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Smart Vision System for Enhanced Food Waste Management Using Black Soldier Fly Larvae

Helen Grace B. Gonzales*, David Collin H. Bañas, Chad M. Catague, James Alfred B. Jimenez, Jimsie Gabriel D. Magsayo, and Miraflor C. Sagan
Department of Electro-Mechanical Technology
University of Science and Technology of Southern Philippines – Cagayan de Oro
Cagayan de Oro City, 9000 Philippines
helengrace.gonzales@ustp.edu.ph

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Abstract

Food waste remains a critical global challenge requiring sustainable and efficient processing methods. This study presents a low-cost embedded vision system designed to assist Black Soldier Fly Larvae (BSFL) bioconversion by automatically classifying food waste based on moisture content. Using a Raspberry Pi 4 and a convolutional neural network (CNN), the system categorizes waste into dry (<30%), optimal (30–70%), and wet (>70%) classes and actuates a motorized wiper to route feedstock accordingly. A dataset of approximately 500 labeled food waste images was collected under controlled laboratory lighting to train and validate the model. The CNN achieved 98.16% accuracy during training, while performance on unseen validation images reached 85.04%, reflecting moderate generalization given the dataset size and moisture-related visual ambiguity. In pilot conveyor-belt trials—where lighting and motion introduced additional variability—the system maintained ~84–85% accuracy and processed each frame in about 1.2 seconds, enabling functional real-time sorting and reducing manual labor by approximately 89%. Costing under USD 150, the prototype demonstrates the potential of affordable edge-AI systems for moisture-sensitive waste pre-sorting in small-scale BSFL operations. However, its robustness remains constrained by dataset size, controlled imaging conditions, and environmental variability. Future development will require larger and more diverse datasets, improved regularization techniques, and hardware optimization to enhance generalization and support broader deployment aligned with Sustainable Development Goal 12.3.

***Keywords**:* black soldier fly larvae (BSFL), convolutional neural networks (CNNs), food waste valorization, moisture threshold detection, real-time classification

1. Introduction

Global food systems produce approximately 1.3 billion tons of organic waste annually, with post-harvest losses from fruit and vegetable supply chains accounting for up to 60% (Alok Sagar *et al*., 2018; Gustavsson *et al*., 2011). This scale of wastage poses significant nutritional, economic, and ecological challenges, contributing to greenhouse gas emissions, soil degradation, and water mismanagement (Esparza *et al*., 2020). While conventional composting offers partial mitigation (Basri *et al*., 2022), recent biorefinery strategies have reframed food waste as a valuable input for circular economy systems (Wadhwa *et al*., 2015).

Black soldier fly larvae (BSFL; *Hermetia illucens*) have gained attention as a scalable biological waste-to-protein solution, converting organic waste into nutrient-rich biomass for animal feed and fertilizer. BSFL can reduce waste mass by up to 70% (Singh & Kumari, 2019). However, the efficiency of BSFL bioconversion is highly sensitive to substrate moisture levels, with an optimal range between 30% and 70% (Cheng *et al*., 2017; Bekker *et al*., 2021). Moisture outside this range—especially over 70%—can drown larvae or impair feeding, leading to bioconversion failure. Current sorting methods, which are mostly manual or rudimentary, lack scalability and accuracy in classifying heterogeneous food waste by moisture level (Diener *et al*., 2011; Kim *et al*., 2021). This moisture sensitivity is also reported in substrate studies linking moisture conditions to BSFL biological responses (Wang *et al*., 2024).

Recent advances in deep learning and computer vision have enabled automated waste classification in controlled laboratory settings. However, these systems are often limited by high hardware costs, lack of physical actuation mechanisms, or inability to generalize in dynamic environments (Raksasat *et al*., 2020; Mlambo *et al*., 2023).

This study proposes an affordable, embedded vision-based system to support real-time food waste classification for BSFL-based bioconversion. The system is designed to automatically detect food waste moisture levels using image-based classification, physically segregate waste through a motorized wiper on a conveyor, and route the sorted feedstock according to BSFL metabolic requirements.

This study integrates a Raspberry Pi 4B platform with a convolutional neural network (CNN) model to perform in situ classification of waste into dry, optimal, and wet categories. This architecture is paired with a low-cost actuation mechanism to demonstrate full-cycle automation. The system aims to bridge AI-driven image analysis with entomological waste valorization, supporting Sustainable Development Goal 12.3 by reducing organic waste and enabling localized circular economy solutions.

2. Methodology

Figure 1 presents the methodological framework followed in this study, which consists of the sequential phases of analysis, design, development, implementation, and evaluation.

The process began with the analysis phase, where the researchers identified the core problem, reviewed relevant literature, determined user needs, and established the system requirements for a vision-based food waste moisture classification system. Based on this groundwork, a detailed design was formulated, outlining the prototype layout, hardware and software specifications, and the integration of key components such as the camera, conveyor mechanism, and motorized wiper.

