

Satellite Image Based Agricultural Monitoring Using Machine Learning and Explainable AI

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ABSTRACT- Approaches for agriculture monitoring should consistently assess vegetation conditions throughout farm fields and limit the need for manual surveys. Satellite-derived information offers one source of spatially-explicit data that can be used to monitor crops using their spectral reflectance properties. Thresholding vegetation indices to classify vegetation conditions may be difficult to interpret across cropland with variable canopy structure, phenology, and reflectance. Here, we introduce a crop monitoring framework which integrates Sentinel-2 multitemporal data, vegetation indices, machine learning, outlier detection, and explainable AI. Sentinel-2 multispectral (MS) and RGB data streams are handled with separate processing components. Vegetation indices including Normalized Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI), Soil-Adjusted Vegetation Index (SAVI), Normalized Difference Water Index (NDWI), and Excess Green Index (ExG) are computed from spectral bands when applicable. Crop condition class labels are predicted with a Random Forest classification model. Thresholding on crop-specific NDVI values is included for comparison as a rules-based method. An Isolation Forest algorithm detects anomalous vegetation conditions. Finally, SHapley Additive exPlanations (SHAP) are used to interpret ML model predictions. Six crop types are included in the framework: cotton, sugarcane, paddy, carrot, wheat, and barley. An initial test of the framework is done using a single Sentinel-2 MS image and five historical records yielded a NDVI value of 0.75 for the satellite image along with a classification of Healthy, 99% model certainty, and 0.0% of pixels identified as stressed vegetation.

KEYWORDS - Crop Health Monitoring, Explainable AI Remote Sensing, Precision Agriculture, NDVI, Sentinel-2, Random Forest, SHAP, Vegetation Indices

I. INTRODUCTION

Crop farming is essential to food security, economical sustainability, and rural livelihoods. Monitoring agricultural crops involves frequent observation of crop development, vegetation conditions, and changes present within cultivated areas. Traditional approaches to crop

monitoring involve field inspection, manual observation, and agricultural expertise. While field observations remain an important source of local agricultural knowledge, intensive applications often become challenging at larger spatial scales. Additionally, repeat visits to agriculture fields can be costly and labor-intensive, especially for farms that span across wide geographic extents. Satellite remote sensing has enabled spatially-distributed observations of the agricultural landscape through spectral measurements. Measurements of surface reflectance recorded by Earth-observation satellites cover a variety of wavelength regions to quantify how changes in vegetation-properties relate to remotely sensed signals. These measurements can be leveraged to describe characteristics of vegetation without needing persistent access to crop fields. Optical satellite imagery is especially relevant to describing cultivated areas because vegetation has unique interactions with visible, near-infrared (NIR), and shortwave-infrared (SWIR) radiation. Differences in reflectance across spectral bands can be interpreted to describe canopy development, vegetation-density, and other biophysical conditions relevant to agricultural growth.

Satellite images acquired by Sentinel-2 include multispectral observations that are relevant to land-cover mapping, vegetation monitoring, crop mapping, and assessing changes in cultivated landscapes over time. Spectral bands included with Sentinel-2 imagery can be combined to calculate vegetation indices, which provide condensed information about specific characteristics of vegetation reflectance. The Normalized Difference Vegetation Index (NDVI) is commonly used to represent vegetation greenness and relative canopy vigor using the relationship between red and near-infrared reflectance. Other spectral indices, such as EVI and SAVI, were designed to mitigate specific limitations related to high canopy-density, atmospheric conditions, and background soil brightness. When available, water-related spectral indices may also provide supplementary information about crop conditions. Vegetation-index thresholds are commonly used to quickly detect areas of low vigour within satellite imagery. However, observed index-values cannot be assumed to represent a specific cause of poor crop conditions. Similar index-values can be produced

under many agricultural conditions due to variability in crop type, growth-stage, soil conditions, irrigation practices, and climate. As a result, using a fixed threshold to interpret a vegetation index may not provide accurate detection across multiple crop types.

Machine learning methods can provide a data-driven approach to analyse relationships between multiple vegetation indices. Ensemble machine-learning algorithms, such as Random Forest (RF), are able to use numerical features derived from satellite imagery to classify observations into distinct crop-condition categories. While automated classifications can efficiently process satellite imagery at the scale of individual pixels, classification models do not explicitly demonstrate which spectral features were most influential for a given prediction. Visual explanations of machine learning-model predictions can be important for end-users who require understandable explanations to support their monitoring activities.

Methods of Explainable Artificial Intelligence (XAI) allow users to examine how input-features influence machine-learning predictions. Specifically, SHapley Additive exPlanations (SHAP) values provide a feature attribution method that can be used to explain machine learning-model predictions. In conjunction with RF predictions, individual SHAP values can be used to describe how specific vegetation indices influenced remote sensing-based crop assessments. Anomaly detection algorithms, such as Isolation Forest, can be used to supplement crop condition assessments by discovering observations that differ from normal vegetation patterns. Combining vegetation indices, crop-specific thresholds, machine learning-classification, and anomaly detection offers a framework to build actionable crop monitoring applications. Implementation of this framework requires additional consideration of satellite-data processing, model-training practices, and crop-specific considerations.

A. Problem Statement and Objectives

Traditional satellite-based crop monitoring solutions often involve isolated processes like computing vegetation indices, performing crop-type classification, or displaying spectral information. While these are certainly useful operations, growers and agronomists might benefit from additional context that relates pixels in an image to more tangible crop-condition insights. One challenge limiting this goal is variability in spectral responses across crop types. Think about cotton, sugarcane, paddy, carrot, wheat, or barley. They all have distinct canopy cover, plant density, and phenology properties. As a result, the same NDVI reading could represent unique actions in the field depending on crop-type, growth stage, and other environmental factors. Simply applying a uniform NDVI threshold across all crops will likely create oversimplified assessments.

This brings us to another limiting factor, which is the relationship between multispectral vs. traditional RGB images. Observations in the former contain classified red and NIR wavelengths needed for NDVI analysis, while regular JPG images lack the NIR data necessary for producing physically meaningful NDVI. If a crop monitoring tool cannot differentiate between these two input types, false measurements will be returned to the user. A similar issue exists for crop-condition estimates derived from machine learning. While a classifier can

identify crop-condition categories, the lack of explainable features may sacrifice interpretability. On top of that, field-level predictions may miss sub-field anomalies that don't represent the rest of the crop area. All together, we aim to solve for an end-to-end crop monitoring pipeline that accounts for the different types of information available in agriculture (e.g. RGB vs. multispectral data), extracts meaningful vegetation indices when appropriate, includes rules for crop-type specific considerations, forecasts crop-condition classes, detects outliers, and describes what influences predictions.

II. LITERATURE REVIEW

A. Satellite Remote Sensing for Agricultural Monitoring

Satellite remote sensing of agricultural landscapes is a widely used tool to monitor spatial variation in vegetation properties. The advancement of multispectral sensors, repeated terrestrial observation capabilities, and computational image-processing algorithms have created new opportunities to monitor crop growth beyond on-site field-level observations. Several studies have reviewed applications of satellite-based agriculture monitoring, including crop type classification, vegetation-condition monitoring, cropland mapping, and crop biophysical parameter estimation. Wu et al. [1] reviewed opportunities and challenges for remote-sensing-based crop monitoring and highlighted the potential utility of satellite observations for agricultural applications. This paper provided a broader scope of remote sensing applications but also presented challenges associated with data availability, environmental variation, and translation of remotely sensed measurements. All of these factors must be considered when designing a monitoring approach to be applied across varying agricultural conditions.

