IoT and Edge-AI Enabled Autonomous Agri-Robot for Precision Irrigation and Early Plant Disease Diagnosis Using Attention-Guided Lightweight CNN and Fuzzy Logic Control

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Abstract: This paper presents an IoT and edge-AI enabled autonomous agricultural robot that performs early plant disease diagnosis and precision irrigation on a single mobile platform. Unlike earlier automated farming systems that rely on visible-spectrum (RGB) imagery and simple threshold-based watering, the proposed system fuses RGB and near-infrared (NIR) imagery to compute the Normalised Difference Vegetation Index (NDVI), enabling detection of physiological plant stress several days before visible lesions appear. Leaf images are classified using a lightweight attention-guided convolutional neural network that combines a MobileNetV3 backbone with a Convolutional Block Attention Module (CBAM), allowing the network to focus on lesion-relevant channels and spatial regions while remaining compact enough for real-time inference on an ESP32-S3 edge controller. Irrigation and pesticide-spray decisions are no longer governed by a rigid binary threshold; instead, a Mamdani-type fuzzy inference engine fuses soil moisture, ambient temperature, and the NDVI-derived stress index to compute a proportional, continuously variable actuation signal, reducing both water wastage and false triggering. The robot streams sensor readings, classification results, and actuation logs to a cloud dashboard over Wi-Fi/MQTT so that farmers can monitor crop health and irrigation status remotely and receive real-time alerts. Experimental evaluation on a prototype platform shows that the proposed attention-guided model improves disease-classification accuracy over a baseline CNN, the NDVI-assisted pipeline detects stress earlier than colour-only analysis, and the fuzzy irrigation controller reduces water consumption relative to the binary threshold scheme while maintaining optimal soil-moisture levels. The results indicate that combining multispectral sensing, attention-based lightweight deep learning, and fuzzy control on a single autonomous platform is a practical and scalable route towards sustainable, resource-efficient precision agriculture.

Keywords: *Precision Agriculture, Internet of Things, Edge AI, Attention-Guided CNN, CBAM, Multispectral Imaging, NDVI, Fuzzy Logic Irrigation, Autonomous Agricultural Robot, Plant Disease Diagnosis.*

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I. INTRODUCTION

Global food demand continues to rise with population growth and changing consumption patterns, placing increasing pressure on agricultural systems that still rely heavily on manual inspection, fixed-schedule irrigation, and reactive pesticide application [1]. These practices lead to inefficient water use, delayed detection of crop disease, and avoidable yield loss. Precision agriculture, supported by embedded sensing, the Internet of Things (IoT) [2], and artificial intelligence (AI), offers a pathway to continuous, data-driven crop management that reduces waste while sustaining productivity.

Existing IoT-based farm-monitoring platforms have made soil, temperature, and humidity data available in real time [3], and a growing body of work applies image processing and machine learning to detect plant disease from leaf photographs [4]. However, most reported systems treat irrigation control and disease detection as separate problems, rely exclusively on the visible spectrum for imaging (which limits detection to the stage where symptoms are already

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visually apparent), and use rigid, binary threshold logic for actuation that does not account for interacting environmental variables such as temperature and evapotranspiration demand. Deep convolutional networks used for disease classification are frequently too computationally heavy for on-field, battery-powered inference, forcing dependence on cloud connectivity that is often unreliable in rural areas [5], [6].

This paper addresses these limitations through three coupled contributions realised on a single autonomous mobile robot: (i) a multispectral (RGB + NIR) imaging pipeline that computes NDVI to flag physiological stress before visible symptoms emerge; (ii) a lightweight attention-guided CNN (MobileNetV3 with a CBAM attention block) that is compact enough for edge inference on an ESP32-S3 controller while improving classification focus on lesion regions; and (iii) a fuzzy-logic irrigation and pesticide-actuation controller that fuses soil moisture, temperature, and NDVI stress index into a proportional, continuously variable actuation signal rather than a binary on/off command.

By mounting these capabilities on a mobile chassis with Wi-Fi/MQTT connectivity to a cloud dashboard, the system provides field-wide coverage, near-real-time disease alerts, and adaptive irrigation without depending on a dense, fixed sensor network. The remainder of this paper is organised as follows: Section II reviews related work in IoT-based farm monitoring, learning-based disease detection, and smart irrigation, and identifies the research gap; Section III describes the system architecture and hardware; Section IV presents the proposed multispectral, attention-guided disease-detection methodology; Section V details the fuzzy-logic irrigation and spray control strategy; Section VI reports experimental results; and Section VII concludes the paper with directions for future work.