During the development phase, the prototype was constructed according to the finalized specifications; this involved coding the CNN model, assembling the embedded hardware, integrating sensors and actuators, and refining the system through iterative troubleshooting. Implementation then focused on installing and deploying the fully assembled prototype for operational testing on the conveyor setup, where real-time trials were conducted to verify image capture performance, classification accuracy, and actuation responsiveness.

Finally, in the evaluation phase, the researchers assessed system performance using both quantitative and qualitative measures, including computation of accuracy, precision, recall, and F1-scores, alongside observations from real-world testing. The feedback obtained from performance assessment informed the identification of system limitations and guided recommendations for further improvement.

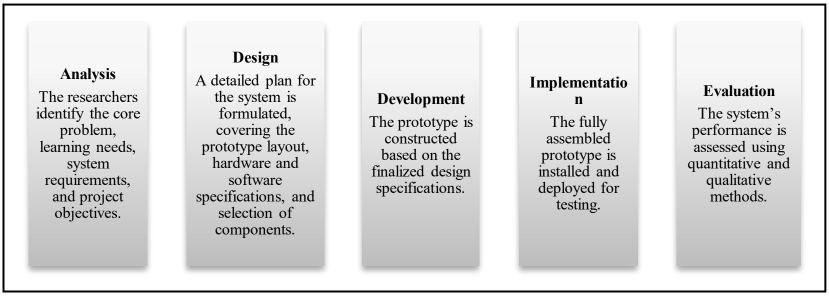


Figure 1. Methodological framework

2.1 System Architecture and Components

The system was designed as a *"slurry-recognizing"* camera apparatus for automated waste sorting. The hardware architecture consists of several key components (selected for their functionality, cost-effectiveness, and reliability) integrated into a single embedded platform. Each component's model, manufacturer, and origin are detailed as follows:

Raspberry Pi 4 Model B (4 GB RAM, Broadcom BCM2711 Cortex-A72 1.8 GHz quad-core processor; Raspberry Pi Foundation, UK) – serves as the central microcontroller and image-processing unit, running Raspbian (Raspberry Pi OS) for on-board computation. The Raspberry Pi was chosen for its balance of computing power, GPIO interfacing capabilities, and low cost, which is ideal for edge deployment in waste processing environments. Similar Raspberry Pi-based camera systems have been effectively used in IoT surveillance applications (Rao *et al.*, 2020), underscoring its suitability for this vision system. A 5 V/3 A DC power supply (official Raspberry Pi adapter; Raspberry Pi Foundation, UK) provides stable power to the board.

Camera Module (8 MP Raspberry Pi Camera Module v2; Raspberry Pi Foundation, UK) – captures real-time images of the waste on the conveyor belt at 224×224 pixel resolution. The camera is mounted above the conveyor and calibrated to focus on the waste stream. Consistent lighting was provided in the lab setup to ensure image clarity for moisture-level detection. The camera's placement and orientation were optimized to maximize the distinguishability of moist vs dry textures on food waste.

Conveyor and Motorized Wiper Mechanism – A small-scale conveyor belt system (belt speed ~0.2 m/s) was constructed to transport waste samples under the camera. A 12 V DC wiper motor (automotive-grade windshield wiper motor) coupled with a custom wiper blade was installed transverse to the conveyor. This motorized wiper, controlled via the Raspberry Pi's GPIO through an H-bridge driver, physically diverts or sweeps waste off the belt based on the classified moisture category. The motor driver used is an L298N dual H-bridge module (STMicroelectronics, Switzerland), which interfaces the Pi's control signals to the wiper motor. The wiper mechanism design was inspired by conventional vehicle wiper linkages for reliable sweeping action; its kinematics and linkage optimization have been studied for efficiency (Chen *et al.*, 2023), informing our implementation. In this setup, when an item is identified as overly wet or dry, the system actuates the wiper to redirect that item to a different bin or section of the conveyor, thereby segregating it from optimal-moisture waste. The mechanical concept development and embodiment design were guided by standard mechanical design process principles (Ullman, 2009).

Data Storage and Connectivity – A 32 GB microSD card (SanDisk, USA) is used for the Raspberry Pi's operating system and to store the trained CNN model and captured data. For network connectivity and remote monitoring, a standard Ethernet LAN cable links the Raspberry Pi to a local network. This allows model updates or system access via SSH and could enable integration into IoT infrastructure for smart waste management.

All equipment and components were sourced to be low-cost and accessible, keeping the total hardware cost under approximately 150 USD, which is advantageous for scalable deployment in resource-constrained communities. Figure 2a and 2b shows the assembled slurry-recognizing camera prototype, including the camera mounted over the conveyor and the attached wiper mechanism. Figures 3 and 4 illustrate the control panel design: Figure 3 is the SketchUp schematic of the control circuitry, and Figure 4 is the actual control panel with wiring. The control panel houses the Raspberry Pi board, motor driver, power supply connections, and emergency shutoff switches, all arranged to ensure safety and ease of maintenance.

