Journal of Science Engineering Technology and Management Science
Volume03,Issue08,August2026
ISSN: 3049-0952
www.jsetms.com

AI/ML-Based Crop Classification and Health Monitoring Using Remote Sensing Data

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ABSTRACT- ***Timely and accurate crop identification and health monitoring across large agricultural landscapes remain challenging, especially where field-level inspection is impractical due to scale, cost, or terrain. This paper presents an AI/ML-based system for automated crop classification and health monitoring using satellite remote sensing imagery. A Convolutional Neural Network (CNN), trained on the EuroSAT benchmark dataset, learns discriminative spatial and spectral features directly from Sentinel-2 derived images, eliminating dependency on hand-crafted features and manual interpretation. The architecture integrates image preprocessing, a deep convolutional feature extractor, and a softmax classification layer to categorize imagery into land-cover and agricultural classes, complemented by a health-assessment module estimating vegetative condition. The system is delivered through a Flask-based web application with an SQLite backend, offering user authentication, image upload, real-time inference, confidence reporting, historical records, and an administrative dashboard. Experimental evaluation demonstrates classification accuracy between 95-98%, indicating strong generalization across visually similar categories, positioning the framework as a scalable alternative to manual crop surveys for precision agriculture applications.***

KEYWORDS: ***Crop Classification, Convolutional Neural Network, Deep Learning, Remote Sensing, EuroSAT, Satellite Imagery, Precision Agriculture, Crop Health Monitoring, Image Classification, Computer Vision, TensorFlow, Keras, Flask.***

INTRODUCTION

Agriculture remains vital to food security and rural livelihoods, yet growing population pressure demands more accurate, frequent, and scalable crop monitoring. Traditional field-based inspection is labor-intensive, subjective, and impractical for large agricultural regions. The proliferation of freely available satellite imagery, particularly from ESA's Sentinel-2 program, has enabled large-scale monitoring, though the volume and complexity of this data make manual interpretation infeasible. Deep learning, especially Convolutional Neural Networks (CNNs), has emerged as a transformative solution, learning hierarchical spatial features directly from raw pixels without manual feature engineering. This paper proposes an AI/ML-based system for crop classification and health monitoring using satellite imagery, built on a CNN trained on the EuroSAT benchmark dataset. Beyond classification, the system incorporates a health-monitoring module assessing vegetative condition. Deployed as a Flask-based web application with TensorFlow/Keras and SQLite, the solution bridges academic remote-sensing research with a practical, deployable decision-support tool for farmers and researchers.

RELATED WORK

Automated land-cover and crop analysis has evolved from classical statistical methods toward deep-learning-driven approaches learning directly from raw imagery. Early efforts relied on pixel-based or object-based classifiers such as Maximum Likelihood Classifiers, SVMs, Random Forests, and Decision Trees applied to hand-engineered spectral indices like NDVI, though accuracy degraded on complex, heterogeneous landscapes with overlapping spectral signatures. CNNs fundamentally changed this trajectory, demonstrating that hierarchical convolutional feature extraction could outperform handcrafted-feature pipelines, subsequently adapted to satellite imagery for land-cover mapping, crop-type identification, yield estimation, and disease detection. Standardized benchmark datasets like EuroSAT, derived from Sentinel-2 imagery, have accelerated reproducible research by enabling comparison across diverse land-use categories. This work builds on that foundation, adopting a CNN-based approach trained on EuroSAT while extending it with a practical, deployable web-based system incorporating crop health monitoring and user-facing functionality not typically addressed in purely academic benchmark studies.