Omia et al. [2] reviewed remote sensing platforms and methods used for monitoring field crops, including sensing technologies, analytical methods, and developments related to phenotyping of crop growth. Their review presents a more detailed look at the growing need to pair relevant sensing technology with computational algorithms to extract useful information from agricultural observations. Remote sensing allows for spatial insights that would be challenging or uneconomical to acquire through ground-level observations. However, extracting value from remotely sensed information relies on properties of the collected data, proper preprocessing of the data, and the correspondence between spectral responses and agricultural condition of interest. For this reason, a crop-monitoring framework should be designed to make sense of the satellite observations given the crop being monitored and available spectral information.

B. Vegetation Indices for Crop-Condition Assessment

Vegetation indices are mathematical combinations of spectral reflectance measurements that can represent spectral relationships associated with vegetation. Indices are formed by combining spectral bands to summarize vegetation greenness, canopy development, and other features of a sensed surface. Vegetation indices are popular because they compress multi-dimensional spectral information into a single, numeric image feature that can be spatially and temporally analyzed. Vidican et al. [3] conducted a review of remote-sensing vegetation indices

and their implementation for discrimination and monitoring of agricultural crops. Their findings highlight contributions of specific vegetation indices to agricultural understanding and characterization of vegetation properties. Index performance will vary according to available spectral bands, canopy conditions, and monitoring requirements.

Radočaj et al. [4] reviewed major vegetation indices used in precision agriculture, including potential applications to agriculture remote-sensing. Results from their review provide evidence supporting vegetation indices as quantitative indicators to include within crop monitoring procedures. Interpretation of vegetation-indices should be made in the context of environmental and vegetation properties which affect spectral reflectance. Bahrami et al. [5] conducted a review of remote-sensing methods used for characterization of crop properties. Their findings support investigation of how sensor technology, spectral information, and analytical methods can impact agricultural observations. Collectively, these studies establish the utility of vegetation indices, while highlighting importance of analyzing images with index properties complimentary to available imagery.

NDVI continues to be utilized as a measure of relative vegetation greenness because near-infrared and red reflectance reacts distinctly to changes in vegetation properties. However, interpretation of NDVI is sometimes affected by background soil, vegetation coverage, atmosphere, and crop status. EVI may serve as a complementary vegetation index when image bands support its calculation. SAVI was developed to mitigate influences of exposed soil reflectance. Water indices may also be calculated when respective bands are available from uploaded images.

Zeng et al. [9] provided a review of optical vegetation indices and their application to terrestrial ecosystem studies. Their results substantiate the need to understand properties and limitations of each index during interpretation of vegetation dynamics. Findings from these studies encourage implementation of complimentary spectral features rather than applying a single index to represent all agricultural conditions.

NDVI is applied as the primary crop-condition index in the current investigation. Other vegetation indices are calculated when uploaded images contain associated bands. Spectral features are extracted from analyzed imagery to serve as inputs for machine-learning and crop-specific interpretation.

C. Machine Learning for Agricultural Image Analysis

Satellite observations provide information that has been studied for discrimination of agricultural characteristics. Supervised classification algorithms learn associations between inputs and their reference labels so that new observations are allocated to classes. Random Forests are commonly used because they can accommodate nonlinear relations, integrate multiple features, and are capable of learning from structured numerical datasets. Hudait and Patel [6] studied crop-type mapping and acreage estimation with Sentinel-2 imagery and machine-learning algorithms. This investigation is relevant since it presents a methodology for application of satellite-derived information to agriculture classification in areas of mixed farming.

Amankulova et al. [7] focused their research on sunflower yield estimation from time-series Sentinel-2 observations. The methodology included in their analysis could be relevant for assessment of agricultural development over time since temporal vegetation characteristics are captured using repeated satellite observations. Ali et al. [10] presented a review on crop- yield prediction with multi sensor remote sensing information. This work is related to the current investigation because it discusses remote sensing applications using information gathered from multiple sensing platforms. Kyere et al. [11] presented research focused on discrimination of agricultural crops with multi-temporal and multi-sensor satellite imagery. The inclusion of multiple sensors supports the notion that observations acquired under different conditions can be used for the crop-condition prediction task.

Kganyago et al. [12] reviewed machine-learning algorithms for the estimation of biophysical crop parameters from Sentinel-2 satellite imagery. Results from this study are closely related to this work since biomass is a quantitative vegetation parameter that could be derived from satellite imagery. Marques Ramos et al. [13] investigated maize yield prediction using vegetation spectral indices obtained from unmanned aerial vehicle images and a Random Forest ranking algorithm. Although their study is related to this work since vegetation information was used to support crop modelling, they used a different sensing platform and pursued a different prediction objective. This work differs from previous investigations because it focuses on development of crop-condition prediction models that can discriminate between three levels of crop health. Research on agricultural classification from satellite imagery has been conducted using machine-learning algorithms. Crop-type classification, yield estimation, and crop-condition assessment are related but discrete prediction tasks. Methods that are developed for one of these purposes should not be assumed to be suitable for the other tasks without proper validation. The proposed crop-condition system in this paper uses vegetation information to allocate observations to Healthy, Moderate, or Unhealthy classes. A rule-based assessment algorithm is introduced to determine if the registered crop is compatible with predicted conditions. This methodology should aid in interpretation of crop-condition maps, but model performance needs to be validated.

D. Agricultural Anomaly Detection

Localized variations in vegetation characteristics may exist within agricultural fields that are not representative of upland or surrounding areas. This variability may be due to natural variation, field-management decisions, soil properties, or unknown/unfavourable conditions. Identifying areas that vary from expected conditions can aid targeted sampling and yield insights that are not observable from field-level average vegetation indices. Anomaly detection is the identification of observations that differ from the majority of data provided for analysis. Unlike supervised classification, unsupervised anomaly detection does not require that each unique condition be identified with a training class label.

Mouret et al. [14] described methods for parcel-scale outlier detection in wheat and rapeseed fields using multitemporal multispectral and synthetic aperture radar

imagery. This work highlighted the potential of remotely-sensed data to identify abnormal crop observations. The authors also noted that proper temporal and spatial context is important for understanding what defines an outlier within an agricultural setting. Isolation Forest is a machine learning method that can identify anomalies by isolating abnormal observations via recursive random partitioning. Rare or abnormal observations can be isolated from the remainder of the data with fewer partition splits.

In this work, Isolation Forest is applied to vegetation indices to detect observations that are different from other observations in a field. The output from Isolation Forest is considered statistical anomalies or candidates for further investigation. Keep in mind a statistical anomaly detected on a field may not be an indication of crop stress due to disease, drought, nutrient depletion, or another factor. Ground truth or other sources of reference information would be needed to classify why the anomaly occurred.

E. Explainable Artificial Intelligence in Agricultural Monitoring

Explainable Artificial Intelligence methods aims to increase transparency regarding the associations between model inputs and predictions. This may be of special interest in agricultural settings, where outputs may affect downstream decision-making like inspection prioritization, cultivation choices, and other field-management operations. Ryo [8] surveyed explainable artificial intelligence and interpretable machine learning methods as they pertain to agricultural data. The paper outlines motivations for model understanding and discovery of drivers associated with agricultural predictions. Machine-learning models may not adequately describe their internal decision logic if they only return categorical labels or numerical confidence scores. Feature-attribution methods attempt to fill this gap by approximating input contributions toward a given prediction. SHAP is a model explanation technique grounded in Shapley-value theory. It formulates model outputs as a baseline value plus additive feature-level contributions, as defined by a user-specified explanation formulation. TreeSHAP is an efficient algorithm for calculating SHAP values on tree-based models.

