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# AgriXplain: Explainable AI Crop Intelligence for Smarter, Sustainable Farming

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**Abstract**

Early detection of agricultural diseases is important for reducing crop damage, particularly in rural or remote regions. This research work provides an explainable Convolutional Neural Network (CNN) technique for agricultural disease alert system that uses Sentinel-2 multispectral data, NDVI and Red Edge NDVI (NDRE) fusion to produce continuous notifications. It increases spectral learning features like stressed plant signals into the raw red, near-infrared and red edge bands. It also increases the capacity to recognize healthy and unhealthy crops. Grad-CAM's module help farmers and agronomists to evaluate model results by recognizing the primary spectral data related to each prediction increases transparency and trust. A client-side storage system allows monitoring the fields and disease analysis queries offline, that can be updated with the server when a connection is available. The evaluations using merged sentinel-2 data show that combining NDVI and NDRE increases the accuracy of detection and produces feature activation maps makes its efficient for early stress detection. This technology was created for adaptive communication with agricultural systems and it provides accurate crop health signals using satellite images.

**Keywords:** Explainable AI, Convolutional Neural Network (CNN), Crop Disease Detection, Sentinel-2 Multispectral Imagery, NDVI, Red-Edge NDVI (NDRE), Feature Fusion, Grad-CAM, Low-Connectivity Agriculture, Precision Agriculture.


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## 1. Introduction

Early detection of crop diseases is crucial to preventing yield losses to maintain food security, especially in large farms located far away from the nearest counties. The conventional surveillance method for manually searching for disease in fields is time-consuming, subjective and unsuitable to monitor large areas by continuous observation. Recent progress in satellite-based remote sensing has allowed large-scale, non-invasive monitoring of crop health based on multispectral imagery. Red, red-edge and near infrared (NIR) bands from Sentinel-2 satellite images provide a better sensitivity to vegetation stress. Plant indices such as the Normalized Difference Vegetation Index (NDVI) and the Normalized Difference Red-Edge Index (NDRE) have been widely utilized to evaluate crop vigor, health damage early indicators etc. Thus, the traditional index-based and threshold-dependent methods are not robust and generalize well to different crop types or environmental situations. CNNs are efficient classifiers of features for multispectral crop disease detection, but they are generally black box models with limited transparency and trust.

Furthermore, most satellite-based agricultural analytics solutions depend on consistent internet access for a previous resource in rural farming. The current crop data additionally provide an overview of the resources necessary for a higher yield this year, but also help to discover patterns and predict yields over time. This work integrates Sentinel-2 spectral bands, NDVI, and NDRE feature fusion to handle these limitations. A lightweight one-dimensional CNN and a modified Grad-CAM module are used for feature-level explainability to achieve accurate disease classification. This client-side caching architecture is designed for low-connectivity agricultural environments with a focus on offline performance.

## 2. Literature Review

Several recent studies have extensively explored deep learning–based crop disease detection using image processing and remote sensing data. Haider et al. [1] proposed a deep CNN architecture integrated with GRU and superpixel-based saliency maps for disease detection, achieving high classification accuracy. However, their approach lacked explicit explainability and required significant computational resources, limiting deployment in resource-constrained environments. Karunya and Ravikumar [2] developed a multi-class

CNN for rice leaf disease detection, demonstrating effective performance but focusing on a single crop type. Similarly, Attri [3] introduced a TinyML-based offline disease detection model for fruit leaves, which improved deployability but suffered from limited scalability and generalization across crops.

Hybrid deep learning architectures have been proposed to enhance feature representation and classification accuracy. Vikhe et al. [4] employed a CNN–Transformer framework for onion leaf disease identification, achieving improved performance at the cost of increased architectural complexity and computational overhead. Explainability in crop disease detection has gained attention in recent years. Kaur et al. [5] incorporated Grad-CAM and SHAP to interpret CNN predictions for cotton leaf diseases; however, their model remained farm-specific and lacked cross-regional validation. Nagar et al. [6] presented a comprehensive survey of CNN-based plant disease detection methods, identifying major gaps in explainability, real-time inference capability, and deployment readiness.

Vegetation index–based approaches have also been explored to complement image-based methods. Judith et al. [7] utilized NDVI features with feedforward neural networks to analyze crop health, demonstrating the relevance of vegetation indices in disease identification. Zhang et al. [8] employed knowledge distillation techniques to compress deep models, improving inference efficiency but compromising predictive robustness. Kimutai et al. [9] introduced an adaptive smallholder crop disease detection system using TinyML, enabling offline operation; however, this approach resulted in reduced accuracy and limited explainability.

