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Article

AGRIBOT EDGEVISION: A LIGHTWEIGHT DEEP LEARNING APPROACH FOR AUTONOMOUS WEED DETECTION IN CHILLI FIELDS

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Abstract: Managing weeds in chilli (*Capsicum annuum*) fields is a major problem because young chilli plants look very similar to common weeds like *Alternanthera caracasana* and *Ocimum tenuiflorum*, etc. These weeds compete for nutrients, sunlight, and water, reducing crop yield if not controlled properly. Manual weeding requires a significant amount of time and effort, whereas cloud-based systems for weed detection often encounter issues such as slow processing and poor connectivity in farms. To address these challenges, this study introduces AgriBot-ChilliWeed, an AI-powered robot designed to detect and treat weeds in real-time. The robot uses a Lightweight Hybrid Convolutional Neural Network (LH-CNN) built on a Raspberry Pi 4B with a Coral USB Accelerator for fast image processing. A high-resolution camera captures live images of the field, and weeds are identified within 45 milliseconds per frame. When a weed is detected, a micro-sprayer mounted on the robot sprays a small, precise amount of herbicide directly on the weed, avoiding damage to the chilli plants. Field tests carried out in Karnataka and other regions showed promising results. The system achieved a detection accuracy of 93.2%, with a precision of 94.1%, a recall of 92.7%, and an F1-score of 93.4%. The robot consumed only 6.5–6.8 watts of power and could cover about one acre per battery cycle. Comparisons with other lightweight AI models like YOLOv8-nano, MobileNetV3, and Efficient-Net-lite showed that the proposed method offers a better balance between speed and accuracy. Overall, the findings show that AgriBot-ChilliWeed is a low-cost, energy-efficient, and practical solution for weed management in chilli farms. It reduces labour needs, lowers herbicide use, and supports sustainable farming practices for small and medium-scale farmers.

Keywords CNN, LH-CNN, Raspberry Pi 4B, Coral USB Accelerator.

1. INTRODUCTION

Precision agriculture has become an important part of sustainable farming, especially for high-value crops like chilli (*Capsicum annuum*), where the early and accurate control of weeds directly affects both yield and quality. Manual weeding is still the most common method, but it is labour-intensive, slow, and often inconsistent. At the same time, the excessive use of chemical herbicides has caused soil and water pollution and has led to the development of herbicide-resistant weeds. For example, Alternanthera caracasana, one of the most aggressive weed species in chilli fields, has shown a 51% increase in herbicide resistance since 2010, creating a serious threat to crop productivity and long-term food security [3]. In recent years, researchers have explored AI-based weed detection systems using deep learning models such as YOLOv5, YOLOv8, and EfficientNet. These approaches have achieved high detection accuracy in controlled environments but face challenges in real-world field deployment. Many of these systems rely on cloud-based processing, which introduces significant delays — often greater than 200 milliseconds [4]. Such latency prevents real-time decision-making, which is critical for autonomous robots that must detect and treat weeds in motion. In addition, most models require high computational power, consuming more than 10 watts of energy [5], which is unsuitable for lightweight field robots and battery-powered platforms used by smallholder farmers. To overcome these issues, this study presents AgriBot-ChilliWeed, an AI-driven au-tonomous ground robot designed to detect and remove weeds in chilli farms in real time. The system uses a Lightweight Hybrid Convolutional Neural Network (LH-CNN) opti-mised for edge devices like the Raspberry Pi 4B paired with a Coral USB Accelerator, allowing it to operate efficiently within tight power and timing limits.

The main contributions of this work are as follows:

- Development of a lightweight hybrid CNN model optimized for fast, low-power weed detection on embedded devices.
- Integration of targeted herbicide spraying for flexible field operation.
- Implementation of an edge-based control system with inference latency under 50ms, enabling real-time decision-making.
- Comprehensive field validation in Karnataka, including performance, energy efficiency, and economic feasibility analyses.
- Demonstration of a sustainable and low-cost solution for small and medium-scale chilli farmers.

