A Comprehensive Framework for Remote Sensing and AI-Driven Real-Time Cotton Health Monitoring and Disease Detection

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Abstract

Effective monitoring of cotton fields, especially at the regional level, while also detecting diseases in individual plants, remains a significant problem in precision agriculture. This paper presents a combined framework for monitoring cotton in Pakistan, using satellite remote sensing and artificial intelligence-based leaf image classification. Multi-temporal Sentinel-2 imagery from the 2022 kharif season was used to map cotton fields and evaluate canopy condition during the growing season. Cotton fields were mapped using a Random Forest classifier with an overall accuracy of 93% and a Kappa coefficient of 0.82. The estimated cotton acreage of 65,269 ha nearly matched official figures. The crop state inside the mapped cotton area was then evaluated using a Fused Health Index constructed from NDVI, EVI, NDMI, NDRE, and SAVI. The results showed geographic variability in canopy condition, with 24.5% of the region falling into the low-health class, 50.9% in the moderate-health class, and 24.6% in the high-health class. A Vision Transformer model achieves 97% accuracy in classifying RGB images of cotton leaves into eight diseases and conditions. The satellite analysis identifies where stress is concentrated at the district scale, while the image-based model gives symptom-level diagnostic help. Together, these results suggest that combining remote sensing and artificial intelligence can improve timely cotton monitoring and allow more targeted field management.

1. Introduction

Cotton is one of the most economically important crops in many agricultural regions, with significant implications for raw material supply, rural livelihoods, and agro-industrial development. Accurate and up-to-date information on crop breadth, growth conditions, and new signs of stress is needed for effective cotton management. In this context, medium resolution Earth observation systems, particularly Sentinel-2 and Landsat, have become increasingly significant for agricultural monitoring due to their ability to provide sufficient spectral information and frequent observations for the assessment of large area crops (Radeloff et al., 2024). In Pakistan, remote sensing has already shown high potential for cotton area detection and production related monitoring, especially in important cotton growing zones of the Indus Basin (Naveed et al., 2023).

Among currently existing satellite missions, Sentinel-2 is particularly well suited for cotton monitoring due to its high return frequency and the availability of visible, near-infrared, red-edge, and shortwave-infrared bands. These attributes facilitate the differentiation of crop varieties and enhance the analysis of crop phenology and canopy condition. Cotton mapping can be effectively accomplished using time series Sentinel-2 imagery (Wang et al., 2021), and the early identification and classification of cotton fields from multispectral imagery can be further enhanced by machine learning classifiers (Garofalo et al., 2024). Although these studies demonstrate the value of satellite-based cotton extent mapping, field extent alone does not accurately reflect the condition of the crop during the growing season.

Monitoring crop health during the growing season is also very important because differences in energy, moisture levels, pest pressure, and other stress factors have a big effect on how well cotton crops do.

Sentinel-2 imagery has been used successfully to estimate cotton water status and related physiological responses (Fu et al., 2022), while machine learning approaches coupled with Sentinel-2 spectral information have also shown promise for monitoring cotton pest-related stress (Shahi et al., 2023). These studies demonstrate that spectral indications obtained from satellite data can help timely assessment of canopy condition. However, satellite images often provide stress signals at the canopy level and may not directly disclose the precise biotic symptoms causing crop health problems. More broadly, integrated geospatial techniques have also been proven to allow near real-time characterization and decision-oriented monitoring in various applicable domains, demonstrating the value of merging spatial analysis with practical management demands (Sarfraz et al., 2014).

At the plant level, image-based deep learning has emerged as an effective method for disease detection in cotton. Transfer learning methods have demonstrated strong performance for cotton disease detection from leaf imagery (Tariq et al., 2025), and more recent architectures integrating transformer-based feature learning have further improved disease and pest classification capability (Dhruw et al., 2025). Furthermore, recent data-driven research has demonstrated that descriptive analysis and visualization can aid in the extraction of understandable patterns from complicated datasets and facilitate decision-making in practical contexts (Maqsood et al., 2023).