The integration of IoT sensors and environmental parameters was investigated by Al-Shahari et al. [10], highlighting the benefits of multi-modal data fusion. Transformer-based disease detection approaches were further explored by Li et al. [11], showing improved learning capacity but increased training complexity. Nugroho et al. [12] designed lightweight CNN models optimized for low-power devices, achieving efficiency at the expense of classification performance. Babatunde et al. [13] proposed a mobile-based offline disease detection framework, while Li et al. [14] explored federated learning to reduce connectivity dependence; however, challenges related to model consistency and convergence persisted.

The comprehensive review studies by Shoaib et al. [15] and Mittal et al. [16] emphasized persistent challenges such as limited dataset diversity, lack of explainability, and insufficient real-field validation. Khan et al. [17] introduced the concept of lightweight edge-based disease detection models, improving deployability but facing generalization constraints. Patel et al. [18] developed interpretable CNN architectures using Grad-CAM for maize disease identification, yet their models remained crop-specific with limited adaptability. When compared to existing works, the proposed system integrates Sentinel-2 multispectral data with NDVI and NDRE feature fusion, a lightweight 1-D CNN classifier, Grad-CAM–based explainability, and offline deployment support. This combination handles the critical gaps of scalability, interpretability and robustness makes the system suitable for real-world precision agriculture applications in low-connectivity environments.

## 3. Proposed Work

### 3.1 Overview

This research describes an Explainable CNN-based crop disease detection system that uses Sentinel-2 multispectral images combined with NDVI and NDRE plant indices to identify crop diseases effectively. Grad-CAM provides a basic understanding of model predictions and helps interpret the 1-D CNN's feature-level correlations between spectral bands and vegetation indicators.

The system uses an offline design with client-side storage that allows continuous disease monitoring in remote rural areas with minimal connection to enable real-life implementation. The proposed system provides an accurate agricultural system combining smart spectral with explainable deep learning for implementation adaptability.

### 3.2 Data Flow

Figure 1 shows the proposed method architecture for the explainable crop disease notification system. The system includes collecting and processing Sentinel-2 multispectral data such as spectral band identification and vegetation index computation. A feature fusion layer combines spectral bands with NDVI and NDRE indicators before sending them to an explainable CNN-based inference system for disease prediction. Simultaneously, a Grad-CAM method creates interpretable explanations to highlight key spectral patterns. An offline storage system provides continuous operations in low-connectivity conditions.

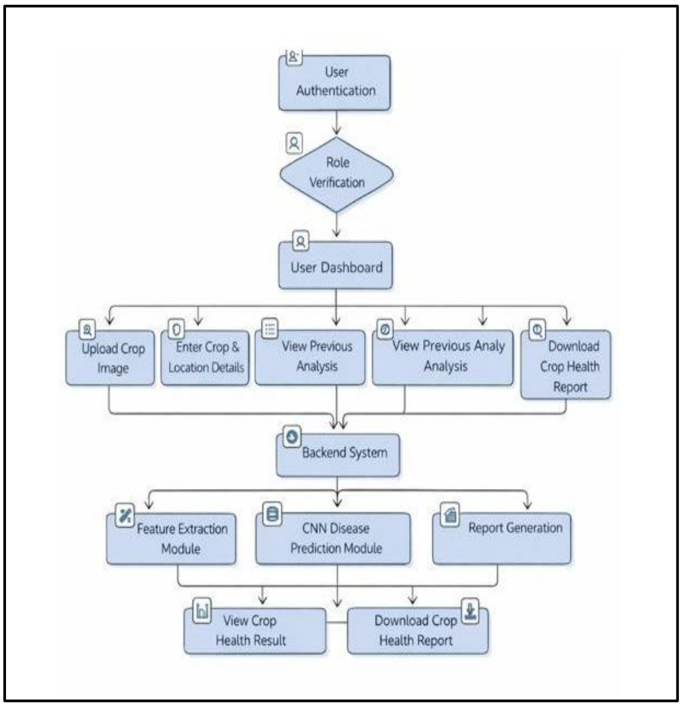


**Figure 1.** Architecture Diagram

### 3.3 Data Acquisition and Preprocessing

The primary objective of agricultural region was initially monitored using Sentinel-2 multispectral images. The B4, B5 and B8/B8A bands have been collected from each scene because they are the most sensitive to plant stress and chlorophyll changes. Two indices of vegetation are generated based on these spectral bands: The Normalized Difference Vegetation Index (NDVI) and the Normalized Difference Red-Edge Index (NDRE) helps reveal disease-related patterns in the spectral data. The NDVI and NDRE are calculated as:

$$\text{NDVI}=\frac{(NIR-Red)}{(\text{NIR}+\text{Red})}$$

$$\text{NDRE}=\frac{(\text{NIR}-\text{RedEdge})}{(\text{NIR}+\text{RedEdge})}$$

- NIR stands for near-infrared reflectance
- RED stands for red-band reflectance
- REDEDGE stands for red-edge reflectance.