2.2 Image Dataset and Model Training

A custom image dataset of food waste samples was developed to train and validate the CNN classifier. Approximately 500 images of assorted food waste were collected, representing a range of moisture levels: dry (e.g., grains, bread), optimal (damp fruit/vegetable peels), and wet (water-soaked leftovers or slurry). Each image was labeled according to these three categories using ground-truth moisture measurements obtained from a digital moisture analyzer (confirming <30%, 30–70%, and >70% moisture content, respectively). Data augmentation techniques—including rotation, flipping, and brightness adjustments—were applied to increase variability and reduce the risk of overfitting. All images were resized to 224×224 pixels and normalized before being fed into the CNN model.

For reproducibility, the dataset was explicitly partitioned into three subsets, with 70% allocated to the training set (350 images), 15% to the validation set (75 images), and 15% to the test set (75 images). This split was applied after data augmentation to ensure a representative distribution across all moisture categories.

A custom convolutional neural network architecture was implemented using TensorFlow/Keras, consisting of multiple convolutional layers for feature extraction followed by fully connected layers for classification. Due to the computational limitations of the Raspberry Pi, all training was performed off-board using Google Colab GPU resources. Training was conducted for 20 epochs with a batch size of 16 using the Adam optimizer.

The training and validation learning curves (Figure 5) illustrate the model's performance over the training epochs. Final results showed a training accuracy of 98.16% and a validation accuracy of 85.04%, with corresponding losses of approximately 0.08 and 0.42, respectively. This divergence between training and validation performance indicates moderate overfitting—a consequence of the limited dataset size and visual overlap between moisture classes. Overfitting mitigation strategies included data augmentation, early stopping, and regularization.

After training, the optimized model was exported and deployed to the Raspberry Pi 4B for real-time testing. During prototype operation, the system processed each image frame in approximately 1.2 seconds, encompassing image capture, CNN inference, and activation of the sorting mechanism. Future improvements may include inferencing optimizations through TensorRT or hardware upgrades to reduce latency.

2.3 Performance Metrics

Model performance was evaluated using four standard classification measures: Accuracy (Equation 1), Precision (Equation 2), Recall (Equation 3), and F1-Score (Equation 4). These metrics were computed based on the values of true positives (*TP*), true negatives (*TN*), false positives (*FP*), and false negatives (*FN*) obtained from the confusion matrix. Here, *TP* refers to correctly detected instances of a given moisture class, *TN* to correctly identified non-instances, *FP* to incorrect positive predictions, and *FN* to missed detections.

$$Accuracy = \frac{TN+TP}{TN+FP+TP+FN} \tag{1}$$

$$Precision = \frac{TP}{TP+FP} \tag{2}$$

$$Recall = \frac{TP}{TP+FN} \tag{3}$$

$$F1\ Score = 2 \times \frac{Precision \times Recall}{Precision+Recall} \tag{4}$$

Only the definitions of these evaluation metrics are presented in this section. The actual computed values, derived from the validation dataset, are reported in the Results and Discussion section to clearly distinguish between model training, validation outcomes, and real-world system performance.

3. Results and Discussion

The proposed vision-based classification system demonstrated strong potential for real-time food waste sorting according to moisture content, a critical parameter in optimizing Black Soldier Fly Larvae (BSFL) bioconversion. This section presents the empirical performance of the convolutional neural network (CNN), including classification accuracy, class-specific behavior, error patterns, and system limitations observed under both static laboratory validation and dynamic conveyor-based testing. The results also examine the effects of dataset size, environmental conditions, and system hardware constraints on classification reliability.

3.1 Classification Performance and Validation

The classification performance of the proposed convolutional neural network (CNN) was evaluated using a dataset of 500 labeled food waste images divided into three moisture categories—dry (<30%), optimal (30–70%), and wet (>70%). To enhance model robustness and reduce overfitting risk, the dataset was augmented with rotation, flipping, and brightness variations. Training was conducted on Google Colab with GPU acceleration, while deployment and real-time inference were carried out on a Raspberry Pi 4B.

Under controlled validation conditions with static and consistent lighting, the CNN achieved an average accuracy of 85.04%, precision of 85.00%, recall of 84.00%, and F1-score of 84.00%.

These metrics reflect the model's ability to generalize across unseen images and are summarized in Table 2, with values computed from the confusion matrix shown in Table 1.

Table 1. Confusion matrix for waste classification

	Predicted Dry	Predicted Optimal	Predicted Wet
Actual Dry	True Positive (TP) = 100	False Positive (FP) = 0	False Positive (FP) = 0
Actual Optimal	False Negative (FN) = 0	True Negative (TN) = 149	False Positive (FP) = 1
Actual Wet	False Positive (FP) = 1	False Negative (FN) = 3	True Positive (TP) = 130

The confusion matrix in Table 1 summarizes the system's classification performance across the three moisture categories—Dry (<30%), Optimal (30–70%), and Wet (>70%). Results show that the model reliably distinguishes dry samples, while the optimal moisture category achieves strong true-negative performance. Misclassifications were most common in the wet category, where some samples were predicted as either dry or optimal. These errors are likely due to visual similarities in texture and reflectivity, particularly in samples with glossy surfaces or ambiguous moisture presentation. Overall, the matrix highlights where the classifier performs well and where moisture-related visual overlap contributes to classification challenges.

