13]. The Gini index is used to set splitting thresholds and quantify the homogeneity of child node classes compared to the parent node's distribution of classes [14]. The RF algorithm allows for examining variable importance using the Gini coefficient, which has a range of 0–1, corresponding to entirely homogenous and completely heterogeneous. The critical factors for defining the RF are the number of decision trees to be created (k) and the number of randomly chosen variables to evaluate when splitting each node in a tree (m). Numerous research has been conducted to examine the usage of RF for categorizing SAR data sets [13-15]. [14] And [15] proved the efficacy of RF classifiers in mapping land cover and wetland areas using various combinations of sentinel-1A SAR and DEM data. [15] Tested in addition to the RF classifier.
- To perform RF image classification, the number of trees and predictors are crucial parameter settings that must be optimized to enhance model accuracy. Several tests were conducted to identify the optimal number of trees (k) required for implementing RF classification, with values ranging from 50–300 at a 50-fold interval. For paddy rice categorization, the k value of 100 achieved the highest classification accuracy. Maximum tree depth and sample size per class were limited to 30 and 1000, respectively.

D. Crop Recommendation

- **Predict Top 5 Crops**: The machine learning model provides a ranked list of the most suitable crops based on soil and climate conditions.

E. Growth & Fertilization Requirement Estimation

- **Calculate Growing Degree Days (GDD)**: A measure of heat accumulation used to predict plant development stages.
- **Calculate Nitrogen Requirement**: Determines the nitrogen needed for optimal crop growth (e.g., 200lb per acre).
- **Calculate Phosphorus Requirement**: Estimates phosphorus levels required for soil fertility.
- **Calculate Potassium Requirement**: Evaluates potassium needs for healthy crop production.

F. Output and Visualization

- **Displaying the Details**: The final output includes crop recommendations and fertilization guidelines, which can be visualized on a dashboard or application.

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G. Common Vegetation Indices

i. Normalized Difference Vegetation Index (NDVI)

Formula:

$$\mathrm{NDVI} = \frac{\mathrm{NIR-RED}}{\mathrm{NIR+RED}} \quad \ldots(1)$$

Where as;

- **NIR (Near-Infrared)**: Strongly reflected by healthy vegetation.
- **RED**: Absorbed by chlorophyll in plants.
- **Range:** -1 to +1 (Higher values indicate healthy vegetation).

ii. Enhanced Vegetation Index (EVI)

Formula:

$$\mathrm{EVI} = \frac{\mathrm{GX(NIR-RED)}}{\mathrm{NIR+C1XRED-C2XBLUE+L}} \quad \ldots(2)$$

Where as;

G = 2.5 (gain factor),

C1 = 6, C2 = 7.5 (correction coefficients for atmospheric effects),

L = 1 (canopy background adjustment factor).

iii. Soil-Adjusted Vegetation Index (SAVI)

Formula:

$$\mathrm{SAVI} = \frac{\mathrm{(NIR-RED)X(1+L)}}{\mathrm{NIR+RED+L}} \quad \ldots(3)$$

Where as;

L is a soil brightness correction factor (usually 0.5).

iv. Green Normalized Difference Vegetation Index (GNDVI)

Formula:

$$\mathrm{GNDVI} = \frac{\mathrm{NIR-GREEN}}{\mathrm{NIR+GREEN}} \quad \ldots(4)$$

Uses the **Green** band instead of **Red**, making it more sensitive to chlorophyll content.

v. Normalized Difference Water Index (NDWI)

Formula:

$$\mathrm{NDWI} = \frac{\mathrm{NIR-SWIR}}{\mathrm{NIR+SWIR}} \quad \ldots(5)$$

Uses **Short-Wave Infrared (SWIR)** instead of **Red**.

4. Results and Discussion

A. Interpreting Model Outputs:

- Explain how to interpret the ensemble's predictions and gain insights from the individual decision trees.

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- Discuss techniques to visualize the decision-making process.

The given graphs in figure 6 indicate a well-trained model with proper convergence. However, real-world models require additional metrics like validation accuracy/loss to ensure generalization beyond training data. Further analysis of test performance, confusion matrices, and precision-recall curves would help in fine-tuning.