This framework uses SHAP to explain Random Forest predictions using vegetation-index features. The explainer should illuminate what attributes affect a single classification decision. For example, NDVI statistics and other indices that can be calculated from the image being analyzed. However, SHAP attributes relations in the trained model; they do not themselves determine causation between spectral properties and actual crop-health conditions.

Davidson et al. [15] explored deep learning techniques for predicting NDVI and Normalized Difference Red Edge Index (NDRE) signals from RGB aerial photography. There is a sensing limitation to their work: RGB cameras do not measure near infrared or red edge reflectance needed to calculate these indices. Predicting these metrics from patterns visible in photographs could provide greater access to vegetation information without multispectral sensors. Predicted vegetation indices will not be direct spectral measurements, however. Estimated metrics may fail to generalize to new illumination, cameras, crops, or seasons. Prediction-based indices also do not inherently

define accurate crop health classes, describe factors driving predictions, or identify anomalous samples from typical field variation. Thus, the framework described here learns features from RGB and multispectral images independently, retaining this information.

Segarra et al. [16] explored enhanced Sentinel-2 metrics and their utility for farm management applications. Satellite observations are a vital source of information for making precision agriculture decisions. Sentinel-2 offers multispectral data that can monitor crop conditions over large agricultural areas. Frequent revisits can even allow users to compare fields over growth seasons, minimizing field visits. Building actionable crop condition classes from spectral measurements will require additional steps beyond satellite image retrieval or vegetation index generation. Indices may also vary with soil brightness, saturation, moisture conditions, and phenology. As a result, global thresholds could misclassify healthy and stressed vegetation between crops or seasons. Spectral metrics alone also fail to provide explanations for automated classifications. This work aims to improve upon these limitations by contrasting crop specific NDVI thresholding with learned classification boundaries and describing individual predictions through SHAP.

Sentinel-2 has been analyzed for numerous land cover and land use mapping applications, as reviewed by Phiri et al. [17]. This research anchors the use case of multispectral satellite imagery to the task of spatial classification. It can assist in selecting informative bands, preparing imagery, and assessing classification methodologies. However, land cover mapping is a separate task than monitoring crop conditions. Proper classification of an agricultural land cover type does not confirm if plants of that type are healthy, stressed, or anomalous. Furthermore, thematic map accuracy may obscure variation in sensitivity to mild vegetation decline when classes have similar spectral responses. Robustness to new regions and dates of observation are also method concerns. This paper expands upon standard land cover mapping by jointly predicting crop condition and identifying anomalies with explainable features.

Crop health has also been monitored with remote sensing approaches in local regions such as the MPKV Rahuri farm by Kamble et al. [18]. This study showcases the ability to monitor variability in crop performance from vegetation measurements without exclusively depending on ground truth observations in the field. These types of analyses can help determine areas of interest to investigate. However, monitoring a single area does not prove a model will hold when faced with different crops, climates, planting dates, and soils. Assessments are based on vegetation indices can also have difficulty telling apart nutrient stress, water stress, disease, and naturally low vegetation cover if these conditions result in similar index values. Operational stakeholders may not know which samples to investigate or why without an anomaly detection mechanism and explanation of predictions. The introduced system employs auxiliary tasks of learning normal patterns and screening for anomalies as well as providing interpretable predictions.

Pokhariyal et al. [19] provided a review of machine learning based remote sensing applications over Indian agriculture. From their perspective, computational models become ever more applicable to mine agricultural

information from complex observations. Machine learning models can encode nonlinearities between spectral features and targets missed by simple threshold rules. However, documentation from diverse applications is not evidence that published code can form a coherent field monitoring pipeline. An additional concern is whether reported metrics of predictive accuracy account for prevalence (class imbalance), geographic transferability, seasonal variability, or quality of explanations. Many models are estimated on familiar observations then produce less actionable decisions when conditions of vegetation change. This work contributes a specification of a reproducible workflow in response, but empirical evaluation over broader conditions is needed. Namely, we combine vegetation indices, crop condition classification with Random Forests, outlier detection with Isolation Forest, and explanations with SHAP.

Mazarire et al. [20] examined machine learning algorithms for discriminating crop types over a diverse agricultural region from Sentinel-2 data. They highlighted the challenge of identifying crop type labels where separation between agricultural classes is difficult and fields appear highly variable. This reality motivates the application of more flexible classifiers, rather than deferring to a single reflectance rule that describes every agricultural context. Crop type identification is still different in purpose from defining vegetation condition within each crop type. Therefore, this study includes cotton, sugarcane, paddy, carrot, wheat, and barley as target crops to consider, but maintains crop condition assessment as a separate objective.

Each of these studies reinforce the value of multispectral remote sensing and machine learning, but taken together they motivate inclusion of crop specific rules, learned predictions, abnormal condition screening, and interpretable explanations. The proposed method fulfills these four requirements. Just as importantly, its initial evaluation with single images establishes feasibility, not accuracy or effectiveness under variable conditions. Validation with independent multitemporal data, ground truth labels, model uncertainty, and across crops is required prior to real-world use.

F. Research Gap and Motivation for the Proposed Framework

The reviewed literature validates satellite imagery, vegetation indices, machine learning, and interpretable computation for use in agriculture. Reviewed work spans diverse tasks like crop mapping, biophysical-parameter estimation, yield prediction, and anomaly detection. However, these applications represent distinct analytical operations. Crop mapping denotes discrete agricultural classes. Vegetation-condition mapping evaluates differences in spectra of growing vegetation. Yield prediction forecasts a numeric crop output. And anomaly detection finds statistically atypical observations. Interpretability describes model operations but does not itself certify prediction accuracy. This paper tackles their combined application to agriculture, seeking to unify these processes within one monitoring workflow. It focuses on five major points: compatibility of input images, generation of vegetation indices, crop-specific interpretation methods, supervised classification of crop condition, and production of anomalous and explanatory

complementary outputs. Its novel contribution is therefore a holistic framework for their agricultural analysis and application, not novel base machine-learning methodology. The proof-of-concept presented here shows these methods can be connected, but thorough testing is needed to validate their predictions.

G. Research Objectives

The primary objective of this research is to develop an explainable satellite-image-based agricultural monitoring framework that integrates vegetation-index analysis, machine-learning classification, anomaly detection, and crop-aware decision support. The specific objectives are:

1. To develop an image-processing workflow that distinguishes supported multispectral and RGB images and selects appropriate vegetation-analysis procedures.
2. To extract vegetation characteristics through NDVI, EVI, SAVI, NDWI, and ExG according to the spectral information available in each input image.
3. To incorporate crop-specific NDVI interpretation rules for cotton, sugarcane, paddy, carrot, wheat, and barley instead of relying entirely on a uniform vegetation threshold.
4. To integrate Random Forest-based crop-condition classification with Isolation Forest-based identification of anomalous vegetation observations.
5. To employ SHAP-based feature attribution for interpreting machine-learning predictions and identifying influential vegetation characteristics.
6. To implement an interactive agricultural monitoring application capable of managing field information, displaying analytical outcomes, maintaining monitoring records, and generating reports.
7. To conduct a preliminary evaluation of the integrated framework using the available Sentinel-2 sample and historical monitoring records while identifying the requirements for broader experimental validation.