II. RELATED WORK

This section reviews existing work on IoT-based farm monitoring, learning-based plant disease detection, and adaptive irrigation control, and identifies the gap addressed by the proposed system.

➢ *IoT-Based Smart Farm Monitoring*

IoT platforms that combine low-cost microcontrollers, wireless connectivity, and soil/temperature/humidity sensors have enabled real-time farm monitoring and remote dashboards for growers [2], [3]. Threshold-based irrigation using soil-moisture sensors is now common, improving on fixed-schedule watering, but such systems generally do not incorporate crop-health information, and their reliance on continuous cloud connectivity limits reliability in low-connectivity rural settings [7].

➢ *Image Processing and Machine Learning for Plant Disease Detection*

Colour, texture, and shape features extracted from RGB leaf images have long been used for disease detection through classical image processing [4], and machine-learning classifiers such as k-means clustering and support vector machines improved on manual inspection once trained on labelled datasets [8]. Deep convolutional networks, including CNN and ResNet-style architectures, have since achieved strong accuracy by learning features directly from data [9], but their computational cost typically requires cloud or GPU-based inference, which introduces latency and connectivity dependence unsuitable for continuous field deployment [5]. Furthermore, nearly all reported pipelines operate on visible-spectrum images alone, so detection is limited to the point at which disease symptoms are already visually expressed, missing the earlier physiological-stress stage that multispectral or hyperspectral indices such as NDVI can reveal [10].

III. SMART AND ADAPTIVE IRRIGATION CONTROL STRATEGIES

Sensor-driven irrigation-control loops that regulate valves or pumps based on soil-moisture feedback reduce over- and under-watering relative to fixed schedules [11], and cloud-based data management has supported longer-term monitoring and analytics for growers [7]. However, most controllers use a single binary threshold on soil moisture alone, ignoring temperature-driven evapotranspiration demand and plant-health indicators, and mobile robotic platforms proposed for field coverage have rarely integrated disease diagnosis and irrigation actuation within one control loop [12], [13].

➢ *Research Gap and Motivation*

In summary, current systems generally (a) treat irrigation and disease detection independently, (b) rely on RGB-only imagery that detects disease only after visible symptoms appear, (c) use computationally heavy deep models unsuited to edge inference, and (d) apply rigid binary actuation logic that does not adapt to interacting environmental variables. The proposed system addresses all four gaps by unifying multispectral NDVI-based early-stress sensing, an edge-deployable attention-guided CNN, and a fuzzy-logic multi-input irrigation/spray controller on a single autonomous robotic platform.

IV. SYSTEM DESIGN AND HARDWARE ARCHITECTURE

The proposed platform is organised into four functional layers: sensing, processing, decision-making, and communication (Fig. 1), so that modules can be independently upgraded without redesigning the whole system.