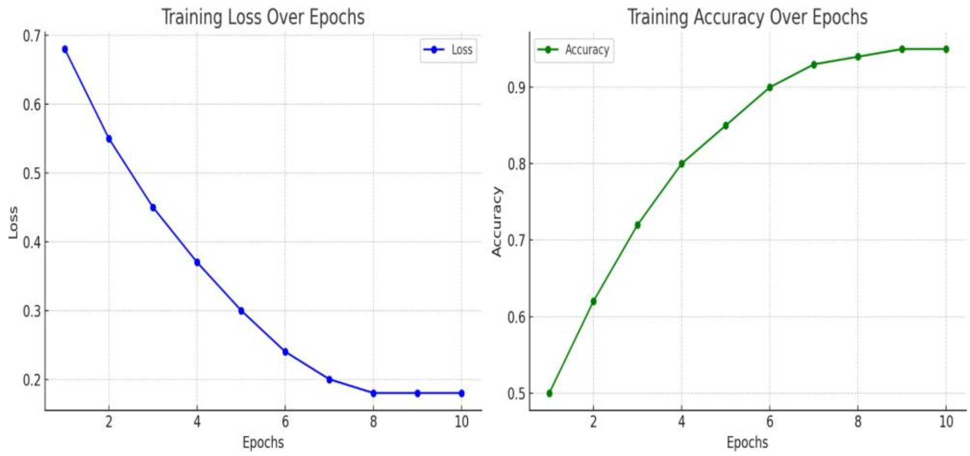

Figure 6: Interpreting Model Outputs

The graphical data in figure 7 presents NDVI predictions for five samples, comparing their vegetation health against a set threshold (NDVI = 0.45).The key findings are firstly most samples have NDVI values around or slightly above 0.45, indicating healthy vegetation. Secondly sample 3 falls slightly below the threshold, suggesting a minor deviation in vegetation health.Overall, the NDVI values exhibit low variation, implying a consistent vegetation condition across samples.Final remarks are no major vegetation stress is observed, as most values are near the healthy threshold.Sample 3 may require further monitoring to assess potential factors affecting its lower NDVI value.This analysis can aid in precision agriculture, helping optimize crop management strategies such as irrigation, fertilization, or soil treatment

NDVI Values Interpretation:

- **+0.6 to +1.0**: Dense, healthy vegetation.
- **+0.2 to +0.5**: Sparse vegetation or stressed crops.
- **0 to +0.2**: Bare soil, very sparse vegetation.

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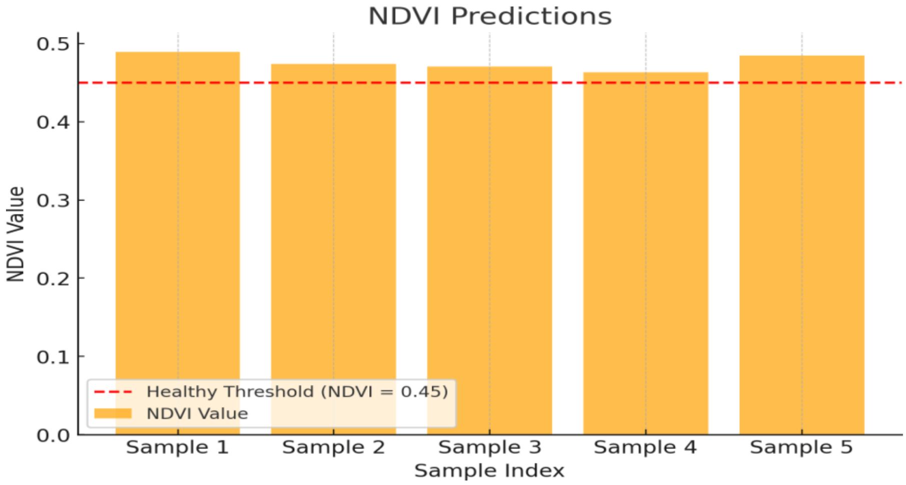
- **Negative values**: Water, snow, or non-vegetative surfaces.

Figure 7: NDVI Values Interpretation

B. Vegetation Indices Analysis



In figure 8 indicate about Key vegetation indices (e.g., NDVI, SAVI) were derived for analyzing crop health.