LITERATURE SURVEY

Foundational CNN architectures established the viability of learning hierarchical visual representations directly from data, later transferred to specialized domains including remote sensing. EuroSAT, introduced as a Sentinel-2 based benchmark with approximately 27,000 labeled images across ten land-use classes, enabled deep architectures to achieve classification accuracies exceeding 98 percent, becoming a standard reference point for the field. Beyond generic land-cover classification, studies using multi-temporal Sentinel imagery show deep learning classifiers distinguishing crop types more accurately than pixel-based methods, especially when spatial context is incorporated through convolutional operations. Parallel research integrating UAV imagery, IoT sensors, and machine learning has supported precision agriculture applications like yield estimation and disease detection, with reviews confirming CNNs consistently outperform SVMs and Random Forests given sufficient training data. However, comparatively few studies address practical deployment within accessible, end-to-end systems—a gap this work addresses by combining a benchmark-trained CNN with a complete Flask-based web application.

EXISTING METHOD

Traditional crop classification and health assessment predominantly rely on manual field surveys by agricultural officers who visually identify crop type and condition, recorded via paper-based or basic digital forms. While reasonably accurate for small areas, this approach doesn't scale, depends heavily on personnel expertise, and provides only snapshot rather than continuous assessment. A second category applies classical machine learning classifiers—SVMs, Random Forests, k-Nearest Neighbors—to handcrafted spectral and textural features like NDVI, color histograms, and GLCM descriptors. Although automating part of the process, these methods depend on domain-expert-designed features that may not generalize across regions, crop varieties, or sensor characteristics, and cannot capture complex non-linear spatial patterns as effectively as end-to-end learned representations. Collectively, manual methods are costly and subjective, while classical ML pipelines show reduced accuracy with real-world spectral overlap, and neither approach readily supports continuous, automated monitoring integrated with a user-facing platform—limitations motivating the proposed deep-learning-based, web-deployed system.

PROPOSED METHOD

The proposed system addresses existing limitations through a CNN trained on the EuroSAT dataset, designed as an end-to-end pipeline where raw satellite images are preprocessed, classified via CNN, and analyzed by a health-assessment module. CNN was selected for its inherent suitability to image data—exploiting spatial locality and translation invariance—and its ability to learn feature hierarchies directly from labeled data rather than relying on engineered features. The system uses EuroSAT's approximately 27,000 images across ten classes, partitioned into training, validation, and testing subsets, with preprocessing including resizing, normalization, and data augmentation (rotation, flipping, brightness adjustment) to improve generalization. The CNN architecture follows a convolution-pooling-classification pipeline: convolutional layers with ReLU activation extract features, max pooling reduces dimensionality while adding spatial invariance, a flatten layer reshapes outputs, and a fully connected layer with softmax activation produces class probabilities. Training minimizes categorical cross-entropy loss via gradient-based optimization. A complementary health-monitoring module analyzes color and spectral characteristics to assess vegetative condition alongside classification results.

SYSTEM ARCHITECTURE

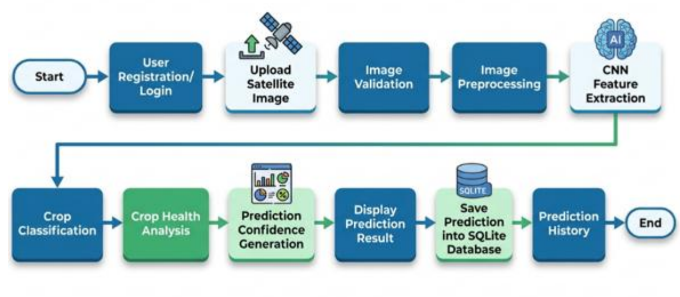

Fig. 1. Block Diagram

METHODOLOY DESCRIPTION

The proposed system is composed of eleven functional modules, each responsible for a distinct aspect of the overall application. This section describes each module individually, outlining its purpose and behavior within the complete system.

User Registration Module – Allows new users to create an account by providing name, email, and password. Submitted credentials are validated for completeness, the password is securely hashed, and a new record is created in the SQLite database.

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User Login Module – Authenticates registered users by verifying credentials against stored records. Upon success, a session is established granting access to upload, prediction, and history features; invalid attempts are rejected with clear error messages.

