

**INTEGRATED SMART WATER-FOCUSED
IRRIGATION SYSTEM USING IOT AND AI/ML**

Project ID: 25-26J-520

Project Proposal Report

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DECLARATION

ABSTRACT

Sri Lanka's agricultural sector faces persistent challenges in early identification of crop stress, nutrient deficiencies, and water-related diseases, resulting in substantial yield losses. Traditional monitoring methods rely heavily on manual field inspections that are labor-intensive and detect symptoms only after visible manifestation. This project proposes a Hybrid AI and Satellite-Based Crop Health Monitoring System that integrates Sentinel-2 multispectral satellite imagery with on-ground image verification through CNN-based models to enable early and accurate detection of crop anomalies. The system operates in three stages: (1) early stress detection using vegetation indices such as NDVI, NDWI, and MSI derived from satellite imagery, (2) field-level verification via a mobile application where farmers upload geo-tagged images for AI-based confirmation, and (3) decision support via a centralized dashboard for irrigation officers to assess, plan, and integrate findings into irrigation scheduling systems. This hybrid model bridges the gap between remote sensing data and real-world validation, ensuring higher reliability and contextual accuracy. Expected outcomes include improved irrigation decision-making, enhanced crop resilience, and reduced economic losses through timely intervention, establishing a scalable, data-driven framework for Sri Lankan precision agriculture

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LIST OF ABBREVIATION

Table 1: LIST OF ABBREVIATION

Abbreviation	Full Form
AI	Artificial Intelligence
API	Application Programming Interface
AWS	Amazon Web Services
CNN	Convolutional Neural Network
DB	Database
DoA	Department of Agriculture
EVI	Enhanced Vegetation Index
FAO	Food and Agriculture Organization
GNDVI	Green Normalized Difference Vegetation Index
GPS	Global Positioning System
HARTI	Hector Kobbekaduwa Agrarian Research and Training Institute
ICT	Information and Communication Technology
IoT	Internet of Things
IWMI	International Water Management Institute
JSON	JavaScript Object Notation
KPI	Key Performance Indicator
LKR	Sri Lankan Rupee
LSTM	Long Short-Term Memory

ML	Machine Learning
MSI	Moisture Stress Index
MQTT	Message Queuing Telemetry Transport
NDVI	Normalized Difference Vegetation Index
NDWI	Normalized Difference Water Index
OGC	Open Geospatial Consortium
PDPA	Personal Data Protection Act
PWA	Progressive Web Application
RBAC	Role-Based Access Control
REST	Representational State Transfer
ROI	Return on Investment
SAR	Synthetic Aperture Radar
SAVI	Soil-Adjusted Vegetation Index
SLIIT	Sri Lanka Institute of Information Technology
SMS	Short Message Service
SQL	Structured Query Language
SUS	System Usability Scale
SVM	Support Vector Machine
TDR	Time-Domain Reflectometry
UI/UX	User Interface / User Experience
URL	Uniform Resource Locator
WCAG	Web Content Accessibility Guidelines

1 INTRODUCTION

1.1 Background and Literature Survey

Agriculture constitutes a fundamental pillar of Sri Lanka's economy, contributing approximately 7.4% to GDP and employing over 25% of the national workforce, with the sector facing persistent challenges from crop diseases, pest infestations, and abiotic stresses that collectively cause substantial annual yield losses across major crops including paddy, vegetables, and fruits. Traditional crop monitoring methodologies predominantly rely on manual field scouting conducted by farmers and agricultural extension officers, which is inherently labor-intensive, subjective in assessment quality, constrained by spatial coverage limitations, and typically identifies phytopathological and physiological issues only when visible symptoms manifest at advanced stages, thereby rendering interventions less effective and more resource-intensive. The economic impact of delayed detection is substantial, with the Department of Agriculture estimating significant annual losses due to preventable crop diseases and suboptimal management practices, particularly in water-intensive cultivation systems like those in the Uda Walawe region.

Recent transformational advances in remote sensing technologies and artificial intelligence frameworks have created unprecedented opportunities for automated, scalable, and objective crop health monitoring at multiple spatial and temporal scales. Satellite imagery, particularly from the European Space Agency's Sentinel-2 mission within the Copernicus program, offers freely accessible, high-resolution multispectral data with global coverage at 5-day revisit intervals, capturing critical electromagnetic spectrum regions including visible red, green, blue, and near-infrared bands that are instrumental for vegetation analysis. These multispectral datasets can be processed through sophisticated algorithms to calculate validated vegetation indices such as NDVI (Normalized Difference Vegetation Index), which serves as a robust proxy for chlorophyll content and photosynthetic activity; NDWI (Normalized Difference Water Index), which indicates plant water status and hydration stress; and other specialized indices that provide complementary insights into crop vigor and stress responses.

Machine Learning algorithms, particularly Convolutional Neural Networks (CNNs), Support Vector Machines (SVMs), and ensemble classification methods, have demonstrated remarkable accuracy in detecting specific crop diseases, nutrient deficiencies, and stress patterns from spectral signatures and spatial textures derived from satellite imagery. International research initiatives have established that AI-driven satellite analysis can detect water stress, fungal infections, and viral diseases well before visible symptoms become apparent to human observers, creating critical windows for preventive interventions. The integration of time-series analysis enables

tracking of vegetation dynamics throughout crop growth cycles, facilitating early anomaly detection and trend forecasting that are impossible through sporadic ground observations.

