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Smart Waste Management and Recycling Based on IoT using Machine Learning Algorithm

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Abstract - Smart waste management and recycling have become critical issues in urban planning and environmental sustainability due to the increasing volume of waste generated by modern societies. In this study, we investigated the performance of Support Vector Machine (SVM) and Neural Network (NN) methods in an Arduino-based waste sorting system. Our testing phase revealed exceptional performance, with SVM achieving an accuracy of 92% and NN achieving 96%, alongside perfect precision, recall, and F1-score metrics. The consistent True Positive (TP) results across all waste categories underscored the system's capability to accurately direct waste into correspondingcolored bins. These findings highlight the significance of automated waste management systems in promoting effective waste sorting practices and facilitating sustainable recycling efforts. Moreover, advancements in technology and machine learning algorithms offer promising prospects for further enhancing the efficiency and scalability of such systems, thereby contributing to a cleaner and healthier environment for future generations. Future research in smart waste management could focus on exploring additional machine learning algorithms, advanced sensor technologies, and Internet of Things integration. Investigating alternative algorithms beyond SVM and NN, adopting advanced sensors like hyperspectral imaging or lidar, and incorporating IoT devices for real-time monitoring could enhance waste sorting accuracy and scalability.

Keywords - Smart waste management, SVM, NN, IoT, Confusion Matrix.

1. INTRODUCTION

Smart waste management and recycling have become critical issues in urban planning and environmental sustainability due to the increasing volume of waste generated by modern societies [1], [2]. Traditional waste management systems often struggle with inefficiencies, high operational costs, and environmental impacts, such as overflowing landfills and pollution [3]. These systems typically rely on manual sorting processes that are time-consuming and prone to human error, leading to significant amounts of recyclable materials ending up in landfills. Furthermore, the lack of accurate data and predictive capabilities makes it challenging to optimize waste collection and recycling processes, resulting in missed opportunities for resource recovery and recycling.

Farjana, et al. (2022) [4] have highlighted the potential of IoT-based smart e-waste management systems in addressing the growing global e-waste problem. By leveraging IoT devices and sensors, these systems can efficiently monitor and manage the collection, sorting, and disposal of e-waste. The real-time data provided by these sensors can optimize the entire process, from collection to disposal, reducing the environmental and public health impacts of e-waste. Furthermore, the integration of machine learning can enhance the separation of metallic and plastic components, facilitating the recycling and repurposing of valuable materials. This approach not only minimizes environmental harm but also maximizes resource recovery, making e-waste management more sustainable. Rani, et al. (2021) [5] present the design and development of a mobile "green" electronic waste (e-waste) management system utilizing Internet of Things (IoT) technology for smart campuses. The system employs a Raspberry Pi 3 Model B v1.2 microcontroller to monitor e-waste object detection, count, and bin fill levels. Using the TensorFlow Lite API, the system runs the SSDLite-MobileNet-v2 model, trained on the MSCOCO dataset, for accurate e-waste object detection in images. Monitoring data is stored and accessed via the ThingSpeak cloud platform using HTTP and MQTT protocols, and displayed through an interactive Android-based mobile user interface. Additionally, the system sends automatic email notifications to waste collectors when the bin reaches a predetermined threshold of 80% capacity, ensuring timely collection. Rahman, et al. (2022) [6] present an advanced architecture for a waste management system integrating deep learning and the Internet of Things (IoT). Their proposed model employs a convolutional neural network (CNN), a popular deep learning paradigm, to sort digestible and indigestible waste. Additionally, they designed a smart trash bin equipped with a microcontroller and multiple sensors. The system leverages IoT connectivity for real-time data monitoring from any location and Bluetooth for short-range data monitoring through an Android application. The classification accuracy of waste based on the CNN model is 95.3125%, and the System Usability Scale (SUS) score is 86%, indicating high efficacy and usability. This research offers an innovative solution that can be adapted for household activities, enabling real-time waste monitoring.

