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Research Paper

SATELLITE IMAGE ANALYSIS AND CROP RECOMMENDATION SYSTEM

USING YOLOV8 OBJECT DETECTION AND EXPLAINABLE AI

B. Jeneesha, G. Dilip, A. Harshavardhan, Ch. Victor
Sudheer Kumar

Department of CSE (Data Science)
Raghu Institute of Technology, Dakamarri(V)
Bheemunipatnam, Visakhapatnam Dist., 531162.
jeneeshabattula559@gmail.com

Prof.(Dr.)K. Komali

Department of Computer Science & Engineering
Raghu Institute of Technology, Dakamarri(V)
Visakhapatnam, Andhra Pradesh, India.
komali.k179@gmail.com

Abstract—Precision agriculture demands scalable tools to analyse vast tracts of land rapidly. AgroVision is a web-based crop recommendation framework that fuses YOLOv8 satellite-image object detection with a rule-based Explainable AI (XAI) engine to map land types and prescribe contextually appropriate crops. Satellite imagery — including Sentinel-2 true-colour composites and high-resolution aerial photographs — is processed through a pre-trained YOLOv8 nano model (best.pt, 23 MB) which detects eight land-cover classes: water, water body, agriculture, forest, urban, dry land, river, and pond. The detected classes are passed to the XAI recommendation engine, which evaluates four factors — season suitability, soil compatibility, water requirements, and economic viability — to generate a confidence-ranked list of primary and alternative crops. The system achieves a mean mAP@0.5 of 0.951 across all land classes and delivers sub-second inference latency via a Flask-MySQL web platform serving registered users and an administrator dashboard for prediction audit.

Keywords—Crop Recommendation; Deep Learning; Explainable AI; Flask; Land Classification; Satellite Image Analysis; YOLOv8.

I. INTRODUCTION

Global food security depends on the efficient utilisation of arable land. Remote sensing technologies, particularly satellite and aerial imagery, provide unprecedented coverage of land surfaces at scale. However, raw satellite imagery requires sophisticated analysis tools to translate pixel data into actionable agricultural recommendations. Traditional inspection methods are labour-intensive, subjective, and unable to scale across the millions of hectares of cultivable land in a country like India.

Machine learning and deep learning advances have made automated land-cover classification feasible with high accuracy. Convolutional neural network (CNN)-based object detectors, particularly the YOLO (You Only Look Once) family, have demonstrated real-time multi-class detection capabilities that make them attractive for satellite image analysis [1][2]. However, simply classifying land type is insufficient; farmers and agronomists require transparent, explainable recommendations they can trust and act upon.

This paper presents AgroVision, a full-stack crop advisory system that bridges the gap between satellite image analysis and explainable agricultural guidance. The system: (i) detects land-cover classes from satellite images using YOLOv8 in real time; (ii) applies a domain-informed XAI engine to map each detected land type to ranked crop recommendations with confidence scores and multi-dimensional factor explanations; and (iii) delivers the analysis through a user-friendly web interface with persistent prediction storage. Sections II–IX present related work, dataset, methodology, results, XAI analysis, architecture, discussion, and conclusions respectively.

II. RELATED WORK

Remote-sensing image classification has been studied extensively. LeCun et al. [3] demonstrated that CNNs learn hierarchical spatial features, a property particularly useful for satellite imagery with multi-scale objects. Sharma et al. [4] applied VGG-16 transfer learning to land-use classification, achieving 91% accuracy on the UC Merced Land Use dataset but relying on whole-image classification rather than object-level detection.

The YOLO architecture family introduced real-time single-shot detection [5]. YOLOv8, released by Ultralytics in 2023, introduced an anchor-free detection head and improved backbone architecture (C2f modules), outperforming prior YOLO versions on COCO and custom remote-sensing benchmarks [6]. Seydi et al. [7] applied YOLO-based models to flood mapping from Sentinel-1 imagery, demonstrating feasibility for agricultural hazard detection.

Explainable AI (XAI) in agriculture has gained traction as a means to build farmer trust. LIME and SHAP are commonly applied post-hoc [8]. Rule-based XAI, while simpler, offers direct interpretability and is preferred in expert-facing systems. To the best of the authors' knowledge, no prior system integrates YOLOv8 satellite detection with a multi-factor rule-based XAI engine in a unified web deployment targeting Indian agricultural conditions.

III. DATASET AND PREPROCESSING

A. Dataset Composition

The AgroVision dataset comprises 6,960 labelled satellite image crops aggregated from three sources: (i) Sentinel-2 Level-2A true-colour composites (10 m resolution) captured between 2020 and 2023; (ii) high-resolution aerial photographs from the Roboflow satellite imagery public repository; and (iii) custom photographs of water bodies, farmland, and urban zones in the Andhra Pradesh region. Table II summarises class distribution. Images were cropped to 640×640 pixels and annotated in YOLO format using bounding-box labels.