Nevertheless, most present research focuses either on satellite-based cotton mapping and stress evaluation or on close-range image-based disease classification as independent tasks. A more operational monitoring strategy demands both perspectives. Therefore, this study presents an integrated approach that integrates Sentinel-2 based cotton mapping and canopy health assessment with AI-driven leaf-level disease identification.

The framework is intended to support district-scale stress identification while also providing plant-level diagnostic insight, thereby improving the practical value of remote sensing and artificial intelligence for precision cotton management.

2. Materials and Methods

2.1 Study Area and Data Sources

The study was conducted in Shaheed Benazirabad (Nawabshah), Sindh, Pakistan, an irrigated agricultural district where cotton is an important kharif season crop. All spatial analyses were restricted to the district boundary and processed in UTM Zone 42N (EPSG:32642) at a working resolution of 10 m.

Three data sources were used in this study. First, Sentinel-2 Level-2A surface reflectance imagery was used for cotton mapping and canopy health monitoring for the 2022 cotton season. Ten multispectral bands were retained for analysis: B2, B3, B4, B5, B6, B7, B8, B8A, B11, and B12. These bands cover the visible, red-edge, near-infrared, and shortwave-infrared regions and were selected to capture variation in crop vigor, canopy structure, chlorophyll response, and moisture status.

Second, geolocated cotton and non-cotton reference points were used for supervised cotton mapping. These labels were derived from the Ground Truthing Survey Data for Crop Type in Pakistan provided by (Asian Development Bank, 2024). The crop type records were converted into a binary label scheme consisting of cotton and non-cotton classes.
Third, leaf-level disease identification was conducted using a cotton image dataset captured under field conditions in Shaheed Benazirabad (Ayaz, 2022), composed of RGB images. The dataset contained eight classes: Aphids, Army Worms, Bacterial blight, Cotton Boll Rot, Green Cotton Boll, Healthy, Powdery mildew, and Target spot. For clarity, the class taxonomy and its grouping into disease/pest/condition categories are summarized in Table 1. The imagery reflects practical scouting scenarios and therefore includes substantial variability in illumination, background clutter, leaf orientation, and symptom severity stages.

Class	Category
Aphids	Pest
Army Worms	Pest
Bacterial blight	Disease
Cotton Boll Rot	Disease
Green Cotton Boll	Condition
Healthy	Healthy
Powdery mildew	Disease
Target spot	Disease

Table 1. Cotton leaf disease dataset class taxonomy

2.2 Sentinel-2 Preprocessing and Feature Generation

Sentinel-2 preprocessing was carried out in Google Earth Engine. Images were filtered to the study area for the July–October 2022 season, and cloud and shadow-affected pixels were removed using the Scene Classification Layer (SCL). Monthly median composites were then generated to reduce noise and residual cloud contamination while preserving seasonal crop dynamics.

Where gaps remained, missing values were filled using adjacent monthly observations. Surface reflectance values were rescaled, and all 20m bands were resampled to a common 10m grid to create a harmonized feature stack. To support cotton mapping and health assessment, five indices were derived from the monthly composites: NDVI, EVI, NDMI, NDRE, and SAVI.

These indices were selected because they provide complementary information on canopy greenness, vigor, moisture status, chlorophyll-sensitive response, and soil background effects. Although some overlap exists among them, their combined use reduces dependence on any single indicator and provides a more stable representation of canopy condition. For cotton mapping, NDVI, EVI, and NDMI were used together with the spectral bands as predictors. For health monitoring, all five indices were used.

2.3 Cotton Mapping Using Random Forest

Cotton extent mapping was formulated as a binary classification problem in which each pixel was assigned to either the cotton or non-cotton class. Predictor values were extracted from the Sentinel-2 spectral-temporal stack at the reference point locations, and only samples with complete observations were retained. A Random Forest (RF) classifier was used to generate the final cotton map. RF was selected because it performs well on multi-temporal remote sensing data, handles nonlinear relationships effectively, and remains robust without extensive feature scaling. The trained model was applied across the study area to produce the cotton mask, which was subsequently used as the spatial domain for canopy health assessment.