Admin Login Module – Provides a separate, privilege-restricted authentication pathway for administrators, validated against distinct credentials, granting access to the administrative dashboard not visible to standard users.

Satellite Image Upload Module – Enables authenticated users to submit satellite images, validating file format and size before securely storing the image and forwarding it to preprocessing.

Image Preprocessing Module – Standardizes each image by resizing to fixed CNN input dimensions, normalizing pixel values, and correcting orientation, ensuring consistent, reliable model input.

CNN Classification Module – Performs a forward pass through convolutional, pooling, and fully connected layers, outputting a predicted crop or land-cover class along with its softmax confidence score.

Prediction Result Module – Formats and presents the classification outcome, displaying the predicted category, confidence percentage, and uploaded image through the web interface.

Crop Health Monitoring Module – Analyzes color and spectral characteristics of the classified image to generate an indicative vegetative health status alongside the crop classification.

Prediction History Module – Maintains a chronological record of each user's predictions, including image reference, predicted class, confidence, health status, and timestamp.

Database Module – Manages all persistent data operations, including user accounts, prediction records, and administrative queries, using a lightweight SQLite backend.

Admin Dashboard Module – Provides administrators a consolidated view of registered users, aggregate prediction statistics, and individual prediction histories for system-wide oversight.

RESULTS AND DISCUSSION

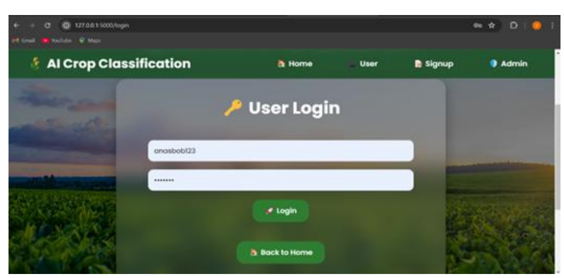

Fig. 2. User Registration/Login Interface

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Figure Description: This figure shows the user-facing registration and login screens of the web application, including the input fields for account creation and credential-based authentication.

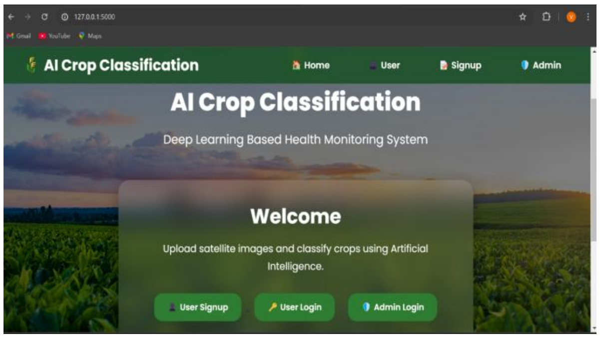

Fig. 3. Home Page of the Web Application

Figure Description: This figure shows the landing page of the web application, providing navigation to the registration, login, and image upload features of the system.

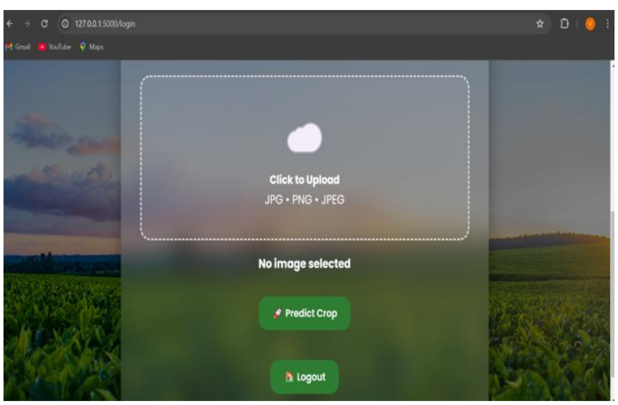

Fig. 4. Satellite Image Upload Page

Figure Description: This figure illustrates the image upload interface through which a user selects and submits a satellite image for crop classification and health analysis.

