Remote Sensing and AI-Driven Sustainable Cotton Farming for a Resilient Future

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Abstract

The remote sensing (RS) and geographic information system (GIS) technologies combined with artificial intelligence (AI) enable more efficient and sustainable agricultural ecosystems. In recent years, the use of the machine learning and the deep learning models trained over the geospatial data have emerged as a pivotal catalyst for sustainable and smart agriculture initiatives. The unmanned aerial vehicle (UAVs; drones) has become a transformative force in the context of crop health monitoring, disease detection and yield predictions combined with supervised and unsupervised machine learning that helps to revolutionize the motoring, deep analysis and timely decision making.
This study presents the integration of remote sensing technologies (e.g., UAVs, drones) combined with data-driven artificial technologies to help the farmers in precision agriculture for cotton framing for plant health monitoring against pest infestation, micro irrigation and crop yield prediction. A UAV-based dataset for cotton crops is prepared from a region in Pakistan. The prepared dataset is evaluated through multiple experiments using classical supervised machine learning algorithms for classification: Naïve Bayes (NB), Support Vector Machine (SVM), and Random Forest (RF). These classification algorithms helped to classify the cotton crop health, healthy or unhealthy. The experimental results indicate that the RF algorithm outperforms the other applied machine learning methods in terms of its accuracy and precision.

1. Introduction

Cotton industry is a vital pillar to boost the economic growth of any country and has a key impact on the life of human for clothing. The insufficient cotton farming practices for soil, health monitoring to detect pest infestations, and water mismanagement have hindered its full potential. Due to these issues, different countries around the globe are facing critical challenges related to cotton farming. Among these countries, Pakistan is facing the mentioned critical challenges including abrupt climate change. Even though Pakistan has been among the world's top cotton producers, often ranking fifth, it still faces major challenges in cotton production.

Cotton is an important cash crop in the world, a novel study (Xun et al., 2021) was taken for cotton mapping index by combining Sentinel-1 SAR and Sentinel-2 multispectral imagery that shows the phenology differences of crops in different regions based on crop types (Ashapure et al., 2020) and (Xiao et al., 2024) developed the artificial neural network (ANN) based machine learning frameworks for cotton yield estimation by using the remote sensing data collected from unmanned aircraft system (UAS). The framework provides a reliable estimation of cotton crop yields.

Geospatial analysis of satellite imagery has been used for the real-time characterization of urban environments for public health (Sarfraz et al., 2014). The Sentinel-2 imagery has been widely utilized for real-time cotton health and growth monitoring, including the analysis of crop responses to meteorological factors (Yang et al., 2024). One of the objectives of this study is to rationalize satellite and UAVs-based multispectral imagery for cotton crop analysis. Furthermore, the calculation of vegetation indices facilitates accurate crop health monitoring, stress detection, and precision agricultural decision-making. There is an emerging need to adopt advanced techniques and technologies in the cotton industry to support a sustainable and resilient future.

According to the relevant literature, satellite and UAV imagery have been widely used for assessing soil characteristics, monitoring water stress and plant health. However, the availability of UAV-based datasets remains limited. While both satellite and UAV imagery can be employed for plant-level observations, satellite data are constrained by spatial resolution and are therefore, less suitable for small-area analysis. In contrast, UAV imagery overcomes this limitation by providing high-resolution data. To address the scarcity of datasets, a UAV-based dataset for cotton crops was developed from a region in Pakistan.

Machine learning (ML) and deep learning algorithms combined with time series analysis have been used to accurately monitor and forecast various real-world issues, including crime (Tariq et al., 2021). The ML is also extremely useful to measure the plant health and to classify the healthy and unhealthy crops, and yield prediction. Based on the core interest either at plant-level or the leaf-level experimentation, different ML can be used depending on the core interest and the datasets availability, either at the field scale using UAV/satellite imagery or at close range using handheld cameras, respectively.