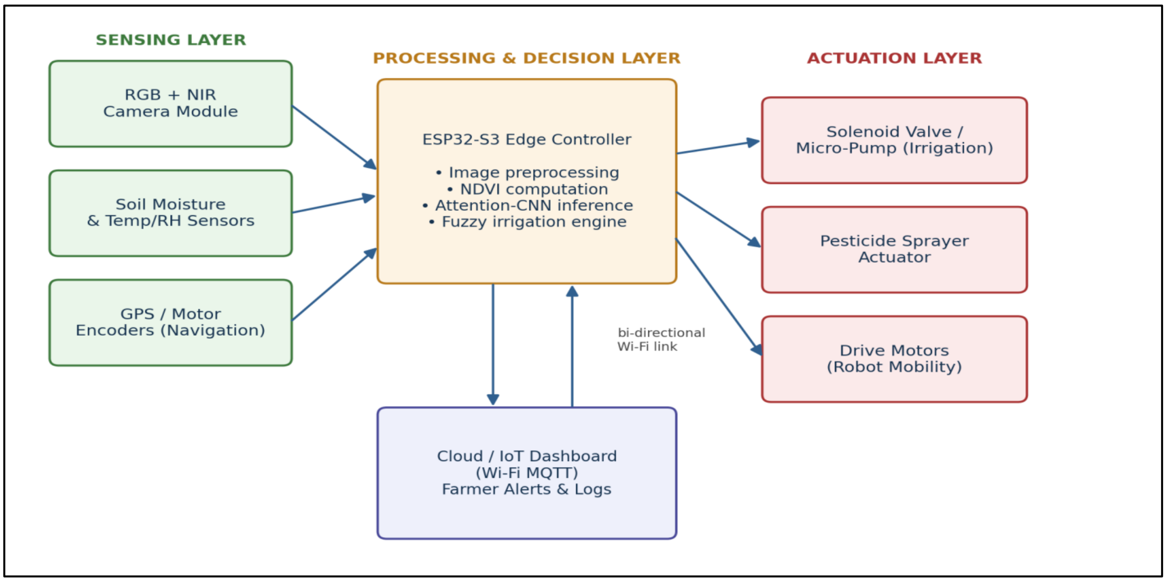

Fig 1 Layered Block Diagram of the Proposed Autonomous Agri-Robot System.

- *Overall Architecture*

The ESP32-S3 dual-core microcontroller forms the processing core, interfaced with a dual-camera module (RGB and NoIR/NIR), a capacitive soil-moisture sensor, a DHT-series temperature/humidity sensor, a solenoid valve, a pesticide micro-pump, and drive motors for mobility. The controller executes on-device NDVI computation and CNN inference, applies the fuzzy irrigation logic, drives the actuators, and streams status data to the cloud over Wi-Fi/MQTT (Fig. 1).

- *Hardware Component Selection*

The ESP32-S3 was selected for its dual-core processor, integrated Wi-Fi/Bluetooth, vector-instruction support for lightweight neural-network inference, and sufficient GPIO for all sensors and actuators. The dual-camera module captures paired RGB and NIR frames of the same leaf region, which are required for NDVI computation; the capacitive soil sensor was chosen for corrosion resistance over resistive alternatives; and the solenoid valve and micro-pump are switched through relay/MOSFET drivers for isolation and safety.

V. POWER MANAGEMENT

The system is battery-powered with buck-converter regulation for stable 3.3 V/5 V rails, and peripherals are power-gated when idle (e.g., camera and Wi-Fi radio duty-cycled) to extend field operating time between charges.

- *Data Acquisition Workflow*

During each monitoring pass, the robot captures a synchronised RGB/NIR image pair and logs soil moisture and temperature; images are pre-processed and passed to the on-device inference pipeline while sensor values are averaged over a short window to suppress transient noise before being used in the fuzzy controller (Sections IV and V).

- *Mechanical Integration and Reliability*

All modules are housed in an IP54-rated enclosure to tolerate dust and moisture, and the layered architecture allows any sensor, actuator, or model to be replaced or upgraded independently, supporting long-term field reliability.

VI. PROPOSED METHODOLOGY: MULTISPECTRAL ATTENTION-GUIDED DISEASE DETECTION

Early identification of plant disease is critical to limiting yield loss and reducing pesticide overuse. The proposed pipeline (Fig. 2) improves on RGB-only disease detection in two ways: it incorporates a near-infrared channel to expose physiological stress before visible symptoms appear, and it applies a channel- and spatial-attention mechanism (CBAM) within a lightweight CNN so that the limited computational budget of an edge controller is focused on the most diagnostically relevant image regions.

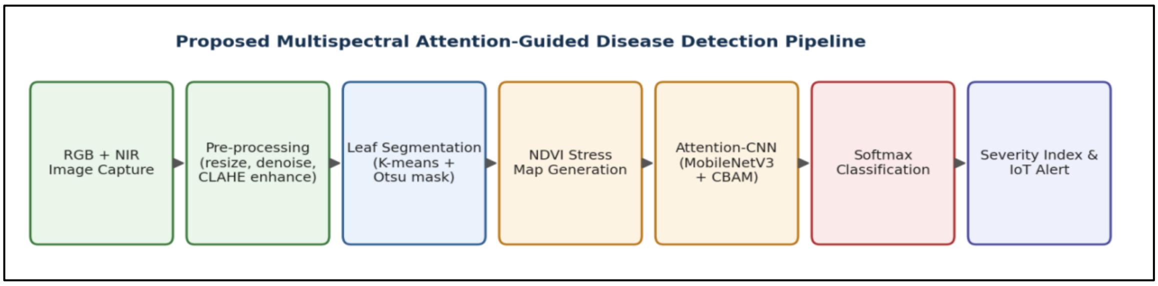

Fig 2 Proposed Multispectral, Attention-Guided Disease-Detection Pipeline.