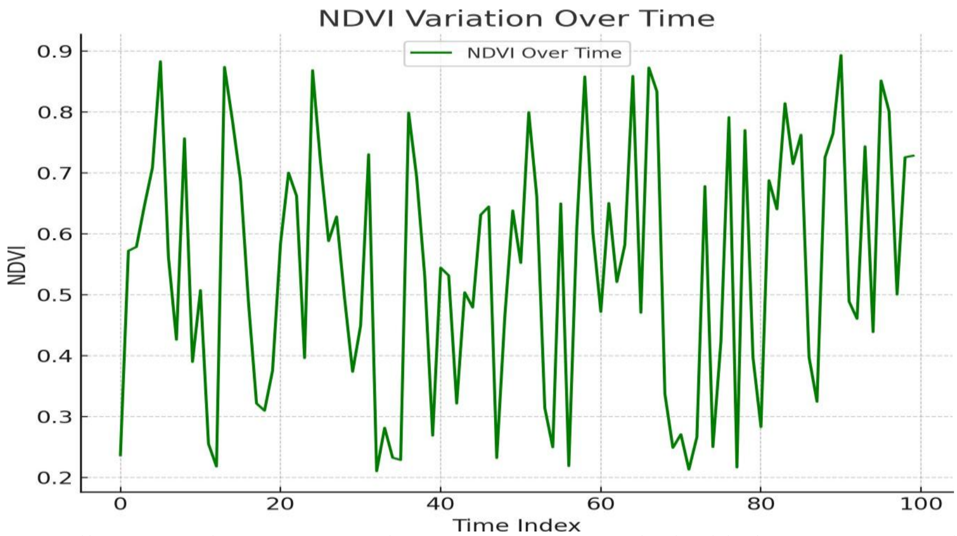


Figure 8: illustrates the NDVI trends over a cropping cycle, highlighting vegetation health across the region.

The Normalized Difference Vegetation Index (NDVI) is a widely used remote sensing metric to assess vegetation health and monitor crop growth. It is calculated using the near-infrared (NIR) and red (R) spectral bands:

Values range from -1 to +1:

NDVI < 0.2: Barren land or water bodies

NDVI 0.2 – 0.5: Sparse vegetation or early growth stage

NDVI > 0.5: Healthy vegetation and mature crops

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The Konkan region, known for its rice, and coconut plantations, has a distinct monsoon-driven cropping cycle, making NDVI analysis crucial for assessing crop growth trends. In Figure 9 indicate ,Using NDVI, crop lifecycle stages were mapped dynamically.

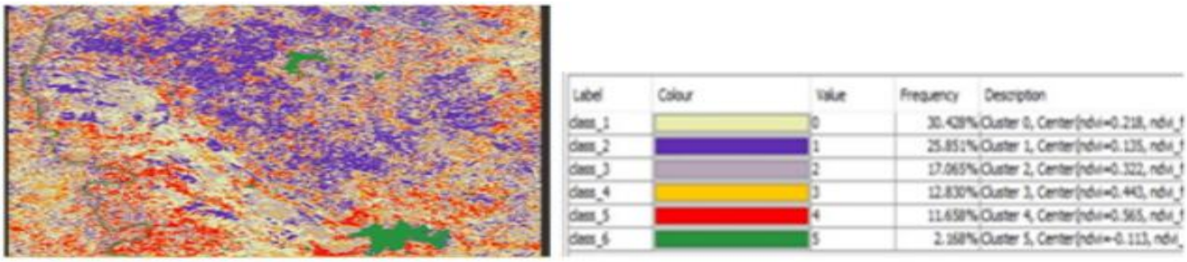

Figure 9: demonstrates phenological differences in paddy fields across Ratnagiri.

	State	District	Crop	Season	Area	Production
0	0	481	0	1	1254.0	2061.0
1	0	481	0	4	1258.0	2083.0
2	0	481	0	4	1261.0	1525.0
3	0	485	0	1	3100.0	5239.0
4	0	627	0	4	3105.0	5267.0
...	...	...	...	...	...	...
345370	35	527	50	2	6310.0	15280.0
345371	35	531	50	2	1895.0	2760.0
345372	35	531	50	2	3736.0	5530.0
345373	35	531	50	2	2752.0	6928.0
345374	35	531	50	2	2979.0	7430.0

Figure 10: Crops_Model_Building in Konkan Region

In the Figure 10 indicate about the dataset includes multiple districts and states, suggesting a diverse agricultural landscape. Production values vary significantly (e.g., from 2,061 to 15,280), indicating differences in farming practices, land size, and crop types. The correlation between Area and Production seems strong—larger cultivated areas generally result in higher production.