The supervised machine learning algorithms Naïve Bayes (NB), Support Vector Machine (SVM), and Random Forest (RF) were applied to multispectral UAV imagery. The prepared dataset was evaluated through multiple experiments using these algorithms for crop classification and analysis. The experimental results indicate that the RF algorithm outperformed the other applied machine learning methods.

2. Material and Methods

Cotton is an important crop grown mainly for its fiber, which is soft, hypoallergenic, and widely used in the textile industry. It also plays a major role in Pakistan's economy, contributing significantly to agriculture, GDP, and foreign exchange earnings, also supports food security by strengthening rural livelihoods.

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About 60 varieties are cultivated across Punjab and Sindh to enhance yield and fiber quality. They also improve resistance to pests and climate stress.

The unmanned aerial vehicles (UAVs; drones)-based dataset for the cotton crop is prepared. Figure 1 shows all the four stages of workflow pipeline for integrating remote sensing and AI-driven technologies in agriculture. The detailed stages of the pipeline are outlined as follows: at the initial stage, crop was cultivated, the drone imagery was collected with DJI Mavic 3M using the autopilot mode. The multispectral drone captures separate images for each spectral band during every acquisition; these images are stitching together to construct an Orthomosaic model and the vegetation heat map; features (healthy or unhealthy) were extracted for the machine learning models for the classification.

2.1 Case Study Area

To prepare the desired dataset, FH-938 cotton variety was cultivated in an experimental field covering an area of approx. 35,540 ft² in the premises of National University of Computer and Emerging Sciences, CFD Campus, Pakistan. It is located at 31°36'8.43"N, 73°2'14.26"E. The cotton variety FH-938, approved by the Punjab seed council, currently offers high fiber quality, strong yield, and resilience to pests and climate stress. Multiple options were available for satellite imagery, such as Sentinel-2, Landsat 8, and MODIS; however, their minimum spatial resolution of approximately 10 m was not suitable for the experimental field conditions. Commercial satellite imagery is relatively expensive; therefore, UAV-based imaging was selected as a cost-effective approach for this study.