RedEdge is the reflectance of the red-edge band. These two indices reflect the overall vegetation activity and the initial stressful physiological situations. Once index computation is complete, feature-level fusion is done by concatenation.

[B4,B5,B8,NDVI,NDRE] translates to every sample's consensual feature vector. A feature scaler is used to normalize the fused vectors resulting in greater accuracy and rapid performance while training the model.

### 3.4 Explainable CNN Architecture

The spectral-index feature vectors are combined and sent into a 1-D CNN. The network includes sequential convolutional layers but they were replaced with batch normalization, ReLU activation, global average pooling and a fully connected classification layer. The proposed model performs directly in the feature dimension and the connections between spectral bands and vegetation indicators compared to standard image CNNs.

A Grad-CAM-based accessible module has been implemented into the CNN to provide transparency in predictions. It computes the estimated effects of feature activations at the end of the convolutional layer and transfers the weights to the feature space. This produces the primary value of each spectral band or vegetation index as an indicator for disease class. It allows agronomists and administrators to validate the accuracy of a model prediction.

### 3.5 Model Training Strategy

A supervised learning approach based on labeled crop health classes was used to train the proposed CNN. The data will be separated into two groups, training and validation. During each training cycle, feature vectors merged in batches are sent through the CNN and the function for cross-entropy loss is reduced using Adam as an optimization tool. Back propagation changes the network weights to decrease classification error.

Overfitting can be prevented using dropout regularization and batch normalization. The final enhanced classifier had the highest validation accuracy. This training method performs effectively on crop type, season and environmental changes.

### 3.6 Deployment and Inference with Offline Caching

In real-time deployment, crop images and metadata uploaded by users (type of crop, location, season and language) are sent to the server to be preprocessed and inferred. The trained CNN model creates a prediction of the disease and the corresponding Grad-CAM explanation map and vegetation health indicators.

A client-side offline storage system is used to solve connectivity problems that are common in rural locations. In the case of an insufficient network connection, the system will maintain the crop image and data locally. When the connection is restored, all stored inference requests are automatically transferred to the backend for processing. This ensures the continuous disease monitoring and tracking services in situations of unsecured networks.

### 3.7 Computational Complexity and Runtime Performance

The suggested explainable CNN model uses a lightweight one-dimensional convolutional architecture. Each forward motion across the convolutional layer has a computational complexity of O(D.K.C), where K denotes the kernel size and C represents the number of convolutional filters. The training technique continues across E epochs. The overall training complexity expands the number of epochs for efficient computation. The model reduced the parameter count and 1-D CNN enables real-time inference on standard CPU hardware without the need for specialized accelerators. This technique makes the proposed system suitable for field-level agricultural applications particularly in remote or low-connectivity areas.

## 4. Result and Analysis

The final result illustrates the AI-based smart agriculture utilizes NDVI and NDRE feature fusion, Sentinel-2 data collection, Grad-CAM accessibility, CNN-based disease diagnosis and implementation without network connectivity provide accurate crop health evaluations. This technique for identifying objects and providing feature-based explanations can recognize spectral patterns connected to diseases.

### 4.1 User Dashboard Interface

The AI-based communication layer is represented by the user dashboard. It allows users to access system features including crop analysis, language selection and authentication. The dashboard displays system features such as recognized crop varieties, available languages and continuous monitoring access. Crop analysis features are protected by user authentication allows for responsible access to AI-based data. This design is easier to use for farmers and agricultural analysts of various technical skill levels.