To address these challenges, the integration of machine learning algorithms into waste management systems offers a promising solution. Machine learning can enhance the efficiency and accuracy of waste sorting by automatically identifying and categorizing recyclable materials through advanced image recognition and data analysis techniques [7], [8], [9], [10]. By deploying sensors and cameras in waste collection points, and utilizing machine learning models trained on diverse datasets, smart waste management systems can accurately distinguish between different types of waste in real-time. This automated sorting not only reduces the reliance on manual labor but also increases the recovery rate of recyclable materials, leading to more sustainable waste management practices. Additionally, machine learning algorithms can provide predictive insights and optimize routing for waste collection vehicles, reducing operational costs and minimizing environmental impact. Through these technological advancements, smart waste management can transform the recycling landscape, making it more efficient, cost-effective, and environmentally friendly.

2. RESEARCH METHOD

The proposed scheme for the smart waste management system begins with the user disposing of waste into a designated rubbish bin. This bin is integrated with an Arduino configured to utilize a machine learning algorithm for waste classification. The Arduino, equipped with sensors and a pre-trained model, evaluates the waste to determine its recyclability. Once the evaluation is complete, the system makes a decision based on the classification results. If the waste is identified as recyclable, it is directed to the Recycle Bin. Conversely, if the waste is deemed non-recyclable, it is directed to the Trash Bin. This automated process ensures efficient sorting of waste, optimizing the recycling process and reducing manual sorting errors.

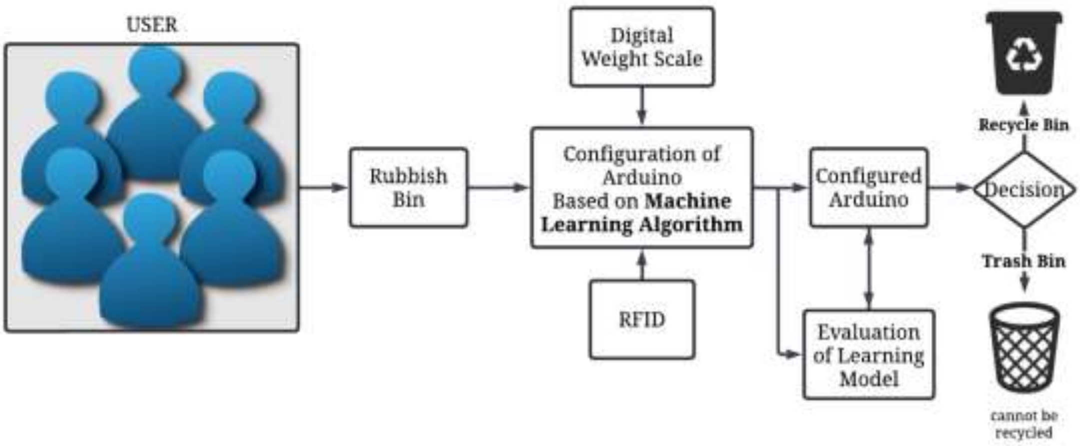

Figure 1. Proposed Scheme

2.1. Data Collection

In the data collection process, real-time waste data is obtained as individuals dispose of their waste. Sensors integrated into the rubbish bins detect and capture information about the type and composition of the waste being discarded. These sensors can include weight sensors, infrared sensors, or optical sensors to assess various characteristics of the waste. As individuals dispose of their waste, the sensors collect data continuously, providing a stream of information to the system. This real-time data collection enables immediate analysis and classification of the waste, facilitating efficient decision-making in directing the waste to either the Smart Recycle Bin or the Smart Trash Bin based on its recyclability.

Table 1. Recycle Collection Before and After Sorting

Type Recycle	**Before Sorting**		**After Sorting**	
Recycle Bin	Pocket Bin (All in one)	Plastic	Red Pocket	Plastic
		Cans/Glass	Green Pocket	Cans/Glass
		Paper	Blue Pocket	Paper
Non-recyclable		Decomposed items	Decomposed items	

2.2. Machine Learning Algorithm

In the proposed smart waste management system, various machine learning algorithms can be employed to enhance the accuracy and efficiency of waste classification. Algorithms such as Support Vector Machines (SVM), Neural Networks (NN). SVMs are effective for binary classification problems and can help in distinguishing between recyclable and non-recyclable waste by finding the optimal hyperplane that separates different classes. Neural Networks, particularly Convolutional Neural Networks (CNNs), excel in image recognition tasks, making them ideal for analyzing visual data from sensors to classify waste based on its appearance. Instance-Based Learning, such as k-Nearest Neighbors (k-NN), classifies waste by comparing new instances to stored examples, allowing for flexible and adaptive learning based on new data inputs.