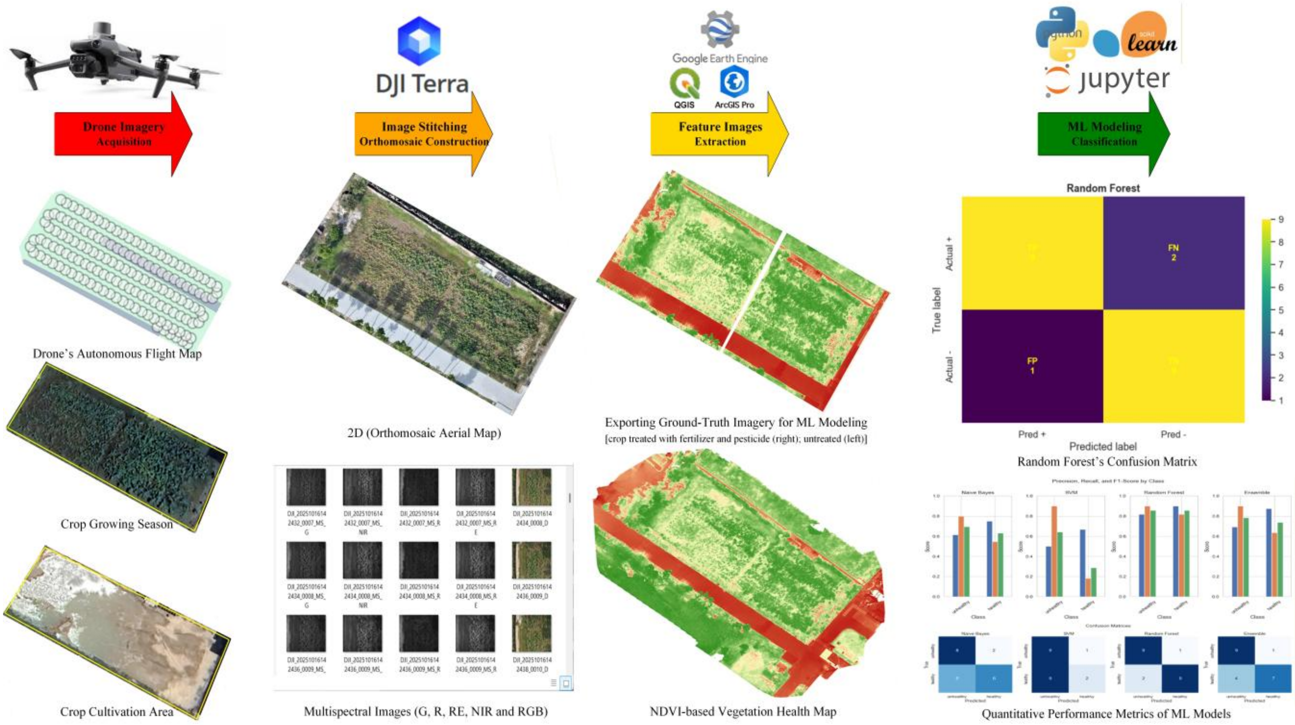

Figure 1. Pipeline’s block diagram for integrating remote sensing and AI-driven technologies in agriculture

2.2 Data Collection

The utilization of the UAVs (i.e., drones) in the agriculture sector is considered to be promising technology in today’s agriculture revolution (Phang et al., 2023). DJI (Da-Jiang Innovations), Parrot, Precisionhawk, AGEagle, and Trimble Navigation are leading manufacturers of UAVs (Doornbos et al., 2024).

The DJI (Da-Jiang Innovations) dominates the global market for commercial, agricultural, and consumer drones holding a significant market in drones technologies. The DJI Mavic 3M is used that has a dual camera, a 20MP 4/3 CMOS RGB and four 5MP multispectral cameras and a RTK for a precise positioning.

The DJI Mavic 3M features three flight modes, normal (N-mode), sport (S-mode), and function/attitude (F-mode/A-mode). Figure 2 shows the F-mode/A-mode autonomous flight route used for drone imagery acquisition with the DJI Mavic 3M over the Area of Interest (AOI). In autonomous mode, the drone performs flight operations automatically without manual pilot intervention.

2.2.1 UAV-Based Multispectral Imagery Acquisition

Multispectral UAV imagery was acquired using multispectral sensor mounted on Mavic 3M. A survey covered approximately 0.9927 ha with an average ground sampling distance (GSD) of 1.86 cm pixel^{-1}. A total of 564 images were collected across four spectral bands, including green, red, red-edge, and near-infrared (NIR). Image acquisition followed an aerial grid/corridor flight configuration to ensure sufficient image overlap and reliable feature matching during photogrammetric reconstruction. Radiometric calibration was applied using camera and sun irradiance correction to minimize illumination variability among spectral bands.

2.2.2 UAV-Based Multispectral Imagery Processing

The DJI Mavic 3M captures multispectral imagery comprising Green (G), Near-Infrared (NIR), Red (R), and Red Edge (RE) bands, along with high-resolution RGB (visible-light; Red, Green, Blue) images, all acquired simultaneously, in every capture used for autonomous flights as shown in Figure 3.