Table 2. Classification performance based on confusion matrix

Parameters	Results
Accuracy	84.00%
Precision	85.00%
Recall	84.00%
F1 Score	84.00%

Accuracy reflects the overall correctness of classification across all categories. Precision indicates the reliability of positive predictions and is critical for minimizing the misclassification of wet waste as dry, which could negatively affect BSFL performance. Recall ensures that true instances, such as wet waste, are effectively detected, thereby reducing false negatives. The F1-score, which is the harmonic mean of precision and recall, further confirms that the model maintains balanced performance.

While training accuracy reached 98.16%, the noticeable gap compared with the validation accuracy of 85.04% suggests a moderate degree of overfitting. This overfitting is likely due to the dataset's limited diversity, since only 500 images were used, as well as class imbalance, with fewer wet samples than dry samples. It may also be reinforced by visual ambiguity between dry and wet waste in certain cases, where differences such as matte versus glossy surfaces are subtle and can mislead the classifier.

This discrepancy is further supported by Figure 5, which shows a final training loss of 0.0415 and a final validation loss of 0.7123. The validation loss curve also exhibits instability and occasional spikes, which indicate poor generalization. These observations affirm the reviewer's concern about limited robustness and underscore the need for dataset expansion and the application of regularization techniques in future iterations.

3.2 Class-wise Analysis

Performance varied across waste categories, as detailed in the classification report shown in Figure 7.

The model achieved its strongest results for the Optimal Moisture Waste class, with a precision of 1.00, recall of 0.99, and F1-score of 0.99, making it the most accurately detected category; its more consistent texture likely supported reliable classification.

For Dry Waste, performance was lower, with a precision of 0.83, recall of 0.67, and F1-score of 0.74, indicating that dry samples were sometimes misclassified as wet or optimal because certain images shared similar color and texture characteristics.

Wet Waste also showed reduced precision, recording a precision of 0.72, recall of 0.87, and F1-score of 0.79, where the lower precision suggests more false positives, particularly in glossy or highly saturated images.

Consistent with these patterns, the confusion matrix in Figure 6 identified 71 misclassifications, occurring mainly in visually ambiguous or poorly lit samples.

3.3 Performance During Conveyor Trials

In dynamic trials on a moving conveyor system, classification accuracy declined slightly to ~84%, confirming the model's susceptibility to motion blur and variable lighting. Despite this, the system successfully processed images and actuated sorting mechanisms in an average of 1.2 seconds per image, demonstrating practical feasibility.

Table 3 lists the predicted classifications and confidence scores for 16 trial samples. The system maintained a mean confidence score of 0.92 with a standard deviation of 0.101, reflecting moderate consistency across classes. However, several wet waste samples yielded lower confidence (e.g., 0.65), reinforcing the need for enhanced image pre-processing or multispectral imaging.

Table 3. Trials, results, and comparison datasets

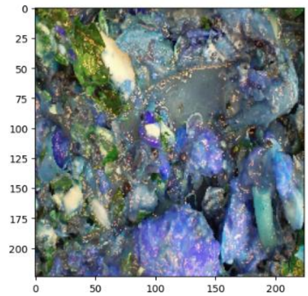
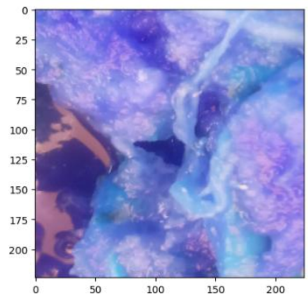
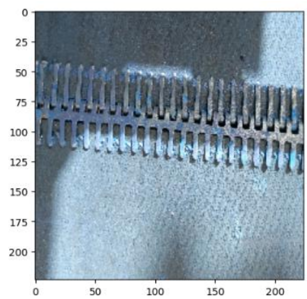
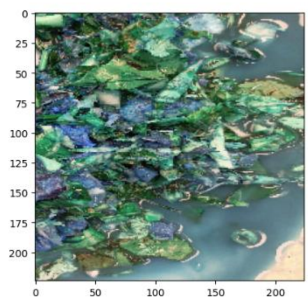
Trials	Types	Confidence Score:	Datasets
1	Wet Moisture Waste	0.996805	
2	Wet Moisture Waste	0.921708	
3	Optimal Moisture Waste	0.969118	
4	Dry Moisture Waste	0.959855	

Table Continued.