2.4 Cotton Health Monitoring Using the Fused Health Index

Cotton canopy health was assessed only within the mapped cotton area. A Fused Health Index (FHI) was constructed from NDVI, EVI, NDMI, NDRE, and SAVI to summarize canopy condition using multiple complementary indicators. Each index was first normalized to a common 0–1 scale, and the monthly FHI was computed as the simple average of the five normalized indices:

$$\mathrm{FHI}_m = \frac{1}{5}\left(\mathrm{NDVI}'_m + \mathrm{EVI}'_m + \mathrm{NDMI}'_m + \mathrm{NDRE}'_m + \mathrm{SAVI}'_m\right) \quad (1)$$

FHI values were stratified into Low, Moderate, and High classes using the 25th and 75th percentiles.

2.5 Leaf-Level Disease Detection Using Vision Transformer

Leaf-level disease detection was performed using a Vision Transformer (ViT) model on the field RGB cotton image dataset. A Vision Transformer (ViT-B/16) model was selected for leaf-level disease detection because its self-attention mechanism captures long-range dependencies and fine-grained visual patterns, making it suitable for field images with variable illumination and heterogeneous leaf textures. Images were resized to 224 × 224 pixels and normalized using the standard preprocessing associated with pretrained ImageNet models. To improve robustness under field conditions, data augmentation was applied during training, including rotations, shifts, zooms, flips, and brightness variations.

Following the experimental setup used in this paper, the dataset was divided into 80% training and 20% testing sets. The model was fine-tuned to classify the eight-cotton disease and condition classes. The ViT model was used as the plant scale diagnostic component of the framework, complementing the satellite-based canopy analysis by providing image-based identification of visible cotton stress categories.

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2.6 Evaluation Metrics

The cotton mapping component was evaluated using standard metrics, including overall accuracy, Kappa coefficient, precision, recall, and F1-score.

The leaf-level disease classification component was evaluated using classification accuracy, precision, recall, F1-score, and confusion matrix analysis on the test subset. Together, these evaluation measures enabled assessment of the proposed framework at both the canopy and leaf scales.

3. Results and Discussion

3.1 Study Area Boundary and Reference Points

The study area corresponds to the administrative boundary of Shaheed Benazirabad District, which defines the spatial extent of the district-scale analysis. The boundary outlines the geographic domain within which cotton distribution and crop condition patterns are examined. As shown in Figure 1, the spatial distribution of reference points used in the analysis is overlaid on the study area boundary, with cotton samples indicated in green and non-cotton samples indicated in red.

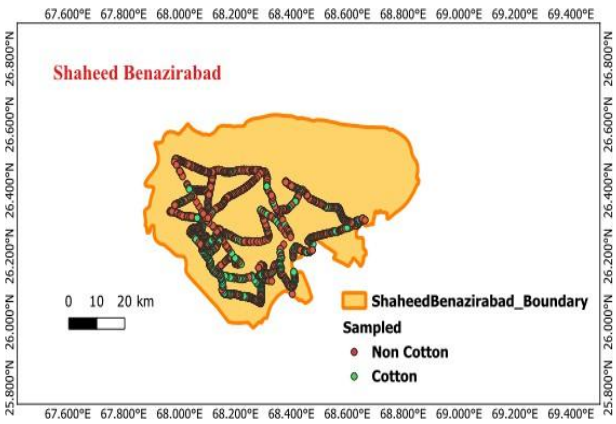
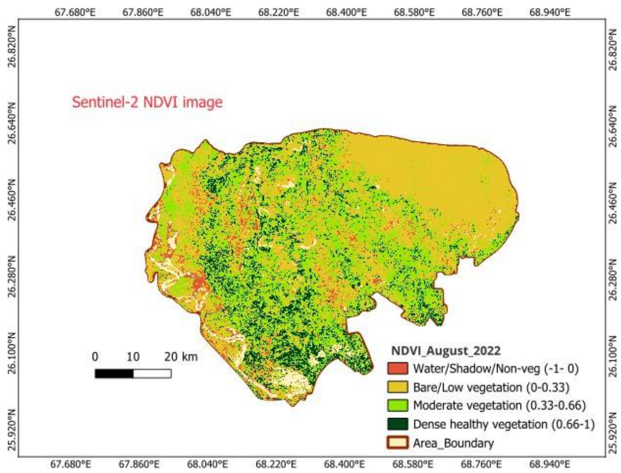