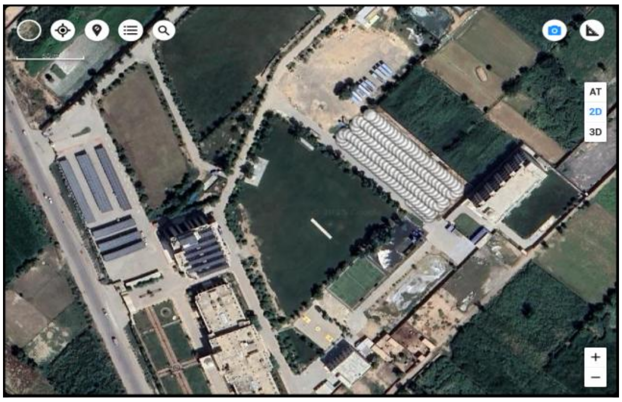

Figure 2. Drone imagery acquisition using the DJI Mavic 3M

The two core principles steps were followed, firstly, flying the drone (DJI Mavic 3M) on the area of interest (AOI) at the proper height of 40m and with the required overlaps of 85%. Secondly creating a 2D (Orthomosaic Aerial Map) and 3D (Digital Elevation Model (DEM) of drone data.

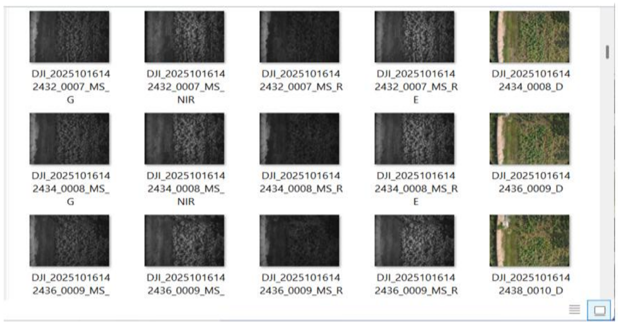

Figure 3. Multispectral drone raw imagery

The acquired multispectral imagery was processed using QGIS, software for photogrammetric reconstruction, orthomosaic generation, vegetation index calculation, and plant phenotyping analysis. Table 1. shows cloud densification details.

Category	Parameter	Details
Image Processing	Image Scale	Multiscale, 1/2 (Half image size, Default)
	Point Density	Low (Fast)
	Minimum Number of Matches	3
3D Reconstruction	3D Textured Mesh Generation	No
	Level of Detail (LOD)	Not Generated
Advanced Settings	Image Groups	Green, NIR, Red, Red edge
	Use Processing Area	Yes
	Use Annotations	Yes
Processing Time	Point Cloud Densification	04 min 03 s
	Point Cloud Classification	NA

Table 1. Point cloud densification details

All 564 images were successfully calibrated and geolocated, resulting in 100% image alignment. Bundle block adjustment and automatic camera optimization produced more than 2.35 million 2D keypoint observations and approximately 67,000 3D tie points, with a mean reprojection error of 0.183 pixels, indicating high geometric accuracy. Keypoint extraction averaged 10,000 keypoints per image, with a median of 4,136 matched keypoints per calibrated image.

2.2.3 Orthomosaics and DSM Generation

The processed and stitched imagery was subsequently used to generate Orthomosaics and NDVI-based vegetation heat maps for assessing vegetation condition, water status, soil moisture indices, and plant phenotypic characteristics. Dense point cloud densification produced approximately 3.5 million points with an average density of 173.46 points m^{-3}. Orthomosaics and digital surface models (DSM) were generated at a spatial resolution of 1×GSD (1.86 cm $pixel^{-1}$) using merged mosaic processing and adaptive surface smoothing. Reflectance maps and vegetation indices including NDVI were derived from the calibrated multispectral imagery, Table 2 details. Geolocation assessment indicated low positional variance with RMS errors below 0.23 m in the X, Y, and Z directions, confirming acceptable spatial accuracy for vegetation and precision agriculture analyses.

