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A MULTIFACETED ANALYSIS OF PIONEERING STRATEGIES AND LEADING-EDGE TECHNOLOGY FOR WASTE SEGREGATION

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Abstract:
This comprehensive review explores a multitude of waste segregation techniques and technologies employed in waste management. It covers various methodologies, including Deep Learning, Hyperspectral Imaging, Robotics, Optical Sensors, and more, each designed to improve waste sorting and enhance recycling efforts. The study provides a detailed comparison of these technologies, highlighting their accuracy rates and the specific types of waste they are designed to handle. These technologies offer promising solutions to address the growing challenge of waste management and environmental sustainability. The findings presented in this review serve as a

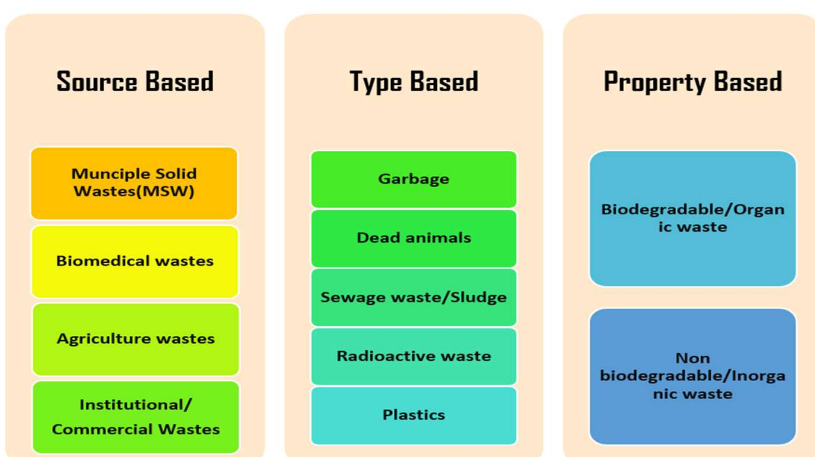
valuable resource for researchers, policymakers, and waste management professionals working towards more efficient and sustainable waste segregation and recycling practices.

Keywords: Waste segregation, Digital Image processing, Solid Waste, CNN, Raspberry Pi, SVM.

Introduction

In a global landscape grappling with the uncertain problem of waste generation, governments are assiduously working to tackle the challenges of waste segregation and collection in the realm of waste management. Solid waste, Liquid waste and gaseous waste are the main classification from the principle of waste management. Many institutes and universities who are capable of handling this international concern, still they are not utilizing their untapped potentials. Municipalities and Urban Local Body (ULBs) are the main managements who were continuously face these pivotal hardships. However, population growth is one of the major problems that are observed. A tremendous change with the industrial revolution, in which 2nd billion was achieved in 1930 and 3rd billion in the year of 1960. Hereafter, the population growth was seen abruptly during the preceding years. Due to this proportional number of resources are utilized which are converted in the form of waste.

Solid waste constitutes the largest proportion in the classification of waste, which is further categorized into source-based, property-based, and type-based. The Figure [1] shows the types of waste comes under these categories. Segregation plays a very important role in identifying the biodegradable and non-biodegradable wastes which help in the process of recycling. This article emphasizes the rate of efficiency obtained through Digital image processing, AI and ML etc. The efficacy of these methodologies is magnified by optimizing the communication distance between the waste collection station and the waste collection point. LPWAN technologies, such as Sigfox and LoRaWan, excel in managing extended-distance communication, although they do bear the drawback of limited data transmission rates.



Figure[1] : Classification of Solid waste.

RELATED WORKS

[1]. LoRa And Tensorflow Deep Learning Model:

The overarching goal of this research endeavor is the creation of an advanced smart waste management system, ingeniously harnessing the power of the LoRa communication protocol in conjunction with a deep learning model based on TensorFlow. This cutting-edge object detection model has been meticulously trained on a diverse array of waste images, resulting in the creation of a frozen inference graph. This sophisticated graph is employed for precise real-time object detection, seamlessly executed by a camera interface seamlessly integrated with the Raspberry Pi 3 Model B+ serving as the central processing powerhouse. TensorFlow is an open source library stands as the bedrock for model machine learning application. LoRa communication protocol undergoes meticulous monitoring and analysis for an elevated level of cloud-based oversight. The maximum current consumption rate of 17mA which is relatively less as compared to WiFi, Zigbee and Bluetooth communication protocol. It is comprised with the Chirp Spread Spectrum as its transmission technique. It can cover upto more than 15km range for the data transmission which is quite largest distance coverage as compared to any other protocol. TensorFlow framework allows to train, object classifiaction and detection.

