AI Based Crop Health Monitoring Using NDVI Time-Series Derived from Satellite Spectral Data

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***Abstract*- Precision agriculture requires intelligent and scalable systems to monitor crop conditions and improve productivity. This paper presents an AI-based crop health monitoring and yield prediction framework using NDVI (Normalized Difference Vegetation Index) time-series derived from satellite spectral data. The system utilizes Sentinel-2 satellite imagery to analyze vegetation patterns across the Kharif season and assess crop conditions at different growth stages.**

Unlike conventional approaches that rely solely on vegetation indices, the proposed system incorporates sowing date information to perform stage-aware crop health analysis. By evaluating NDVI values in relation to crop growth stages, the system accurately distinguishes between early-stage crops and stressed vegetation, thereby improving reliability in real-world scenarios. Machine learning models are further employed to predict crop yield during later stages of the season, with prediction accuracy improving as more temporal data becomes available.

The system follows a client–server architecture, where the frontend provides an intuitive dashboard for monitoring crop condition, production risk, and expected yield, while the backend handles data processing and predictive modeling. Communication between components is achieved through RESTful APIs. The proposed framework enables near real-time crop monitoring and supports data-driven decision-making for agricultural management.

***Index Terms*- Precision Agriculture, Crop Health Monitoring, NDVI Time-Series, Satellite Remote Sensing, Sentinel-2, Vegetation Analysis, Growth Stage Analysis, Yield Prediction, Machine Learning, Time-Series Analysis, Crop Monitoring System, RESTful APIs, Web-Based Dashboard.**

I. INTRODUCTION

Agriculture plays a crucial role in ensuring food security, economic growth, and rural development. However, modern agricultural practices face several challenges, including climate variability, water scarcity, pest infestations, and unpredictable crop performance. Monitoring crop health at the right time is essential to minimize losses and improve productivity. Traditional methods of crop assessment rely on manual field inspections and farmer experience, which are often time-consuming, subjective, and not scalable for large agricultural regions.

With the advancement of satellite remote sensing technologies, it has become possible to monitor crop conditions over large areas using vegetation indices such as the Normalized Difference Vegetation Index (NDVI). NDVI provides valuable insights into plant health by analyzing spectral reflectance from satellite imagery. Time-series NDVI data, collected across different stages of the crop growth cycle, enables the analysis of vegetation patterns and crop development throughout the season.

However, relying solely on NDVI values can lead to inaccurate interpretations, especially during early growth stages where low vegetation values may be misclassified as crop stress. To address this limitation, it is important to consider crop growth stages while analyzing vegetation data. Incorporating contextual information such as sowing date allows for stage-aware interpretation of crop health, improving the accuracy and reliability of monitoring systems.

In this context, artificial intelligence and machine learning techniques can be effectively used to analyze NDVI time-series data and predict crop yield based on observed growth patterns. This paper proposes an AI-based crop health monitoring and yield prediction system that integrates satellite-derived NDVI data with growth stage analysis. The system is designed as a web-based application with a user-friendly interface, enabling users to monitor crop condition, assess production risk, and obtain yield forecasts without requiring technical expertise. The proposed approach aims to support near real-time crop monitoring and enhance decision-making in agricultural management.

II. LITRATURE REVIEW

The increasing demand for efficient agricultural monitoring systems has led to the widespread adoption of remote sensing and data-driven approaches in precision agriculture. Traditional crop assessment methods, which rely on manual observation and field surveys, are often limited in scalability and accuracy. Researchers have emphasized the importance of satellite-based monitoring systems to provide timely and objective insights into crop conditions across large agricultural regions [1], [5].

Vegetation indices derived from satellite imagery, particularly the Normalized Difference Vegetation Index (NDVI), have been extensively used for crop health analysis. NDVI captures the reflectance characteristics of vegetation and provides a reliable indicator of plant vigor and biomass. Several studies have demonstrated the effectiveness of NDVI time-series data in analyzing crop growth patterns, detecting stress conditions, and monitoring seasonal vegetation changes [2], [6]. Time-series analysis enables tracking of crop development across different growth stages, improving the understanding of temporal variations in vegetation health.

Machine learning techniques have further enhanced the capabilities of agricultural monitoring systems by enabling predictive analysis based on historical and real-time data. Models such as Random Forest, Gradient Boosting, and Support Vector Machines have been widely used for crop classification, yield prediction, and stress detection [3], [7]. These models can learn complex relationships between vegetation indices and crop performance, providing accurate and scalable prediction frameworks.