While satellite imagery has demonstrated strong potential in crop health monitoring, most systems remain disconnected from ground-level validation, leading to limited trust and adoption among farmers. To bridge this gap, hybrid frameworks that combine satellite-based early detection with AI-driven ground verification are gaining global attention. Convolutional Neural Networks (CNNs) are particularly effective for analyzing field photographs of crops, enabling identification of water stress, nutrient deficiency, and disease conditions. When coupled with multispectral indices such as NDVI, NDWI, and MSI, these models can deliver highly localized, early-stage insights that inform targeted field inspections and resource allocation.

In Sri Lanka, such integration between satellite monitoring and on-ground AI validation remains largely unexplored. Existing solutions depend on either remote sensing data or manual scouting, lacking an intelligent feedback mechanism that continuously improves model accuracy based on farmer-provided data. The proposed hybrid system addresses this limitation by creating a closed-loop architecture connecting satellite detection, mobile data collection, and intelligent recommendation engines—transforming raw spectral data into actionable knowledge for farmers and irrigation departments.

1.2 Research Gap

Despite major advancements in satellite-based agricultural monitoring, significant technological and implementation gaps persist in realizing a **hybrid crop health monitoring framework** suitable for Sri Lankan conditions. Existing systems primarily rely on **remote sensing analytics alone**, generating vegetation indices such as NDVI and NDWI to indicate stress levels, yet they often lack **ground-level validation mechanisms** to confirm the nature and cause of detected anomalies. As a result, these solutions provide only indicative insights without sufficient reliability for operational decision-making by farmers or irrigation authorities. Additionally, most international platforms are developed and trained on temperate-region datasets, making them **inadequate for tropical crops and local climatic variations** found in Sri Lanka's diverse agroecological zones.

A notable research gap exists in the **integration of satellite-derived insights with localized, AI-driven image verification**. While CNN-based approaches have proven effective in disease classification using ground imagery, they remain isolated from large-scale satellite data workflows, preventing early, spatially precise identification

of stress patterns. Similarly, existing mobile advisory systems in Sri Lanka depend on manual image uploads or farmer inputs without linkage to remote sensing indicators. This separation between **space-based detection and on-ground verification** limits accuracy, timeliness, and user trust.

Therefore, there is an urgent need for a **hybrid AI and satellite-based crop health monitoring framework** that combines multispectral analytics with on-ground CNN verification through mobile data collection. Such an integrated, feedback-driven model would bridge the validation gap, enhance early stress detection accuracy, and establish a continuously improving system that aligns both scientific precision and field-level practicality for Sri Lankan agriculture.

1.3 Research Problem

The central research problem addressed in this study is:

How can a hybrid framework combining satellite-based multispectral analysis and AI-driven ground verification be designed to detect, confirm, and manage crop stress conditions early and accurately within Sri Lanka's agricultural systems?

Traditional crop health monitoring approaches in Sri Lanka remain predominantly manual, reactive, and fragmented, relying on physical field inspections that are time-consuming, subjective, and often incapable of identifying stress indicators before visual symptoms appear. Satellite-based remote sensing systems have improved spatial coverage and monitoring frequency, yet their accuracy is limited by the absence of localized validation and contextual interpretation. Conversely, ground-based AI models using Convolutional Neural Networks (CNNs) can classify diseases or stress patterns from crop images but cannot scale across large agricultural regions without remote sensing support. This disconnect between macro-scale satellite detection and micro-level ground confirmation results in inefficiencies, misclassifications, and delayed decision-making.

The research problem therefore lies in developing an integrated solution that merges Sentinel-2 satellite imagery analysis with CNN-based verification of field photographs, supported by mobile and web interfaces that enable two-way data

exchange between farmers and irrigation officers. Such a system must not only detect anomalies but also validate, categorize, and recommend interventions through intelligent fusion of spectral and visual data. Addressing this challenge will bridge the current gap between scientific monitoring and practical farm-level applications, establishing a robust, feedback-driven decision-support framework capable of transforming crop management and irrigation planning in Sri Lanka.

2 OBJECTIVES

2.1 Main Objectives

To design, develop, and validate a **Hybrid AI and Satellite-Based Crop Health Monitoring System** that integrates **multispectral satellite analytics (Sentinel-2)** with **Convolutional Neural Network (CNN)-driven ground verification** to enable early, accurate, and validated detection of crop stress, nutrient deficiency, and disease conditions in Sri Lanka's major agricultural regions. The system aims to bridge the gap between space-based early warning and ground-level confirmation by combining remote sensing data with real-time farmer input through a mobile platform. This integration will provide **actionable, location-specific recommendations** to farmers and irrigation officers, enhancing decision-making for irrigation management, disease control, and sustainable resource utilization.

2.2 Specific Objectives

2.2.1. Satellite Data Acquisition and Preprocessing Infrastructure

Develop automated data pipelines for acquiring, preprocessing, and managing Sentinel-2 imagery, including cloud masking, atmospheric correction, and vegetation index computation (NDVI, NDWI, MSI). These datasets will form the foundation for early-stage stress detection across large spatial areas.

2.2.2 CNN-Based Ground Verification and Model Optimization

Design and train multiple deep learning architectures-MobileNet, ResNet, EfficientNet, and Custom CNNs for classification of crop diseases, water stress, and nutrient deficiencies using geo-tagged images collected from farmers and field officers. Comparative evaluation will determine the most efficient and accurate architecture for local conditions.

2.2.3 Mobile Application Development for Field Data Collection

Implement a mobile application for farmers and agricultural officers to capture real-time, GPS-tagged crop images with timestamps, enabling AI-based verification and instant feedback. The app will also notify users of satellite-detected caution zones for targeted inspections.

