

## Integration Of Neural Networks and Robust Control for an Agricultural Robotic Arm Using Crop-Based Data

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### **Abstract:**

Data-driven robotic systems are critical in modern agriculture, enhancing crop yield through adaptive decision-making and visual recognition. While robust control ensures high-performance manipulation of robotic arms, it is limited in nonlinear and uncertain environments. This study presents a hybrid control framework integrating feedforward neural networks (NNs) with robust control using crop-specific datasets, improving adaptability and precision. Visual classification based on the Heaviside threshold method is employed to identify produce quality and color, demonstrated here for potato harvesting.

Experimental validation was performed in a greenhouse using a 6-DOF robotic arm, with sensors for soil moisture, temperature, and real-time image capture. Results show that the hybrid control system effectively classifies crops and adapts arm movements under varying environmental conditions, achieving both stability and adaptability. Limitations of the model, such as restricted generalization to extreme weather conditions, are discussed.

**Keywords:** Agricultural Robotics, Neural Networks, Robust Control, Crop Data, Heaviside Method, Visual Recognition.

### **1. Introduction**

Precision agriculture requires adaptive automation to improve yield and reduce environmental impact [1]. Robotic systems capable of perceiving the environment and making autonomous decisions are increasingly utilized for harvesting, monitoring, and quality assessment.

The performance of agricultural robots is influenced by:

1. Control system robustness, especially for articulated manipulators.
2. Data-driven decision-making, enabling adaptation to environmental variability.

Robust control handles disturbances and uncertainties effectively but may fail in highly nonlinear environments. Neural networks provide complementary adaptive capabilities, learning nonlinear mappings from crop-specific datasets including soil properties, growth stages, and weather conditions. Integrating robust control with NNs enables robotic systems that are both stable and adaptive.

Visual perception further enhances precision. Real-time color-based classification using the Heaviside function allows effective decision-making during harvesting. This study proposes a hybrid control framework combining robust control, neural networks, and Heaviside-based visual classification, validated through both simulation and real experimental trials.

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### Related Work

Several studies have explored AI-driven decision-making and control in agricultural robotics: Ghodbane et al. [3] demonstrated 6-DOF manipulator control with obstacle avoidance using inverse kinematics. Wang [6] highlighted the limitations of robust control in friction-stir welding systems, demonstrating the need for adaptability. Lamy [7] and Rivals [10] illustrated the potential of neural networks in control and process modeling. Few studies integrate robust control and NNs using real agricultural datasets. This work contributes a unified hybrid architecture for adaptive decision-making and motion control of agricultural robotic arms with experimental validation.

## 2. Methodology

### A. Agricultural Robot Arm Modeling

Forward kinematics is computed using the Denavit-Hartenberg (DH) convention to define joint parameters and ensure precise positioning [2], [4].

Equation (1) :

$$T_0^{i+1} = \begin{pmatrix} \cos\theta_i & -\sin\theta_i \cos\alpha_i & \sin\theta_i \sin\alpha_i & r \cos\theta_i \\ \sin\theta_i & \cos\theta_i \cos\alpha_i & -\cos\theta_i \sin\alpha_i & r \sin\theta_i \\ 0 & \sin\alpha_i & \cos\alpha_i & d_i \\ 0 & 0 & 0 & 1 \end{pmatrix}$$

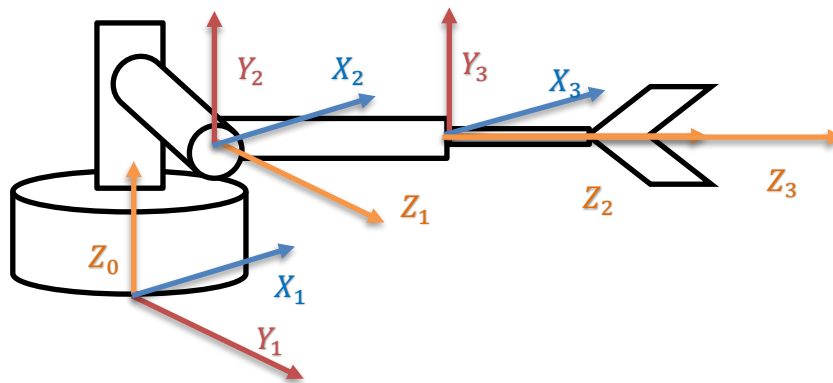


Fig. 1: Schematic of the robotic arm with DH parameters.