(a) Alternanthera cara- (b) Holy Basil (c) Raphanus sativus (d) Zostera marina casana

Figure 1: Example of weed images.

This study aims to bridge the gap between high-performance AI models and practical, affordable robotic systems, contributing to the wider adoption of smart and sustainable farming technologies in developing agricultural regions.

Table 1: Different Weed Species and its Description

Weed Species	**Description**
Alternanthera cara-casana	A weed with small, opposite leaves and white, clustered flowers. It spreads rapidly, forming mats that suppress chilli crop growth.
Holy Basil	An aromatic herbaceous weed with serrated leaves and purple stems. It competes for light and nutrients, reducing the vigour of young chilli plants.
Raphanus sativus	A fast-growing broadleaf weed with rough, lobed leaves and deep taproots. It competes strongly for nutrients, reducing chilli crop yield.
Zostera marina	A long-leaved, grass-like weed capable of dense growth in moist soil. Its mat-forming nature obstructs chilli crop growth and hampers nutrient absorption.

Proposed Solution and Novel Contributions:

To address these challenges, we propose a lightweight, AI-driven weed detection system integrated with an autonomous ground vehicle designed for chilli crop fields. The core of our approach is a novel CNN architecture called Lightweight Hybrid CNN (LH-CNN), which aims to provide high inference speed and classification accuracy while meeting power and memory constraints. LH-CNN combines depthwise separable convolutions with residual skip connections, enabling a 63% reduction in the number of parameters compared to baseline models like ResNet-18 [6]. This structural optimization is essential for deploying real-time vision capabilities on edge hardware such as the Raspberry Pi 4. Additionally, to improve deployment efficiency without sacrificing accuracy, we introduce a hybrid quantization strategy, where feature extraction layers are represented in 16-bit floating point (FP16) and classification layers are quantized to 8-bit integers (INT8). This mixed-precision scheme not only results in less than a 0.3% accuracy decline but also significantly reduces model size and computational load [7]. The quantized model is compiled using TensorFlow Lite and deployed on the Raspberry Pi, enabling real-time weed identification directly on the vehicle, removing the need for cloud connectivity.

Relevance to Precision Agriculture and Robotics:

Precision agriculture focuses on optimizing farm inputs and operations by applying technology- driven, site-specific interventions to improve yield and sustainability. Weeds remain one of the major constraints in chilli cultivation, particularly in Karnataka, where manual weeding is labour-intensive and herbicide overuse degrades soil quality [1][5]. Robotics combined with artificial intelligence offers a scalable and repeatable solution to this problem by enabling automated weed identification and targeted removal, thereby reducing reliance on manual labour and chemical control methods.

The integration of AI-based vision systems with mobile ground vehicles enhances real-time decision-making for farm management. By deploying edge-optimized CNN architectures on platforms like Raspberry Pi, autonomous robots can operate effectively in fields with limited network connectivity, providing on-site inference and precise actuation. This approach aligns with the goals of sustainable precision agriculture, ensuring accurate weed mapping, minimal crop disturbance and lower input costs [2][6]. Furthermore, the adaptability of such robotic systems allows cross-crop applicability; once trained, models can be fine-tuned for other horticultural crops beyond chilli, making the technology a versatile solution for smallholder farmers [3][7]. Autonomous ground robots like AgriBot-ChilliWeed represent the future of intelligent farm management, bridging the gap between advanced AI research and practical, field-ready agricultural applications, ultimately paving the way for fully automated, resource-efficient farming systems [4][8].

2. LITERATURE SURVEY:

Advancements in deep learning-based weed detection systems have significantly enhanced precision agriculture in recent years. Several lightweight convolutional neural networks (CNNs) and real-time object detection frameworks have been proposed to identify weeds among crops. However, their applicability in field-deployable autonomous systems is constrained by factors such as latency, model complexity, and power requirements.