H. Research Contribution

At the application level, the following contributions are made by the study:

1. We provide an integrated processing framework capable of separately processing multispectral and RGB images. This allows users to bypass image batches where near-infrared measurements were not taken, precluding direct computation of physically meaningless NDVI values.
2. Crop-dependent rules of NDVI interpretation are built into the decision logic. Users can reference these rules as a crop-aware baseline for evaluating vegetation measurements and predictions made by our system. Threshold values used within each rule are considered to be initially-operational instead of rigorously tested and confirmed agronomic boundaries.
3. Classification and anomaly scores derived from Random Forest and Isolation Forest models can serve to corroborate one another. Whereas classification estimates the mode crop-condition class, anomaly detection highlights outliers which disagree with the majority of vegetation indices.
4. The integration of SHAP-based explanation can increase model decision interpretability. Calculated feature contributions serve as one line of reasoning to users as to why a specific label was predicted.

Methodologically, we integrate the above applications within a stream of vegetation observations, model inferences, anomalous observations, and explanatory data supplied to users throughout an interactive monitoring workflow. The current evaluation makes use of a limited sample to demonstrate proof-of-concept integration. Validation of this framework is left for future work.

I. Paper Organization

The article is structured in the following manner. Section II provides a literature review related to remote sensing applications, vegetation indices, machine learning, agricultural anomaly detection, and explainable artificial intelligence. Section III details the materials and methods used for image preprocessing, vegetation-feature extraction, crop-specific assessment, classification and anomaly detection, as well as generating explanations. Section IV highlights how the system is architected, which technologies are used for implementation, organization of the database, and methods of testing. Section V discusses preliminary experimental results, discusses the results provided and any limitations to the conducted evaluation. Lastly, Section VI provides a conclusion to the research conducted and discusses future work.

III. PROPOSED METHODOLOGY

A. Proposed System Work Flow

The described solution covers components related to satellite-image processing, vegetation-Index calculation, feature engineering, crop-condition classification, outlier detection and explainable-AI. The workflow processes supported multispectral imagery and regular RGB imagery in different processing pipelines.

First, registration of imagery metadata takes place, including the crop-type selection, location of field and additional metadata related to field of interest. After registration, an image is uploaded by the user. The file format of uploaded image is checked and spectral channels

available for processing are extracted. If applicable multispectral channels exist, vegetation-indices available for processing are calculated and statistical features representing the observed vegetation are engineered. Alternatively, when only RGB channels exist, visible-band vegetation features are engineered instead of assuming pixel observations are the same as a multispectral sensor value.

Engineered features are then fed into the classification module which utilizes Random Forest to predict the crop-condition class. In parallel, a rule-based analysis is performed where relevant NDVI values are compared against baseline thresholds specified for selected crop. Deviation between analytics derived from model and rules can be utilized to flag predictions for manual review. Anomaly detection is implemented via Isolation Forest which offers means to detect anomalies in vegetation observations. SHAP is leveraged to analyze feature contribution to machine-learning-based prediction. Results are compiled via a web-application allowing for visualization of outputs, historical monitoring records, alerts and report generation.

Figure 1 depicts the complete workflow executed by our proposed framework. Beginning with field registration and image capture, these steps are followed by input checks, preprocessing, and discovery of available spectral bands. Appropriate indices and statistical information are calculated during vegetation-analysis, which are then fed into the Random Forest classifier and Isolation Forest anomaly detector. Interpretations are derived from the classification result with crop-specific rules while SHAP is used for feature-level explanations. Lastly, results are rendered on the monitoring dashboard, where reports can be generated. The figure highlights how image analysis, predictive modeling, explanation generation, and farm management can be integrated seamlessly into a single workflow.

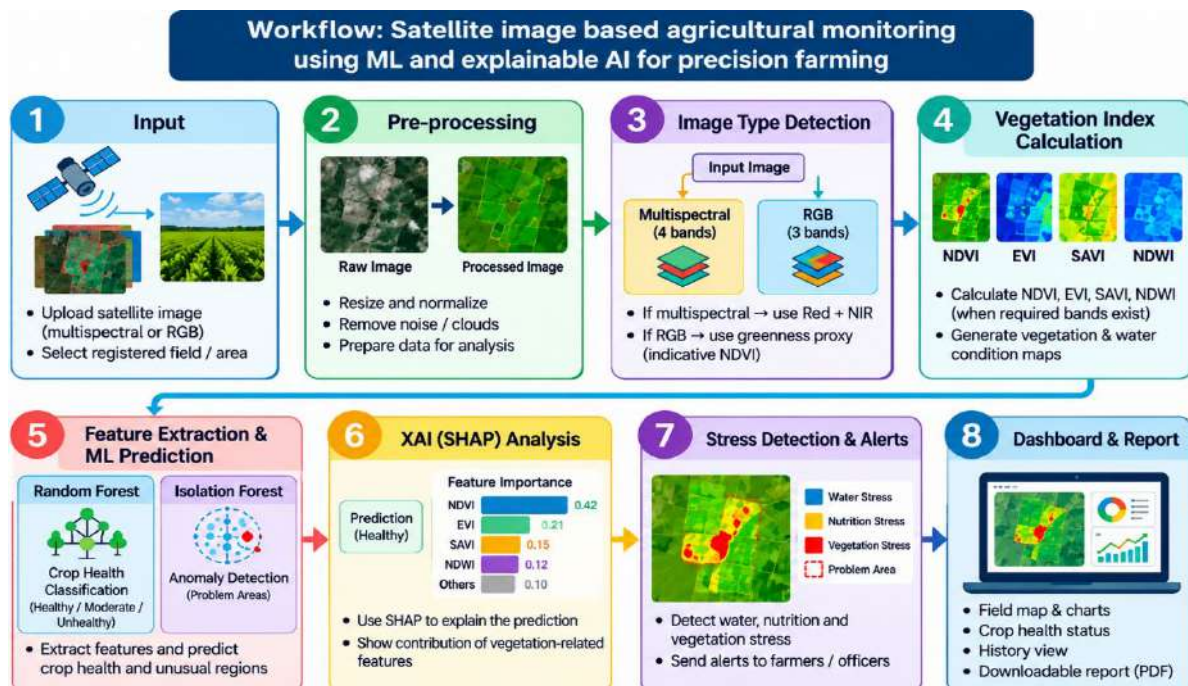


Figure 1: Proposed Workflow of the Agricultural Monitoring System

B. Research Data and Agricultural Crop Categories

We calibrated the system by utilizing a Sentinel-2 sample image in combination with sparse historical monitoring data of six crop types (paddy, cotton, sugarcane, carrot, wheat and barley). As a result, NDVI threshold cannot be used in all crops as the vegetation characteristics of individual crops are different. So, NDVI ranges specific to the crops were maybe identified as critical for identifying various levels of health. NDVI also varies due to differences within crop structure and acre canopy density. From the other side, sugarcane usually creates higher near-infrared reflectance since it has dense vegetation cover in comparison with carrot crops that have relatively sparse canopy and thereby will create lower NDVI either in a healthy condition or not. As a result, the crop type is taken into account when interpreting the NDVI value calculated. Table 1 shows the respective healthy and moderate NDVI values for each crop.