Figure 1. Study area boundary with labels

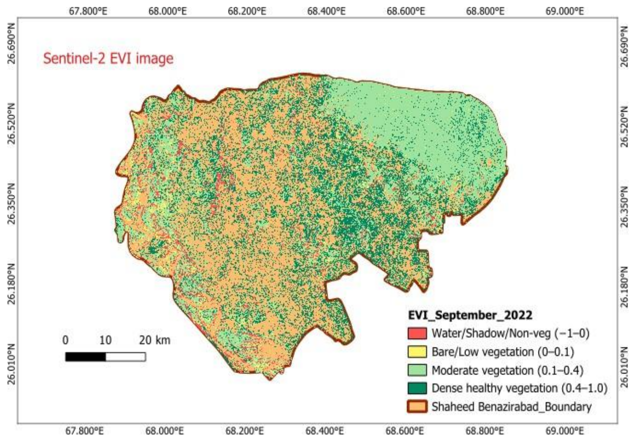
The reference points are distributed across the district and occur within intensively cultivated agricultural zones as well as areas characterized by mixed land use. This distribution allows visual inspection of the spatial relationship between labeled observations and the surrounding landscape. The combined display of the district boundary and reference point locations provides an overview of the spatial coverage of the labeled data relative to the study area. This context supports the interpretation of mapped cotton patterns by allowing the reader to assess where reference observations are located in relation to agricultural and non-agricultural areas.

3.2 Vegetation Index Patterns

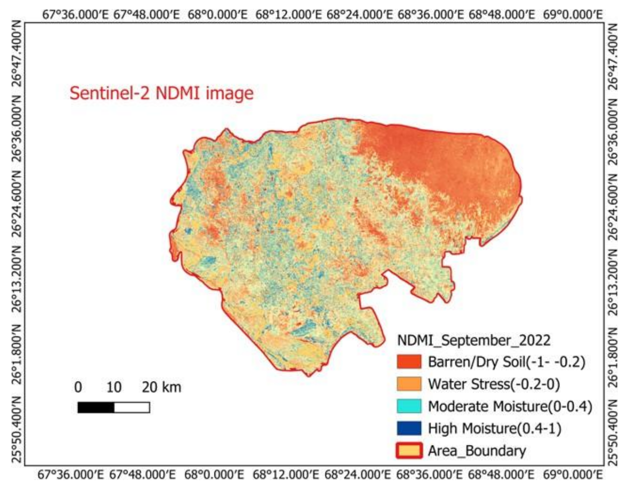
To examine the spatial variability of crop condition during the 2022 cotton season, representative Sentinel-2 vegetation and moisture indices were analyzed across Shaheed Benazirabad. Figure 2 presents NDVI, EVI, and NDMI maps, which together show clear heterogeneity in canopy greenness, vigor, and moisture status across the district. Lower vegetation and moisture responses are more evident toward the eastern and northeastern parts of the study area, whereas comparatively stronger canopy development appears in the central and southern agricultural zones. These spatial differences indicate that crop condition was not uniform during the growing season and provide important spectral context for the subsequent cotton mapping and health assessment results.



(a) NDVI



(b) EVI



(c) NDMI

Figure 2. Spatial distribution of vegetation indices

These three indices offer complementary information rather than repeating the same pattern. NDVI reflects overall vegetation greenness, EVI improves sensitivity to canopy vigor in denser vegetation, and NDMI highlights moisture-related differences that are less visible in greenness-based layers alone. Their combined interpretation therefore provides a stronger basis for understanding cotton condition than any single index used independently.

This interpretation is also consistent with the broader framework of the study, in which NDVI, EVI, and NDMI support cotton mapping, while NDRE and SAVI are retained in the fused health stage to represent chlorophyll-sensitive response and soil-background effects.