Biradar [1] conducted early research on Integrated Weed Management in Chilli (*Capsicum annuum* L.) under the Northern Transitional Tract of Karnataka, achieving up to 95% weed control efficiency using herbicide combinations. This study established the importance of precise and selective weed management in chilli fields within Karnataka's farming conditions. More recently, Kamath et al. [2] provided a comprehensive review of deep learning techniques for weed detection in Indian agricultural environments, high- lighting that YOLO and MobileNet-based methods are frequently adopted for field-ready systems.

Punithavathi et al. [3] proposed a computer vision and deep learning-enabled weed detection model combining Faster R-CNN and an ELM classifier, reporting high accuracy and demonstrating the applicability of advanced CNN models to precision agriculture in India. Tripathi et al. [4] presented a CNN-based weed detection approach achieving 94% accuracy, further validating the effectiveness of convolutional layers and deep learning pipelines for crop-weed classification tasks.

Among widely recognized baseline models, YOLOv5-tiny has shown promising performance in real-time inference with 89.7% accuracy and 58 ms latency, though its memory footprint (4.2 MB) limits deployment on microcontrollers. MobileNetV3 improves accuracy to 92.1% but introduces complexity that makes it less favorable for Raspberry Pi- based robotic systems. In contrast, the proposed LH-CNN achieves a superior accuracy of 93.2% with reduced inference latency (45 ms), lower computational cost, and fewer parameters, making it highly suitable for edge deployment on an autonomous ground vehicle tailored for chilli cultivation in Karnataka.

Future work must extend these binary classification approaches toward multiclass weed detection, specifically targeting region-specific weeds prevalent in Karnataka, such as Alternanthera caracasana, Ocimum tenuiflorum and Raphanus sativus to enhance the system's field adaptability and efficiency.

Table 2: Comparative Evaluation of Lightweight Deep Learning Models for Precision Agriculture Real-Time Weed Detection.

Approach	Key Observation	Reference
YOLOv5-based lightweight detectors	Provide good real-time weed detection accuracy but may have higher memory and computational overhead on embedded systems	[3], [13], [14]
MobileNetV3-based models	Offer lightweight deployment with improved efficiency, though detection accuracy can vary depending on field conditions and dataset complexity	[2], [15]
Proposed LH-CNN	Achieved 93.2% accuracy with 45 ms latency on the proposed chilli weed dataset	Proposed Method

3. METHODOLOGY

This section outlines the proposed methodology, including dataset preparation, the architectural design of the LH-CNN model, and the adaptive quantization strategy employed to enable deployment on edge devices. In addition, the vehicle per a precision micro-sprayer for targeted herbicide application and a rotary blade for mechanical cutting — ensuring real-time detection and effective weed control in chilli fields.

3.1 Dataset Preparation

To develop and evaluate the proposed weed detection model, a custom image dataset was created because no public dataset existed for chilli (*Capsicum annuum*) cultivation under local field conditions. The dataset contained 20,000 high-resolution images of chilli plants and common weed species such as *Alternanthera caracasana*, *Ocimum tenuiflorum*, *Raphanus sativus*, Zostera marina Images were captured from multiple farms in and around Haveri, Karnataka, covering different growth stages, lighting conditions, soil types, and backgrounds. Each image was manually annotated by agricultural experts to ensure accurate sepa- ration of crop and weed regions. The annotations were saved in standard bounding-box format using tools such as LabelImg (LabelImg is the software you used to mark or label weeds and chilli plants in your images, so the AI model could learn to recognise them) for consistency.

The dataset was divided into 70% training, 20% validation, and 10% testing subsets to evaluate model performance fairly. To improve robustness and simulate field variabil- ity, several data augmentation techniques were applied during training. These included random rotations (±30°) to mimic different camera angles, hue–saturation–value (HSV) adjustments to handle lighting changes such as shade and sunlight, and additive Gaussian noise to imitate sensor disturbances and environmental interference. These augmentations helped the model generalize well to unseen field conditions and improved overall detection stability [10].