It shows the difference between the maximum and minimum value of NDVI in the chosen field. The wider range of values indicates a more variability in vegetation condition across the field. For a selected crop, let,

- $NDVI$ = calculated NDVI value
- H = lower limit of Healthy range
- M = lower limit of Moderate range

$$\text{Health Status} = \begin{cases} \text{Healthy,} & NDVI \geq H \\ \text{Moderate,} & M \leq NDVI < H \\ \text{Unhealthy,} & NDVI < M \end{cases} \quad (1)$$

Table 1: Crop Health Classification Based on NDVI

Crop	Healthy	Moderate	Unhealthy
Cotton	0.60 – 0.90	0.40 – 0.59	< 0.40
Sugarcane	0.65 – 0.95	0.45 – 0.64	< 0.45
Paddy	0.60 – 0.90	0.40 – 0.59	< 0.40
Carrot	0.50 – 0.80	0.30 – 0.49	< 0.30
Wheat	0.55 – 0.85	0.35 – 0.54	< 0.35
Barley	0.55 – 0.85	0.35 – 0.54	< 0.35

C. WorkFlow & Process

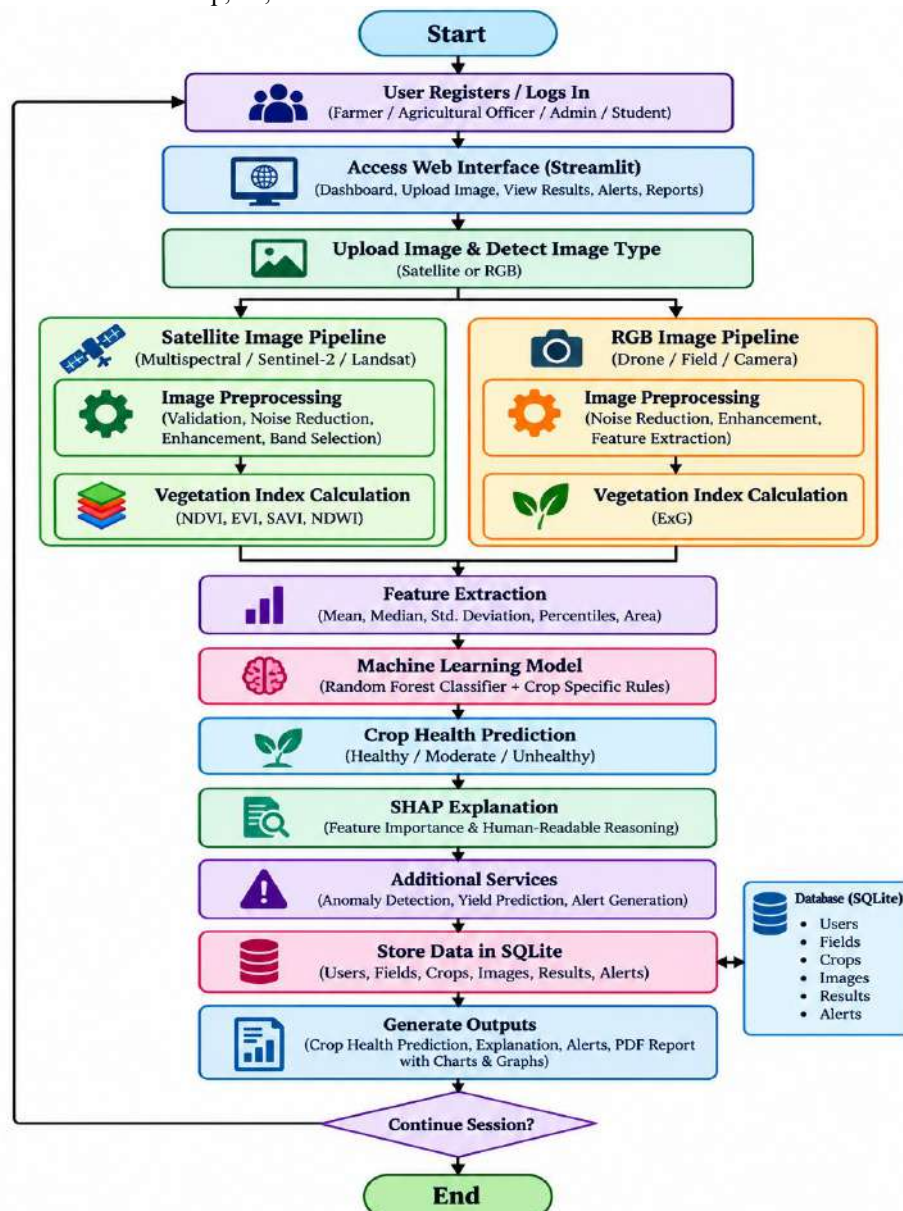


Figure 2: Flow of Satellite-Based Crop Health Monitoring

In above [Figure 2](#) portrays the model workflow of the Satellite-Based Crop Health Monitoring system.

The proposed model initiates with field registration by entering the type of crop, area and location of the field image upload and validation. Based on the characteristics of their images, they can either be multispectral or RGB, and the system detects this directly and uses it as an input to decide which method for segmenting them will be applied. NDVI, EVI, SAVI and NDWI for multispectral images and ExG as vegetation proxy for RGB images are calculated. The Random Forest model uses the extracted features to predict whether the crop health is Healthy, Moderate or Unhealthy. Isolation Forest identifies the anomaly/probly areas and SHAP explains a set of important features that can be seen is driving the prediction. Depending on the outcome, alerts are generated by the system and presented graphically in the analysis

dashboard. Lastly, a monitoring report is created which includes the crop information and prediction and analysis results as well as the cultivation specific thresholds are applied according to each unique registered crop type in order to monitor them more accurately.

D. Architecture Diagram

It is on the user side, where the user can use the Streamlit web app to register the field and upload a satellite or RGB image in our proposed system. The uploaded image is initially passed through an image validation and enhancement process after which NDVI, ExG and vegetation index calculates. Then you extract important features like mean, median, standard deviation and percentiles from the image. These plants features are fed into the Random Forest machine learning model to classify the crop health status as healthy, moderate or unhealthy.