Category	Parameter	Details
Resolution	DSM and Orthomosaic Resolution	1 × GSD (1.88 cm/pixel)
DSM Filters	Noise Filtering	Enabled
	Surface Smoothing	Enabled (Sharp type)
Raster DSM	Generation Status	Generated
	Interpolation Method	Inverse Distance Weighting (IDW)
	Merge Tiles	Yes
Orthomosaic	Generation Status	Generated
	Merge Tiles	Yes
	Generation Status	Generated
	Resolution	1 × GSD (1.88 cm/pixel)
Reflectance Map	Merge Tiles	No
	Index Type	NDVI
	Export Format	Polygon Shapefile
Vegetation Index	Grid Size	400 cm/grid
	DSM Generation	1 min 28 s
	Orthomosaic Generation	10 min 31 s
Processing Time	Reflectance Map Generation	20 min 11 s
	Index Map Generation	29 s

Table 2. DSM, orthomosaic, and NDVI processing details

Figure 4 shows DSM digital surface model. The vegetation indices can be calculated from Orthomosaic either using the built-in NDVI tools or mathematically to monitor the crop health by classifying healthy, stressed/unhealthy or bare soil/no vegetation based on the high, medium and low normalized difference vegetation index values respectively. The NDVI is calculated from the visible and near-infrared light reflected by vegetation. The NDVI ranges from -1 to 1, the lower values indicate the absence of vegetation (e.g., water) and higher ones indicates the abundance of healthy vegetation, it is calculated as:

$$NDVI = \frac{NIR - Red}{NIR + Red}$$

The healthy plant absorbs most visible light that hits it and reflects larger near-infrared light; on the other hand, unhealthy

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plant reflects more visible light and less near-infrared light (de la Iglesia Martinez, 2024). The NDVI values indicate plant health; -1 to 0 shows no vegetation or dead plants, while higher values represent increasing vegetation. The values from 0.2–0.5 indicate stressed or moderate health, and above 0.5 (especially 0.7–1) represent healthy to very healthy vegetation. So, the higher NDVI values indicate greener, denser, and healthier plants otherwise unhealthy.

Similarly, the normalized difference water index (NDWI) is an excellent index for evaluating the water content of vegetation and is it calculated as follows:

$$NDWI = \frac{Green - NIR}{Green + NIR}$$

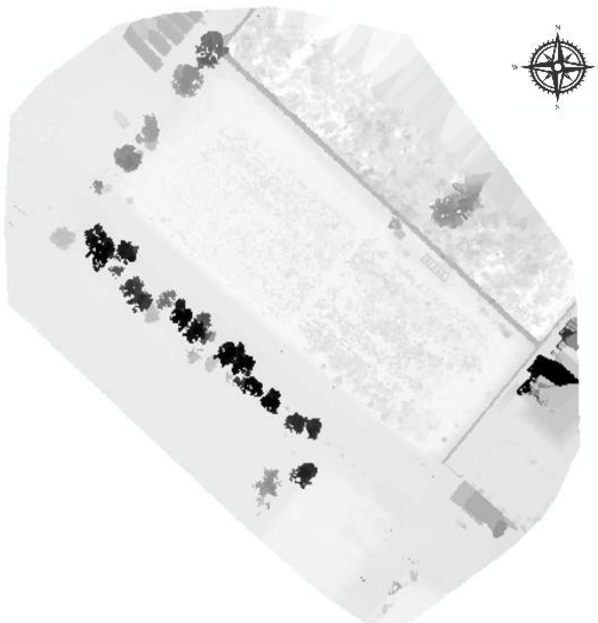

Figure 4. DSM digital surface model

Moreover, the soil moister index is also highly effective for quantifying moisture levels. The healthy vegetation absorbs most of the visible light that strikes it, and thus reflects a large portion of the near-infrared light. Whereas unhealthy reflects more visible light and less near-infrared light (Aierken et al., 2024).

2.3 AI/ML Modeling

Traditional machine learning (ML) algorithms, such as Random Forest (RF) and Support Vector Machine (SVM) are well suited for remotely sensed data (e.g., UAV and satellite imagery) for plant-level health monitoring, whereas deep learning algorithms particularly Convolutional Neural Networks (CNN) and ResNet models are more effective for close-up image-based disease detection and identification (Dhaka et al., 2021). Furthermore, deep learning approaches are capable of automatically extracting complex spatial and spectral features, thereby enhancing classification accuracy and improving the robustness of precision agriculture applications.