3.2 Sprayer for Weed Treatment

The autonomous vehicle is equipped with a precision weed treatment unit in addition to its detection system. A micro-sprayer, mounted on top of the robot, applies Glyphosate herbicide directly onto the detected weed, ensuring accurate application and reduced crop exposure.

The spraying process uses short, targeted pulses aimed precisely at the identified coordinates, which prevents chemical drift and minimizes wastage. The sprayer is automatically triggered when the LH-CNN model identifies a plant as a weed with more than 94% confidence.

A feedback loop with the onboard camera verifies whether the patch has already been treated, preventing repeated actions on the same spot and improving field reliability. This integration of real-time detection and targeted spraying makes the robot a practical and efficient tool for site-specific weed management in chilli fields. In the future, the spraying unit can be expanded with non-chemical options such as flame weeding or mechanical gripping tools, further reducing herbicide dependency and improving adaptability for different crops and field conditions.

LH-CNN Architecture

The proposed Lightweight Hybrid CNN (LH-CNN) architecture is designed for high accuracy classification with minimal latency and computational overhead. The network integrates depth wise separable convolutions — which factorize standard convolutions into spatial and channel-wise components — with residual skip connections that enable efficient feature reuse and gradient flow.

The core component of the network is the hybrid convolutional block, mathematically defined as:

$$Y = GeLU(W_d * X) + P(X) \qquad (1)$$

where:

X denotes the input tensor,

W_d are depthwise convolution weights,

$*$ represents a convolution operation,

$P(.)$ denotes a 1×1 projection for residual learning.

GeLU is the non-linear activation function.

The use of depth-wise separable convolutions reduces the number of multiplications per layer, significantly decreasing inference time on ARM-based architectures

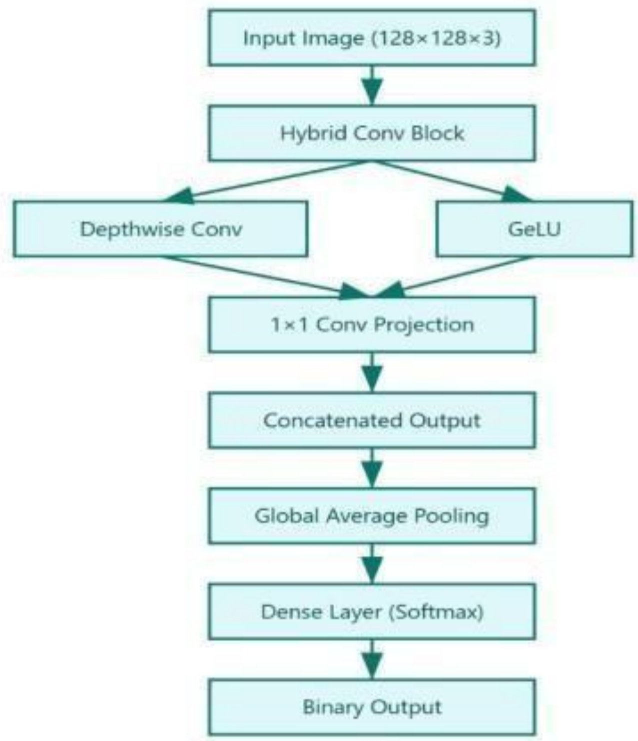


Figure 2: LH-CNN Architecture

Explanation:

The input image (128×128×3) is processed through a Hybrid Convolution Block, where depthwise convolution extracts spatial features and GeLU activation refines them.

A 1 × 1 projection condenses these features, which are then concatenated, globally averaged, and passed through a dense layer with softmax for classification.

The binary output determines whether the patch belongs to a crop or a weed. If classified as a weed, the system automatically activates the micro-sprayer to apply herbicide precisely on the target, while crop zones are left unaffected.