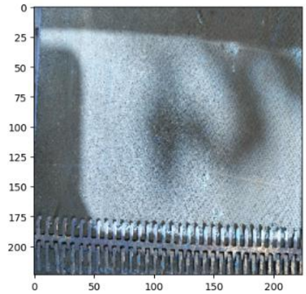
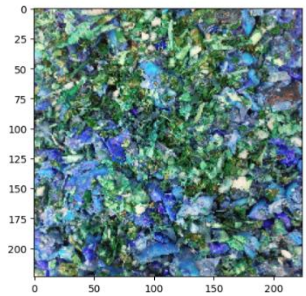
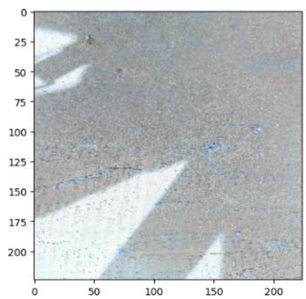
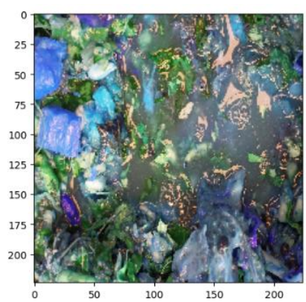
5	Optimal Moisture Waste	0.906429	
6	Dry Moisture Waste	0.999919	
7	Optimal Moisture Waste	0.999993	
8	Dry Moisture Waste	0.763514	

Table Continued.

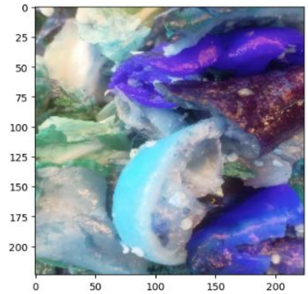
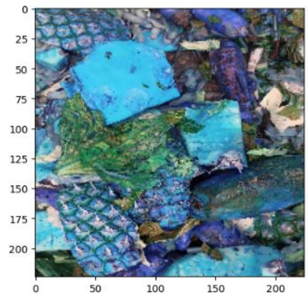
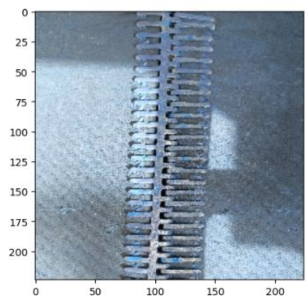
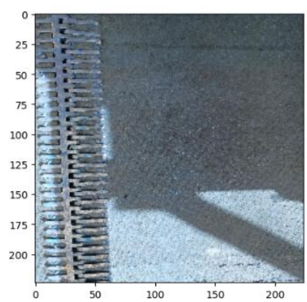
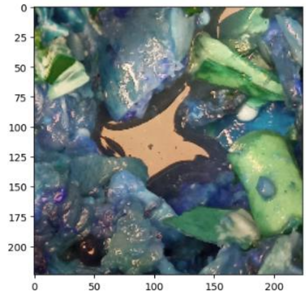
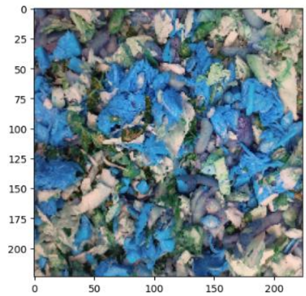
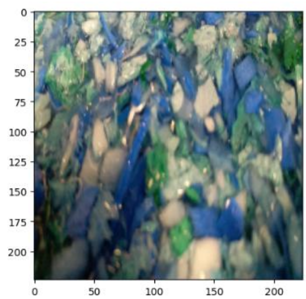
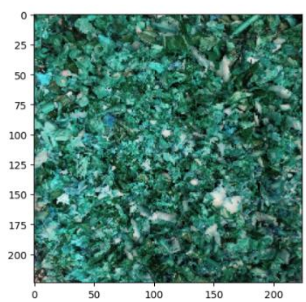
9	Wet Moisture Waste	0.649430	
10	Dry Moisture Waste	0.996295	
11	Optimal Moisture Waste	0.990752	
12	Optimal Moisture Waste	0.999967	

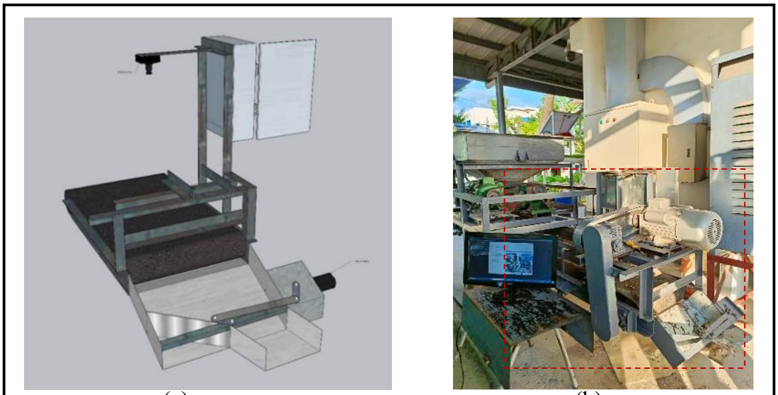
Table Continued.