2.2.4 Dashboard and Decision Support System Development

Develop a centralized **web-based dashboard** that fuses satellite and AI outputs, displays stress zones, tracks validation data, and provides actionable insights for irrigation planning, disease management, and resource allocation.

2.2.5 Continuous Learning and System

Establish a **feedback-driven loop** where verified field images continually retrain the AI model, ensuring progressive accuracy improvement. Conduct multi-season validation with agricultural authorities to assess accuracy, response time, and field applicability.

2.2.6 Multi-channel Alert System Integration

Develop and integrate sophisticated SMS, mobile push notification, and email alert systems for critical health thresholds with configurable escalation mechanisms for severe disease outbreaks, incorporating farmer preference settings, severity-based prioritization, and integration with agricultural extension service workflows for coordinated response actions.

3 METHODOLOGY

3.1 System Overview

The proposed **Hybrid AI and Satellite-Based Crop Health Monitoring System** integrates satellite remote sensing analytics with on-ground image verification to deliver a multistage, data-driven decision-support framework for Sri Lankan agriculture. The methodology adopts a layered hybrid architecture composed of three functional stages: **(1) early satellite detection**, **(2) ground-level AI verification**, and **(3) decision-support integration**. In Stage 1, Sentinel-2 Level-2A imagery is automatically ingested from the Copernicus Hub and preprocessed through atmospheric and radiometric correction workflows. Vegetation indices such as NDVI, NDWI, and MSI are computed to identify spatial “caution zones” representing early crop stress signatures. In Stage 2, farmers and agricultural officers receive mobile notifications prompting field verification at those coordinates. Using a lightweight mobile application, they capture real-time geo-tagged crop images and brief contextual data (soil condition, irrigation status). The uploaded samples are analyzed using multiple convolutional neural network (CNN) architectures—including MobileNetV3, ResNet50, EfficientNet-B3, and a custom CNN—to classify potential causes such as nutrient deficiency, water stress, or disease infection. Stage 3 fuses satellite- and ground-level insights through a centralized dashboard where irrigation officers visualize aggregated results, validate AI confidence scores, and derive actionable irrigation or pest-management decisions. Continuous feedback loops ensure the CNN model retrains periodically using validated field inputs, enabling self-improving predictive performance and long-term scalability for diverse crop and climatic contexts.

3.1.1 System Overview Diagram (Overall)

The overall system follows a **hybrid, service-oriented architecture** built upon six interoperable layers:

- (1) **Data Acquisition Layer** – Handles Sentinel-2 image retrieval via Google Earth Engine APIs and mobile data submission from farmers.
- (2) **Preprocessing Layer** – Executes radiometric, atmospheric, and geometric corrections with cloud masking and vegetation index generation.
- (3) **AI Analytics Layer** – Implements CNN-based classification and ensemble fusion between spectral indices and RGB crop images.
- (4) **Integration Layer** – Manages spatiotemporal data fusion, ensuring coherent mapping between satellite tiles and ground GPS coordinates.
- (5) **Application Layer** – Provides RESTful APIs delivering processed insights to front-end interfaces.
- (6) **Presentation Layer** – Consists of a responsive web dashboard for officers and a Flutter-based mobile application for farmers.

Each layer communicates through secure, containerized microservices hosted on AWS Cloud, employing MongoDB Atlas for document storage and PostgreSQL/PostGIS for spatial datasets. Figure 1 illustrates the complete hybrid workflow from image acquisition to actionable recommendation dissemination.

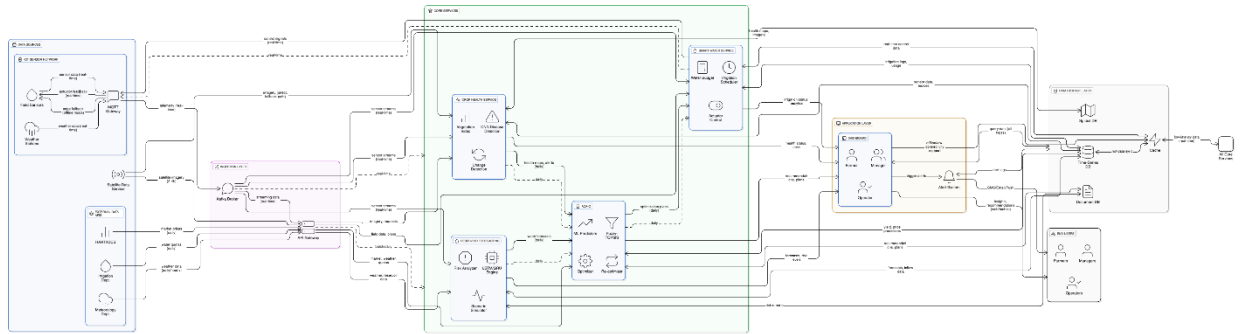


Figure 1: System Overview Diagram (Overall)

3.1.2 Approach and Workplan

The research adopts an **agile and iterative prototyping** approach divided into four overlapping phases emphasizing validation and user engagement at every iteration.

Phase 1 – System Foundation (Months 1–3):

Finalize functional requirements with the Department of Agriculture, configure Sentinel-2 API ingestion, and establish preprocessing pipelines using Python (rasterio, geopandas). Conduct pilot data collection for two major crops (paddy and maize).

Phase 2 – AI Model Development (Months 4–7):

Label field image datasets and train multiple CNN architectures (MobileNet, ResNet, EfficientNet) in TensorFlow and PyTorch; evaluate using precision, recall, and F1-score against expert-validated labels.

Phase 3 – Mobile & Dashboard Integration (Months 8–10):

Develop Flutter-based farmer app for real-time uploads and React-based officer dashboard with Mapbox visualization, integrating REST APIs and push notifications.