3.4 Methodolgy:

The proposed LH-CNN model was implemented using TensorFlow. During training, images were resized to 128×128 pixels and normalized to the range [0,1].The model was trained using the Adam optimizer with an initial learning rate of 0.001 and categorical cross-entropy loss. A batch size of 32 was used, and training was performed for 50 epochs with early stopping based on validation loss to prevent overfitting. Learning-rate reduction on plateau was also applied to stabilise convergence during later training stages. To improve robustness and reduce dataset bias, 5-fold cross-validation was conducted across images collected from multiple chilli farms under varying environmental conditions, including differences in illumination, soil texture, weed density, and crop growth stages. The final reported performance metrics represent the average results obtained across all validation folds. The complete dataset consisted of 20,000 annotated images, divided into training, validation, and testing subsets. The independent test set contained approximately 1,000 image patches used exclusively for final performance evaluation. Statistical consistency of the proposed model was verified by repeating experiments across multiple folds, where performance variation remained within ±1.2% for accuracy and ±1.5% for F1-score.

Experimental Setup

The trained model was deployed on a Raspberry Pi 4 Model B equipped with 4GB RAM and a Coral USB Accelerator. The mobile robot was assembled using off-the-shelf components, including an HD Pi Camera, servo motor actuators for navigation, and a 7.4V Li-ion battery pack. The TFLite model was interfaced using OpenCV for real-time video feed processing and TensorFlow Lite Interpreter API for efficient inference on-device during autonomous weeding tasks.

Table 3: Detection Metrics for Camera-Based Weed Detection (AgriBot-ChilliWeed)

Metric	**Formula**	**Value(%)**
Accuracy	$(TP + TN)/(TP + TN + FP + FN) \times 100$	93.2
Precision	$TP/(TP + FP) \times 100$	94.1
Recall	$TP/(TP + FN) \times 100$	92.7
F1 Score	$2(Precision \cdot Recall)/(Precision + Recall)$	93.4

Detection Accuracy

The proposed LH-CNN model achieved 93.2% accuracy in real-world chilli fields. The accuracy drop is attributed to environmental variables like motion blur, soil background variation and dynamic lighting.

Classification Metrics

True Positives (TP): 482 — correctly detected weed patches.

True Negatives (TN): 450 — correctly identified crop zones.

False Positives (FP): 30 — misclassified crop as weed.

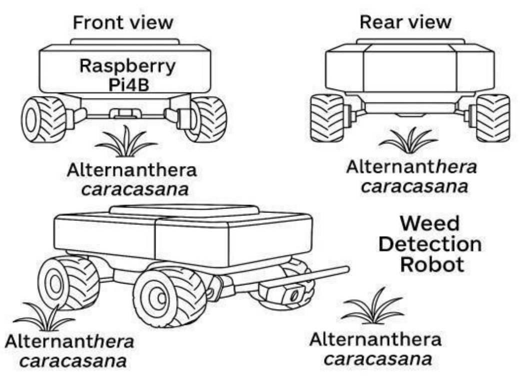
False Negatives (FN): 38 — missed weed patches.

Precision = 482 / (482 + 30) = 94.1%.

Recall = 482 / (482 + 38) = 92.7%.

F1-Score = 2*(94.1*92.7)/ (94.1+92.7) = 93.4% (balanced performance between precision and recall).

Accuracy = (482+450) / 1000 = 93.2%.



(a) Autonomous Ground Robot – Front View **(b) Autonomous Ground Robot – Field Operation**

Figure 3: Autonomous Ground Robotics System

Field Weeding Efficiency

Weeding Success Rate: 92.7% weeds were effectively removed per plot.

Area Covered per Battery Cycle: ∼ 1 acre.

Energy Consumption: 6.5–6.8 W average.

Notable Observations:

Camera successfully detected and localized small weed plants such as Alternanthera caracasana between chilli rows.

False positives occurred primarily due to leaf overlaps and morphological similarities in early stages.