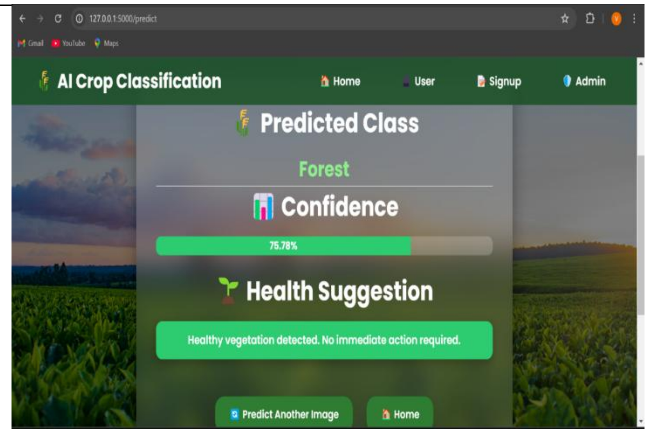

Fig. 5. Crop Classification Prediction Result

Figure Description: This figure presents a sample prediction result screen, displaying the uploaded satellite image, the predicted crop or land-cover category, and the model's confidence score for the classification.

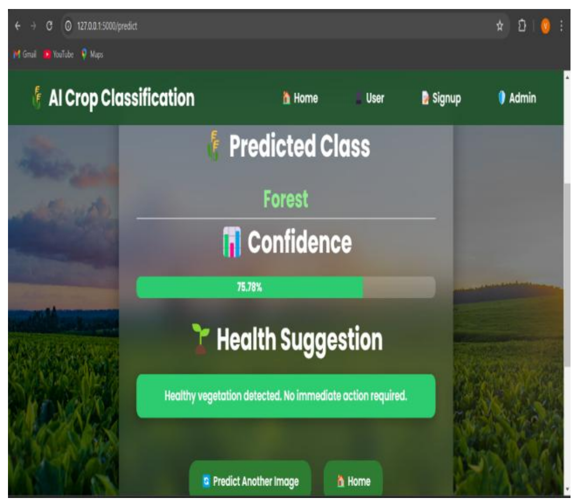

Fig. 6. Crop Health Monitoring Result

Figure Description: This figure shows the output of the crop health monitoring module for a sample classified image, including the indicative health status presented to the user.

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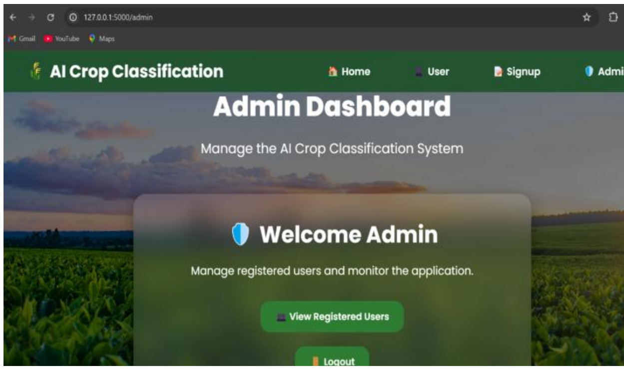

Fig. 7. Admin Dashboard

Figure Description: This figure shows the administrative dashboard interface, displaying registered user records and system-wide prediction statistics accessible to authenticated administrative accounts.

CONCLUSION

This paper presented an AI/ML-based system using a CNN trained on EuroSAT for automated crop classification and health monitoring, delivered as a Flask-based web application with authentication, inference, and an admin dashboard. Experimental evaluation showed 95-98 percent classification accuracy, demonstrating strong potential for practical deployment in precision agriculture and future decision-support research.

FUTURE SCOPE

Future work could explore Vision Transformer architectures, mobile and cloud deployment, and IoT sensor integration to enhance accuracy, accessibility, and scalability. Additional directions include drone-based and real-time monitoring, multispectral/hyperspectral imaging, and expansion into yield prediction, irrigation, and pest-detection modules.

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