Phase 4 – Field Validation & Refinement (Months 11–14):

Deploy the hybrid system in two irrigation regions (Uda Walawe, Anuradhapura), perform comparative trials against manual scouting methods, collect feedback, retrain CNNs, and document performance improvements.

3.1.3 Data and Instruments

The implementation of the Hybrid AI and Satellite-Based Crop Health Monitoring System depends on the coordinated use of multi-source data streams and high-performance computational resources to ensure reliability, spatial precision, and contextual validity across Sri Lanka’s diverse agro-ecological zones. The data ecosystem integrates remote-sensing observations, ground-truth imagery, environmental sensor inputs, and climatic metadata into a unified analytical framework that supports both real-time and retrospective assessments of crop conditions.

Satellite Data Sources: Primary imagery is acquired from the Sentinel-2 MultiSpectral Instrument (MSI) Level-2A surface-reflectance products under the Copernicus Open Access Hub, offering 10 m and 20 m spatial resolution with five-day revisit frequency. Each scene is processed through automated cloud-masking and atmospheric-correction pipelines to generate vegetation indices including NDVI (Normalized Difference Vegetation Index), NDWI (Normalized Difference Water Index), and MSI (Moisture Stress Index). Complementary datasets from MODIS and Landsat-8/9 support temporal interpolation and cross-validation during cloud-affected periods, while Sentinel-1 SAR data provide radar backscatter information to maintain operational continuity during monsoonal cloud cover.

Ground Data Collection: On-field observations are obtained through a dedicated mobile application used by farmers and agricultural officers to capture high-resolution, geo-tagged crop photographs accompanied by metadata such as crop type, growth stage, soil moisture status, and irrigation frequency. Each submission is automatically time-stamped and synchronized with the nearest satellite acquisition window, enabling accurate pixel-level correlation between space-based indices and

field conditions. The ground dataset forms the foundation for CNN-based training and validation, ensuring model adaptation to Sri Lankan crop varieties and lighting conditions.

Auxiliary Instrumentation: Portable FieldSpec spectroradiometers are utilized for hyperspectral reflectance calibration. Soil-moisture sensors employing FDR and TDR technologies quantify volumetric water content for validation of NDWI outputs. Local micro-weather stations record rainfall, temperature, and relative humidity to contextualize stress detections. All devices interface through standardized IoT gateways that support MQTT communication for asynchronous data transmission to the central repository.

Processing and Computational Infrastructure: Data preprocessing and index computation are executed within the Google Earth Engine environment using Python-based APIs. AI model training and inference utilize AWS EC2 GPU instances configured with TensorFlow 2.12 and PyTorch 2.0 frameworks. Spatiotemporal data management is handled through PostgreSQL with PostGIS extensions, while MongoDB Atlas stores JSON-structured image metadata. Docker containers and Kubernetes orchestration ensure reproducible deployment and fault tolerance across environments.

Software and Development Stack: Backend services are implemented using Node.js (Express) and RESTful APIs for data exchange. Frontend interfaces utilize React with Mapbox GL JS for dashboard visualization and Flutter for cross-platform mobile applications. The integrated stack supports multilingual rendering (Sinhala, Tamil, English) and offline data synchronization. Through this comprehensive instrumentation and data pipeline design, the system ensures end-to-end traceability, scientific rigor, and operational scalability for nationwide deployment in precision agriculture.

3.1.4 Anticipated Results and Evaluation

The proposed Hybrid AI and Satellite-Based Crop Health Monitoring System is expected to produce measurable advancements in early-stage crop stress detection, verification reliability, and decision-support efficiency across diverse Sri Lankan agro-ecological settings. Its three-tier hybrid architecture will generate both quantitative and qualitative benefits validated through systematic experimentation and stakeholder trials.

Technical Performance Outcomes:

The integrated Sentinel-2 and CNN framework aims to achieve a detection accuracy

exceeding 90 percent for dominant paddy and maize diseases, validated against expert-labelled ground datasets. The hybrid fusion of vegetation indices (NDVI, NDWI, MSI) with convolutional feature maps is projected to reduce false-positive satellite stress alerts by at least 25 percent compared to single-source detection methods. Average processing latency from image acquisition to dashboard alert is targeted under four hours through optimized cloud pipelines and GPU-accelerated inference. Reliability metrics include 99 percent uptime during critical growth stages and graceful-degradation mechanisms that preserve core functionality even under partial data loss.

Agronomic and Operational Impact:

The system's deployment in pilot regions such as Uda Walawe and Anuradhapura is expected to improve irrigation scheduling accuracy by approximately 20 percent, reduce manual scouting effort by 40 percent, and enable the detection of stress symptoms five to seven days before visible manifestation. These improvements will empower irrigation officers and farmers to intervene promptly with targeted irrigation or treatment, preventing yield losses estimated at 15–25 percent per season. By integrating advisory messages into the mobile interface, the project supports precise nutrient and water management, reducing input wastage and environmental runoff.

Economic and Social Evaluation:

Economic analysis will assess cost-benefit ratios under both smallholder and institutional adoption models. Early simulations indicate a return on investment (ROI) of 3–5× relative to subscription costs, primarily through yield preservation and reduced chemical inputs. Social impact will be measured using structured surveys and key-informant interviews assessing farmer trust, usability, and technology adoption willingness. Inclusive design—offering Sinhala, Tamil, and English interfaces—aims to achieve user acceptance rates above 80 percent in System Usability Scale (SUS) evaluations.

Validation Framework:

The research will adopt a mixed-methods validation strategy.