2.2.1 Support Vector Machines (SVM)

SVM is a supervised machine learning algorithm commonly used for classification and regression tasks [11], [12], [13]. SVM works by finding the hyperplane that best separates the data points of different classes in a high-dimensional space.

2.2.2 Neural Networks (NN)

NN are a set of algorithms, modeled loosely after the human brain, designed to recognize patterns [11], [14], [15]. They interpret sensory data through a kind of machine perception, labeling, or clustering of raw input. The basic structure of a neural network consists of layers of interconnected nodes, or neurons, where each node represents a function that takes one or more inputs and produces an output.

After selecting the SVM and NN algorithms for the smart waste management system, the subsequent step involves training both algorithms using relevant datasets pertaining to the waste to be sorted. The training process aims to enhance the algorithms' capability in recognizing and classifying waste into appropriate categories. Upon completion of training, the resultant models are integrated into the Arduino microcontroller, as illustrated in Figure 2.

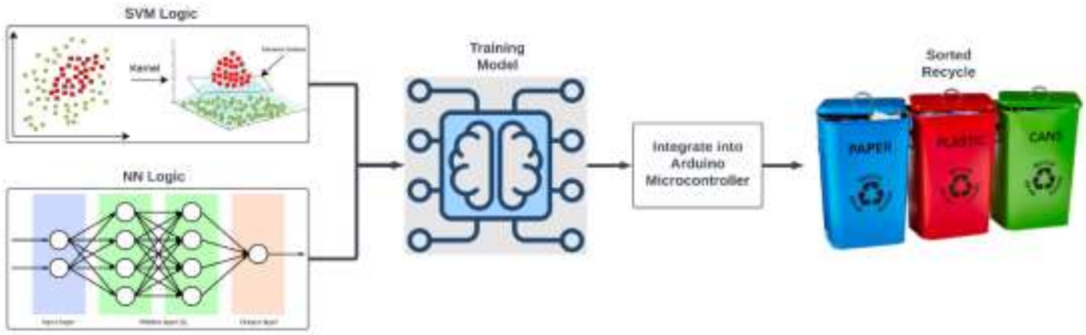

Figure 2. Training Model and Integrate into Microcontroller

2.3. Arduino Microcontroller Configuration

The Arduino microcontroller configuration for the smart waste management system involves setting up pins to interface with various sensors and actuators, which facilitate the automatic classification and sorting of waste. Initially, the pins for sensors (to detect waste properties) and actuators (to direct waste to the appropriate bins) are defined and initialized. The microcontroller reads real-time data from the sensors, processes this data using a pre-trained machine learning model to classify the waste, and then activates the corresponding actuators to sort the waste into designated bins. This configuration allows for efficient, real-time management of waste, leveraging both hardware and intelligent software components.

The provided pseudocode outlines below, the logical flow and structure of a smart waste management system using an Arduino microcontroller. It begins with initializing pins for sensors and actuators to set up the hardware interface, and declaring variables for waste type (wasteType) and classification (classifiedCategory). The readSensorData function captures real-time sensor data, serving as input for the machine learning model. The classifyWaste function analyzes this data using the model to predict the type of waste, storing the result in wasteType. The sortWaste function then directs the waste to the appropriate bin based on its type by activating the corresponding pin. The main loop continuously performs these steps—reading sensor data, classifying waste, and sorting it—while including a delay to prevent sensor overload and ensure smooth operation. Based on arduino logic algorithm can be seen in table 2.