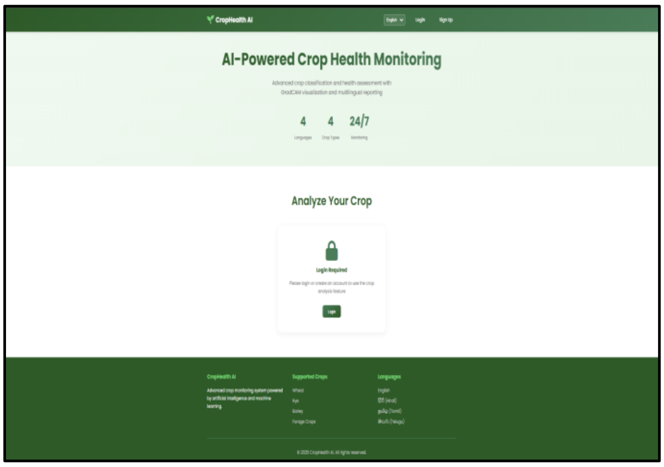


**Figure 2.** User Dashboard Interface

Figure 2 shows the dashboard panel allows for simple interaction between users and the AI-based crop health evaluation system. It provides online access to agricultural analytical services and contains system data such as recognized crops and multilingual features. The interface is lightweight, adaptive, and cross-platform, ensuring usability. This module is the key platform for reporting crop data and collecting AI-generated health assessments.

### 4.2 User-Driven Crop Health Analysis Interface

The crop data Input interface serves as the operational input step for the explainable AI process. Users input crop metadata and field location data before uploading images are analyzed by a CNN model combined with Grad-CAM explainability. The aligned input design reduces user errors.

Figure 3 explains the virtual crop analysis platform allows authorized individuals to perform AI-based crop health evaluations. It collects details such as crop type, field-type, seasonal data and crop images. The data is sent to the AI inference system for analysis of vegetation and disease prediction leading to specific reports and verifiable outputs for precision agricultural applications from the submission.

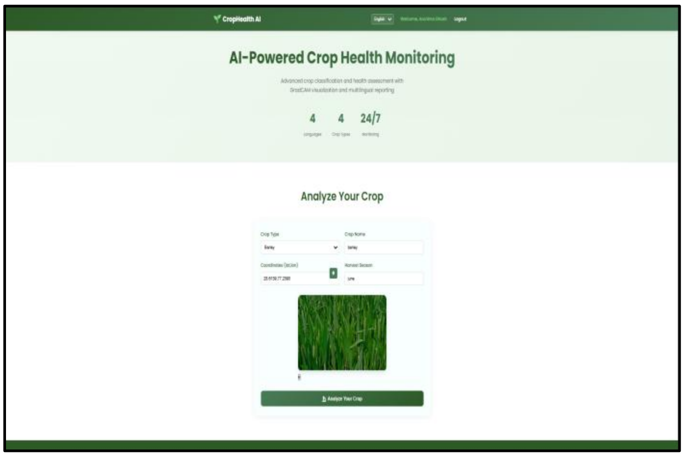


**Figure 3.** User-Driven Crop Health Analysis Interface

### 4.3 Analysis Results and Explainability Visualization

It provides specific detailed analysis of the predicted crop type, measured vegetation health indicators (NDVI and NDRE) and current weather conditions. A risk evaluation system combines different variables to calculate the overall crop health status. The Grad-CAM-based visualizations shown with the initial image to increase transparency by highlighting geographical region affects the CNN's decisions.

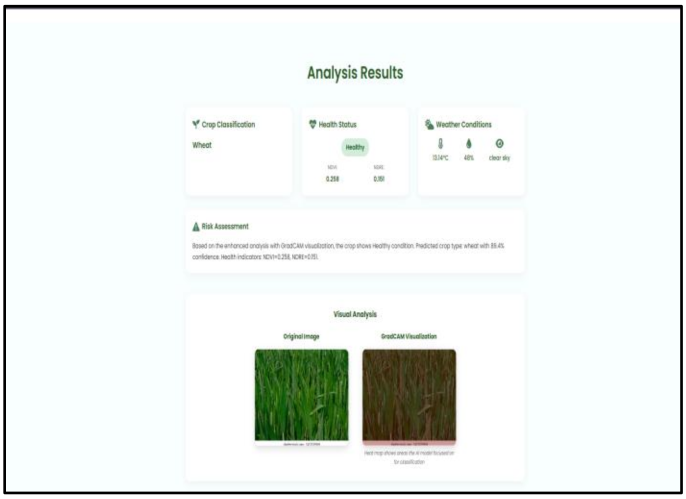


**Figure 4.** Analysis Results Dashboard

Figure 4 illustrates the crop health result analysis produced by the suggested explainable AI system. The display shows crop categorization predicts health status using NDVI and NDRE indicators, real-time weather conditions and a unified risk assessment.