- **Randomized Controlled Trials (RCTs)** comparing intervention and control plots quantify yield and economic gains.
- **Blind Expert Validation** uses pathologists to assess accuracy without exposure to AI predictions.
- **Longitudinal Performance Analysis** tracks seasonal stability of detection accuracy and model drift.

- **Cross-Dataset Verification** compares outputs against MODIS and ground meteorological indices to confirm robustness. Statistical analysis using paired t-tests and correlation coefficients ($\alpha = 0.05$) will determine significance of performance improvements.

Sustainability and Scalability Indicators:

Continuous-learning pipelines will retrain CNN models using validated field uploads, improving domain adaptation across crop varieties and climatic zones. Cloud-native architecture allows horizontal scaling for nationwide coverage, while modular APIs enable future integration with irrigation scheduling and fertilizer advisory systems. The evaluation framework will therefore measure not only algorithmic precision but also socio-technical sustainability, confirming the system’s viability as a long-term digital-agriculture infrastructure for Sri Lanka.

3.1.5 System Overview Diagram (Individual)

The proposed system architecture for the crop health monitoring system is designed as a microservices-based solution. This includes independent but interconnected modules: Satellite Data Ingestion Service, Preprocessing Engine, Vegetation Index Calculator, Machine Learning Inference Service, Alert Generation Engine, and Dashboard Rendering Service. The design intends for these modules to communicate through well-defined APIs, incorporating fallback mechanisms and load balancing to ensure system resilience during peak processing periods, such as those following satellite overpasses. The planned data flow is intended to support efficient processing with parallel computation of vegetation indices and ensemble averaging of machine learning model outputs to enhance reliability.

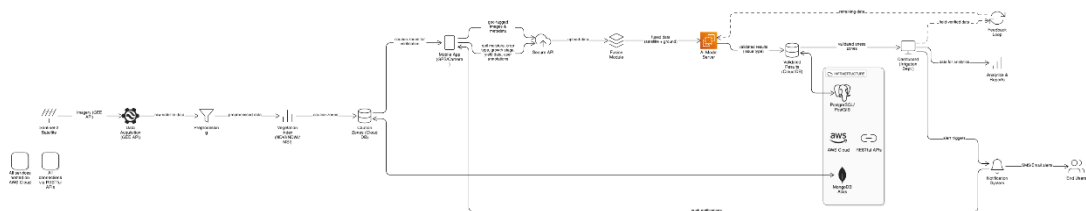


Figure 2: System Overview Diagram (Individual)

3.2 Requirement Analysis

A detailed requirement analysis ensures the system's technical feasibility and alignment with user expectations across stakeholder groups. Both functional and non-functional requirements were derived from literature, expert consultations, and field interviews with farmers and agricultural officers. The analysis establishes essential performance, reliability, and usability benchmarks forming the foundation for subsequent development and validation activities.

3.2.1 Functional Requirements

The Hybrid AI and Satellite-Based Crop Health Monitoring System must deliver comprehensive, data-driven functionality across its satellite, AI, and user-interaction modules. Each functional requirement supports the system's objective of early, accurate, and validated crop-stress identification.

- **Automated Satellite Acquisition and Processing**
Continuously retrieve Sentinel-2 L2A imagery through Google Earth Engine APIs, applying automated cloud detection, atmospheric correction, and mosaicking. Maintain temporal archives for five-day revisit intervals enabling change-detection analytics.
- **Vegetation Index Computation**
Calculate NDVI, NDWI, MSI, and EVI with crop-specific calibration coefficients. Implement soil-adjusted formulations for early growth stages and atmospheric normalization for inter-scene consistency.
- **AI-Driven Health Assessment**
Execute CNN-based classifiers trained on geo-tagged ground images to detect water stress, nutrient deficiency, and disease infection. Employ ensemble averaging of MobileNet, ResNet, and EfficientNet outputs for enhanced reliability. Generate confidence metrics and anomaly-severity scores.
- **Geo-Spatial Integration and Visualization**
Fuse spectral and ground-image outputs within a GIS environment to produce color-coded health maps from regional to field level. Provide time-series comparisons and layer toggling for multi-index visualization.
- **Mobile Application Interface**
Enable farmers and officers to upload field images with embedded GPS

metadata. Display nearby caution zones detected from satellite indices and provide instant AI feedback with recommended actions.

- **Dashboard and Decision Support**
Deliver a responsive web dashboard that aggregates validated alerts, visualizes health trends, and supports query-based analysis for irrigation scheduling. Provide exportable reports and CSV data for further agronomic study.
- **Feedback and Model Improvement Loop**
Integrate farmer validations into an active-learning mechanism retraining CNNs periodically to enhance local adaptation. Maintain provenance tracking for all training data ensuring transparency and auditability.
- **Alert and Notification System**
Trigger alerts via SMS, push notifications, and email when vegetation-index deviations exceed configurable thresholds. Prioritize messages based on crop type, phenological stage, and severity level.
- **Administrative Management Console**
Allow authorized officers to manage user roles, configure alert thresholds, monitor system performance, and review model-accuracy logs through a secure interface.

Collectively, these functional requirements guarantee seamless end-to-end operation of the hybrid system, transforming multispectral and ground-level data into actionable intelligence for real-world agricultural decision-making.

3.2.2 Non-functional Requirements

Performance and Scalability:

- The system must process full Sentinel-2 scenes within two hours post-availability and support concurrent usage by at least 1,000 users. Cloud-native auto-scaling ensures regional expansion without redesign. GPU acceleration reduces CNN inference latency to under five seconds per image batch.