Recent research also highlights the importance of integrating temporal and contextual information into crop monitoring systems. Studies indicate that incorporating factors such as crop growth stages and environmental conditions significantly improves the interpretation of vegetation indices and reduces false predictions [4], [8]. This is particularly important in early crop stages, where low NDVI values may not necessarily indicate poor crop health.

Despite these advancements, challenges remain in developing systems that are both accurate and user-friendly for practical deployment. Many existing solutions focus heavily on technical analysis while lacking intuitive interfaces for end users. Additionally, variability in agricultural conditions and data limitations can affect model generalization across regions [6], [10].

To address these gaps, this study proposes an integrated framework that combines NDVI time-series analysis with growth stage-based interpretation and machine learning techniques. The proposed system focuses on providing meaningful and simplified insights to users through a web-based application, enabling effective crop monitoring and yield prediction in a practical and scalable manner.

III. SYSTEM ARCHITECTURE AND DESIGN

A. High-Level Architecture Overview

The system follows a three-tier client–server architecture consisting of presentation, application, and data layers. This design ensures clear separation of responsibilities and supports independent scaling of system components.

The presentation layer includes a React-based web application that allows users to input farm location and sowing date and visualize crop health information. All client requests are handled through RESTful APIs, enabling smooth communication between frontend and backend.

The application layer is implemented using Python-based frameworks such as Flask or FastAPI. It handles NDVI data processing, growth stage analysis, and crop condition evaluation. The system logic is organized in a modular manner to improve maintainability and scalability.

The data layer consists of structured NDVI datasets derived from Sentinel-2 imagery, along with metadata such as location, year, and sowing date. This layer supports efficient data retrieval and processing.

B. Module Organization

The backend is organized into multiple modules including data processing, API routing, analysis engine, and utility components. This modular structure ensures separation of concerns and simplifies system expansion.

The data processing module handles NDVI extraction and preprocessing. The analysis module performs time-series evaluation and growth stage determination. The API module manages communication between frontend and backend, while utility functions support date calculations, normalization, and data handling.

C. Authentication and Authorization
The current system is designed primarily for accessibility and demonstration purposes and does not require complex authentication mechanisms. However, the architecture supports integration of authentication features such as token-based access control if extended for multi-user deployment.

D. Frontend Architecture
The frontend is developed using React.js with functional components and hooks. It provides an interactive dashboard where users can:

- Enter farm location and sowing date
- View crop growth stage
- Analyze crop condition
- Monitor seasonal trends

The interface is designed to be simple, responsive, and user-friendly, enabling non-technical users to easily interpret results.

E. External Data Integration
The system integrates satellite-derived NDVI data obtained from Sentinel-2 imagery. These datasets provide spectral information necessary for vegetation analysis.
The system processes monthly NDVI values for the crop season and uses them to evaluate vegetation health and growth patterns over time.

F. Data Flow and Processing
The system follows a structured workflow:

- User inputs farm location and sowing date
- NDVI time-series data is retrieved for the selected region
- Growth stage is calculated based on sowing date
- NDVI values are analyzed with respect to growth stage
- Crop condition is determined (Healthy / Moderate / Stressed)
- Results are displayed on the dashboard

This flow ensures consistent and accurate crop health interpretation.

G. Scalability and Reliability Considerations
The system is designed to support scalability through modular architecture and API-based communication. The use of RESTful services enables easy integration with additional data sources or mobile applications.
Efficient data handling and preprocessing ensure reliable system performance. The architecture can be extended to support larger datasets, real-time updates, and additional analytical features in future implementations.

IV. METHODOLOGY

This study proposes an AI-based crop health monitoring and yield prediction system using NDVI time-series derived from satellite spectral data. The methodology includes system design, data acquisition, preprocessing, feature engineering, growth stage analysis, machine learning model integration, and system implementation. The framework is designed to support near real-time crop monitoring and provide meaningful insights through a web-based application.

A. System Design
The proposed system follows a client–server architecture consisting of three main components:

I. Presentation Layer (Frontend)
II. Application Layer (Backend)
III. Data and AI Layer

The frontend provides a user-friendly interface where users can input farm location and sowing date, and view crop condition, production risk, and expected yield. The backend handles data processing, stage determination, and model inference. The system integrates satellite-derived NDVI data with machine learning models through RESTful APIs to ensure modularity and scalability.