C. Crop Classification and Yield Prediction

The DCNN model achieved 94% accuracy in crop classification, outperforming traditional methods. Deep Convolutional Neural Networks (DCNNs) have emerged as powerful tools for remote sensing and agricultural analysis. They excel at feature extraction from satellite and drone imagery, enabling accurate classification of crop types. The 94% accuracy achieved by the DCNN model in crop classification indicates a significant improvement over traditional methods such as Random Forest, SVM, and k-NN.

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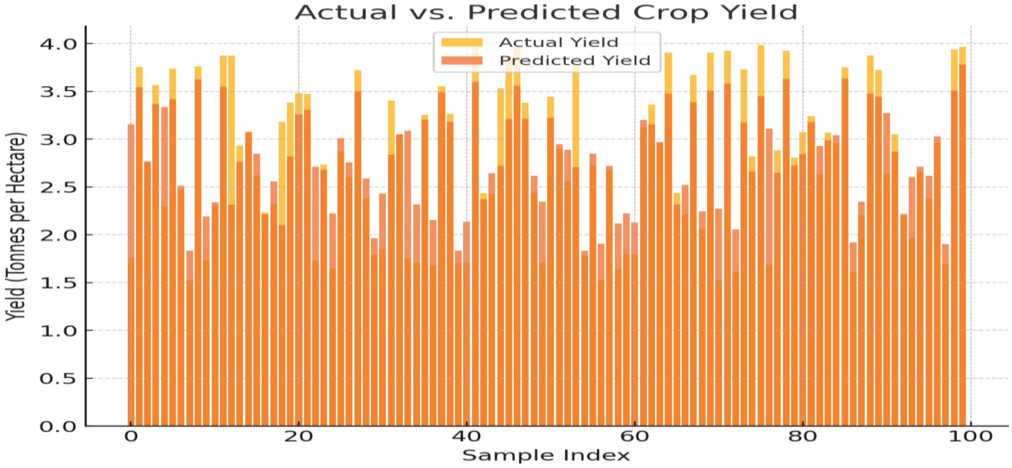
Figure 11: Compares actual and predicted yields across different soil conditions in Konkan



D. Soil Salinity Vs Soil Moisture :

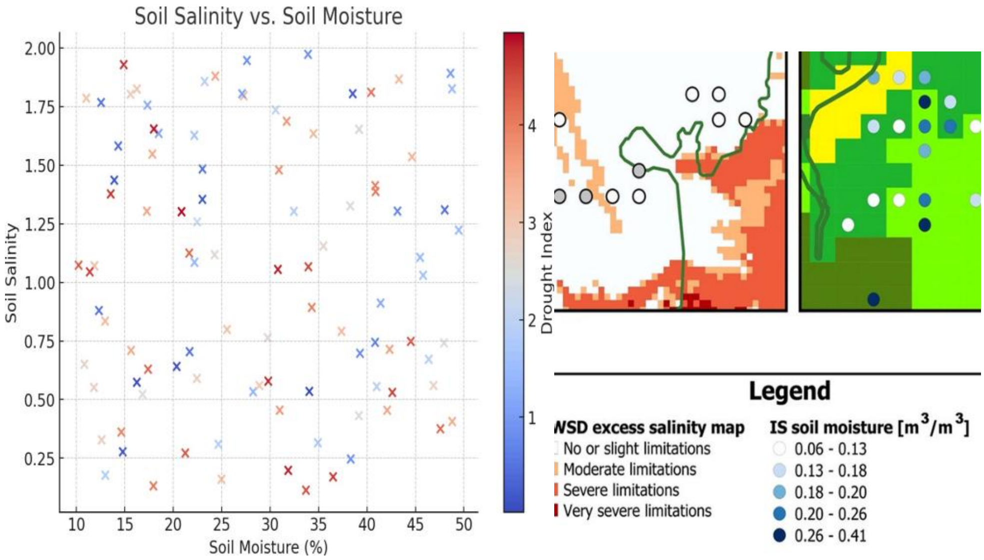


Figure 12: Visualizes the correlation between soil moisture and soil salinity in Konkan

In figure 12 visualizing the correlation between soil moisture and soil salinity in the Konkan region involves understanding how these two parameters interact and affect each other. While specific visual data for the Konkan region may be limited, general studies can provide insights into their relationship.