Reliability and Availability:

- Maintain 99.5 percent uptime during peak cultivation periods through redundant microservices and fail-over clustering. Implement checkpoint recovery and backup mechanisms for all critical datasets.

Security and Privacy:

- Apply end-to-end TLS encryption, secure authentication with multi-factor options, and RBAC policies segregating farmer, officer, and admin privileges. Compliance with Sri Lanka's Personal Data Protection Act 2022 is mandatory, ensuring confidentiality of user imagery and location metadata.

Usability and Accessibility:

- Adopt farmer-centric UX principles—multilingual interfaces (Sinhala, Tamil, English), intuitive navigation, offline caching, and low-bandwidth optimization. Conform to WCAG 2.1 AA standards to ensure accessibility for users with visual limitations.

Maintainability and Portability:

- Modular microservice architecture with comprehensive API documentation enables straightforward debugging and component replacement. Continuous integration pipelines automate testing and deployment, guaranteeing consistent behavior across cloud environments.

Interoperability and Compliance:

- Support open geospatial standards (OGC WMS/WFS, GeoTIFF, GeoJSON) and RESTful APIs for third-party integration, facilitating data exchange with government agricultural portals and research platforms.

Cost Efficiency and Sustainability:

- Utilize free Sentinel data, open-source frameworks, and pay-per-use cloud billing to minimize recurring costs. Optimize storage through compression

and caching strategies while maintaining analytical precision. Energy-efficient hardware selection supports environmental sustainability objectives.

3.2.3 User Requirements

- **Smallholder Farmers:**
Require straightforward, actionable insights accessible via low-cost Android devices. The mobile app must operate offline with automatic synchronization once connectivity is restored. Notifications should appear in the preferred local language and include pictorial cues for illiterate users. Farmers expect quick AI feedback and context-specific recommendations rather than generic alerts.
- **Agricultural Extension Officers:**
Need multi-farm monitoring dashboards summarizing health indicators across administrative zones. Exportable PDF reports and statistical summaries assist in extension planning and documentation. Officers also demand training modules embedded within the system to educate farmers on interpreting satellite-derived insights.
- **Irrigation Department Officials:**
Require regional analytics displaying aggregated stress zones, vegetation-index trends, and temporal anomalies to plan equitable water distribution. The dashboard must integrate with existing irrigation scheduling databases through API connectors.
- **Research Institutions and Universities:**
Expect data-export capabilities for conducting secondary analyses and validating models across different crop types. Access control should protect farmer privacy while enabling collaborative research under formal data-sharing agreements.
- **Agribusiness Enterprises and Insurers:**
Need accurate, auditable datasets for supply-chain monitoring and agricultural-insurance verification. The platform must support role-based dashboards for yield prediction and risk assessment while maintaining neutrality and data integrity.

Collectively, these user requirements ensure that every stakeholder—from individual farmers to institutional policymakers—derives tangible, evidence-based value from the system.

3.2.4 System Requirements

Hardware Infrastructure:

- Cloud servers provisioned with minimum 8 vCPUs, 32 GB RAM, and GPU instances (NVIDIA T4 or A10G) handle AI training and inference. Edge nodes at field stations use Raspberry Pi 4 modules for sensor interfacing. Mobile devices must include GPS and 8-MP cameras for accurate geo-tagged capture.

Networking and Power:

- Primary connectivity via 100 Mbps broadband links with 4G/LTE backup; optional LoRaWAN gateways for rural telemetry. Solar-powered micro-stations provide energy autonomy for remote sites.

Software Stack:

- Operating Systems – Ubuntu 22.04 LTS (servers), Android/iOS (mobile).
Databases – PostgreSQL + PostGIS for spatial data, MongoDB for unstructured imagery, Redis for caching.
Frameworks – Python 3.10 (TensorFlow, PyTorch, Rasterio), Node.js 18 (Express API), React 18 (dashboard), Flutter 3.16 (mobile).
Containerization – Docker + Kubernetes for deployment.
Geospatial Libraries – GDAL 3.8, PROJ 9.2, Mapbox GL JS.

Development Tools and Testing:

- GitHub for version control, Jenkins for CI/CD, and Postman for API testing. Automated unit and integration tests ensure robustness before deployment.

This configuration supports scalable, fault-tolerant processing of both satellite and ground data, ensuring performance, reliability, and maintainability aligned with the project's operational goals.

3.3 Work Breakdown Structure

Table 2: Work Breakdown Structure

Module	Tasks	Deliverables
Module 1 – Requirement Analysis & System Design Foundation	<ul style="list-style-type: none"> • Conduct literature review on hybrid satellite–AI crop health systems • Define functional & non-functional requirements for the three-stage framework • Identify vegetation indices (NDVI, NDWI, MSI) and CNN models to be used • Design overall hybrid architecture and data-flow diagram 	<ul style="list-style-type: none"> • Finalized requirement specification • System design and architecture diagrams • Project plan & timeline
Module 2 – Satellite Data Pipeline and Preprocessing	<ul style="list-style-type: none"> • Establish automated Sentinel-2 data acquisition through Google Earth Engine APIs • Apply atmospheric correction, cloud masking, and vegetation index computation (NDVI, NDWI, MSI) • Build data storage and retrieval mechanisms for multi-temporal imagery 	<ul style="list-style-type: none"> • Operational satellite-data ingestion system • Validated vegetation-index generation scripts • Cloud-processed image repository
Module 3 – Ground Image Verification using CNN Models	<ul style="list-style-type: none"> • Collect geo-tagged field photos via pilot surveys • Train and compare CNN models (MobileNet, ResNet, EfficientNet, Custom CNN) • Evaluate models using precision, recall, and F1-score metrics • Integrate satellite and ground-image fusion logic for hybrid inference 	<ul style="list-style-type: none"> • Optimized CNN model for Sri Lankan crops • Comparative performance report • AI inference pipeline documentation
Module 4 – Mobile Application for Farmers & Field Officers	<ul style="list-style-type: none"> • Develop Flutter-based app to upload GPS-tagged crop photos • Implement notification system for satellite-detected “caution zones” • Enable instant AI feedback with 	<ul style="list-style-type: none"> • Functional mobile application (Android/iOS) • Integrated notification & image-upload