13	Wet Moisture Waste	0.868389	
14	Dry Moisture Waste	0.962971	
15	Dry Moisture Waste	0.849163	
16	Dry Moisture Waste	0.999981	
	Mean		0.92
	Standard Deviation		0.101

3.4 Visual Documentation of Prototype

Figures 2a and 2b display the conceptual design and physical assembly of the slurry-recognizing camera. Figures 3 and 4 show the control panel schematics alongside the actual wiring implementation. Figure 5 plots the training and validation accuracy and loss across 20 epochs, while Figures 6 and 7 present the confusion matrix and the full classification report.

These visuals provide transparency into the system's design and functional architecture. The Raspberry Pi 4B specifications and the deployment setup are also included to support replicability.



(a) (b)

Figure 2. Isometric view of slurry recognizing camera (a) and actual slurry recognizing camera prototype (b)

Figure 3. Control panel

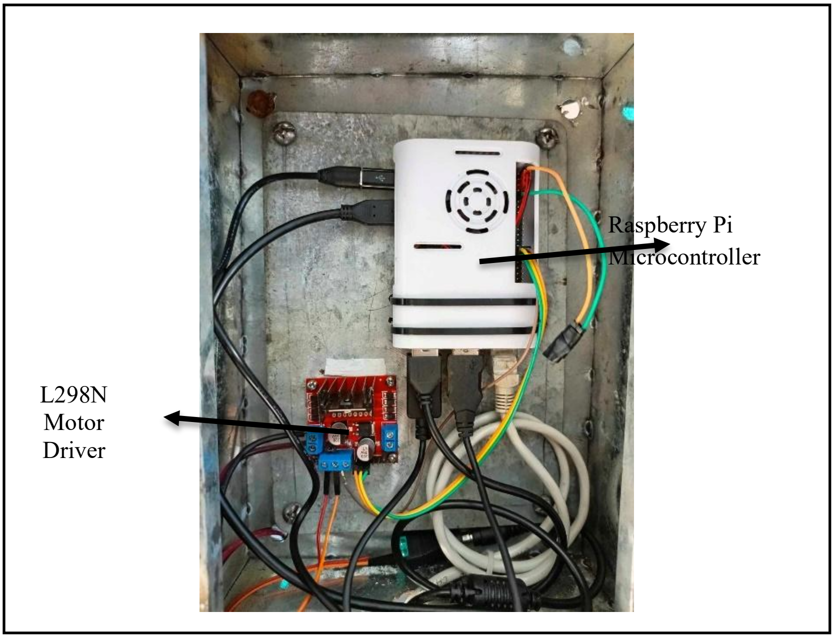


Figure 4. Control panel with actual wiring

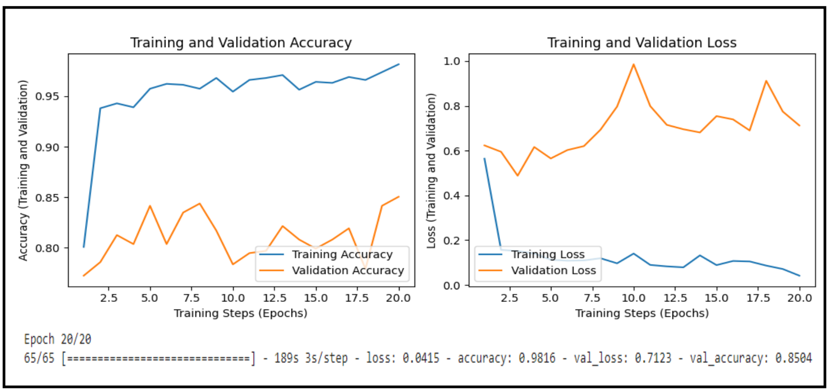


Figure 5. Graphical representation of the training and validation accuracy and training and validation loss