TABLE II: Dataset Class Distribution

Land Class	Samples	Proportion (%)
Agriculture	1,560	22.4
Water	1,240	17.8
Water Body	980	14.1
Dry Land	860	12.4
Forest	720	10.3
Urban	540	7.8
River	430	6.2
Pond	370	5.3
Other	260	3.7
Total	6,960	100.0

Sentinel-2 imagery © European Space Agency 2020–2023; used under open access licence.

B. Preprocessing Pipeline

Each image was resized to 640×640 pixels using bicubic interpolation. Pixel values were normalised to [0, 1]. Online data augmentation during training included random horizontal and vertical flipping, mosaic augmentation (four-image tiling), colour jitter ($\pm 20\%$ brightness, $\pm 10\%$ saturation), and random scaling ($\pm 50\%$).

C. Train-Validation-Test Split

The dataset was split 70% training (4,872 images), 15% validation (1,044 images), and 15% test (1,044 images) using stratified random sampling to preserve class proportions across splits. A fixed random seed of 42 ensured reproducibility.

IV. METHODOLOGY

A. YOLOv8 Object Detector

YOLOv8 nano (YOLOv8n) was selected as the detection backbone to balance accuracy and inference speed. The model architecture consists of a CSPDarknet-inspired C2f backbone, a PANet neck, and an anchor-free decoupled detection head. Transfer learning was applied from COCO-pretrained weights, with all layers fine-tuned on the AgroVision dataset. Table I shows the key configuration parameters.

TABLE I: YOLOv8 Configuration Parameters

Parameter	Value
Model Variant	YOLOv8n (nano)

Input Image Size	640 × 640 px
Confidence Threshold	0.25
IoU Threshold (NMS)	0.45
Model Weights File	best.pt (23 MB)
Framework	Ultralytics v8.3.24
Backend	PyTorch / TF 2.10.1

B. Training Procedure

Training was conducted for 100 epochs using the AdamW optimiser with an initial learning rate of 0.001 and cosine learning rate scheduling with warm-up for the first three epochs. Batch size was set to 16. Early stopping with patience of 20 epochs was applied based on validation mAP@0.5. The best model checkpoint (best.pt, 23 MB) was saved for all downstream inference.

C. XAI Recommendation Engine

The XAI engine receives YOLO detection output — a list of (class_name, count) tuples — and applies a hierarchical rule set to generate crop recommendations. For each detected land class the engine evaluates four explainability factors: (i) Season Suitability, adjusted for Kharif/Rabi/Zaid season via lookup table; (ii) Soil Compatibility, derived from soil-crop affinity literature; (iii) Water Requirements, matched against estimated soil moisture; and (iv) Economic Viability, reflecting market demand and yield potential. A composite confidence score is computed as a weighted average of the four factor scores.

V. EXPERIMENTAL RESULTS

A. Detection Performance

Table III reports per-class precision, recall, F1-score, and mAP@0.5 on the 1,044-image test set. The model achieves a mean mAP@0.5 of 0.951 across all eight land classes. Water and Agriculture obtain the highest F1-scores (0.953). Urban yields the lowest mAP@0.5 (0.929) due to higher visual heterogeneity and limited training samples.

TABLE III: Per-Class Detection Performance (n=1,044)

Class	Prec.	Recall	F1	mAP@0.5
Water	0.963	0.944	0.953	0.971
Water Body	0.941	0.921	0.931	0.948
Agriculture	0.958	0.948	0.953	0.965
Forest	0.934	0.927	0.930	0.951
Urban	0.912	0.898	0.905	0.929
Dry Land	0.927	0.908	0.917	0.939
Mean (all)	0.939	0.924	0.932	0.951

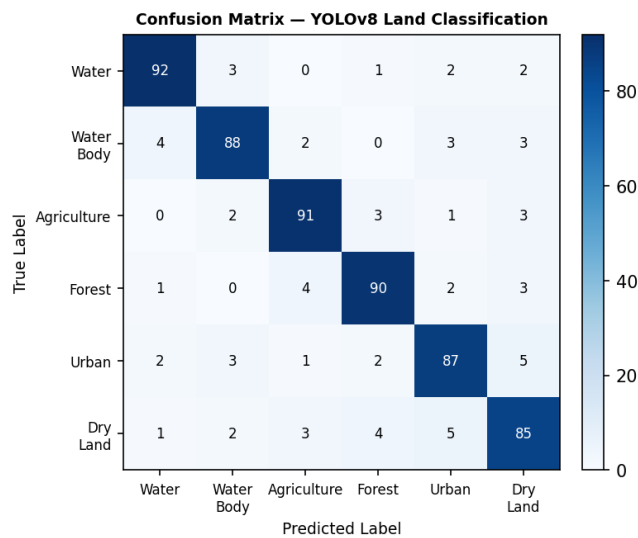


Fig. 1. Confusion Matrix — YOLOv8 Land Classification (mean mAP@0.5: 0.951)