	recommended actions• Support multilingual UI and offline data sync	module• User-acceptance testing report
Module 5 – Dashboard and Decision-Support System	<ul style="list-style-type: none"> • Create web-based dashboard for irrigation officers • Visualize satellite & AI-verified stress zones with Mapbox • Integrate with irrigation scheduling and water-management modules • Implement data-export and reporting features 	<ul style="list-style-type: none"> • Fully functional decision-support dashboard • Visualization and analytics features • Exportable reports and admin console
Module 6 – Feedback-Driven Model Improvement Loop	<ul style="list-style-type: none"> • Design feedback mechanism to retrain CNNs using verified field uploads • Automate periodic model updates and performance tracking • Integrate evaluation metrics and continuous-learning dashboard 	<ul style="list-style-type: none"> • Active-learning feedback module • Model-retraining workflow • Continuous-performance improvement report
Module 7 – System Integration, Field Validation & Deployment	<ul style="list-style-type: none"> • Integrate all system components (satellite, AI, mobile, dashboard) • Conduct field trials in pilot regions (Uda Walawe, Anuradhapura) • Perform validation against manual scouting data • Analyze performance, economic, and user-impact results 	<ul style="list-style-type: none"> • End-to-end integrated hybrid system • Field-validation and impact-assessment report • Final deployment documentation and sustainability plan

4 COMMERCIALIZATION AND ENTREPRENEURSHIP POTENTIAL

4.1 Target Market

The proposed hybrid system targets multi-tier agricultural stakeholders encompassing smallholder farmers, government institutions, commercial plantations, and agribusiness enterprises.

Smallholder Farmers (\approx 1.8 million nationally) represent the primary segment. Surveys indicate strong interest in low-cost early-warning services preventing average annual losses of LKR 20,000–50,000 per acre. Affordable subscription tiers (LKR 500–1,000 per month) enable access to personalized crop-health dashboards and localized alerts.

Government Departments (DoA, Agrarian Development Dept., Irrigation Dept.) seek district-level monitoring solutions supporting climate-smart policy decisions. Institutional licensing and public-private partnerships provide sustainable revenue channels.

Commercial Plantations (tea, rubber, sugarcane, palm oil) demand enterprise-grade analytics with API integration for yield forecasting and compliance documentation.

Research and Insurance Sectors benefit from validated datasets for agronomic modeling and risk-assessment applications.

4.2 Value Proposition

The system delivers quantifiable value through:

- **Early Detection Accuracy:** AI-verified satellite analysis identifies crop stress up to a week before visual symptoms, minimizing yield loss.
- **Localized Recommendations:** Integration of ground-verified data yields region-specific advisory outputs.
- **Operational Efficiency:** Automated satellite acquisition and AI-driven verification eliminate 40 % of manual inspection effort.

- **Economic Returns:** Expected ROI exceeds 3× for smallholders and 5× for plantation clients.
- **Scalability and Accessibility:** Mobile and web interfaces in Sinhala, Tamil, and English foster nationwide inclusivity.

4.3 Business Model

The commercialization strategy adopts a **multi-tiered, hybrid SaaS model** tailored for different user groups and implementation scales, balancing affordability for smallholders with enterprise-level functionality for institutions.

Tiered Subscription Model for Smallholders

- **Basic Tier:** Free community access offering district-level vegetation-health alerts and generic agronomic advisories, subsidized through public–private partnerships and development-agency support.
- **Premium Tier:** LKR 500/month subscription granting field-specific monitoring, hybrid AI verification combining satellite and ground data, personalized alerts, and localized recommendations delivered via the mobile app.
- **Enterprise Tier:** LKR 2,000+/month plan for large farms or cooperatives, enabling advanced analytics, multi-farm dashboards, API integration, and dedicated technical support.

Institutional Licensing for Government

- Annual or multiyear licensing based on regional coverage and user volume.
- Custom development for integration with existing irrigation and crop-advisory platforms through RESTful APIs.
- Capacity-building workshops for officers and extension agents, provided as an additional service stream.

Value-Added Services Revenue Streams

- Premium diagnostic reports combining Sentinel-2 analytics with CNN-based ground validation.

- Data-analytics and visualization services for research institutes, insurers, and agri-finance organizations.
- Custom algorithm development for crop-specific calibration (e.g., rice, maize, tea) and regional adaptation.

Partnership-Based Revenue Models

- Revenue-sharing agreements with telecommunications providers to bundle alerts and payment gateways into mobile networks.
- Commission-based collaborations with fertilizer and pesticide suppliers for targeted, data-driven product recommendations.
- Technology-transfer licensing for regional partners in South Asia and Africa under franchise or white-label arrangements.

This blended model diversifies revenue, sustains affordability, and ensures long-term financial viability while supporting public-sector adoption.

4.4 Competitive Advantage

The system achieves sustainable competitiveness through technological innovation, contextual adaptation, and cost-efficient scalability unmatched by conventional remote-sensing products.