**Model Limitations:** The DH model assumes rigid links and negligible joint backlash; thus, performance may degrade in high-load or highly dynamic field environments.

### B. Crop-Oriented Database

A structured database stores environmental and crop parameters, including:

- Soil moisture and temperature
- Crop quality metrics
- Insect presence
- Organic content

These inputs feed the neural network for real-time adaptive control.

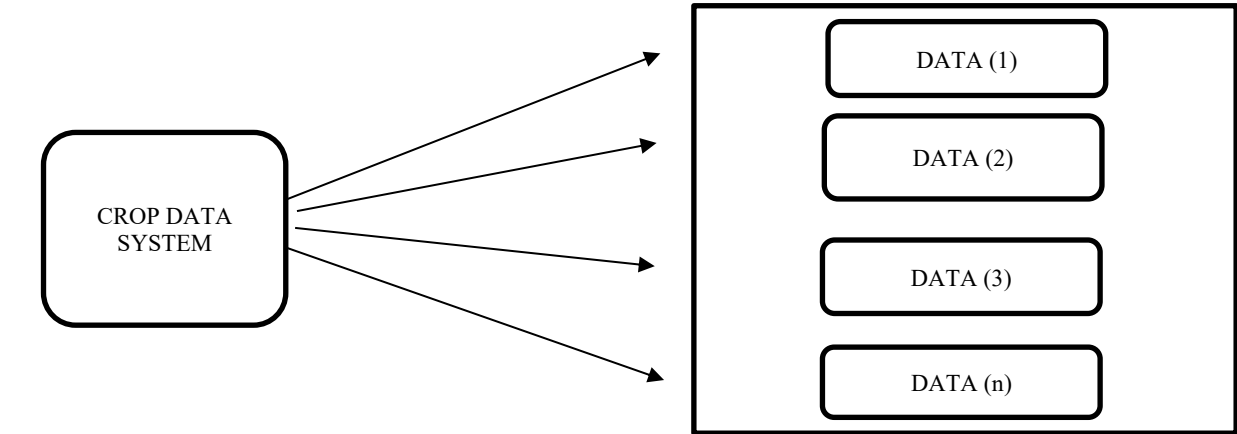


Fig. 2: Database schema.

C. Visual Perception and Color-Based Classification

The Heaviside function classifies produce colors in real-time:

$$y = H(x - \theta)$$

The decision logic is governed by the Heaviside step fuction :

Equation (2) :

$$H(x) = \begin{cases} 0, & x < \theta \\ 1, & x \geq \theta \end{cases}$$

Where  $\theta$  is the threshold for visual classification.