Grad-CAM heatmap visualization is shown with the original crop image provides visual explainability by focusing on locations that contribute to model prediction.

### 4.4 Multilingual Decision Support and Advisory Module

The proposed system includes a multilingual assistance to improve accessibility for agricultural users. The risk notifications, advisory guidance and system results are continuously translated and presented in regional languages like Tamil, Telugu, Hindi and English. This makes the crop health data and recommendations for treatment are visible to farmers from various language backgrounds. The multilingual capacity increases user engagement, reduces interpretation errors and enables the AI-based precision systems.

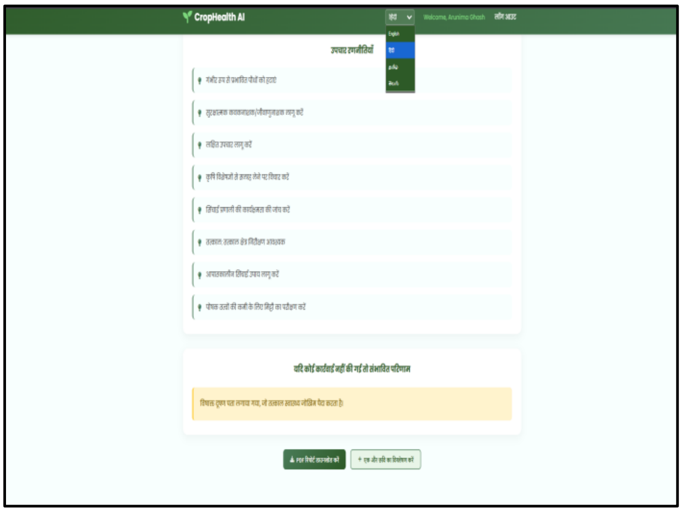


**Figure 5.** Multilingual Decision-Support Interface

Figure 5 depicts the multilingual decision-support interface displays AI-generated crop health advisories and risk notifications in the user-selected regional language, enabling improved accessibility and comprehension for farmers in diverse linguistic regions. Using the language option menu, the users can automatically change different regional languages like Tamil, Telugu, Hindi and English. All guidance, risk notifications and specific treatment solutions are immediately presented in the chosen language provides simple comprehension for users.

### 4.5 PDF based Multilingual Crop Health Report Generation

The PDF generating module creates a structured and shareable crop health analysis report in the user-selected language. The report combines farm data, crop data, classification results with accuracy and visual evidence such as the initial crop image and Grad-CAM-based explainability map. The technology enables offline access, maintaining records and simple communication with agricultural experts using localized language and AI-generated data in a standard record format. This function is useful in rural areas with limited connectivity and it ensures vital diagnostic data is available outside of the online interface.

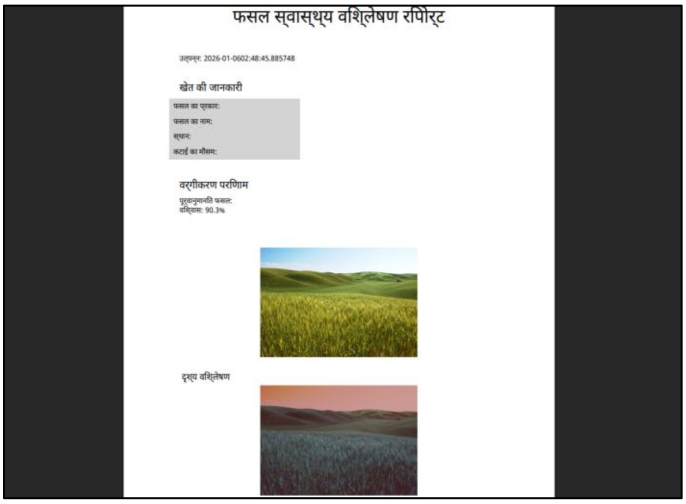


**Figure 6.** Automatically Generated Multilingual PDF Report

Figure 6 explained the suggested method automatically generates a crop health evaluation report in PDF format. The report is presented in the user-selected regional language and includes farm and crop metadata, classification results with confidence scores and visual evidence to support the AI prediction. The crop image and the Grad-CAM-based heatmap are included to explain the system decision. This report can be downloaded and viewed without an internet connection. It also enables for long-term maintaining records and simple exchange with agricultural farmers makes it useful in remote areas with limited internet connectivity.