In addition to developing a UAV-based dataset for the cotton crop, another objective of this work was to implement traditional machine learning algorithms for the classification of overall plant health at the plant level rather than the leaf level.

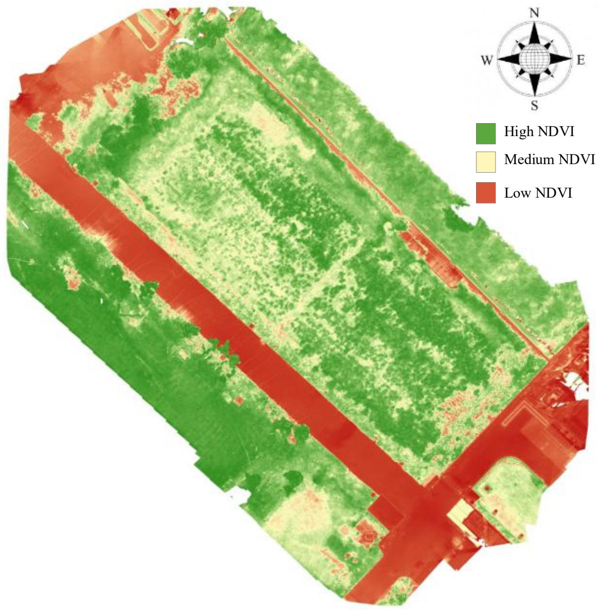

Figure 5. NDVI-based vegetation heat map

The Naive Bayes is an effective supervised machine learning classification algorithm based on probability theory. It predicts a class (e.g., healthy or unhealthy) by calculating the probability of that class given the observed features (Géron, 2023). The core of the algorithm, used to calculate conditional probabilities is as follows:

$$P(\text{Class}|\text{Features}) = \frac{P(\text{Features}|\text{Class}) \text{ x } P(\text{Class})}{P(\text{Features})}$$

The support vector machine (SVM) algorithm finds an optimal hyperplane that best separates data points one class from another class as shown in Figure 6 (MathWorks).

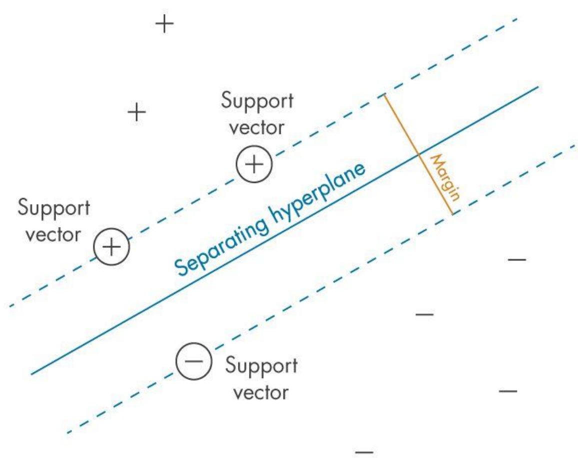

Figure 6. SVM (Support vectors & hyperplanes)

The core principle is to find the optimal decision boundary (hyperplane) that maximally separates the data points into different classes, thereby maximizing the margin between the closest data points called the support vectors (Géron, 2023).
The Random Forest (RF) can be expressed as an ensemble of decision trees whose predictions are aggregated as follows:

$$\hat{y} = \text{mode}\{h_k(x)\}_{k=1}^{K}$$

where $h_k(x)$denotes the prediction of the k-th decision tree and $K$is the total number of trees. Each tree is trained on a bootstrap sample $D_k \subset D$ and uses a random subset of features at each split leading to:

$$h_k(x) = \arg\max_{c \in C} P_k(c \mid x)$$

where $P_k(c \mid x)$ represents the class probability estimated by the k-th tree.