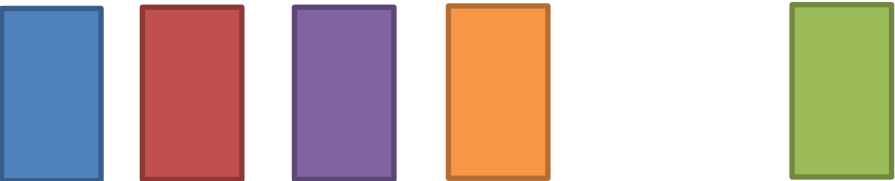
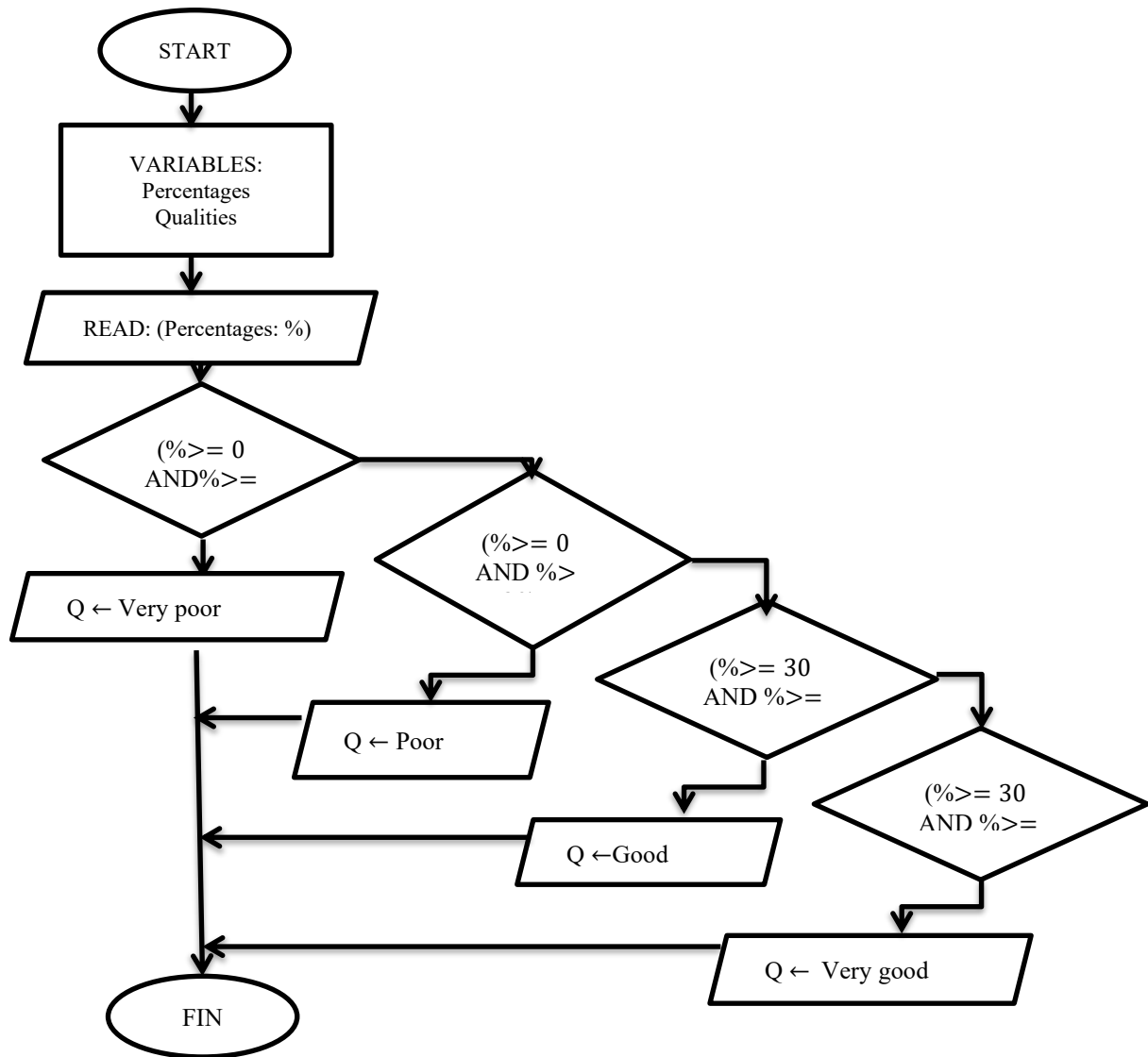


Fig. 3: Flowchart of visual classification.



#### D. Neural Network and Robust Control Integration

Multivariable control addresses systems with multiple inputs and outputs. In this work, robust control techniques are enhanced through the integration of neural networks to manage complex and uncertain environments more effectively [6].

#### 1) Neural Network Architecture

A single-hidden-layer feedforward network maps environmental inputs to actuation commands. Inputs include soil, crop, and environmental data.