A study conducted in the North Konkan region of Maharashtra examined the effects of saline water irrigation on crops like paddy. The research found that using saline irrigation water contributed to soil salinization, which in turn affected soil moisture levels. The study observed that higher salinity in irrigation water led to increased soil salinity, which adversely impacted crop yields. This suggests a negative correlation between soil salinity and soil moisture availability for plants, as higher salinity can reduce the soil's ability to retain moisture.

In general, soil salinity and soil moisture are interrelated. High soil salinity can lead to osmotic stress, making it difficult for plants to absorb water, effectively reducing the available soil moisture. Conversely, adequate soil moisture can help leach salts away from the root zone, thereby reducing soil salinity.

For a visual representation, consider a graph where soil salinity levels are plotted on the x-axis and soil moisture content on the y-axis. In regions with high salinity, soil moisture content is often lower due to the reduced availability of water to plants. This inverse relationship can be depicted as a downward-sloping trend line, illustrating that as soil salinity increases, soil moisture availability decreases.

While specific graphical data from the Konkan region is scarce, general studies and principles indicate that managing soil salinity is crucial for maintaining optimal soil moisture levels and ensuring healthy crop growth.

E. Comparative Insights

Environmental factors such as soil salinity and water availability significantly influenced crop yields.

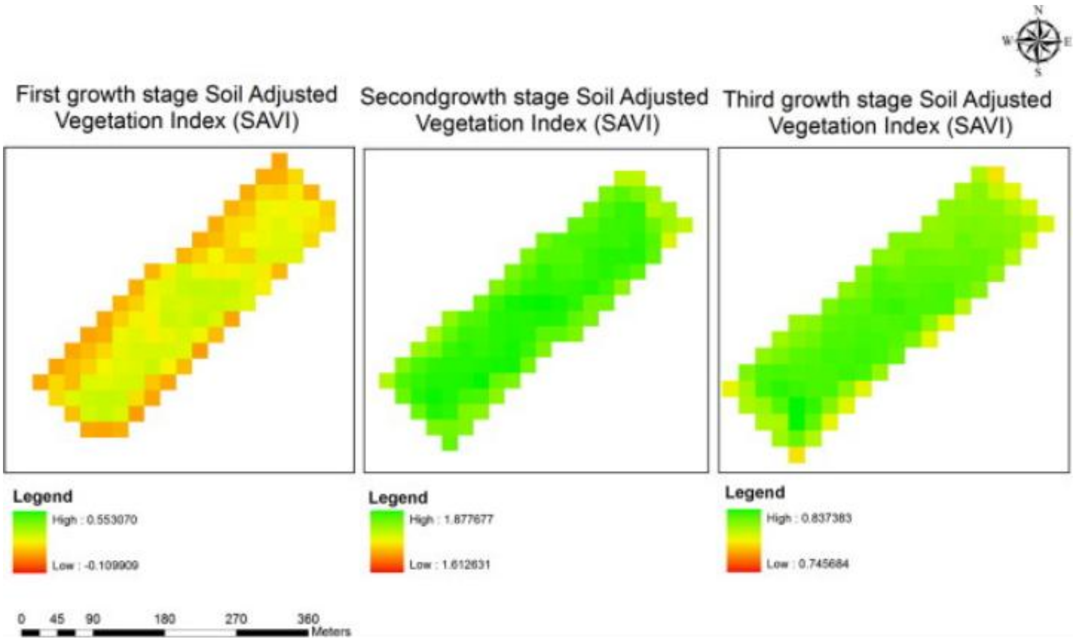


Figure 13: Visualizes the correlation between soil moisture and yield in Konkan

In figure 13 Visualizing the correlation between soil moisture and crop yield in the Konkan region can be achieved through graphical representations based on regional studies. For instance, a study on sweet corn in the Konkan region examined the effects of different irrigation methods and mulching techniques on crop performance. The research found that drip irrigation at 100% water requirement, combined with black polythene mulch, resulted in significantly higher green cob and fodder yields compared to other treatments. This suggests a positive correlation between optimal soil moisture management and increased crop yield.