a)Implementation of sensors and LoRa communication protocol:

A camera module is used to capture the image, connected to Raspberry Pie. A transmitted radio waves are received through RFID module which is connected to Rasberri Pi and also RFID module trigger the Arduino Uno, responsible for switching the electronic components. The RFID reader takes care of sending and receiving radio waves, making it all work smoothly. Since RFID follows backscattering system, it faces an affect due to position of RFID tag and reader. This challenge is resolved by strategically positioning both the RFID reader and the tag, ensuring an unobstructed line of communication, where the symphony of signals flows uninterrupted, harmonizing data exchange with flawless precision. The chamber mainly consists of four compartments for the separate collection of waste such as metal, paper, plastic and remaining are collected in general waste compartment. Precise calculation of filling level in each compartment is done through the Ultrasonic sensors where it uses sonar to determine the time taken by the signal to reach the transmitter end and the receiver end. Time difference between transmitter and the receiver gives amount of waste collected in the compartment.

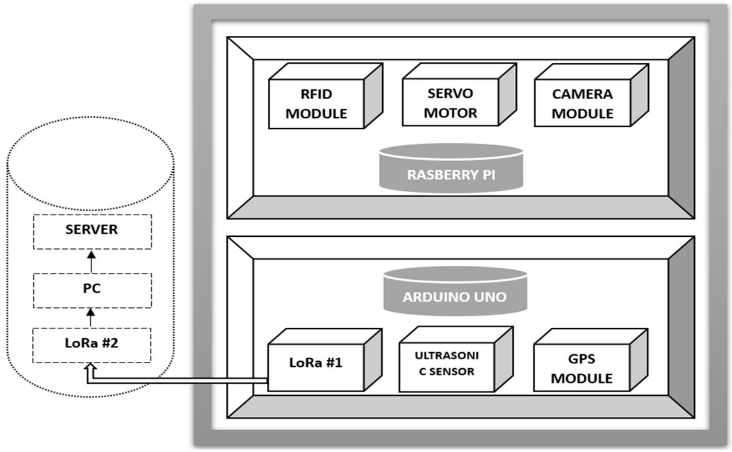


Figure [2]: Interfacing of Arduino and Raspberry Pi.

The above figure represents the interfacing of RFID, Servo motor, Cemera module with Raspberry Pi and an Ultrasonuc sensor, GPS module and LoRa Module with Arduino UNO. Within the system, waste segregation is intelligently conducted directly on the board itself. Segregation of waste materials is achieved through the operation of servo motor which is triggered through Raspberry Pi. To allow this system to operate in mobile devices, MobileNetV2 network architecture is used, ensuring optimal performance. To avoid unnecessary cloud analysis this system uses the mobile CPU with the MobileNetV2 which reduce the time-power consumption and latency of waste classification.

Figure [3] represents the flow chart of object detection model. Initially, it will gather the images of wastes and labelling is done for each. Based upon the different styles of data the model gets trained. Testing is done followed from interference graph. A conditional statement which triggers on the basis of accuracy. If the accuracy lees than 80%, then again model undergoes to training. Semi-automated image annotation method is used in this system which allows to manually label the images.