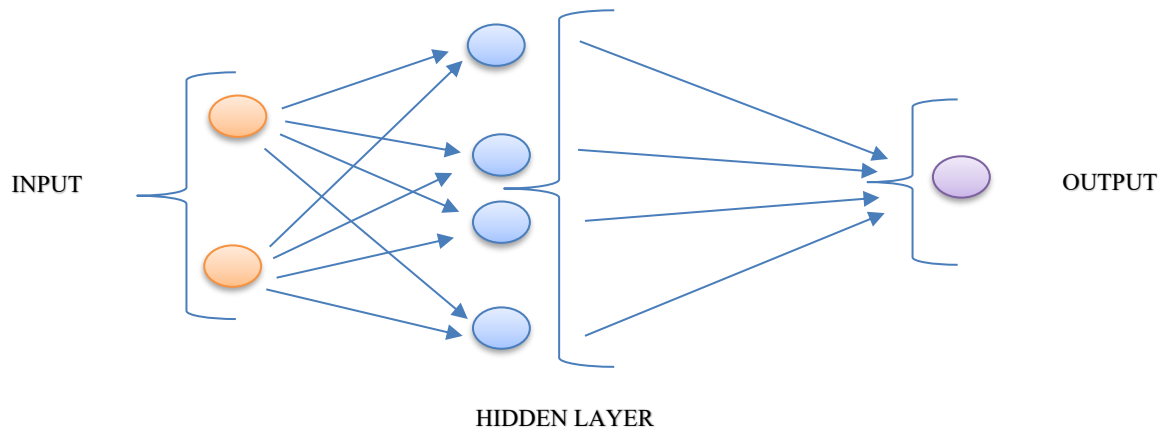


Fig. 5: NN architecture.

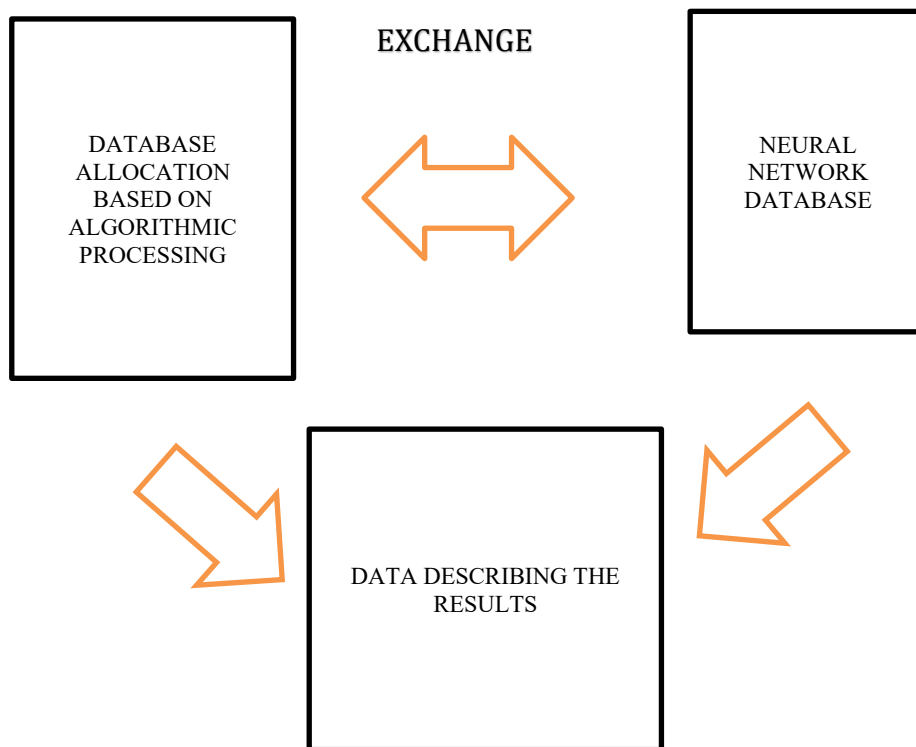
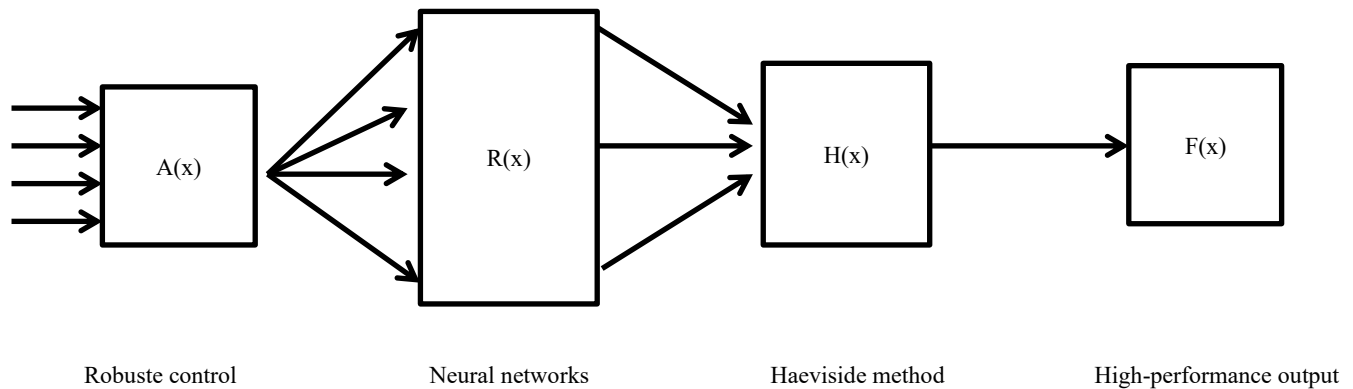