For regression tasks, the ensemble output is computed as the average:

$$\hat{y} = \frac{1}{K} \sum_{k=1}^{K} h_k(x)$$

The RF classifier is employed to distinguish between healthy and unhealthy plant conditions by aggregating predictions from multiple decision trees trained on randomly sampled subsets of features and data. The RF randomly samples subsets of the training data using a process known as bootstrap aggregating (bagging). The model is trained on these smaller datasets, and their predictions are combined. Through sampling with replacement, the same data instances can be selected multiple times, and the final output is determined by majority voting as shown in Figure 7 (Reinstein, 2017).

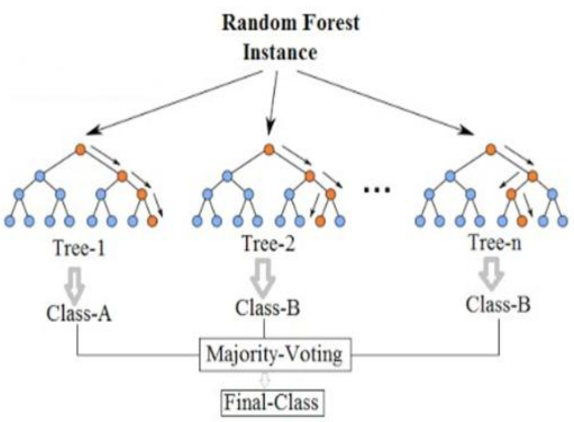

Figure 7. Random forest

The final classification is determined through majority voting, enhancing robustness and reducing the overfitting in complex agricultural datasets.

2.3.1 Model Training

The Naive-Bayes, SVM and Radom Forest are used to extract the plant's health information for decision making process. These algorithms are good for measuring the stress of an entire plant or crop system rather than individual leaves. These algorithms work on extracted features rather than learning the features automatically (e.g., CNN, ResNet etc.) that are computationally expensive but good for disease detection and identification at leaf-levels (Géron, 2023).
The experimental field area was divided at the time of cultivation into two sections: one for healthy corps treated with fertilizer & pesticide, the other left untreated and considered unhealthy. It helped to separate the images into healthy and unhealthy for the ML model using the ground-truth. Figure 5 shows the ground-truth observations and NDVI-based vegetation heat map. The features are extracted using QGIS by classifying the data into healthy and unhealthy vegetation categories based on ground-truth. These features are used for machine learning model training and testing. The dataset is divided using an 80/20 split where 80% of the data is used for training the model and the remaining 20% is used for the testing to evaluate its performance.

2.3.2 Model Evaluation

The commonly used evaluation metrics for classification (healthy vs. unhealthy) are accuracy, sensitivity (recall), specificity, and precision.

$$\textit{Accuracy} = \frac{\mathrm{TP+TN}}{\mathrm{TP+TN+FP+FN}} \in [0,1],$$

$$\textit{Sensitivity} = \frac{\mathrm{TP}}{\mathrm{TP+FN}} \in [0,1],$$

$$\textit{Specificity} = \frac{\mathrm{TN}}{\mathrm{TN+FP}} \in [0,1],$$

$$\textit{Precision} = \frac{\mathrm{TP}}{\mathrm{TP+FP}} \in [0,1].$$

The accuracy represents the percentage of correctly classified instances among all instances, while sensitivity (recall), specificity, and precision measure performance on positive and negative classes separately, such as correctly identifying positive cases and negative cases (Rainio et al., 2024).

The models are evaluated in this study by measuring the precision, recall (sensitivity) and F1-Score. F1-score is a combination of precision and recall, specifically their harmonic mean and is it calculated as follows:

$$F1 = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$$

The confusion matrix is used to evaluate how well a classification model is performing by comparison between actual values (true labels) and the predicted values (model output).

3. Results and Discussions

The FH-938 cotton variety was cultivated in the experimental field and the UAVs imagery was collected over the cotton area; the imagery is stitched together to construct an Orthomosaic and vegetations heat map. The NDVI is calculated from the visible and near-infrared light reflected by vegetation. The NDVI ranges from -1 to 1, the lower values indicate the absence of and higher values indicate abundance of vegetation.