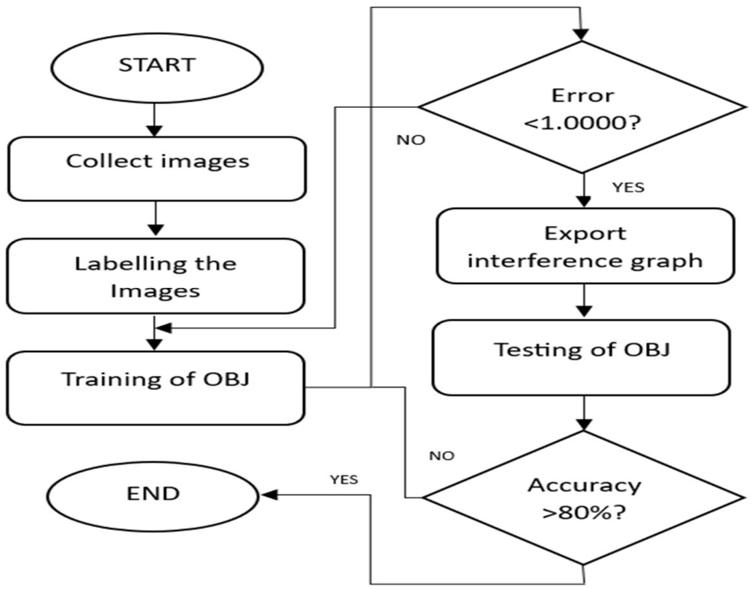


Figure [3]: Flow of OBJ.

[2]. IR Hyperspectral Imaging System:

This system performs the sorting through identifying the chemical component found in the waste. Due to its wide range of electromagnetic spectrum, unique characterization in sorting makes the hyperspectral imaging system convenient for segregation. To comprehensively analyse and segregate waste materials, a shortwave infrared (SWIR) scanning system is employed. Low Density Polyethylene (LDPE), High Density Polyethylene (HDPE), Polyvinyl Chloride (PVC), Polyethylene Terephthalate (PET), Polystyrene (PS), and Polypropylene (PP) represent various types of plastics used in this system. Additionally, cardboard, paper, metal, glass and plastics are used for the testing.

1) Implementation details: The core component are illumination system, imaging system and a conveyer belt. Two halogen lamps are placed beside of the conveyer belt to avoid the effects due to low ambient illumination. The imaging system comprises a SWIR camera, a camera lens, and a SWIR imaging spectrometer as its integral components.

Before scanning the materials to measure reflectance, the system captures both a white reference image and a black reference image. The bands with noise between 2300 and 2500 nm have been filtered out. The plastic polymers are numbered with 1 to 6 in code recycling. Four datasets are under consideration, encompassing the aforementioned waste materials. The noise is removed by the Savitzky -Golay filtering followed by some preprocessing algorithm. The multiplicative and baseline correction is done through the SNV (Standard Normal Variate) and ASLS (Asymmetric Least Square Method) respectively. The accuracy rate little reduced because of the transparent nature of the glass. The one way to filter this deficiency by interfacing with glass detector sensors. The calculation of accuracy rate is done through the MCA (Mean Calculation Accuracy) method. Post processing is carried out to enhance the accuracy of classification at rate of 0.5%. This system represents a comprehensive approach to waste recycling applications. Figure [4] represents the morphological view on four different data sets.

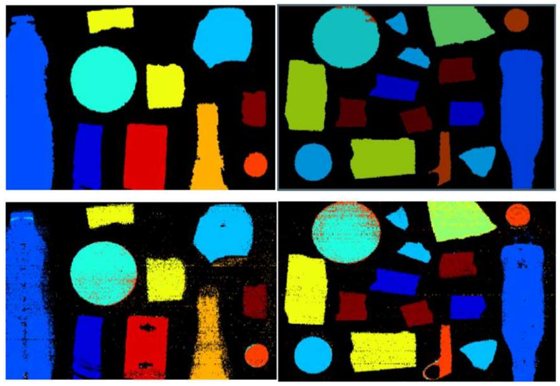


Figure [4]: View of Data sets.

[3]. Robotic Waste Segregation Technology:

In this system the sorting and identification is inspired by deep learning technology to create a low-cost computer module. The computer vision module is integrated with robotic system that identifies the recyclables. Creating a robotic system for industry requires through testing in tough, real-world conditions. Conveyer Belt, Waste feeder, Camera, robot and vacuum gripper are major components of this system. Overall, it has two separate parts: one for physical separation through a robotic manipulator and another for vision-based detection and categorization. Initially, there will be a revolving punch plate, called a trommel, is used for filtering (removes smaller objects). Then it will fall onto to conveyer belt which is moving in a constant velocity ensures that the real time position of the object. Vacuum is generated through the chamber consist of blower spin synchronized rotor. The first step in creating a waste categorization module for industrial use is building a diverse dataset of recyclable waste images, as existing open-source datasets primarily cover outdoor scenarios. Instead of manually labeling images against various backgrounds, this work automates annotation by generating masks to indicate regions of interest. They create a rich dataset by applying geometric transformations, resulting in single-object images on a black background, and then combine objects on colorful backgrounds to simulate complex industrial scenarios, facilitating the training of machine learning models for waste classification.