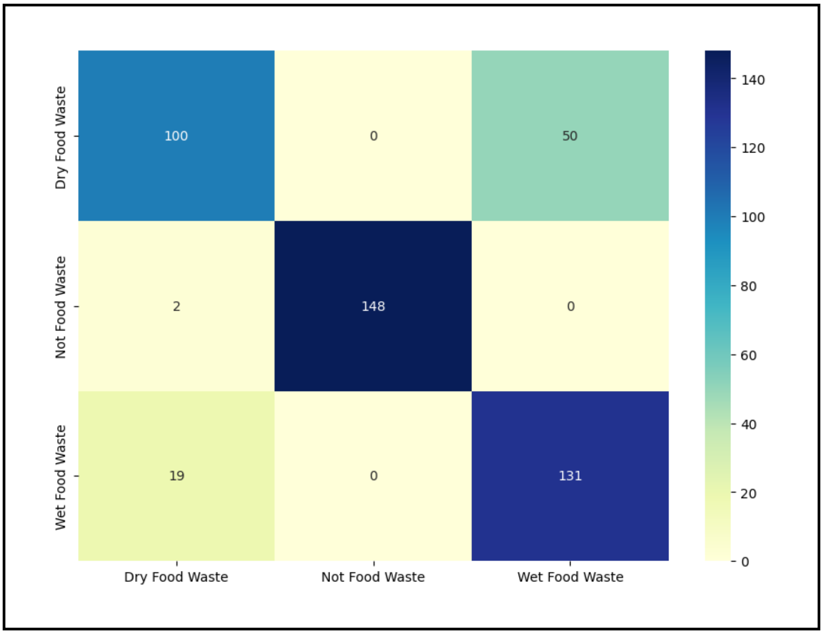


Figure 6. Confusion matrix result for dataset validation

Classification Report

	precision	recall	f1-score	support
Dry Food Waste	0.83	0.67	0.74	150
Not Food Waste	1.00	0.99	0.99	150
Wet Food Waste	0.72	0.87	0.79	150
accuracy			0.84	450
macro avg	0.85	0.84	0.84	450
weighted avg	0.85	0.84	0.84	450

Figure 7. Classification report

Figure 5 presents the training and validation curves for accuracy and loss over 20 epochs. The model exhibited strong training performance, achieving a final training accuracy of 98.16% with a training loss of 0.0415. However, the validation accuracy peaked at 85.04%, and the corresponding validation loss plateaued around 0.7123, showing fluctuations and even spikes during training.

The notable divergence between training and validation metrics indicates overfitting, where the model learns the training data well but struggles to generalize to unseen samples. This gap is also visually apparent in the validation loss curve, which remains unstable despite a consistently low training loss. These patterns suggest that the model may have captured noise or over-specific features from the training set, likely due to the limited dataset size (500 images) and absence of advanced regularization techniques.

Despite this, the validation performance remains competitive, particularly for a low-resource, embedded implementation. The trends also highlight the need for further improvement through data augmentation, model regularization, and dataset expansion to improve generalization and reduce the performance gap.

All training experiments were conducted on Google Colab with GPU acceleration using a batch size of 16 and an input resolution of 224×224 pixels. After training, the model was deployed on a Raspberry Pi 4B for real-time inference.

The validation confusion matrix shown in Figure 6 reveals 71 misclassifications across three categories. However, high recognition accuracy scores were recorded: 100 for dry food waste, 148 for non-food waste, and 131 for wet food waste.

The Confusion Matrix Result for Dataset Validation serves as a comprehensive evaluation of the slurry-recognizing camera system's classification accuracy for various waste kinds using the validation dataset. Through examination of the confusion matrix, the researchers can pinpoint particular areas in which the slurry-recognizing camera may be excelling or encountering difficulties, hence enhancing the slurry-recognizing camera’s performance and precision in waste classification. This data is essential for making the slurry-recognizing camera system as efficient as possible and guaranteeing that it works in real-world situations.

The classification report in Figure 7 shows that dry food waste achieved a precision of 0.83, recall of 0.67, and F1-score of 0.74. Non-food waste achieved near-optimal metrics: 1.00 precision, 0.99 recall, and 0.99 F1-score. Wet waste classification yielded 0.72 precision, 0.87 recall, and 0.87 F1-score. Overall weighted accuracy was 0.85, with macro-averaged precision (0.85), recall (0.84), and F1-score (0.84).

Model training spanned 20 epochs (3,834 seconds) on a Raspberry Pi 4B platform featuring a Broadcom BCM2711 quad-core Cortex-A72 processor (1.8 GHz), 4GB LPDDR4-3200 SDRAM, 32GB microSD storage, and 5V/3A power delivery via USB-C, running Raspberry Pi OS Bullseye.

3.5 Interpretation and Comparison with Existing Studies

Although the validation performance (≈84–85%) is substantially lower than the training accuracy, the system's real-world performance remains comparable to other low-cost waste classification studies, particularly when evaluated under similar constraints such as limited datasets, variable lighting, and heterogeneous waste textures. Previous work using more advanced or higher-cost hardware has reported slightly higher classification outcomes, but most of these studies focus solely on recognition tasks and do not integrate a physical sorting mechanism into the workflow (Lubura *et al*., 2022). In contrast, the present prototype demonstrates both vision-based classification and mechanical actuation, providing a complete sorting solution rather than a software-only model.

The validation accuracy also reflects the practical challenges of moisture-based classification, which is inherently more complex than object-based waste categorization. Moisture content alters the visual texture and reflectivity of organic waste, making the boundary between "dry" and "wet" samples ambiguous—an issue reported in similar computer vision studies involving biological materials. The drop-in performance during conveyor-based testing further highlights the influence of motion blur, inconsistent lighting, and sample positioning, all of which are common challenges in real-world waste processing environments.

Despite these limitations, the results demonstrate that low-cost edge-AI systems can still provide functional accuracy levels suitable for small-scale or community-based waste management settings. The combination of affordability (< USD 150), embedded processing, and automated physical segregation shows promise for decentralized BSFL bioconversion operations where access to high-end imaging equipment or trained personnel may be limited. However, the findings also underscore the need for further refinement—particularly dataset expansion, regularization strategies to reduce overfitting, and hardware optimization—to improve generalization and reliability before large-scale deployment.