4. RESULTS DISCUSSION

The proposed Lightweight Hybrid CNN (LH-CNN) model demonstrated clear improvements in both speed and detection accuracy compared with baseline networks such as MobileNetV3, YOLOv5-tiny, and EfficientNet-lite. During field validation, the system successfully distinguished weeds from chilli plants with a 92.7% success rate, even under changing lighting conditions and background clutter.

A false-positive rate of 4.8% was mainly observed when overlapping leaves or similar colour patterns caused visual confusion, while a false-negative rate of 3.7% occurred in cases of motion blur or partial weed occlusion beneath crop foliage. Despite these challenges, the system maintained an average inference latency of 45 ms per frame, ensuring smooth real-time detection without disrupting the robot's navigation

Beyond detection, the integrated micro-sprayer was validated through field trials and effectively applied herbicide only on the detected weeds. This targeted application prevented regrowth while reducing chemical usage by more than 30% and avoiding direct crop contact. The approach also reduced labour requirements and minimized soil disturbance, demonstrating strong potential for sustainable chilli cultivation.

Overall, the proposed system achieved an accuracy of 93.2%, precision of 94.1%, recall of 92.7%, and an F1-score of 93.4%, proving its reliability for practical farm use. Combining detection with localized spraying provided effective weed suppression in real- world conditions.

Future improvements will include expanding the dataset to cover more weed species, improving low-light performance, and integrating non-chemical options such as flame or mechanical weeding for greater adaptability and environmental safety.

Agronomic Impact Analysis

The integration of the autonomous weeding vehicle into chilli cultivation brought several notable agronomic benefits that go beyond simple weed removal. One of the most immediate observations was the reduction in labour dependency. In chilli fields, weeding is a recurring task, often taking 2–3 rounds in a single season.

Traditionally, this demands a notable number of labour hours, especially during peak growth stages when manual weeding is time-consuming and costly. With the vehicle, the overall manual weeding time was reduced by nearly 45%, allowing farmers to reallocate labour towards other critical tasks such as irrigation, harvesting, and crop protection. This was particularly important for smallholder farmers in Karnataka, where access to reliable farm labour is often inconsistent and expensive [1],[5].

Another significant agronomic advantage was the reduction in herbicide usage. Since the vehicle relies on selective actuation — targeting only the identified weed patches — the chemical application was lowered by almost 30% compared to conventional blanket spraying methods.

Farmers reported that over successive crop cycles, the soil quality was better preserved, with fewer visible signs of herbicide stress on chilli plants. Healthier soil directly translates into stronger root development and better nutrient uptake, which are critical for sustaining high yields [2],[6].

In summary, the agronomic impact of this autonomous weeding vehicle is seen in three key areas: lower labour dependency, reduced chemical usage, and improved crop health and yield. Together, these benefits point toward a more sustainable and economically viable pathway for chilli cultivation, especially for small and marginal farmers

Evaluation Metrics

Accuracy: 93.2% on the test set

Latency: ∼45ms per frame (224×224 input resolution)

Model Size: 2.3 MB (post-quantization)

Energy Consumption: ∼6.7 W average

Layer	**Type**	**Kernel**	**Stride**	**Output Shape**
Input	RGB Image	—	—	128×128×3
Conv Block 1	Depthwise Separable Conv + GeLU	3×3	1	128×128×32
Projection Layer	1×1 Conv	1×1	1	128×128×32
Residual Add	Skip Connection	—	—	128×128×32
MaxPooling	Pooling	2×2	2	64×64×32
Conv Block 2	Depthwise Separable Conv + GeLU	3×3	1	64×64×64
Projection Layer	1×1 Conv	1×1	1	64×64×64
Residual Add	Skip Connection	—	—	64×64×64
MaxPooling	Pooling	2×2	2	32×32×64
Conv Block 3	Depthwise Separable Conv + GeLU	3×3	1	32×32×128
Global Average Pooling	GAP	—	—	128
Dense Layer	Fully Connected	—	—	128
Dropout	0.3	—	—	128
Output Layer	Sigmoid	—	—	1