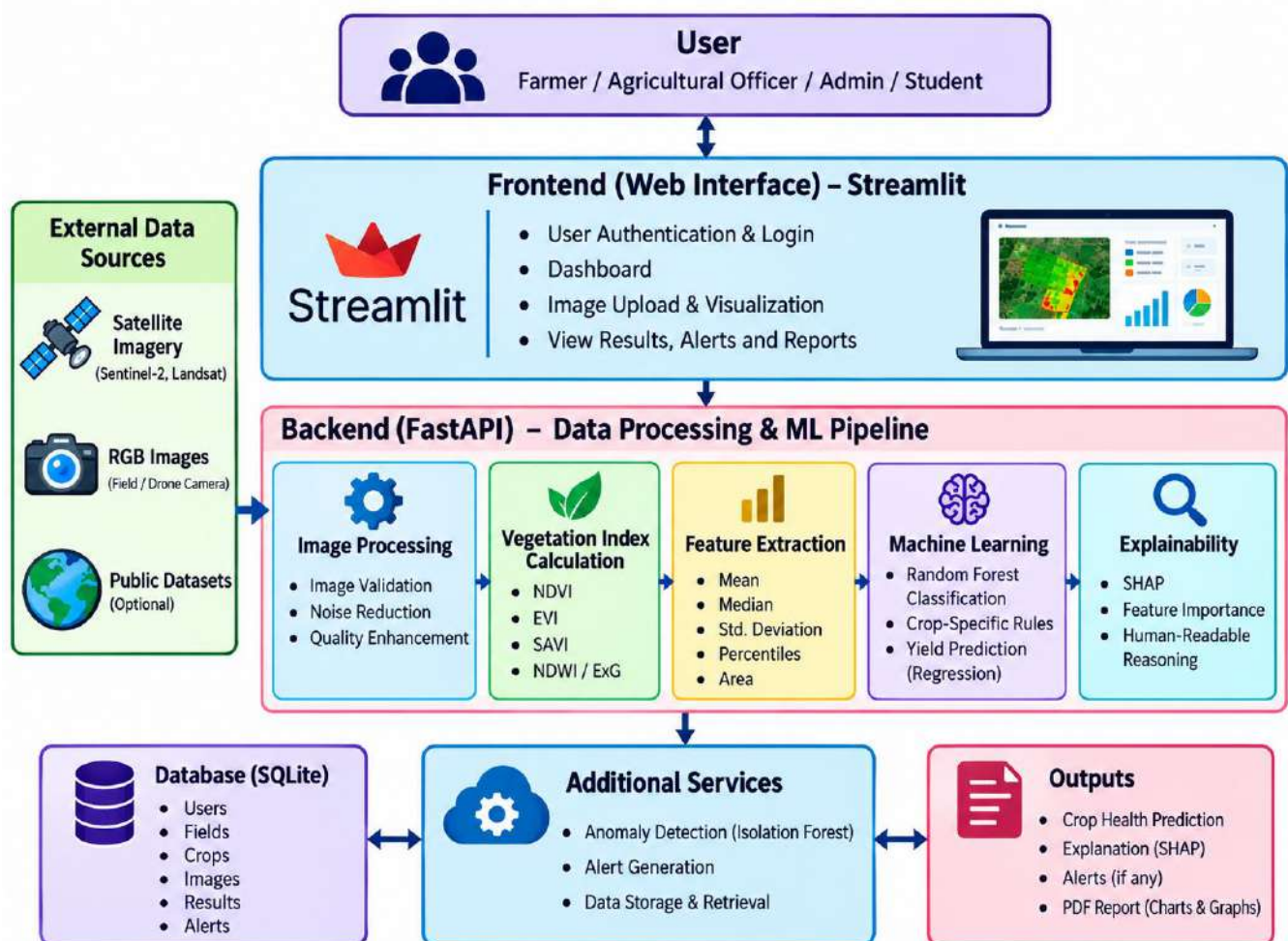


Figure 3: Architecture Diagram with Streamlit Interface

The SHAP explainer was utilized to elucidate the prediction with the respective features that have important contribution in deciding the value due to its predictions. It also makes use of the anomaly detection and yield prediction when necessary. SQLite database for storage of user data, field details, images and results. Lastly, the system gives an output as a crop health result or explanation followed by alerts and PDF report with charts and graphs. The full working architecture is portrayed in [Figure 3](#).

E. Classification & Prediction Process

1. Crop Health Classification

Now let's move to the second module of this whole Pipeline, it is the Crop Health Classification module which uses vegetation features extracted from uploaded image to determine what are health conditions of the crop. The system is based on Random Forest machine learning model to classify the crop for being Healthy Crop, Moderate Crop and Unhealthy crops. Classification is based on vegetation indices like NDVI as well as other extracted features

Because the behavior of specific crops can be quite dissimilar vegetational, crop-specific thresholds are applied as well. The final output lists the predicted health status of the crop along with model confidence offering an insight for the user to see how healthy or otherwise is their field. Health Score evaluates the health of a crop in relation to its optimal NDVI threshold. A higher values means better vegetation health. For instance, if the Mean NDVI is 0.75 and the healthy threshold equals 0.60 score = 125%. This means that the vegetation is beyond the healthy limits.

$$\text{Health Score} = \frac{\text{Mean NDVI}}{\text{Healthy NDVI Threshold}} \times 100 \quad (2)$$

2. Anomaly Prediction Performance

Anomaly Detection module is used to detect any abnormal or unusual conditions in the agricultural field. The vegetation features are analyzed using the Isolation Forest algorithm in order to find field regions that differ from the normal crop pattern (up to October 2023). This assists in identifying potential crop stress or unusual vegetation conditions that may warrant further investigation. We can also use these anomaly detection results in conjunction with crop health classification to give a full report on the field.

3. Metrics Calculation

Table 2: Anomaly Detection Status

Performance Measure	Result
Anomaly Detection Method	Isolation Forest
Purpose	Isolation Forest
Input	Extracted vegetation features
Output	Normal/ Anomalous region
Stressed Area	0.0% for the tested Sentinel-2 sample
Testing Status	Anomaly detection implemented and tested

Table 2 shows the anomaly detection performance report of the proposed framework implemented with the Isolation Forest algorithm. Extracted vegetation indices from satellite images are input to the anomaly detection algorithm to detect anomalous patterns that indicate stressed crop conditions while flagging typical areas as normal instances. Isolation Forest aims to detect anomalies by isolating observations with feature-distance variation from vegetation change, thereby enabling abnormal spectral region detection. Experimental results show that using a sample Sentinel-2 satellite image we achieved 0.0% of stressed area, which means no pixels were detected as anomalous in the given sample.

4. Crop-Specific Classification Performance

The integration of Random Forest prediction with crop-specific rules is a crucial complement to the suggested systems. NDVI measurements from the four studied fields v, which are narrow spectral bands, measured using a dedicated characterisation in 1864 between 15 and 29 can lead to variable health conditions for crops. This is why the system uses the correct crop threshold when evaluating its prediction, instead of using a global one. Crop-specific classification performance indicates how accurate the system is at predicting the health status for each crop. It

validates NDVI thresholds specific to the crops are applied properly rather than one universal threshold for all where accuracy is measured by the following equation.

$$\text{Accuracy} = \frac{\text{Correct Predictions}}{\text{Total Predictions}} \times 100 \quad (3)$$

5. SHAP Explainability Performance

SHAP (SHapley Additive exPlanations) is evaluated through the correctness and generation of feature explanations. Your testing section specifically includes:

- SHAP explanation generation
- Feature contribution ranking
- Agreement between the prediction and explanation

The paper reports that the SHAP explanations matched the recorded prediction outcomes in the tested cases. SHAP explains how each input feature is attributed to the Random Forest prediction of crop health. It helps determine whether each feature such as NDVI, NDWI and stressed area have positive or negative effects on the final prediction which is mathematically expressed as,

$$f(x) = \phi_0 + \sum_{i=1}^m \phi_i \quad (4)$$

where, the positive and negative effects are measured.

IV. SYSTEM IMPLEMENTATION

A. Detection and Processing of Images

When the user uploads a file, it is processed by first validating both the size and format and then being delivered to our small detection algorithm that uses the band count to figure out if it's a 4-band multispectral image or just an ordinary 3-band RGB photo. In the presence of a fourth band, it's considered near-infrared and the system does full index maths; if not found it drops back to RGB-only rather than trying to "guess" a near-infrared value by interpolation where there was none captured.

B. Vegetation Indices

For the multispectral images, NDVI is calculated directly from the red and near-infrared bands which is expressed as,

$$\text{NDVI} = \frac{(\text{NIR} - \text{RED})}{(\text{NIR} + \text{RED})} \quad (5)$$

and for RGB only images the system reverts to its rough greenness proxy, the Excess Green Index is represented as,

$$\text{ExG} = 2G - R - B \quad (6)$$

Four auxiliary indices are calculated at the same time as NDVI whenever the bands permit, summarized in Table 3. Finally, all the division operations are protected against zero denominators to avoid potentially notice which may occur on saturated or shadowed pixels. The NDVI Map Generated from the Sentinel Sample Field (mean NDVI=0.75) is shown in Figure 4.