B. Data Acquisition and Preprocessing
Data Acquisition
NDVI data is extracted from Sentinel-2 satellite imagery using spectral bands:

- Near Infrared (NIR – Band 8)
- Red (Band 4)

NDVI is calculated as:
NDVI=(NIR−Red)(NIR+Red)NDVI = \frac{(NIR - Red)}{(NIR + Red)}NDVI=(NIR+Red)(NIR−Red)

Monthly NDVI values are collected for the Kharif season (June to October) across multiple farm regions and years.
Each dataset record includes:

- Farm ID
- Location (District, Village)
- Year
- Monthly NDVI values (June–October)

Data Preprocessing

- The collected data undergoes several

preprocessing steps:

- Data Cleaning: Removal of missing and inconsistent values
- Interpolation: Filling missing NDVI values using temporal interpolation
- Normalization: Scaling NDVI values for uniformity
- Noise Reduction: Handling irregular variations in satellite data
- The dataset is structured into a wide format where each row represents a farm region for a specific year.

C. Feature Engineering

To enhance model performance, additional features are derived from NDVI time-series data:

- Seasonal Mean: Average NDVI across June–October
- Seasonal Maximum: Highest NDVI value during the season
- Growth Rate: Difference between NDVI in September and June
- NDVI Range: Difference between maximum and minimum NDVI

These features capture vegetation growth patterns, crop vigor, and seasonal variability, which are critical for yield prediction.

D. Growth Stage-Based Crop Health Analysis

A key component of the system is stage-aware crop health evaluation. Instead of interpreting NDVI values directly, the system considers the crop growth stage based on the sowing date.

The number of days after sowing is calculated to determine the crop stage:

- Sowing Stage (0–15 days)
- Early Growth Stage (15–35 days)
- Vegetative Stage (35–65 days)
- Peak Growth Stage (65–95 days)
- Maturity Stage (95+ days)

NDVI values are interpreted differently for each stage to avoid misclassification. For example, low NDVI values during early stages are considered normal, while similar values during later stages indicate crop stress. This approach improves the accuracy and reliability of crop health assessment.

E. Machine Learning Model Integration

Machine learning models are used to predict crop yield based on NDVI features.

Model Objectives

- Predict crop yield (tonnes per hectare)
- Estimate production risk based on crop condition

Model Selection

The following models are considered:

- Random Forest
- Gradient Boosting
- XGBoost

These models are suitable for small and structured agricultural datasets.

Training and Evaluation

- Dataset split into training and testing sets
- Cross-validation applied to improve generalization
- Evaluation metrics include:
    - R^2 Score
    - Mean Absolute Error (MAE)
    - Root Mean Square Error (RMSE)

Yield prediction is performed during mid to late crop stages when sufficient temporal data is available.

F. System Implementation

The system is implemented as a web-based application:

- Frontend: Developed using React.js for interactive visualization
- Backend: Implemented in Python (Flask/FastAPI)
- Integration: RESTful APIs used for communication

Workflow:

1. User inputs farm location and sowing date
2. System retrieves NDVI data for the region
3. Growth stage is determined
4. Crop condition is evaluated
5. Yield prediction is generated (in later stages)
6. Results are displayed in a simplified dashboard

G. Real-Time Monitoring and Updates and Validation

The system supports near real-time monitoring by periodically updating crop conditions based on newly available satellite data. As the season progresses, the accuracy of crop health assessment and yield prediction improves.

The output presented to the user includes:

- Crop Condition (Healthy / Moderate / Stressed)
- Season Status (Normal / Delayed Growth)
- Production Risk (Low / Medium / High)
- Expected Yield (in later stages)

The system is validated using historical NDVI datasets and corresponding yield data. The performance of the model is evaluated based on prediction accuracy and consistency across different farm regions.Results indicate that incorporating growth stage information along with NDVI time-series significantly improves crop health interpretation and yield prediction reliability.

V. RESULTS AND DISCUSSION

The proposed NDVI-based crop health monitoring system was implemented using time-series vegetation data derived from Sentinel-2 imagery. The system was evaluated using sample NDVI datasets across selected farm regions for the Kharif season, incorporating user-provided sowing dates to analyze crop growth patterns.

The results demonstrate that NDVI time-series analysis provides clear insights into vegetation changes across different stages of crop development. By observing NDVI trends over time, the system is able to track crop growth progression and identify variations in plant health during the season. This enables continuous monitoring instead of relying on single-time observations.