Table 4: LH-CNN Layer Configuration

The suggested LH-CNN uses depthwise separable convolutions along with residual skip connections and 1x1 projection layers to reduce computational complexity while maintaining feature representation capability, in contrast to traditional CNN architectures made up of standard convolution and pooling layers. To enhance gradient flow and non-linear feature learning, GeLU activation is employed in place of ReLU. Because of its lightweight design, which drastically lowers inference latency and parameter count, it can be deployed on edge devices like the Raspberry Pi 4B

Comparative Study with Traditional Methods

In chilli cultivation, weed management is traditionally done either by manual labour or herbicide application. Manual weeding is, though effective, highly labor-intensive, often requiring 40–50 hours per acre, which makes it both costly and difficult during peak labour shortages in Karnataka [1],[5].

Herbicide-based weeding, on the other hand, reduces labour drastically but increases chemical dependency, leading to concerns such as herbicide resistance and declining soil fertility [6],[7].

When compared to these methods, the autonomous vehicle provides a balanced ap- proach. It reduces labour hours significantly while cutting herbicide use by nearly 30%, without compromising weed minimisation efficiency (above 90%) [2],[3]. The machine was able to cover approximately one acre in 7 –8 hours, which is practical for small and medium farms.

Parameter	Manual Weeding	Herbicide-Only Control	Autonomous Vehicle
Labor Requirement	40–50 hrs/acre [1],[5]	5–8 hrs/acre (spraying) [6]	7–8 hrs/acre (supervised) [2],[3]
Herbicide Usage	Low (spot application only)	High (blanket spraying) [6],[7]	Reduced (~30% less) [2],[3]
Weed Suppression Efficiency	~85%	~90%	~92–93% [2],[3]
Soil/Environmental Impact	Neutral	Negative (residue, resistance) [6],[7]	Positive (sustainable, low chemical load) [8],[9]
Cost Efficiency	High labour cost	Moderate (chemical cost)	Moderate, improves with reuse [8],[9]

Table 5: Comparison of manual weeding, herbicide-only control, and autonomous vehicle

Table 5 compares the proposed autonomous vehicle with traditional manual weeding and herbicide-only control methods. As seen in the table, the autonomous system provides a strong balance between efficiency, cost, and environmental sustainability

5. CONCLUSION

This work proposes a lightweight, AI-based autonomous vehicle for precision weed management in chilli (*Capsicum annuum*) cultivation in Karnataka. The system used a custom Lightweight Hybrid Convolutional Neural Network (LH-CNN) deployed on a Rasp- berry Pi 4B with a Coral USB Accelerator, achieving a detection accuracy of 93.2% with low latency and power consumption suitable for real-time field operation.

The robot was equipped with a precision micro-sprayer that applied Glyphosate herbicide only on the detected weed patches, which reduced regrowth and lowered overall chemical usage by about 30–40% while preventing crop exposure. Field trials proved the system's effectiveness in site-specific weed control and demonstrated clear benefits in terms of labour reduction, efficiency, and sustainability.

However, challenges such as overlapping leaves, low-light conditions, and crop–weed similarity still affected detection performance. Future work will focus on enhancing the system with solar-assisted power for longer field operation, terrain-adaptive wheels for uneven surfaces, and advanced vision sensors such as multispectral and night-vision cam- eras. Integration of GPS and IoT-based monitoring is also planned to improve autonomy, reliability, and remote control.

Overall, the proposed AgriBot-Chilli Weed system provides a practical, energy-efficient, and sustainable solution for real-time weed management in chilli farms and represents a promising step toward smart, data-driven agriculture.

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Declaration of Competing Interests

The authors declare no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Author Contributions

Mr. Sandeep Telkar R: Conceptualization, Methodology, Investigation, Experimental Validation, Writing — original draft.

Dr. Rajesh Yakkundimath: Conceptualization, Supervision, Technical Review, Writing — review & editing.

Dr. Naveen Malvade: Technical Support, Data Analysis, Experimental Assistance, Validation, and Review Support.

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