Seasonal variations in waste composition, such as more liquid-containing PET bottles in summer, highlight the robot's potential benefits in waste management. The Mask R-CNN-based solution excelled at categorizing aluminum cans and PET bottles due to their consistent shape and color, while distinguishing between cartons and nylon proved challenging even for human observers. The proposed technology has the potential to revolutionize future waste treatment plants, aiming for highly automated facilities where humans won't interact directly with waste, and almost all recyclable materials can be efficiently recovered.

[4]. Optical Sensor Based Sorting Technology:

The visual features such as colors, shapes, and textures in sorting waste particles where solid waste is typically a complex mixture, requiring multiple visual features for recognition, especially for standardized shapes like batteries and bottle covers. Optical sensors like industrial area scan cameras are recommended for acquiring and recognizing multiple visual features of single waste particles. In this work, a single line array of LED lamps was used, distributed across the width of the belt with a 10mm spacing to ensure uniform lighting. These LEDs had a color temperature of approximately 6300K, simulating daylight, which minimized color capture deviations. Five waste mixtures were tested, including non-ferrous metals (copper, brass, aluminum), two polymer types (PP and ABS), and two standard particle mixtures (euro coins, bottle covers). Sorting relied on features like particle colors and belt positions for metals and polymers, and colors, 3D parameters, and belt positions for standard particles, yielding positive results.

[5]. Waste Sorting System with Robotic Arm :

The system comprises a stainless-steel robotic arm controlled via an Android app developed in Java, utilizing a Bluetooth module to operate servo motors. The mobile app, created with MIT App Inventor, supports Android versions 2.1 and above, while the detection module employs inductive, voltage, and IR sensors to differentiate waste materials, particularly metallic objects using proximity sensing based on coil and oscillator principles. The developed system was evaluated in an academic setting, achieving an accuracy for detecting 9 out of 11 waste items. However, it struggled with objects mixed with multiple materials and exhibited occasional inaccuracies with the voltage sensor, favoring the more reliable inductive sensor for metal detection.

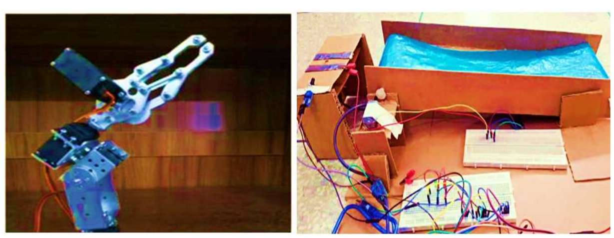


Figure [5]: Robotic Arm and Conveyer.

[6]. Computer Vision-Based Waste Sorting System:

A readily available garbage image dataset for ideal garbage classification and recognition experiments is currently nonexistent. Data allocation for image classification requires the creation of a representative and error-free training dataset, crucial for improving classification accuracy, with the additional condition that images in the test set should not be part of the training data to assess the model's generalization. This method acknowledges that humans excel at recognizing new objects with minimal samples, while machines require extensive data support. It outlines the use of support vector machines and convolutional neural networks to classify garbage images, highlighting the transition from traditional hand-crafted feature extraction in machine learning to

CNN's capability of autonomously learning features from training data. HOG (Histogram of Oriented Gradients) is a feature extraction method used for tasks like pedestrian detection, which breaks down the detection window into cells and calculates gradient direction histograms. In this specific application with 128×128 input images and 4×4 pixel cells, it generates 34,596-dimensional features by considering 2×2 cell blocks and 31 scanning windows in both horizontal and vertical directions.

The GLCM (Gray Level Co-occurrence Matrix) texture feature extraction method, introduced by Haralick, analyzes image texture by examining pixel gray levels and their spatial relationships. It provides insights into surface characteristics but not the full object attributes. This approach calculates four directional features (contrast, energy, correlation, homogeneity) from the GLCM and derives the average and variance of these features to obtain comprehensive image texture characteristics. SVM leverages optimization theory to address binary classification problems and extends to handle nonlinear cases. This approach compares AlexNet and VGG19 models for garbage image classification. AlexNet, with 8 layers including convolution and fully connected layers, employs dropout and ReLU activation to mitigate overfitting. VGG19, a deeper network using 3×3 convolution kernels, provides high performance but demands more computing resources. Transfer learning is used due to limited data, fine-tuning the pre-trained models, and enhancing image data. Training involves 672 iterations, with data divided into training, verification, and test sets in a 6:2:2 ratio.