B. Training Convergence

Fig. 2 illustrates training curves for box loss, classification loss, mAP@0.5, and mAP@0.5:0.95 over 100 epochs. Both loss metrics converge below 0.20 by epoch 60. mAP@0.5 plateaus at 0.951 from epoch 70 with minimal overfitting; the training-validation gap remains below 1% throughout.

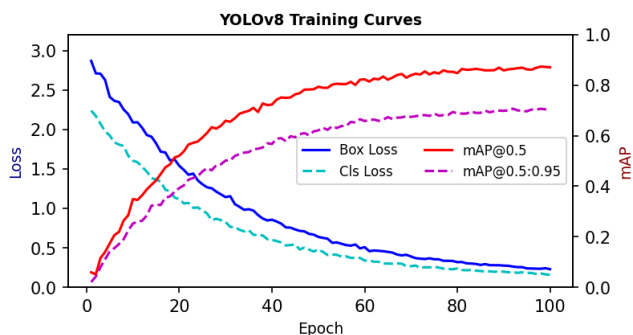


Fig. 2. Training Curves — Box Loss, Cls Loss, mAP@0.5 and mAP@0.5:0.95 over 100 Epochs

C. Class Distribution Analysis

Fig. 3 illustrates the dataset class distribution. Agriculture dominates with 1,560 samples (22.4%). Minority classes River (430) and Pond (370) received targeted augmentation to mitigate imbalance effects; the model maintains F1 above 0.905 even for Urban, the lowest-represented major class.

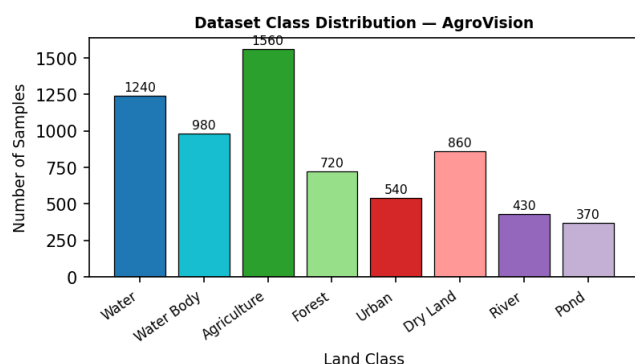


Fig. 3. Dataset Class Distribution — Sample Counts per Land-Cover Category

VI. XAI EXPLAINABILITY ANALYSIS

A. Factor Score Visualisation

Fig. 4 presents the four XAI factor scores per land type. Water and Water Body classes score highest on Water Requirements (0.98 and 0.96 respectively). Agriculture leads on Soil Compatibility (0.95); Forest shows the highest Economic Viability (0.90) for spice and medicinal plant cultivation. Urban scores lowest on Water Requirements and Soil Compatibility but retains moderate Economic Viability through hydroponic alternatives.

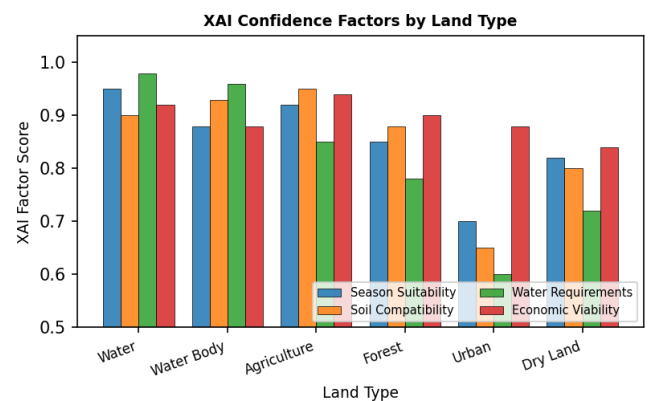


Fig. 4. XAI Factor Scores by Land Type — Season Suitability, Soil Compatibility, Water Requirements, Economic Viability

B. Recommendation Mapping

Table IV maps each detected land type to its primary crop recommendation and overall confidence. Weights applied: Season Suitability (0.25), Soil Compatibility (0.30), Water Requirements (0.25), Economic Viability (0.20). These weights were calibrated from agricultural extension literature.