The UAV imagery was collected using autonomous flight route (self-flying mode). Furthermore, the features were extracted using QGIS by classifying the data into healthy and unhealthy features for the ML modelling for the classification. In this paper, the supervised machine learning algorithms for the classification, the Naive-Bayes (NB), Support vector machine (SVM) and Radom Forest (RF) and ensemble learning were used for the classification of the cotton crop as either healthy or unhealthy.
The evaluation matrices used in the experimentation are Precision, Recall and F1 score. Among these algorithms, the RF has performed well on this dataset as compared to other algorithms in terms of its accuracy and precision. The confusion matrix of RF is shown in Figure 8.

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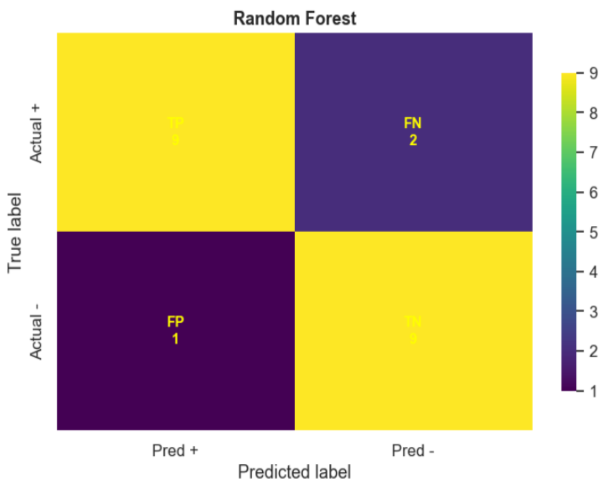

Figure 8. Random Forest’s confusion matrix

The RF scored 0.82, 0.90, and 0.86 for unhealthy and 0.90, 0.82, 0.86 for healthy class in terms of precision, recall, f1-score respectively as compared to SVM and Naive-Bayes which scored comparatively less. The ensemble learning machine learning technique is also applied where multiple models are combined to make better predictions than a single model. The experimental results shown in Figure 9 indicate that the RF algorithm outperforms the other applied machine learning algorithm (methods) in terms of its accuracy and precision.

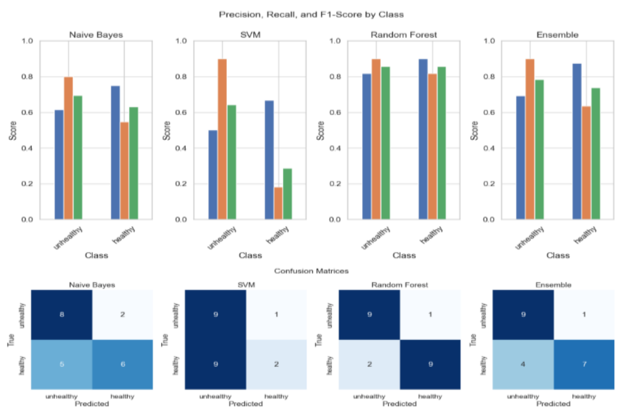

Figure 9. Performance comparison of ML classifiers

4. Conclusion

The integration of remote sensing technologies and unmanned aerial vehicle combined with data-driven artificial technologies would help the farmers in precision agriculture for cotton framing to monitor against pest infestation, micro irrigation and crop yield prediction.

The satellite data is constrained by spatial resolution and is therefore, less suitable for small-area; UAVs overcome this limitation. The use of remotely sensed dataset (using UAVs) helps to train the AI classifiers for classifying the crop health and mitigate related issues on time leading to sustainable cotton farming for a resilient future. The UAVs-based dataset further could be used for the disease detection. The experiments showed the superior performance of Radom Forest for the classification on the UAVs-based imagery is significantly better as compared to the other traditional classifiers used in this research, Naïve-Bayes and SVM.

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