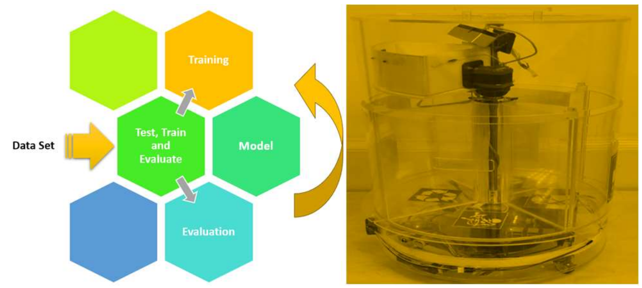
[7]. Profiling and Analysis of Waste through ML:

A proposed system processes images of garbage bins to identify dry, wet, or mixed waste, generating reports to pinpoint areas not adhering to government waste segregation norms, enabling awareness campaigns to promote proper waste disposal practices. The proposed system utilizes an Android application to capture waste images, which are then sent to a custom web server for processing with machine learning (TensorFlow, Inception v3) to classify waste as biodegradable, non-biodegradable, and assess banned plastic content, providing an assessment of waste condition in accordance with government norms. The proposed system consists of the following procedures:

1) Creating the dataset and conducting data training.
2) Training and Optimization of model.
3) Web server development.
4) Utilizing the Inception V3 model.
5) Creating the Android application.

[8]. Automated Waste Sorting through CNN (Convolutional Neural Network):

The study utilizes transfer learning to adapt pre-trained CNN models (e.g., VGG16, VGG19, Resnet101, DenseNet121, EfficientNet-B0, and EfficientNet-B1) initially trained on ImageNet to enhance waste classification. EfficientNet-B0, Resnet101 and EfficientNet-B1 are chosen for their effectiveness. Majority voting among these models' predictions is employed to determine the final waste label, ensuring reliable and accurate results. The network's effectiveness is assessed using accuracy, calculated from the confusion matrix by comparing system predictions to actual labels. Accuracy represents the percentage of correctly classified images.



(a) (b)

Figure [6]: a. Work flow of dataset model. b. Garbage classifier through BNN.

The dataset is split into three sets: 50% for training, 25% for validation, and 25% for testing, with Fastai library aiding in training. Optimizing the learning rate, crucial for model adaptation, involves a grid search by incrementally increasing it during training batches.

[9]. Waste sorting through Binarized Neural network:

This work presents a low-latency embedded system for waste sorting on an FPGA development board, introducing a garbage classification model based on Binary Neural Networks (BNN). Additionally, it features an energy-efficient coprocessor for FPGA acceleration and an innovative mechanical structure for practical garbage classification. CNNs excel in artificial intelligence and machine vision but often require hardware accelerators for challenging tasks. However, these accelerators struggle to meet CNNs' resource demands. BNNs offer a solution by constraining feature maps and weights to +1 or -1, significantly reducing memory and computational complexity, making them a compelling alternative for various layers, including convolutional layers, which can employ XNOR operations instead of traditional multiplications.

This approach introduces a customized binarized neural network (BNN) model for garbage classification featuring four convolutional layers and two fully connected (FC) layers, with only 57.80K bits of weight parameters. This compact structure is suitable for resource-constrained embedded devices, with input images and convolutional layers binarized to reduce computational complexity. This model is depicted in Figure [6] b. The model achieves a high accuracy on garbage image classification, optimizing computational efficiency with combined activation and batch normalization (BNA) operations. The system utilizes image processing and motor control on an FPGA board within a garbage can, employing a USB camera and LED light for operations.