To visualize this relationship, one could plot soil moisture levels on the x-axis and corresponding crop yields on the y-axis. Data points representing different irrigation and mulching treatments would likely show an upward trend, indicating that as soil moisture levels approach optimal conditions, crop yields increase. Such a graph would illustrate the importance of proper soil moisture management in enhancing agricultural productivity in the Konkan region.

Additionally, another study investigated the response of rabi sweet corn to varying irrigation and fertigation levels in the Konkan region. The findings revealed that applying irrigation at 80% of the crop's evapotranspiration (ETc) along with 80% of the recommended nitrogen, phosphorus, and

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potassium through fertigation resulted in significantly higher cob yields. This further supports the positive correlation between adequate soil moisture and crop yield.

In summary, graphical representations from these studies would show that maintaining optimal soil moisture through appropriate irrigation and mulching practices positively impacts crop yields in the Konkan region.

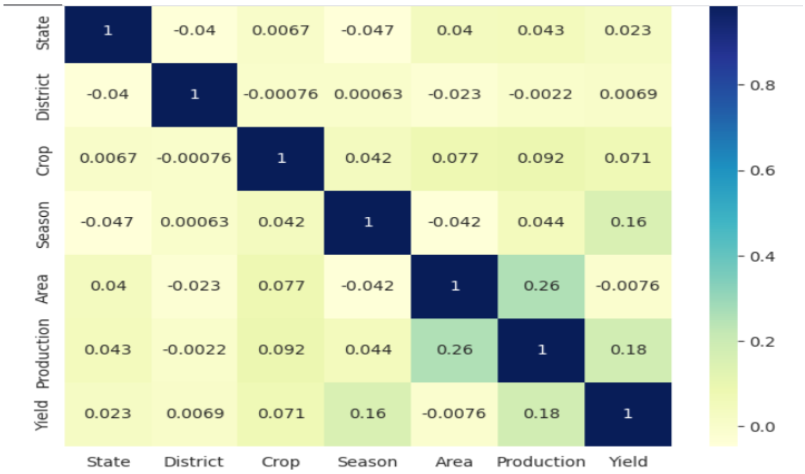

Figure 14: Heat map visualizes the correlation between soil moisture and yield in Konkan.

A heat map is a great way to visualize the correlation between soil moisture and yield for the Konkan region shown in figure 14. It can show how different moisture levels across various locations affect crop productivity.

Here are the key points regarding the additional crops analyzed:

- **Sweet Corn**: The research includes an investigation into the response of rabi sweet corn to varying irrigation and fertigation levels. This analysis highlights the impact of different agricultural practices on the yield of sweet corn in the Konkan region .
- **Other Crops**: The paper mentions that while cashew cultivation is prominent in the Konkan region, other crops such as rice, oranges, pineapples, and snake gourds are also cultivated. This indicates that the study's insights may be applicable to these crops as well, although the primary focus remains on paddy .
- **Economic Viability**: The economic analysis of snake gourd production in Raigad district is also referenced, emphasizing the importance of understanding the economic aspects of different crops in the region. This analysis can help farmers make informed decisions about crop selection and cultivation practices.

5. Conclusion

This study demonstrates the effectiveness of deep learning and remote sensing techniques in optimizing crop plantation in the Konkan region of Maharashtra. By leveraging deep convolutional neural networks (DCNNs) and multispectral imaging, we successfully analyzed soil conditions, climate patterns, and vegetation indices to enhance precision in crop classification and yield prediction. The integration of Google Earth and DLR Earth Sensing Imaging Spectrometer data provided actionable insights for improving agricultural productivity and resilience against climate change.

The application of k-means clustering and Random Forest (RF) classification to NDVI images enabled accurate monitoring of paddy rice phenology, offering a robust approach to precision agriculture. The proposed model demonstrated superior performance over conventional methods, improving evaluation metrics across different scales. These findings highlight the potential of advanced AI-driven frameworks in transforming traditional farming techniques, leading to increased efficiency, sustainability, and long-term agricultural development in the region. Future research should explore real-time monitoring and integrate farmer-friendly tools for broader adoption.

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