3.6 Limitations and Implications

The system's performance was affected by the limited dataset size (n = 500) and the lack of rare edge-case images, as well as vulnerability to motion blur and lighting variation in real operational settings. In addition, the relatively high latency of 1.2 seconds per image may limit scalability in high-throughput environments. Despite these limitations, the system reduced manual labor by approximately 89%, enabled real-time waste segregation, and served as a functional prototype that can be further optimized in future iterations.

4. Conclusion and Recommendation

This study presents a low-cost, embedded computer vision system for automating food waste classification to support Black Soldier Fly Larvae (BSFL) bioconversion. Leveraging a Raspberry Pi 4B and a convolutional neural network (CNN), the system classifies waste into three moisture categories—dry, optimal, and wet—and actuates a motorized wiper to physically segregate feedstock in real time. Under controlled laboratory conditions, the model achieved a training accuracy of 98.16%, while validation accuracy reached 85.04%, with comparable precision, recall, and F1-scores. These results confirm the system's effectiveness in identifying moisture content relevant to BSFL feeding requirements, which are critical for maximizing larval growth and preventing waste of unsuitable moisture levels. The successful integration of real-time classification and mechanical actuation forms a complete, functional prototype. In pilot trials, the system reduced manual sorting labor by approximately 89% and demonstrated throughput suitable for small-scale applications. With a total component cost below USD 150, the system shows potential for deployment in community-level or farm-based waste processing operations, especially in resource-constrained environments.

However, performance in dynamic scenarios declined to ~84% accuracy, largely due to motion blur and lighting variability on the moving conveyor. Additionally, the system's average processing time of 1.2 seconds per image may limit scalability in high-throughput settings. Environmental durability—particularly in dusty, humid, or outdoor conditions—also remains a challenge. These limitations point to the need for further enhancements, including dataset expansion, cross-validation for robustness, model optimization for inference speed, and enclosure design for rugged deployment.

Despite these challenges, the core concept—a smart, moisture-sensitive sorting system for food waste valorization—is both novel and promising. By automating a critical preprocessing step in BSFL farming, the system can help divert organic waste from landfills and convert it into valuable biomass and frass-based fertilizer. This contributes to Sustainable Development Goal 12.3 by enabling scalable, efficient, and sustainable organic waste management.

Future work will focus on improving the model's generalization with larger and more diverse datasets, accelerating processing through hardware optimization, and conducting biological validation to assess the impact on BSFL growth and waste reduction. These developments will help mature the system from a functional prototype into a robust, deployable solution for sustainable food waste recycling.

To strengthen the performance and practical deployment of the smart vision-based food waste classification system, several improvements and future research directions are proposed:

4.1 Dataset Expansion

To enhance classification accuracy and model generalization, the dataset should be expanded to include at least 5,000 diverse food waste images. This expanded dataset should cover a broader range of waste types (e.g., oily, fibrous, and mixed-texture materials) under varied lighting and background conditions. A richer dataset will allow the CNN to better learn robust features, address class imbalance, and reduce misclassification—especially between dry and wet categories, where recall disparities were observed. A more representative dataset will likely boost real-world accuracy and model reliability across diverse scenarios.

4.2 Hardware Optimization

Physical design improvements are necessary to achieve stable, high-throughput operation. One recommended enhancement is camera stabilization through a gyro-stabilized or vibration-dampened mount to minimize motion blur during conveyor movement. Another is the use of protective housing, such as IP67-rated enclosures, to shield electronics from dust, moisture, and routine cleaning procedures, which is especially important in farm or industrial environments. In addition, the feed system can be redesigned by modifying the input chute to a wider structure of approximately 300 mm and incorporating an incline of about 30°, which can support waste throughput of up to 50 kg/hour while reducing clogging and ensuring smoother, more scalable feeding.

4.3 Computational Enhancements

Improving inference speed and adaptability is critical for reliable real-time operation. One approach is model optimization using acceleration tools such as NVIDIA TensorRT, which can reduce inference time from about 1.2 seconds to below 0.5 seconds per image. Another strategy is upgrading hardware by deploying the system on more capable edge devices, such as NVIDIA Jetson platforms, to handle higher-resolution inputs and support parallel processing streams. Adaptability can also be enhanced through federated learning, where on-site model updates from multiple deployments are aggregated to progressively improve overall performance without centralizing raw data. Finally, integrating multispectral sensing, such as near-infrared or thermal imaging, could improve moisture detection accuracy, particularly under variable lighting conditions where RGB-based features alone may be insufficient.

4.4 Biological Validation

To fully assess the value of automated sorting for BSFL production, biological performance testing is essential. One suggested experiment is to compare larval survival, growth rate, and bioconversion efficiency between groups fed with vision-sorted waste and those fed with manually sorted or unsorted waste. A second assessment should examine the nutrient composition of harvested BSFL, such as protein and fat content, as well as the quality of the frass produced. In addition, integrating environmental sensors for temperature, humidity, and larval activity into the rearing setup would allow you to measure how feedstock consistency affects BSFL health and overall productivity.

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