3.3 Cotton Extent Mapping

Cotton extent for the 2022 growing season was delineated using the Random Forest classifier. The corresponding classification metrics are summarized in Table 2, and the resulting distribution is presented in Figure 3.

The model achieved an overall accuracy of 93% with a Kappa co-efficient of 0.82, indicating strong agreement between the classified output and the reference data. The final mapped cotton extent was 65,269 ha, differing by only 1.6% from the official statistics reported by (Ministry of National Food Security and Research, Government of Pakistan, 2023).

Metric	Value
Overall Accuracy	93%
Precision	82%
Recall	92%
F1-score	87%

Table 2. Classification accuracy metrics

The mapped output shows cotton as fragmented field-scale patches rather than as continuous cover across the district. More concentrated cotton patches are visible in the central and southern parts of the district, while comparatively fewer patches occur toward the northeastern side.

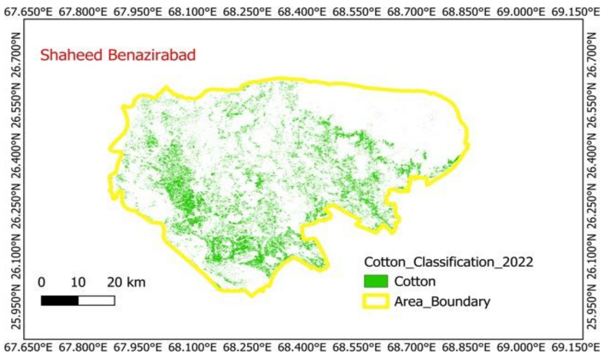


Figure 3. Mapped cotton area

This distribution reflects the heterogeneous structure of the irrigated agricultural landscape and confirms that cotton cultivation is organized at the plot level. The cotton extent layer also provides the spatial basis for the subsequent canopy health analysis by limiting the health assessment to mapped cotton pixels.

3.4 Cotton Canopy Health Assessment

Cotton canopy condition was assessed within the mapped cotton area using the seasonal Fused Health Index (FHI). The corresponding area statistics are summarized in Table 3 and the resulting health stratification is presented in Fig 4. The mapped output shows a clear dominance of the moderate-health class, while low-health and high-health zones occupy smaller but comparable shares of the cotton area.

Health Class	Area (ha)	Percentage (%)
Low Health	15,685.84	24.5
Moderate Health	32,646.37	50.9
High Health	15,762.16	24.6

Table 3. Cotton health classification area distribution

In percentage terms, the health distribution was 24.5% low, 50.9% moderate, and 24.6% high, indicating substantial within district variability in cotton condition during the 2022 season.

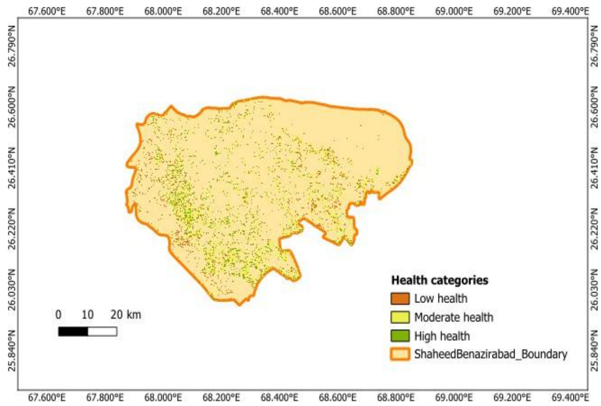


Figure 4. Seasonal mean Fused Health Index (FHI)

The spatial pattern of the health classes is heterogeneous rather than continuous. Moderate health cotton appears widely across the district as dispersed field-scale patches, forming the dominant visual pattern, while low health areas occur intermittently among moderate fields, and high health areas appear as smaller localized clusters, with more noticeable concentrations in the central to southern belt. This distribution suggests that cotton performance was not uniform across the district and that field-to-field differences remained important throughout the season. Instead of focusing on specific disease diagnoses, health categories should be viewed as indications of general health.