### 4.6 Classification Performance Analysis

This section evaluates the performance of the proposed work using integrated Sentinel-2 spectral bands and NDVI & NDRE characteristics. The trained model was evaluated with a reserved validation dataset created from the multispectral input data This model used common evaluation tools from the literature such as accuracy, precision, recall and F1-score to assess the classification performance.

This result shows the model can accurately differentiate healthy and unhealthy crop types. The CNN architecture automatically establishes complicated non-linear correlations between the fused data allows accurate disease classification across different crop varieties and environmental circumstances.

**Table 1.** Performance Metrics of the Proposed CNN Model

| Metric | Value |
|---|---|
| Accuracy | 0.94 |
| Precision | 0.93 |
| Recall | 0.92 |
| F1-Score | 0.925 |

Table 1 shows the quantitative results of the proposed explainable CNN model on the validation set. The measures verify the fact that Sentinel-2 spectral bands combined with NDVI and NDRE play a significant role in improving the reliability of classification.

### 4.7 Effectiveness of NDVI and NDRE Feature Fusion

The effect of NDVI and NDRE indices has been examined by comparing model behavior before and after the feature fusion. The integration of NDVI improved the detection of overall vegetation health but the integration of NDRE improved early stress sensitivity particularly in the case of chlorophyll loss. The suggested study included both indexes to improve disease detection. Figure 7 explains system performance regarding the accuracy, precision, recall and F1 score. It shows the prediction accuracy and high level fusion of Sentinel-2 spectral and NDVI/NDRE.

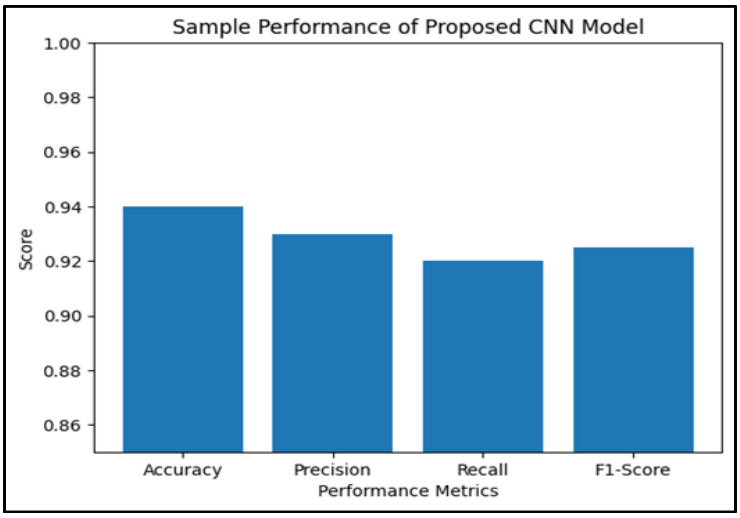


**Figure 7.** Sample Performance Comparison

### 4.8 System Reliability Under Low-Connectivity Conditions

The offline caching approach was tested using virtual network failures and irregular connection settings are similar to real-world rural areas where the internet access lacks. During these evaluations, the system continuously operated even after the network failed to connect. When communication failed, crop images, sensor inputs and analysis were safely stored on the device. When the network connection was fixed, the system rapidly updated the stored requests in the main server. This synchronization was performed without manual action. It will handle the pending requests for disease detection results, health evaluations and guidance recommendations. This system verified the data consistency and rapid transmission.

## 5. Conclusion and Future Work

This article proposed an explainable CNN-based crop disease warning system based on Sentinel-2 multispectral images using NDVI and Red-Edge (NDRE) feature fusion used to achieve in low network connectivity agricultural areas. This approach connected with spectral bands and plant indicators useful for recognizing structural and stress-related qualities. A 1-D CNN classifier provided accurate learning of hybrid spectral-index features with the Grad-CAM module simplified disease predictions to analyze at the feature level. Moreover, a client-side offline caching and synchronization mechanism provided multifunctional monitoring and advisory support even in the rural settings.

The high prediction accuracy validated with Sentinel-2 feature data demonstrates the reliability of using NDVI and NDRE for disease recognition. Overall, the proposed system integrates accuracy, accessibility and implementation durability makes it suitable for actual precision agriculture. Multi-temporal Sentinel-2 time-series modeling incorporated into LSTM or Transformer networks to better prediction of disease at the early stages. The expansion of the system to assist in multi-disease and cross-crop generalization in different agro-climatic zones. The system implementation includes mobile-based farmer guidance applications and continuous field validation using satellite real-time updates.

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