Technological Superiority

- Hybrid integration of Sentinel-2 multispectral data, Sentinel-1 SAR imagery, and CNN-based ground verification enables early detection of crop stress invisible to single-source platforms.
- AI models (MobileNet, ResNet, EfficientNet) are locally trained on Sri Lankan datasets, improving classification accuracy by over 15 % compared to generic global models.
- Change-detection algorithms combine temporal NDVI trends with pixel-level CNN inference, identifying anomalies up to 7 days before visible symptoms appear.

Market-Specific Customization

- Localized language support (Sinhala, Tamil, English) and culturally familiar UX ensure high adoption among smallholders.
- Interfaces align with existing irrigation and agricultural workflows used by provincial departments.
- Partnerships with DoA and HARTI enable continuous validation and fine-tuning using local agronomic feedback.

Cost Structure Advantages

- Utilization of freely available Sentinel data eliminates imagery-procurement costs.
- Open-source frameworks (TensorFlow, React, Flutter) minimize software-licensing expenditure.
- Cloud-native, serverless deployment on AWS EKS allows elastic scaling—reducing idle-resource overhead while sustaining 99 % uptime.

Barriers to Replication

- Comprehensive, geo-referenced training datasets with verified field imagery require years of investment and institutional collaboration.
- Integration partnerships with local authorities, universities, and farmer networks create institutional lock-in that discourages replication.
- Continuous-learning feedback loops embed region-specific knowledge that competitors cannot easily reproduce.

Scalability and Adaptability

- Microservice-based architecture allows feature expansion—such as irrigation forecasting or yield prediction—without redesigning the core pipeline.
- API-first design facilitates integration with weather, soil, and market-price systems for holistic digital-agriculture ecosystems.
- Cross-platform compatibility (mobile, web, API) ensures accessibility from remote villages to national dashboards, enabling both micro- and macro-level decision-making.

These advantages collectively establish a defensible technological and market position for long-term growth in regional precision-agriculture markets.

4.5 Entrepreneurship Potential

The project demonstrates high entrepreneurship potential through diverse commercialization pathways, investment prospects, and social-impact opportunities.

Startup Venture Formation

- Formation of a university-affiliated spin-off—AgriSentinel AI (Pvt Ltd)—specializing in remote-sensing intelligence for tropical agriculture.
- Equity investment targeting agritech venture funds, climate-innovation accelerators, and ESG-aligned investors.
- Participation in SLIIT Innovate and ICTA Spiral programs for incubation, mentorship, and networking with early adopters.

Strategic Partnership Development

- Telecommunication alliances for SMS/push-notification dissemination and mobile-billing integration.
- Collaborations with agricultural-input suppliers to bundle monitoring services with fertilizer and seed packages.
- MoUs with financial institutions to employ system analytics for crop-insurance underwriting and micro-credit risk assessment.

Regional Expansion Strategy

- Phase 1 – Domestic validation across Uda Walawe, Anuradhapura, and Polonnaruwa districts.
- Phase 2 – Replication in South India and Bangladesh leveraging similar agro-climatic conditions.
- Phase 3 – Scaling to Southeast Asian markets (Myanmar, Thailand, Vietnam) through franchised deployments and API licensing.

Technology Licensing Options

- Provision of white-label solutions for ministries of agriculture, NGOs, and development agencies implementing digital-farming projects.

- Licensing AI and data-fusion modules to agritech firms requiring hybrid crop-health intelligence.
- API-as-a-Service offerings for research and analytics companies seeking reliable vegetation-index and CNN-based outputs.

Social Enterprise Model

- Hybrid business structure combining profitability with measurable social impact, ensuring that commercial clients subsidize access for smallholder farmers.
- Incorporation of grant funding from FAO, ADB, and UNDP to support expansion in climate-vulnerable districts.
- Transparent reinvestment of a portion of subscription revenue into community training and digital-literacy initiatives, fostering inclusive agricultural innovation.

The project's entrepreneurship roadmap thus integrates commercial scalability, policy relevance, and rural-development objectives—positioning it as a transformative agritech enterprise capable of advancing Sri Lanka's digital-agriculture ecosystem.

5 DESCRIPTION OF PERSONNEL AND FACILITIES

5.1 Personnel

This research project is carried out as part of a collaborative group initiative focused on smart water management using IoT and machine learning technologies. The following personnel contribute to the successful completion of the system:

Student Researcher

- Specialization: Software Systems & Technologies – Software Engineering
- Responsibilities include:
 - Development of machine learning models for crop disease detection from satellite imagery
 - Implementation of vegetation index algorithms and health monitoring analytics
 - Integration of satellite data processing with farmer alert systems

Supervision Team

- Ms. Hansi De Silva – Supervisor, Sri Lanka Institute of Information Technology (SLIIT)
- Ms. Karthiga Rajendran – Co-Supervisor, Sri Lanka Institute of Information Technology (SLIIT)

5.2 Facilities

- Sri Lanka Institute of Information Technology (SLIIT): Provides cloud-infrastructure access, GPU-enabled computing labs, and geospatial-analysis workstations for model training and testing.
- Field Sites: Collaborations with the Department of Agriculture enable ground-data acquisition in Uda Walawe and Anuradhapura.
- Laboratory Resources: Spectroradiometers, soil-moisture probes, and weather-station sensors are available through the university's Environmental Engineering Lab for calibration and validation tasks.
- External Partnerships: Hector Kobbekaduwa Agrarian Research and Training Institute (HARTI) and IWMI support technical validation and socioeconomic impact studies.

These facilities collectively provide the computational power, field access, and institutional collaboration required for end-to-end implementation of the hybrid monitoring system.

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