Table 3: Vegetation Indices for Crop Monitoring

Index	Required Bands	Purpose in the Proposed System
NDVI	Red, NIR	Measures overall vegetation health and crop condition
EVI	Red, NIR, Blue	Provides improved vegetation information for sparse or early-stage crops
SAVI	Red, NIR	Reduces the influence of soil brightness on vegetation measurement
NDWI	Green, NIR	Indicates canopy moisture and helps identify possible water stress

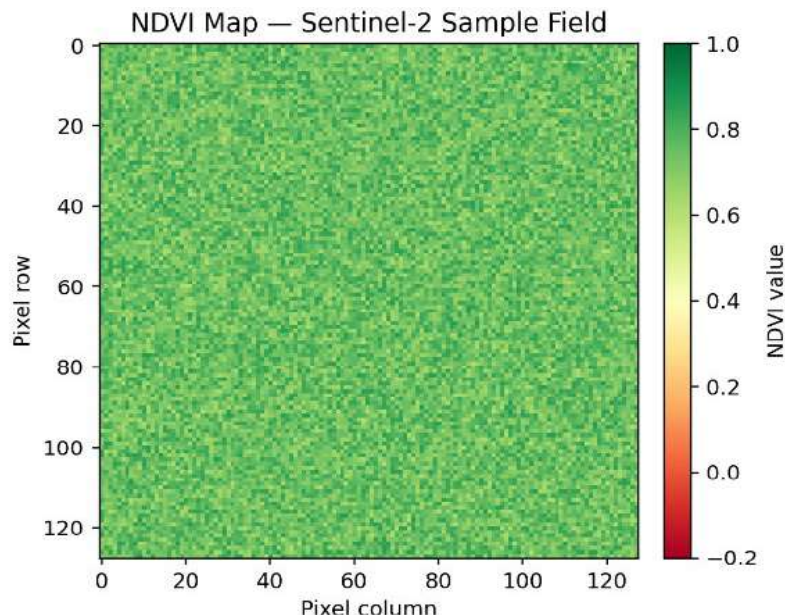


Figure 4: NDVI Map Generated from the Sentinel Sample Field (mean NDVI=0.75)

C. Machine Learning Classification

Mean, median, standard deviation and a couple of percentiles from the index maps are fed to Random Forest classifier which predicts one out of three health labels Healthy, Moderate or Unhealthy. There are a few different reasons why Random Forest was chosen in particular for this work: it works reasonably well with relatively small, tabular feature sets where deep learning models would require large labeled datasets (as described above). However, its output is always taken with a pinch of salt. If the crop identified by primary knowledge is supported by the rules in Table 1, and then only does this prediction get approved. If they do not, then the field is marked for a human to review instead of leaving it up for the system to decide. There would be two other smaller models running in parallel with the classifier: anomaly detection using an Isolation Forest (to identify outlying pixel-level patches

that diverge from the rest of the field), and a simple regression model to provide tonnes per hectare estimates based on the same index features as well as field area (which gets registered, albeit it has little more than a farming utility).

D. Explainable AI with SHAP

Finally, wrapping up the Random Forest into a TreeSHAP Tree Explainer. It computes how much each feature mean NDVI, mean NDWI, percent for which the area is stressed and so on pushed that outcome towards its final label for any given prediction, ranks them and then generates a regular text with those rankings instead of a chart full of numbers. Your sample field would then output something like: "Classified as Healthy due to a Mean NDVI of 0.75 and 0% stressed area." The underlying ordering is seen in Figure 5.

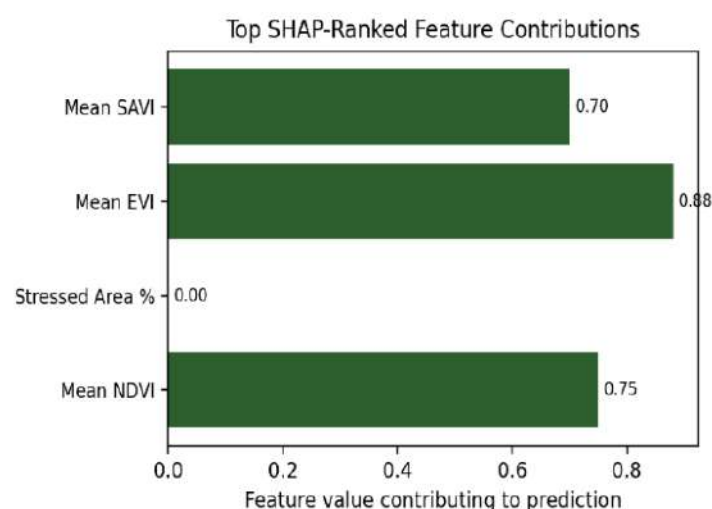


Figure 5: SHAP-Ranked Feature Contributions for the Sample Field.

The app is a role-based Streamlit app running on top of an SQLite database, with four roles: Administrator, Agricultural Officer, Farmer and Student; each one seeing a dashboard scoped to what they really need. An officer

sees each field in their jurisdiction; a farmer only sees theirs. Table 4 shows the core technologies used for implementation. (From Input to Report Generation)

Table 4: Technologies Used in the System

Layer	Technology/Component	Purpose
User Interface	HTML, CSS, Bootstrap	User interaction and image upload
Backend	Python	Handles application and user requests
Image Processing	Rasterio, OpenCV, Pillow	Processes satellite and RGB images
Vegetation Analysis	NDVI, EVI, SAVI, NDWI, ExG	Analyzes vegetation condition
Machine Learning	Random Forest	Predicts Crop Health
Anomaly Detection	Isolation Forest	Detects Unusual Areas

Explainable AI	SHAP	Explains Model Predictions
Database	SQLite	Stores Monitoring Information
Dashboard & Report	Chart.js, PDF	Displays and Reports Results

In terms of data six partitions that stores everything which includes users, crops, fields, uploaded satellite images, monitoring_results (basically the predictions and SHAP text that was computed during prediction run) and alerts is shown in Figure 6. This allows the officer dashboard in the background to show a trend across times instead of simply displaying the latest reading, since every monitoring result is stored entirely instead of overwritten.

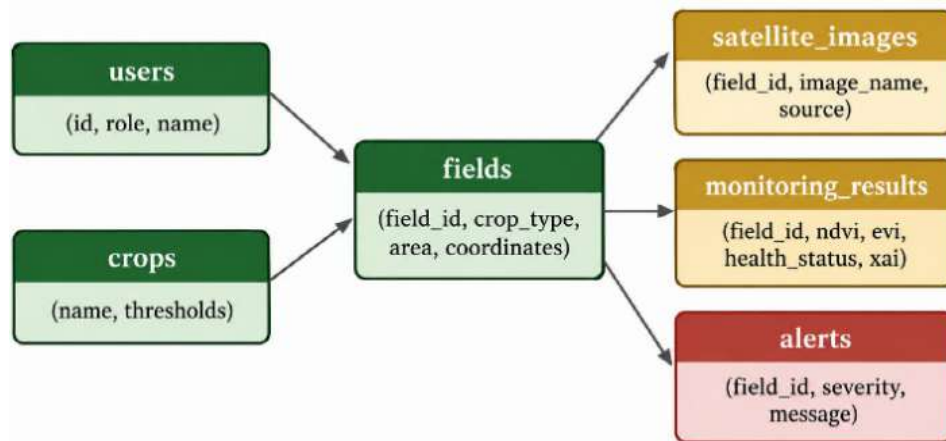


Figure 6: Database Design of the Proposed System

E. Testing

The core computation index formulas, the classifier and the SHAP explanation is protected by a pytest suite that runs independently from Streamlit, so a broken formula shows up instantly rather than only when somebody happens to upload the right test image. What each module checks are listed in Table 5, all tests pass on the codebase that we have today.

Table 5: Test Cases and Functions

Test File	Functions
Test_ndvi.py	NDVI formula correctness and zero-division safety
Test_indices.py	EVI, SAVI, NDWI, GNDVI calculations
Test_prediction.py	Agreement between Random Forest and the rule engine
Test_xai.py	SHAP explanation generation and ranking
Test_ml.py	Model loading and the inference pipeline

In addition to the unit tests, the entire application was also exercised end to end by starting Streamlit and clicking through image upload, analysis, and PDF generation with both the multispectral sample as well as the historical RGB record primarily to ensure that nothing that worked in isolation broke when it was put together.