Table 2. Arduino Logic Algorithm

Algorithm 1: Arduino logic algorithm	

1. Initialize pins for sensors and actuators
initialize *SensorPin*
initialize *PlasticBinPin*
initialize *CansGlassBinPin*
initialize *PaperBinPin*
initialize *DecomposedItemsBinPin*
 	
2. Initialize variables
initialize *wasteType*
initialize *classifiedCategory*
 	
3. Function to read sensor data
function *readSensorData*():
// Read data from sensors
sensorData = read from SensorPin
return *sensorData*
 	
4. Function to classify waste using machine learning model
function *classifyWaste*(*sensorData*):
// Process sensor data using pre-trained machine learning model
wasteType = machineLearningModel.predict(sensorData)
return *wasteType*
	5. Function to sort waste into appropriate bins
	function *sortWaste*(*wasteType*):
	if wasteType == "*Plastic*":
	activate *PlasticBinPin*
	else if wasteType == "*Cans/Glass*":
	activate *CansGlassBinPin*
	else if wasteType == "*Paper*":
	activate *PaperBinPin*
	else if wasteType == "*Decomposed Items*":
	activate *DecomposedItemsBinPin*
	
	6. Main loop
	loop:
	// Step 1: Read sensor data from the rubbish bin
	sensorData = *readSensorData*()
	// Step 2: Classify the waste based on sensor data
	classifiedCategory = *classifyWaste*(*sensorData*)
	// Step 3: Sort the waste into the appropriate bin based on the classification
	sortWaste(*classifiedCategory*)
	// Small delay to avoid sensor overload
	delay(1000)

3. RESULTS AND DISCUSSION

In this phase, the focus shifts towards the integration of machine learning models into the microcontroller, as depicted in Table 3. This phase delves into the practical implementation of the trained SVM and NN algorithms onto the Arduino platform, which serves as the central processing unit for the smart waste management system.

Table 3. SVM and NN Model Algorithm

Algorithm 2: Integrate SVM Algorithm	*Algorithm 3: Integrate NN Algorithm*
1. Initialize Pins: - Initialize pins for sensors and actuators. - Assign pins for SVM algorithm integration. 2. Initialize Variables: - Declare variables to hold sensor data. - Define variables for SVM classification results. 3. Read Sensor Data: - Read real-time data from sensors. - Store sensor data in appropriate variables. 4. SVM Classification: - Process sensor data using SVM algorithm. - Classify waste type based on SVM classification results. 5. Activate Actuators: - Based on SVM classification, activate corresponding actuators. - Direct waste to appropriate bins. 6. Main Loop: - Continuously execute steps 3 to 5. - Ensure real-time processing and sorting of waste.	1. Initialize Pins: - Initialize pins for sensors and actuators. - Assign pins for NN algorithm integration. 2. Initialize Variables: - Declare variables to hold sensor data. - Define variables for NN classification results. 3. Read Sensor Data: - Read real-time data from sensors. - Store sensor data in appropriate variables. 4. NN Classification: - Process sensor data using NN algorithm. - Classify waste type based on NN classification results. 5. Activate Actuators: - Based on NN classification, activate corresponding actuators. - Direct waste to appropriate bins. 6. Main Loop: - Continuously execute steps 3 to 5. - Ensure real-time processing and sorting of waste.

After initializing the algorithms on the microcontroller, performance measurements were conducted through two main phases: the training phase and the testing phase. During the training phase, the SVM and NN models were trained using a dataset that included various types of waste to optimize classification accuracy. In this phase, the models learn to recognize specific patterns and characteristics from the labeled data. Once the models were trained, the testing phase commenced, where the trained models were applied to new, unseen waste data to evaluate the system's actual performance. Measurements were taken to assess the accuracy, precision, recall, and processing speed of the integrated algorithms, ensuring that the system can correctly and efficiently classify and sort waste in real-world conditions.

3.1. Training Phase

In this phase, the data sorting process for recyclable waste types was evaluated using a confusion matrix. This matrix enabled a detailed analysis of the classification performance by comparing the actual classes of waste items with the predictions made by the Arduino-based system. For each type of recyclable waste—such as plastic, cans/glass, and paper—the true positives, false positives, true negatives, and false negatives were recorded. This allowed for the calculation of key performance metrics, including accuracy, precision, and recall. Results of confusion matrix can be seen in table 4.