Fig. 6: Mapping of database parameters to NN input layer.

## 2) Hybrid Control Model

The hybrid control system combines:

- Robust control for disturbance rejection
- Neural networks for adaptive nonlinear mapping
- Heaviside function for decision boundaries in visual classification



**Fig. 7: Integrated hybrid control model**

Justification: NN provides adaptive mapping, robust control ensures stability, Heaviside classification guides arm motion in real-time.

### 3. Result and Discussion

#### A. Experimental Setup

Environment: Greenhouse (20–25 °C, 40–60 % humidity)

Robotic Arm: 6-DOF, equipped with a gripper and camera

Sensors: Soil moisture, temperature, RGB camera

Procedure: The robot performed 30 harvesting trials on 100 potatoes with varying colors and qualities.

Parameter	Good Quality	Poor Quality
Rainfall (%)	30 - 60	<20 or > 80
Temperature °C	20 - 25	<10 or >35
Earthworms m <sup>2</sup>	600	260
Organic Carbon	6.91	2.15
Insects (%)	30	70

**Table I summarizes soil data distinguishing good vs. poor quality.**

	$\alpha_i$	$\theta_i$	$d_i$	$\sigma_i$	$r_i$
1	0	180°	30	0	0
2	$\frac{\pi}{2}$	0	0	0	20

3	0	180°	15	1	0
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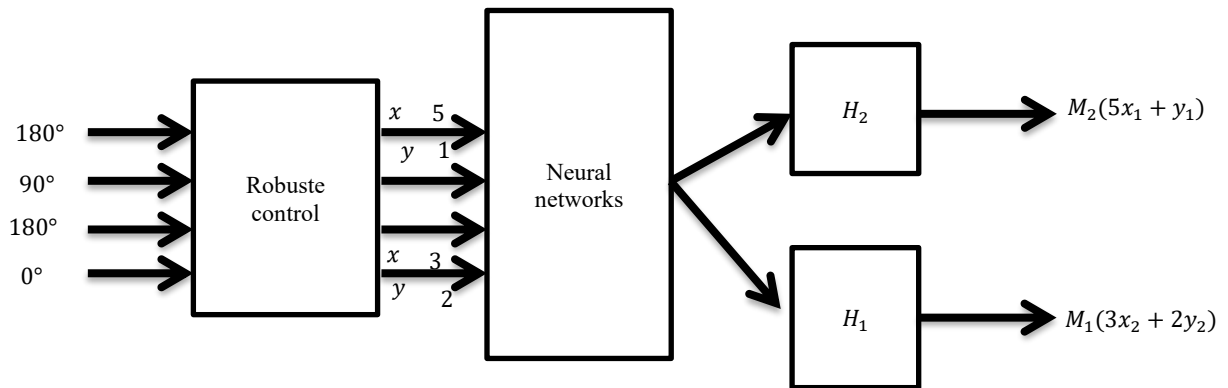
**Tableau II. D-H Calculation Parameters**