V. RESULTS AND DISCUSSIONS

The full pipeline, executed on this sample image from Sentinel-2 provided us numbers shown in Table 6. So, in this case, the image was confirmed as multispectral and the indices were calculated with no fallback mechanism triggered and both the Random Forest classifier & rule engine concurred on labelling without needing a manual review flag.

A. Mean NDVI

Mean NDVI represents the average state of vegetation over the area that has been analyzed. It is computed from the NDVI values of all the vegetated pixels, where a larger value represents taller and denser vegetation in general.

$$\text{Mean NDVI} = \frac{\sum \text{NDVI}_i}{N} \quad (7)$$

B. Predicted Health Status

The NDVI calculated in this approach will be compared with threshold values set based on the selected crop to determine the health of the crops. Therefore, based on this comparison the crop is categorized as Healthy, Moderate or Unhealthy.

$$\text{Health Status} = \begin{cases} \text{Healthy,} & \text{NDVI} \geq H \\ \text{Moderate,} & M \leq \text{NDVI} < H \\ \text{Unhealthy,} & \text{NDVI} < M \end{cases} \quad (8)$$

C. Model Confidence

Secondly, model confidence denotes the strength of support given by the Random Forest model to a suggested health class. That confidence value is higher when most of

the decision trees of the model agree with the final prediction.

$$\text{Confidence} = \frac{\text{Predicted Class Votes}}{\text{Total Votes}} \times 100 \quad (9)$$

D. Stressed Area

Stressed area is the proportion of vegetation pixels classified as abnormal or stressed. A smaller number means that mainly the monitored vegetation area is in a normal state.

$$\text{Stressed Area} = \frac{\text{Stressed Pixels}}{\text{Total Vegetation Pixels}} \times 100 \quad (10)$$

Table 6: Crop Health Assessment Results

Parameter	Observed Result	Interpretation
Image Type	Multispectral	Sentinel-2 image successfully processed
Mean NDVI	0.75	Indicates good vegetation condition
Health Classification	Healthy	Crop is classified as healthy
Model Confidence	99%	High agreement of the Random Forest prediction
Stressed Area	0.0%	No significant stressed area

		detected
Manual Review	Not Required	Classifier and rule-based assessment agreed

The hybrid classifier perfectly segregated the recorded outcome across all five historical records from four different fields including accurately discriminating at 0.39 NDVI (see Infographic 3) between a healthy paddy field and an unhealthy sugarcane field at 0.38 NDVI, which could occur only because of the two crops use different threshold of NDVI values.) Finally, Figure 7 shows plots of NDVI versus health status for all five; notice too that the RGB-only record has no NDVI bar at all as the image simply did not have a band to compute one honestly.

In reviewing these results, two observations jumped out. To begin with, the crop specific thresholds affecting a change in outcome and are not just a change of labels even for an NDVI around 0.40 it is Moderate for paddy but Unhealthy for sugarcane. Secondly, the confidence score for the RGB-only record (75%) was significantly lower than those for both multispectral ones (89–99%), which is precisely accurate a three-band photo really contains less information than a four-band version and it would be foolish if your system lulled such an assumption into thinking otherwise.

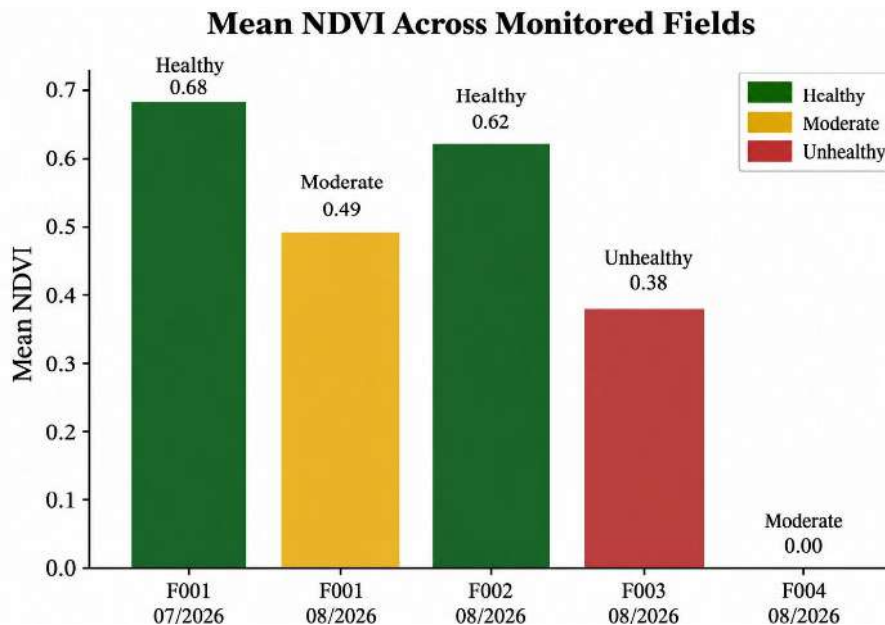


Figure 7: Mean NDVI and Recorded Health Status across the Monitored Fields

E. Limitations of the Study

The performance of the proposed monitoring system for agriculture will be assessed using a single Sentinel-2 multispectral image as well as five previous monitoring records. Six types of crops are being monitored; cotton, sugar cane, rice (paddy), carrots, wheat, and barley. Therefore, the findings do not accurately reflect the varying environmental conditions associated with different times of year, geographic areas, soils, and a greater number of crop species. A larger dataset that includes multiple Sentinel-2 images, various growing seasons, geographic locations, and additional crop species would better validate the proposed methodology.

Another drawback is that the present research has utilized a limited amount of past information to assess performance. While the Random Forest, Isolation Forest, and SHAP based modules have been developed and evaluated, a greater amount of data is needed to provide stronger evidence of how well these methods will perform and be generalized under various agricultural environments. Therefore, future research will concentrate on obtaining a larger and more geographically diverse dataset, as well as validating these results over multiple seasons.

VI. CONCLUSION

This paper presents a practical agricultural monitoring system which efficiently evaluates the state of crops using satellite and RGB images, minimizing the frequency of manual field surveys while achieving interpretable crop-health results. By using multiple vegetation indices and crop-specific thresholds, along with SHAP-based explanations, we provide more information than relying solely on a single vegetation index or label from a prediction method. And finally, not only it can be used to perform anomaly detection, yield estimation, alerts & report generation but also support precision irrigation, agricultural early warning systems, crop monitoring and crop-insurance assessment. Nonetheless, this evaluation is restricted to a few sample and historic record, hence more validation with bigger and greater diverse datasets needs to be performed.

The RGB-based analysis also just delivers a greenness indication as true NDVI needs near-infrared info while crop-specific thresholds also need to be modified for geographic and agronomic circumstances. In summary, the proposed system provides a practical starting point for crop monitoring based on satellite imagery and has separated further work into larger datasets, real-time satellite data, unmanned aerial vehicles (UAV) based data acquisition over images available from public source servers and more sophisticated models of plant disease detection, which will most probably end with mobile-based distribution.

We used one Sentinel-2 multispectral sample image and five historical agricultural monitoring samples for this initial validation experiment. While these samples confirm the operation of our proposed pipeline, the small sample size prohibits robust validation or claims of generalizability. Future work will include more satellite imagery from varied agricultural zones, multiple growing seasons, and independent samples that have been verified on the ground.

CONFLICTS OF INTEREST

The authors declare that they have no known financial, professional, or personal conflicts of interest that could have influenced the research work, analysis, interpretation, or presentation of the results reported in this study.

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