[10]. Visual and Tactile Recognition system:

This article presents a robotic waste sorting system that combines vision and tactile sensing to recognize materials in containers and packaging. It employs an object detector, grasp affordance map, tactile sensor, and material classifier to sort waste based on material type. The contributions include a tactile material recognition framework, an affordance-based grasp method, and a validated robotic waste sorting system for efficient material sorting. Furthermore, it explores the use of tactile sensing to recognize materials, offering a more effective approach to waste sorting by combining visual and tactile information for improved material recognition in a broader range of objects. The proposed robotic waste sorting system comprises a Kinect One camera, UR5 robotic arm, specialized robotic hand with tactile sensing, and a sorting table, focusing on single-stream recycling. It employs a vision-guided tactile sensing approach for containers and packaging recycling. The Kinect One camera captures the mixed waste scenario, and an object detector locates containers and packaging. A grasp affordance map guides the robotic hand to pick up the waste, and tactile data collected during grasping are used for material identification, enabling efficient recycling based on material type. The experimental validation involves two key aspects: Grasp Detection and Material Identification. Grasp Detection utilizes a trained detector to identify containers and packaging amidst cluttered waste scenarios using class-specific affordance maps, allowing for precise object grasping orientation.

[11]. Waste Sorting Employing SIFT-PCA Feature Extraction and Support Vector Machine-Based Classification:

This research utilizes the robustness of the SIFT algorithm for key point and descriptor functions, PCA for efficient data compression, and SVM as a reliable classification method to perform waste classification with SIFT-PCA feature extraction. This research employs a multi-step process involving data collection from the Trashnet dataset, data splitting for training and testing, SIFT feature extraction for robust feature points, and k-Means clustering for efficient data grouping. The study achieves optimal accuracy with an 85%:15% data split ratio and utilizes the SIFT algorithm to extract invariant key points and descriptors from waste images, ensuring resilience against various factors such as noise, scale, rotation, and illumination. Finally, k-Means clustering is applied to create a vector space for further analysis and classification. In this research, the feature vectors' histograms are computed using a predefined vocabulary for both training and testing data, enabling quantization. Principal Component Analysis (PCA) is applied to reduce dimensionality, preserving essential information efficiently. Support Vector Machine (SVM) is employed for classification, with the RBF kernel function enhancing data separation. The SVM model is trained and tested using the optimized parameters, contributing to effective multi-class classification.

[12]. Arduino based Automatic Waste Segregator and Monitoring System:

This project aims to implement an Internet of Things (IoT) based Automatic Waste Segregator for efficient waste management. It focuses on promoting the 3R (reduce, reuse, recycle) concept, developing a prototype of an Automatic Waste Segregator and Monitoring System, and creating smart dustbins that open automatically when someone approaches. This project implements an Automatic Waste Segregator and Monitoring System using various hardware components, including microcontrollers, sensors (ultrasonic and inductive proximity), LCD, speaker, and Wi-

Fi (ESP8266) and GSM modules. The system detects the presence of people, scans waste items using sensors, opens bin lids with servo motors, and plays sound as a token of appreciation. It also integrates IoT capabilities for remote monitoring of waste levels and data collection, allowing users to access information and download it in Excel format via a mobile phone or laptop.

[13]. Capsule Neural Networks and Visualization Based Segregation of Wastes:

Capsule Neural Networks (Capsule-Net) address limitations of conventional CNNs by preserving spatial relationships and handling orientation variations efficiently. Capsules in Capsule-Net, inspired by brain modules, enable nested layers, and routing mechanisms, facilitating more robust and precise object recognition. Real-time waste segregation is achieved through a hardware setup featuring a conveyor belt driven by a wind shield wiper motor, equipped with a top-view webcam. A gate, controlled by a stepper motor and an Arduino board, directs waste items to the camera for classification using the Capsule-Net architecture. In the waste segregation setup, the Capsule-Net architecture classifies materials based on probability values. If the probability exceeds 0.5, the gate redirects the material to the plastic bin; otherwise, it is directed to the non-plastic bin via serial communication with an Arduino. When the system identifies non-plastic material (probability < 0.5), the gate remains fully open, allowing the material on the conveyor belt to move straight to the end and fall into the bin. In experiments using GPU-enabled TensorFlow and Keras, parameter tuning for Capsule-Net involved optimizing settings like epochs (1000 yielded the best results), learning rate (0.01), batch size (32), and filters (256 with a kernel size of 9) to efficiently segregate plastic and non-plastic trash, paving the way for future waste segregation applications. The proposed architecture comprises three layers: input, hidden, and output. Pre-processing resizes the input image to 28x28, followed by a convolution layer with a kernel size of 6. Capsules are formed after convolution and primary caps. The last layer includes a fully connected layer with sigmoid activation, using binary cross entropy as the loss function.