The following motion parameters were used [4]:

$${}^0T_1 = \begin{bmatrix} -0.59 & 0.8 & 0 & 0 \\ -0.8 & -0.59 & 0 & 0 \\ 0 & 0 & 1 & 30 \\ 0 & 0 & 0 & 1 \end{bmatrix} \text{ et } {}^1T_2 = \begin{bmatrix} 1 & 0 & 0 & 20 \\ 0 & 0 & -1 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \text{ et } {}^0T_1 = \begin{bmatrix} -0.59 & 0.8 & 0 & 0 \\ -0.8 & -0.59 & 0 & 0 \\ 0 & 0 & 1 & 15 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

#### B. Soil Quality Assessment

A visual algorithm based on the Heaviside method is used to classify potatoes. The classification model is a single-neuron network whose output controls arm movement.



**Fig. 8 : Robot simulation for color-based potato classification.**

Observation: Soil parameters directly influence robot decisions through the NN, validating adaptive control.

#### C. Potato Harvesting Simulation and Real Trials

Classification Accuracy: Simulation: 92 %, Real greenhouse: 89 %

Visualization:

- Red: Restricted movement
- Yellow/White: Active harvesting

The classification mechanism was applied using a single-neuron neural network. The Heaviside function differentiates data regions based on color:

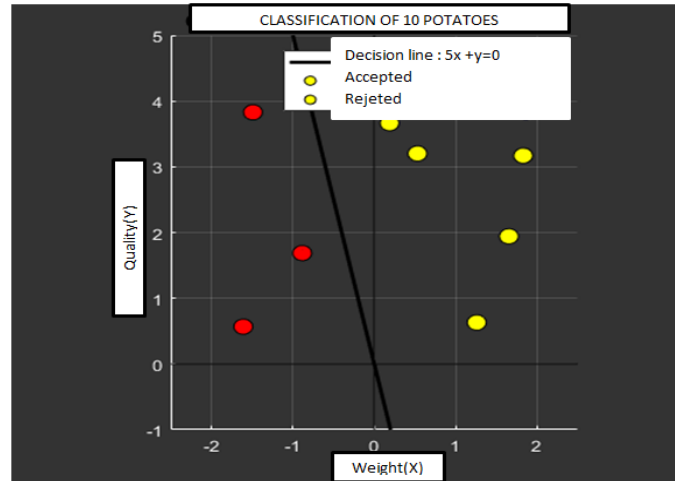
$$M_1(5x_1 + y_1) = (-1, 2)$$

$$M_1(5x_1 + y_1) = (1, 1)$$

$$M_1(5x_1 + y_1) = \begin{cases} 1 & \text{si } 5x_1 + y_1 \geq 0 \\ 0 & \text{otherwise} \end{cases}$$

Calculation procedure:

$$\begin{aligned} M_1(5x_1 + y_1) &= -3 \\ M_1(5x_1 + y_1) &= 6 \end{aligned}$$



**Fig. 9: Red: Restricted movement; Yellow: Harvest zones.**

In this graph, two colors are visible. Red indicates areas where the robot's movement is restricted, while yellow represents areas where the robot moves to harvest potatoes of the specified color.