Table 4. Confusion Matrix Evaluation

Methods	Accuracy	Precision	Recall	F1-Score
SVM	92%	100%	100%	100%
NN	96%	100%	100%	100%

The results from Table 4, "Confusion Matrix Evaluation," were analyzed using the following formulas:

$$Accuracy = \frac{(TP + TN)}{(TP + TN + FP + FN)} \quad (1)$$

$$Precision = \frac{TP}{(TP + FP)} \quad (2)$$

$$Recall = \frac{TP}{(TP + FN)} \quad (3)$$

$$F1 - score = \frac{2 * (Precision * Recall)}{(Precision + Recall)} \quad (4)$$

The evaluation results using the confusion matrix can be described as follows: True Positives (TP) represent the instances where plastic waste is correctly identified as plastic by the system. For example, if 30 plastic items are accurately classified, TP equals 30. False Positives (FP) occur when non-plastic waste is incorrectly identified as plastic; for instance, if 5 paper items are misclassified as plastic, FP equals 5. True Negatives (TN) are the cases where non-plastic waste is correctly identified as non-plastic, such as 50 correctly classified non-plastic items, resulting in TN of 50. False Negatives (FN) happen when plastic waste is incorrectly identified as non-plastic; for example, if 10 plastic items are misclassified as paper or glass, FN equals 10. This comprehensive evaluation using the confusion matrix allows us to calculate critical performance metrics like accuracy, precision, recall, and F1 score, providing a detailed understanding of the system’s effectiveness in identifying and sorting different types of waste.

3.2. Testing Phase

During the testing phase, the performance of the smart waste management system was evaluated, and the results can be observed in Table 5. This table presents a detailed breakdown of the system's classification accuracy for various types of waste, including plastic, cans/glass, paper, and decomposed items.

Table 5. Testing Phase

Methods	Plastic	Cans/Glass	Paper	Decomposed Items
SVM	TP	TP	TP	TP
NN	TP	TP	TP	TP

During the testing phase, as summarized in Table 5, both the SVM and NN methods showed consistent True Positive (TP) results across all categories: plastic, cans/glass, paper, and decomposed items. This indicates that the Arduino-based waste sorting system successfully identified and classified each type of waste with high accuracy. Consequently, it can be concluded that the system is capable of correctly directing waste into the appropriate colored bins—red for plastic, green for cans/glass, blue for paper, and the designated bin for decomposed items. This demonstrates the system's effectiveness in automating the sorting process, ensuring proper waste management and recycling.

4. CONCLUSION

In conclusion, the testing phase revealed exceptional performance of both the Support Vector Machine (SVM) and Neural Network (NN) methods in the Arduino-based waste sorting system. With an accuracy of 92% for SVM and 96% for NN, along with perfect precision, recall, and F1-score metrics, the system demonstrated remarkable efficiency and reliability in correctly identifying and sorting various types of waste. The consistent True Positive (TP) results across all waste categories further affirm the system's capability to accurately direct waste into the corresponding colored bins. This underscores the significance of automated waste management systems, such as the one implemented here, in promoting effective waste sorting practices and facilitating sustainable recycling efforts. Moving forward, advancements in technology and machine learning algorithms hold promising prospects for enhancing the efficiency and scalability of such systems, contributing to a cleaner and healthier environment for future generations.

For future research, there are several avenues worth exploring to further advance smart waste management systems. Firstly, investigating the integration of additional machine learning algorithms, beyond SVM and NN, could provide insights into alternative approaches for waste classification and sorting. Furthermore, exploring the use of advanced sensor technologies, such as hyperspectral imaging or lidar, may offer more detailed and accurate data for waste characterization. Additionally, studying the implementation of Internet of Things (IoT) devices and cloud-based platforms could enhance the scalability and real-time monitoring capabilities of waste management systems. Moreover, conducting field trials and longitudinal studies to assess the long-term performance and environmental impact of these systems in real-world settings would be valuable. Overall, continued research in these areas holds the potential to drive innovation and further optimize smart waste management practices, ultimately contributing to a more sustainable and environmentally conscious future.

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