[14]. Deep Learning and Support Vector Machines for Autonomous Waste Sorting:

Convolutional Neural Networks (CNNs) offer advantages for image recognition by considering spatial structure. They use local receptive fields, connecting each neuron to a specific image region, creating shift-invariant models. Weight sharing allows neurons to learn and detect features across the entire image, making CNNs highly effective for various recognition tasks. Pooling layers further simplify output, with techniques like max-pooling reducing the number of parameters and focusing on detected features' presence rather than their exact location. AlexNet is a deep neural network with 7 layers, including 650,000 neurons, 60 million parameters, and 630 million connections. The advantage of CNNs lies in their ability to act as shift-invariant filters, recognizing objects regardless of their position in an image. Training was conducted on an HP laptop with an Intel i7 processor and an NVIDIA 740 M GPU. NVIDIA DIGITS and the machine learning library Caffe were used for CNN training, while SVM training utilized MATLAB 2016a. Mean image normalization was applied to enhance detection accuracy by treating images of the same content but different brightness levels as identical. The SVM model, trained for waste classification, was implemented on a Raspberry Pi 3 with a high-definition camera. A MATLAB script enabled image capture upon button press, classification, and LED display for waste categories, achieving rapid classification with an average time of 0.1 seconds.

[15]. Image Processing based Automatic Waste Sorting:

The autonomous waste sorting system utilizes a Raspberry Pi, web camera, and conveyor to sort materials (e.g., metal, paper, plastic) into respective containers. It operates in two modes: training and operating. In training mode, it captures and processes images, extracts features, and trains a neural network for material recognition. In operating mode, it identifies materials using the trained network, activates the conveyor and motor to sort waste, and returns the motor to its initial position after sorting. Artificial Neural Networks (ANNs) mimic biological neural networks and consist of interconnected layers. They learn from data patterns through experience, not programming, and adjust connections (weights) during training to minimize errors. Back propagation is used to train multi-layer ANNs, adjusting weights to respond correctly to various materials in waste sorting based on computed errors.

TABLE 1. Comparison among different Waste Management system with Segregation techniques, Sensors, and it's Accuracy.

Reference	**Segregation Techniques**	**Sensors**	**Type of Waste**	**Accuracy Rate**
[1]	LoRa And TensorFlow Deep Learning Model	Pi Camera, Ultrasonic Sensor	Metal	86.7%
			Plastic	96.3%
			Paper	82.3%
[2]	IR Hyperspectral Imaging System	N/A	Plastic, Paper, Metal and Glass	94.55%
[3]	Robotic Waste Segregation Technology	IR Sensor, Camera Module	Metal, Paper, Nylon, PET bottles	91.8%
[4]	Optical Sensor Based Sorting Technology	BASLER avA1000-120 km/kc	Polypropylene (PP) and Acrylonitrile Butadiene Styrene (ABS) particles, Black Polymer	98%
[5]	Waste Sorting System with Robotic Arm	IR Sensor, Voltage Sensor and Inductive Sensor	Organic Waste, Metal, Plastic and Mixed Waste (Metal and Plastic)	82%
[6]	Computer Vision-Based Waste Sorting System	Camera Module	Fishbone, Pericarp, Tea residue, Vegetable leaves,	97%

			Ceramics, Cigarette butt, Tableware, Trash bag	
[7]	Profiling and Analysis of Waste through ML	Camera (Mobile)	Bio-Degradable Waste	88%
			Non-Bio-Degradable Waste	84%
[8]	Automated Waste Sorting through CNN	N/A	Metal. Paper, Cardboard, Plastic and Organic Waste	94.11%
[9]	Waste sorting through Binarized Neural Network	USB Camera	Plastic, Paper, Cardboard, Glass, Metal and Organic waste	96.8%
[10]	Visual and Tactile Recognition system	Piezoresistive Tactile Sensor	Plastic, Paper, Glass and Metal	62.5%
[11]	SIFT-PCA Feature Extraction and Support Vector Machine	N/A	Plastic, Paper, Cardboard, Glass, Metal and Trash	62%
[12]	Arduino based Automatic Waste Segregator	Ultrasonic Sensor, Liquid Sensor, Inductive Sensor, LDR	Transparent Plastic	97.78%
			Paper	81.54%
[13]	Capsule Neural Networks and Visualization	Camera Module	Plastic and Non-Plastic waste	96%
[14]	Deep Learning and Support Vector Machine	Pi Camera	Plastic	96%
			Paper	99%
			Metal	90%
[15]	Image Processing	Webcam	Plastic	93%
			Paper	92%
			Metal	93%