Cotton pixels were classed as low, moderate, or healthy based on seasonal canopy performance as measured by satellite data. A low or declining health could be a sign of pests or disease, but it could also be the result of changes to irrigation, nutritional deficiencies, heat stress, or other management circumstances. The health map works best as a screening layer to find areas of likely stressed cotton rather than a predictor of particular diseases.

3.5 Leaf-Level Disease Classification

Leaf-level disease classification served as a plant-level diagnostic element in the proposed framework. The Vision Transformer model produced an overall accuracy of 97%, and the outstanding performance was further validated by precision, recall, and F1 score values shown in Table 4.

The model correctly labelled both healthy and diseased cotton samples under a variety of field settings, as seen in Figure 5. These illustrations show how the model can retain classification reliability in the face of variations in illumination, background complexity, leaf positioning, and symptom appearance.

Figure 6 confusion matrix demonstrates that the predictions are largely diagonally aligned, indicating consistent accuracy across classes. Errors were limited to disease types that were visually comparable, rather than affecting other categories.

Class	Precision	Recall	F1-score	Support
Aphids	1.00	1.00	1.00	39
Army worm	1.00	0.97	0.99	40
Bacterial blight	0.97	0.97	0.97	40
Cotton Boll Rot	1.00	0.89	0.94	61
Green Cotton Boll	0.89	1.00	0.94	59
Healthy	1.00	1.00	1.00	39
Powdery mildew	1.00	1.00	1.00	38
Target spot	0.95	0.98	0.96	41
Accuracy		0.97		357
Macro Avg	0.98	0.98	0.98	357
Weighted Avg	0.97	0.97	0.97	357

Table 4. Performance metrics results

Figure 5. Predictions from Vision Transformer model

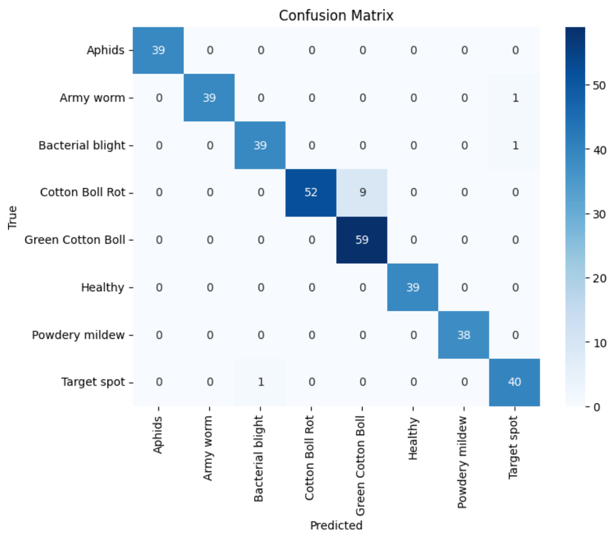


Figure 6. Confusion matrix for Vision Transformer disease classification

The most common confusion in the test set was Cotton Boll Rot and Green Cotton Boll, but other misclassifications were small and dispersed. This error pattern is consistent with the visual similarity of the symptoms in these cases, validating the overall good results of the model.

These results indicate that the ViT model was effective for field condition cotton imagery and can provide a useful diagnostic layer alongside the satellite-based canopy analysis. While the Sentinel-2 component identifies where stress is concentrated at the district scale, the image-based model contributes class-specific visual evidence at the plant scale, improving the interpretability of stressed zones identified in the canopy health maps.

4. Conclusions

This study introduces an integrated framework for cotton monitoring that combines satellite-based remote sensing with AI-driven leaf-level disease detection. The proposed framework improves both district-scale cotton mapping and plant-level diagnostics by linking multi-temporal Sentinel-2 data with deep learning. This approach provides a more robust, timely, and spatially explicit means for cotton health monitoring. The framework demonstrates the potential of integrating remote sensing and artificial intelligence to enhance decision-making in precision agriculture. Future work will extend this framework through field validation, broader seasonal observations, and the development of farmer-facing decision support tools.

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