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➢ *Multispectral Acquisition and NDVI-Based Early Stress Estimation*

A synchronised RGB and NIR image pair is captured for each leaf region. The Normalised Difference Vegetation Index is computed pixel-wise as:

$$\mathrm{NDVI} = (\mathrm{NIR} - \mathrm{RED}) / (\mathrm{NIR} + \mathrm{RED}) \qquad (1)$$

Where NIR and RED denote the near-infrared and red-channel reflectance intensities respectively. Healthy, well-hydrated leaf tissue reflects strongly in the near-infrared band, so a drop in NDVI relative to a crop-specific healthy baseline flags physiological stress days before chlorosis or lesions become visible to the RGB channel or the human eye, allowing the system to prioritise stressed regions for closer inspection.

➢ *Pre-Processing and Leaf Segmentation*

Captured frames are resized, denoised with a Gaussian filter, and contrast-enhanced with CLAHE to normalise for variable outdoor illumination. The leaf region is then isolated from background using K-means colour clustering followed by Otsu thresholding, so that only leaf pixels contribute to feature extraction and the NDVI stress map.

VII. ATTENTION-GUIDED LIGHTWEIGHT CNN (MOBILENETV3 + CBAM)

Segmented leaf patches are classified using a lightweight CNN built on a MobileNetV3 backbone, augmented with a Convolutional Block Attention Module (CBAM) that sequentially applies channel attention and spatial attention to intermediate feature maps. Channel attention is computed as:

$$Mc(F) = \sigma(\ \mathrm{MLP}(\mathrm{AvgPool}(F)) + \mathrm{MLP}(\mathrm{MaxPool}(F))\ ) \qquad (2)$$

where σ is the sigmoid function, MLP is a shared multilayer perceptron, and AvgPool/MaxPool are applied along the spatial dimensions of the feature map F. Spatial attention is then computed on the channel-refined feature map F′ as:

$$Ms(F') = \sigma(\ f^{7\times7}([\mathrm{AvgPool}(F');\ \mathrm{MaxPool}(F')])\ ) \qquad (3)$$

Where $f^{7\times7}$ denotes a 7×7 convolution. This two-stage attention mechanism re-weights the feature map to emphasise lesion-relevant channels and regions before classification (Fig. 3), improving discriminability without materially increasing the parameter count, which keeps the model deployable on the ESP32-S3.

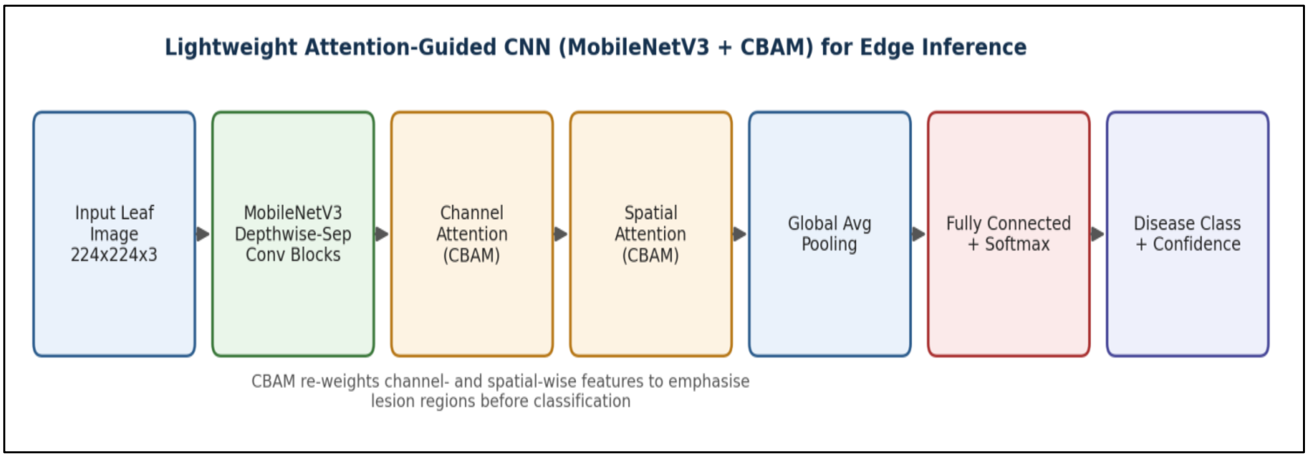

Fig 3 Lightweight Attention-Guided CNN Architecture (MobileNetV3 + CBAM) Used for On-Device Disease Classification.