A key outcome of this work is the improvement in crop health interpretation through growth stage-based analysis. Unlike conventional methods that directly interpret NDVI values, the proposed system evaluates NDVI in relation to crop growth stages derived from sowing date. This approach reduces misinterpretation of early-stage crops, where low NDVI values are natural and do not indicate stress. At later stages, similar low NDVI values are correctly identified as potential indicators of crop stress or delayed growth.

The web-based interface enhances usability by presenting results in a simple and accessible format. Users can view crop condition, growth stage, and seasonal status through an interactive dashboard without requiring technical expertise. The system also supports periodic updates as new satellite data becomes available, enabling timely monitoring of crop conditions.
Overall, the results indicate that integrating NDVI time-series analysis with growth stage awareness improves the reliability of crop health assessment. The proposed system provides a practical and scalable solution for monitoring agricultural fields and supporting informed decision-making in precision agriculture.

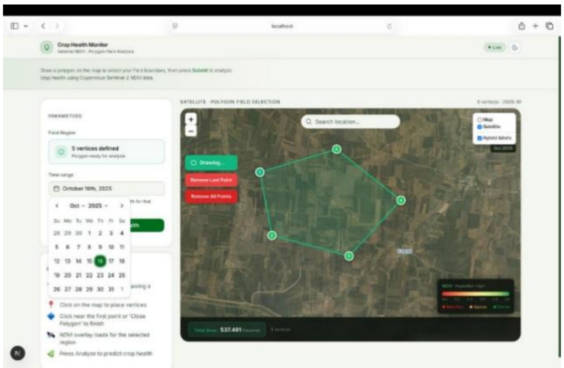

Fig 5.1: Satellite based field selection using polygon mapping

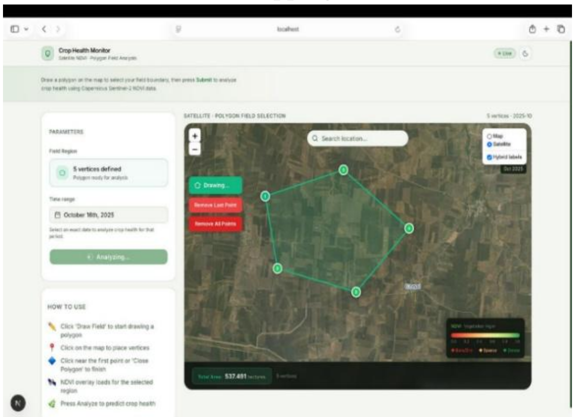

Fig 5.2 : Field selection with date inpuyt for NDVI Ananlysis

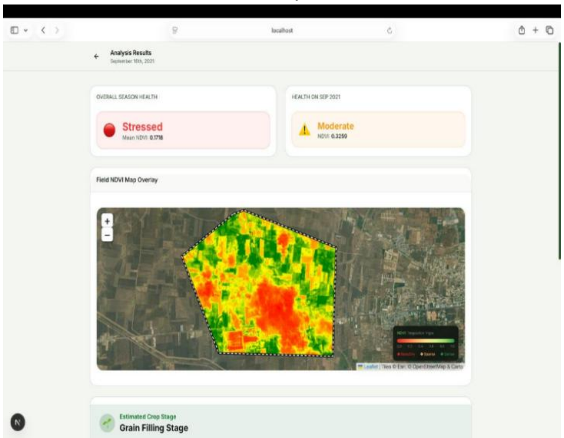

Fig 5.3 NDVI Based crop health visualization

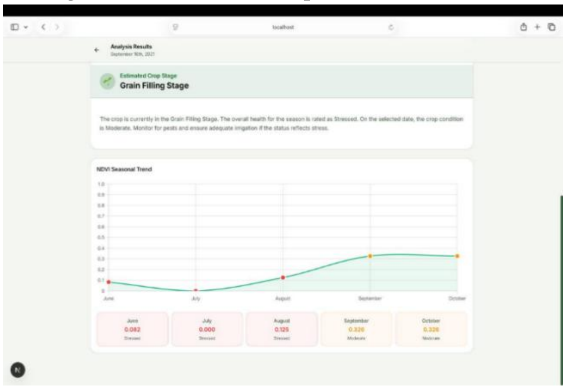

Fig 5.4: Crop health Analysis result and NDVI time series Trend

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