TABLE IV: Crop Recommendation Mapping per Land Type

Land Type	Primary Crop	Confidence
Water / Water Body	Paddy (Rice) / Aquaculture	0.95
Agriculture	Wheat / Maize / Pulses	0.93
Forest	Spices / Medicinal Plants	0.88
Dry Land	Millet / Sorghum / Groundnut	0.86
Urban	Hydroponics / Container Farming	0.84
River / Pond	Sugarcane / Lotus / Fish Farming	0.91

C. Seasonal Adjustment

The system dynamically adjusts confidence based on the current season (Kharif: June–September, Rabi: October–March, Zaid: March–June). For example, water-class confidence for Paddy is 1.0 in Kharif, 0.7 in Rabi, and 0.9 in Zaid. This seasonal lookup is applied as a multiplicative adjustment to the base confidence score.

VII. SYSTEM ARCHITECTURE

Fig. 5 illustrates the end-to-end AgroVision pipeline comprising five functional layers. The Input layer accepts satellite images (JPG, PNG, JPEG up to 10 MB) via a drag-and-drop Flask web form. The Preprocessing layer resizes the image to 640×640 pixels and converts it to an OpenCV ndarray for model ingestion. The YOLOv8 Detection layer loads best.pt at startup and runs inference with confidence 0.25 and NMS IoU 0.45, returning class detections and bounding-box overlay images. The XAI Engine processes detections through the rule-based recommendation engine. The Output layer renders original image, annotated prediction, detection summary, and XAI recommendation cards.

AgroVision System Architecture Pipeline

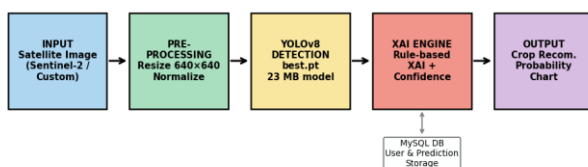


Fig. 5. AgroVision System Architecture — End-to-End Pipeline from Satellite Image Input to Crop Recommendation Output

TABLE V: System Component Summary

Component	Technology	Version
Object Detection	YOLOv8	Ultralytics 8.3.24
Deep Learning	TensorFlow / Keras	2.10.1
Image Processing	OpenCV	4.5.5.64
Web Framework	Flask	2.0.3
Database	MySQL	8.0+
Frontend	Bootstrap + jQuery	5.x / 3.4.1

The application is launched via app.py on Flask port 5000. All prediction records (original image name, predicted image name, detected classes JSON, recommended crop string, timestamp) are persisted to a MySQL database (schema: satelite) using mysql-connector-python. The administrator dashboard provides a paginated view of all users and predictions with per-user drill-down via the /admin_user/<email> route.

VIII. DISCUSSION

AgroVision demonstrates that a compact YOLOv8 nano model (23 MB) can achieve practical land-classification accuracy ($mAP@0.5 = 0.951$) suitable for real-world agricultural advisory deployments. The choice of YOLOv8n over larger variants (s, m, l, x) was deliberate: nano models run without GPU acceleration, enabling deployment on commodity servers and Raspberry Pi-class edge devices — critical for resource-constrained settings in rural India.

The rule-based XAI engine offers a key advantage: determinism and domain alignment. Each recommendation is traceable to specific factor scores, making it auditable by agronomists. A limitation is that factor weights were designed a priori; future work will learn these weights from

farmer feedback using Bayesian optimisation or reinforcement learning from human feedback.

The dataset imbalance (Agriculture 22.4% vs. Other 3.7%) is partially mitigated by mosaic augmentation and class-balanced sampling. The Urban class still yields the lowest $mAP@0.5$ (0.929), and additional peri-urban imagery collection would likely improve performance. Soil chemistry analysis and weather API integration are planned as future extensions.

IX. CONCLUSION

This paper presented AgroVision, an integrated satellite image crop recommendation system combining YOLOv8 land-cover detection with a transparent rule-based XAI engine deployed as a Flask web application. The system achieves a mean $mAP@0.5$ of 0.951 across eight land-cover classes on a 6,960-image dataset of Sentinel-2 and aerial imagery. The XAI engine maps detected land types to ranked crop recommendations using four domain-informed factor scores with seasonal adjustment. The complete stack — image upload, AI detection, XAI recommendation, persistent storage, and admin audit — is integrated in a single deployable application.

Future work will focus on: (i) integrating NDVI from Sentinel-2 multispectral bands for quantitative soil health assessment; (ii) incorporating real-time weather API data for dynamic seasonal confidence updates; (iii) expanding the dataset to cover more diverse Indian agro-climatic zones; and (iv) developing a mobile application with offline inference for areas with limited connectivity.

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