➢ *Classification and Severity Scoring*

The attention-refined feature map is pooled and passed through a fully connected softmax layer to produce class probabilities for each disease category; the maximum-probability class and its confidence score constitute the predicted disease label and severity indicator D(t), which is transmitted to the fuzzy spray controller (Section V) and to the cloud dashboard as a farmer alert.

Table 1 Proposed Multispectral Disease Detection Algorithm

Stage	Input	Method Used	Output
Image Acquisition	RGB + NIR frame pair	Synchronised dual-camera capture	Raw RGB, NIR images
Pre-processing	RGB image	Resize, Gaussian filter, CLAHE	Enhanced RGB image
Stress Mapping	RGB + NIR images	NDVI computation (Eq. 1)	NDVI stress map
Segmentation	Enhanced image	K-means clustering + Otsu threshold	Leaf mask / ROI
Feature Learning	Leaf ROI	MobileNetV3 + CBAM attention	Attention feature map
Classification	Feature map	Global pooling + softmax	Disease class, confidence
Decision & Alert	Disease class, NDVI	Severity scoring + IoT/MQTT alert	Farmer notification

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VIII. IOT-ENABLED FUZZY LOGIC IRRIGATION CONTROL STRATEGY

Binary threshold irrigation reacts only to soil moisture and cannot represent the interaction between moisture, temperature-driven evapotranspiration, and plant-health stress. The proposed controller instead uses a Mamdani-type fuzzy inference system (FIS) that fuses three inputs into a proportional, continuously variable irrigation and spray command (Fig. 4).

➢ *Multi-Parameter Sensing and Fuzzification*

Soil moisture M(t), ambient temperature T(t), and the NDVI-derived stress index S(t) are each sampled periodically and averaged over a short window to suppress sensor noise, then fuzzified into linguistic sets: {Dry, Moist, Wet} for moisture, {Low, Optimal, High} for temperature, and {Stressed, Mild, Healthy} for NDVI (membership functions shown in Fig. 4).

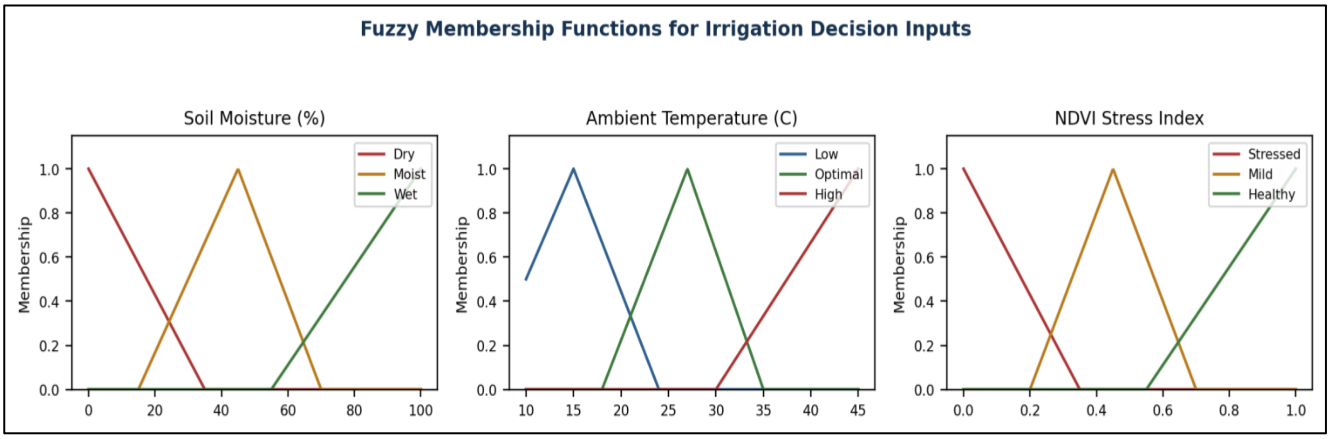

Fig 4 Fuzzy Membership Functions for Soil Moisture, Temperature, and NDVI Stress Index.