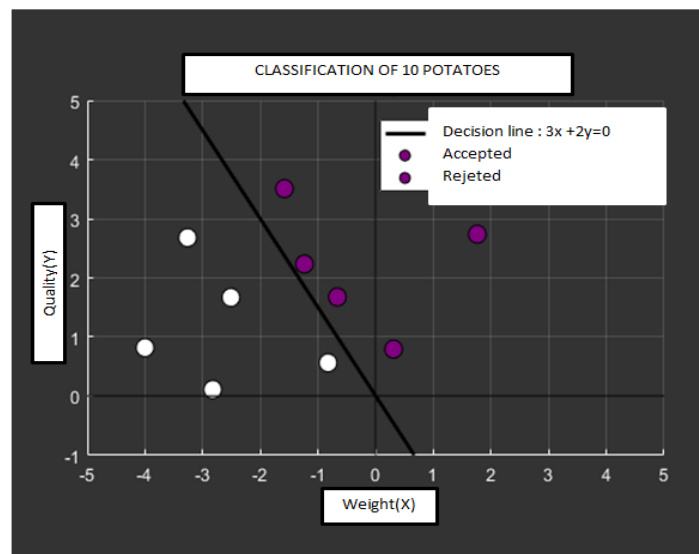
$$M_2(3x_2 + y_2) = \begin{cases} 1 & \text{if } 3x_2 + 2y_2 \geq 0 \\ 0 & \text{otherwise} \end{cases}$$

$$M_2(3x_2 + 2y_2) = (1, 2)$$

$$M_2(3x_2 + 2y_2) = (-3, 2)$$

$$M_2(3x_2 + 2y_2) = 7$$

$$M_2(3x_2 + 2y_2) = -5$$



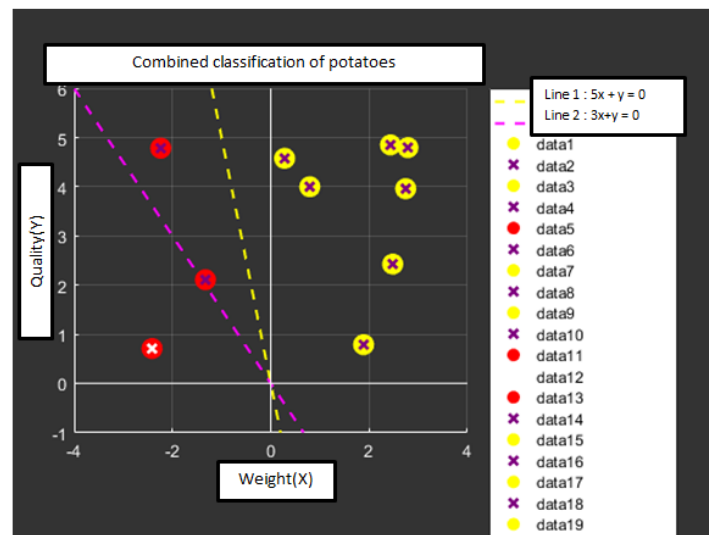
**Fig. 10: Violet: No movement; White: Active harvesting.**

Again, two colors are present. Violet represents areas with no robot movement, while white indicates the robot's harvesting



motion.

These results were obtained using software with a single neuron to distinguish between the two colors. Combining both color-based approaches produces the following visualization:



**Fig. 11: Combined classification results using weight (x-axis) and quality (y-axis).**

The hybrid model showed strong separation between good and defective crops. Red dots indicate low quality; yellow dots represent high quality.

#### 4. Conclusion and Future Work

This study demonstrates a hybrid control strategy integrating robust control, neural networks, and Heaviside-based visual classification for agricultural robotic arms. Experimental validation confirms adaptability and accurate crop classification.

Future Work:

1. Integration of real-time sensor fusion for multiple environmental factors
2. Extension to diverse crops (tomatoes, carrots)
3. Field deployment with fully autonomous operations

Contribution Statement:

Novel integration of Heaviside-based visual classification with NN-robust hybrid control using crop-specific datasets, validated in real experimental conditions.

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