TABLE 2. Comparison among different Waste Management system with Machine Learning model, Pros and Cons.

Reference	Machine Learning Architecture	Microcontroller	Pros	Cons

[1]	MobileNetV2	Raspberry Pi, Arduino UNO	Low Power and Long-Range Data Transmission	To achieve an increase in overall accuracy, a high level of data training is required.
[2]	SVM	Computer	PET, HDPE, PVC, LDPE, PP and PS are accurately classified	Rate of accuracy is reduced due to the transparency of glass
[3]	CNN, ResNet-50	Computer	The implementation of a blower-based vacuum system aimed to enhance the capacity of robotic systems in handling recyclables.	Processing Speed is reduced due to blower valve
[4]	N/A	Computer	Classification is based on Size, Shape, Color	Complex signal Processing due to optical sensor
[5]	N/A	Arduino UNO	Reduced Labor Cost and Safety	A high-fidelity prototype of the proposed system was created and tested exclusively within an academic setting.
[6]	CNN, SVM	Computer	High rate of accuracy on identifying tea residue and cigarette butt	Try to classify multiple kinds of garbage’s in more complex background
[7]	N/A	Computer	Faster in Execution	Accuracy performance same as existing system
[8]	CNN	Computer	Able to classify 7 different trashes including organic	Reduced accuracy is a result of inadequate training data.

			Trashnet collected from dataset	
[9]	BNN	Computer	Ability of online learning	Complexity of Network Training
[10]	SVM	Computer	Vision-guided tactile sensing approach	Only plastic, paper and glass are highly recognized
[11]	SVM	Computer	Able to identify specific shapes, patterns, and textures associated with different types of waste.	Accuracy is reduced by PCA dimensional reduction, and achieving higher accuracy may require a larger number of image classes.
[12]	N/A	Arduino UNO	It has the ability to send SMS notifications when the bin reaches its threshold limit.	There may be some errors due to the sensor values of different materials falling within the same range, such as paper and wet waste.
[13]	Capsule-Net	Arduino	Capable of providing accuracy even with a small dataset.	The overall accuracy is reduced due to minor prediction errors in TP, TN, FP and FN.
[14]	CNN, SVM	Raspberry Pi	The highest accuracy is achieved in the classification of metal, plastic, and paper, and it executes faster compared to the existing models.	More training with images is required to achieve greater accuracy, and due to the limited size of GPU memory, we can't effectively address an overfitting problem.
[15]	ANN	Raspberry Pi	In the future, it can connect with GUI apps for user-friendliness.	The limit was 100 images due to GPU memory constraints

CONCLUSION

Upon a comprehensive comparison of various waste segregation technologies and their accuracy rates, several standout options emerge. The "Optical Sensor-Based Sorting Technology" impressively achieves a 98% accuracy rate in sorting materials like Polypropylene (PP), Acrylonitrile Butadiene Styrene (ABS), and Black Polymer, making it a compelling choice for precise waste sorting. Additionally, the "Computer Vision-Based Waste Sorting System" demonstrates a 97% accuracy rate in classifying bio-degradable and non-bio-degradable waste, employing camera modules and neural networks to achieve reliable results. The "Arduino-based Automatic Waste Segregator and Monitoring System" is another commendable option, boasting a 97.78% accuracy rate for transparent plastic and 81.54% for paper, thanks to its utilization of multiple sensors, including ultrasonic and inductive sensors. These technologies offer highly accurate and efficient waste sorting solutions, but the selection should consider specific waste compositions, operational requirements, and available resources. A combination of these technologies may be the optimal approach to enhance waste sorting and recycling processes for a more sustainable and environmentally responsible future.

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