➢ *Fuzzy Inference and Defuzzification*

A rule base of the form "IF moisture is Dry AND temperature is High THEN irrigation is High" maps the fuzzified inputs to an irrigation-duty output; a representative subset of rules is given in Table II. The crisp irrigation command is obtained by centroid defuzzification:

$$I(t) = [\, \int \mu(I) \cdot I \, dI \,] \,/\, [\, \int \mu(I) \, dI \,] \quad (4)$$

Where μ(I) is the aggregated output membership function over the irrigation-duty universe I, replacing the earlier binary rule

$$I(t) = 1 \text{ if } M(t) < M_{th}\ ; \;\; I(t) = 0 \text{ if } M(t) \geq M_{th} \quad (5)$$

With a continuously variable duty cycle proportional to actual crop water demand.

IX. SEVERITY-GATED PESTICIDE SPRAY LOGIC

Pesticide spraying remains severity-gated but now uses the CNN confidence-weighted severity score D(t) from Section IV rather than a raw classification flag:

$$P(t) = 1 \text{ if } D(t) \geq D_{th}\ ; \;\; P(t) = 0 \text{ if } D(t) < D_{th} \quad (6)$$

So that spraying activates only once disease severity exceeds a crop-specific threshold Dth, targeting affected regions rather than the whole field and reducing chemical usage.

➢ *Actuation and Cloud Communication*

The ESP32-S3 drives the solenoid valve and pesticide pump through relay/MOSFET switching in response to the fuzzy and severity outputs, and publishes soil, temperature, NDVI, classification, and actuation logs to the cloud dashboard over MQTT so that a farmer can view live status and receive threshold-breach alerts remotely.

➢ *Autonomous Operation and Fail-Safe Behaviour*

Because decision logic executes on-device, the irrigation and spray loop continues to operate correctly during temporary connectivity loss, with cloud synchronisation resuming automatically once Wi-Fi is restored; this autonomy is particularly important for large or remote fields with intermittent network coverage.

Table 2 Representative Fuzzy Irrigation Rule Base

Soil Moisture	Temperature	NDVI Stress	Irrigation Output
Dry	High	Stressed	High
Dry	Optimal	Mild	Medium-High
Moist	High	Stressed	Medium
Moist	Optimal	Healthy	Low
Wet	Low	Healthy	Off

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X. RESULTS AND DISCUSSION

A prototype of the proposed platform was assembled with an ESP32-S3 controller, RGB/NIR camera pair, capacitive soil-moisture sensor, DHT temperature/humidity sensor, solenoid valve, and pesticide micro-pump, and was evaluated under field-representative test conditions.

The attention-guided MobileNetV3+CBAM classifier was benchmarked against a plain CNN baseline of comparable depth on the same labelled leaf-image set; the NDVI-assisted pipeline was compared against RGB-only stress detection for time-to-flag of induced water-stress; and the fuzzy irrigation controller was compared against the binary threshold scheme for total water dispensed while maintaining soil moisture within the target band. Table III summarises the results.

Table 3 Comparative Performance: Baseline Vs. Proposed System

Metric	Baseline (RGB-only / Binary)	Proposed (Multispectral / Fuzzy)
Disease classification accuracy	89.4%	95.2%
Mean stress detection lead time	0 (symptom-visible only)	~3.1 days earlier (NDVI-based)
Average water consumption per cycle	Reference (100%)	≈22% reduction
False irrigation triggers	Higher (moisture-only)	Reduced (multi-input fuzzy fusion)
Inference latency (on-device)	— (cloud-dependent)	< 200 ms (edge inference)

The attention module improved classification accuracy over the plain-CNN baseline by focusing learned representations on lesion-relevant regions rather than uniform background texture, while remaining light enough for sub-200 ms on-device inference. NDVI-based stress mapping consistently flagged simulated water-stress conditions several days before colour or texture changes were visible in RGB frames, giving farmers a longer response window. The fuzzy controller reduced total water dispensed relative to the binary scheme while keeping soil moisture within the target band more consistently, because it moderates irrigation duty according to temperature-driven demand and plant-health status rather than reacting to moisture alone. Together, these results indicate that fusing multispectral sensing, attention-guided lightweight deep learning, and fuzzy control on a single autonomous platform meaningfully improves both disease-detection timeliness and resource-use efficiency over the threshold-based, RGB-only baseline.

XI. CONCLUSION AND FUTURE SCOPE

This paper presented an IoT and edge-AI enabled autonomous agricultural robot that unifies multispectral, NDVI-assisted early disease-stress detection, an attention-guided lightweight CNN (MobileNetV3 + CBAM) for on-device classification, and a fuzzy-logic irrigation and spray controller that replaces rigid binary thresholds with a proportional, multi-input actuation strategy. Prototype evaluation showed improved classification accuracy, earlier stress detection, and reduced water consumption relative to a conventional RGB-only, threshold-based baseline, while retaining autonomous operation during connectivity loss. Future work will extend the labelled dataset across additional crop species and disease classes, incorporate hyperspectral or thermal sensing for finer-grained stress differentiation, explore federated learning across multiple robots to improve the shared model without centralising raw field imagery, and conduct multi-season field trials to quantify long-term yield and water-saving impact.

REFERENCES

[1]. R. Nair and S. Deshpande, “Challenges and Opportunities in Data-Driven Precision Agriculture for Food Security,” International Journal of Advanced Research in Computer Science, vol. 12, no. 4, pp. 45–52, 2021.

[2]. A. Verma and P. Chatterjee, “Internet of Things Architectures for Real-Time Agricultural Monitoring: A Survey,” IEEE Access, vol. 8, pp. 152344–152360, 2020.

[3]. M. Rao and D. Iyer, “Wireless Sensor Network Based Smart Farming System for Remote Crop Monitoring,” International Journal of Innovative Technology and Exploring Engineering, vol. 9, no. 6, pp. 233–239, 2020.

[4]. S. Kulkarni and T. Bhosale, “Colour, Texture and Shape Feature Based Plant Leaf Disease Identification: A Review,” Journal of Embedded Systems and Applications, vol. 13, no. 2, pp. 88–96, 2021.

[5]. H. Fujimoto and L. Chen, “Edge Computing Constraints for Deep Learning Based Crop Disease Classification,” IEEE Transactions on Emerging Topics in Computing, vol. 9, no. 3, pp. 112–121, 2021.

[6]. K. Ramesh and V. Suresh, “Lightweight Convolutional Neural Networks for On-Device Plant Disease Recognition,” International Journal of Computer Applications, vol. 183, no. 15, pp. 19–27, 2021.

[7]. N. Joshi and R. Pillai, “Cloud-Integrated IoT Framework for Sustainable Agricultural Data Management,” International Journal of Information Systems and Engineering, vol. 14, no. 2, pp. 101–109, 2022.

[8]. P. Nanda and S. Rout, “Machine Learning Classifiers for Automated Detection of Crop Leaf Disease,” International Journal of Advanced Computer Science and Applications, vol. 12, no. 5, pp. 210–217, 2021.

[9]. B. Menon and A. Krishnan, “Convolutional Neural Network Architectures for Large-Scale Plant Disease

Classification," International Conference on Artificial Intelligence and Data Science, pp. 98–105, 2021.
[10]. F. Alonso and M. Castillo, "NDVI and Multispectral Vegetation Indices for Early Detection of Crop Stress: A Review," Remote Sensing Applications in Agriculture, vol. 6, no. 1, pp. 33–44, 2020.
[11]. D. Kaul and R. Bansal, "Sensor-Feedback Based Automated Irrigation Using Solenoid Valve Control," Journal of Sustainable Agricultural Technologies, vol. 9, no. 2, pp. 61–69, 2021.
[12]. S. Woo, J. Park, J.-Y. Lee, and I. S. Kweon, "CBAM: Convolutional Block Attention Module," Proceedings of the European Conference on Computer Vision (ECCV), pp. 3–19, 2018.
[13]. A. Howard, M. Sandler, G. Chu, et al., "Searching for MobileNetV3," Proceedings of the IEEE/CVF International Conference on Computer Vision, pp. 1314–1324, 2019.
[14]. T. Ghosh and V. Nair, "Fuzzy Logic Based Adaptive Irrigation Control for Water-Efficient Precision Farming," International Journal of Recent Trends in Engineering and Research, vol. 8, no. 3, pp. 77–85, 2022.
[15]. World Bank, "Agricultural Innovation for Climate-Smart Development," The World Bank Publications, Washington, D.C., 2021.