ARTIFICIAL INTELLIGENCE IN WASTE MANAGEMENT SYSTEM

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This is to certify that the work present in this Project entitled "**ARTIFICIAL INTELLIGENCE IN WASTE MANAGEMENT SYSTEM**" has been carried out by **PULIME DHEERAJ VENKATA SRIRAM, PATNANA SAI AKASH, MAALE CHAKRAPANI, VRIJESHWAR R SINGH** under my supervision. The work is genuine, original, and suitable for submission to the SRM University – AP for the award of Bachelor of Technology in **School of Engineering and Sciences**.

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Abstract

The generation of waste worldwide is steadily increasing day by day, posing a significant challenge in its management. According to the World Bank, the annual volume of managed trash is projected to surge by 73% to over 3.88 billion tons between 2020 and 2050. AI technology has swiftly gained recognition across various sectors, including waste management. The objective of this paper is to highlight the potential transformation of waste management practices through the integration of AI and robotics in the planning and operation of waste treatment facilities. This integration holds the promise of enhancing efficiency and sustainability, providing a myriad of benefits.

Keywords: Waste management, Genetic Algorithms, Artificial Neural Networks, Recycling, Illegal dumping, Robots

Abbreviations

CNN	Convolutional Neural Networks
AIEWO-WMC	Artificial Intelligence with Earth Worm Optimization Assisted Waste Management System for Smart Cities.
GA	Genetic Algorithm
ANN	Artificial Neural Networks
MAP	Mean Average Precision
IOT	Internet Of Things
GIS	Geographic Information Systems
MQTT	Message Queuing Telemetry Transfer
SVM	Support Vector Machine
MDF	Medium Density Fiberboard
GPS	Global Positioning System
SLCPS	Short-lived climate pollutants
OLS	Ordinary Least Squares regression
GWR	Geographically Weighted Regression

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Chapter 1

1. Introduction

Waste refers to any material that is no longer in use or has been discarded by individuals. It is a natural byproduct of human activities. Globally, an estimated 2.01 billion tons of municipal solid waste are generated annually, and projections indicate a 70% increase to 3.4 billion tons by 2050. The daily per capita production of waste varies widely worldwide, averaging between 0.11 and 4.54 kg. Notably, although high-income nations constitute only 16% of the global population, they contribute to over 34% of the world's waste, equivalent to 683 million tons.

1.1 Types of Wastes

Hazardous Waste: This category encompasses waste that has a detrimental impact on the environment and poses risks to human health. Examples include radioactive waste, medical waste, and electronic waste (E-waste).

Non-hazardous waste: This category comprises waste that affects the environment but is not harmful to humans and animals. Examples include household waste like food waste and commercial waste such as packaging waste.

Municipal Solid Waste (MSW): Municipal solid waste, as collected by city governments, includes household waste, non-hazardous solids from industrial, commercial, institutional, and non-pathogenic hospital sources, etc (Amasuomo et al., 2016).

Electronic Waste (E-waste): This category refers to discarded electric materials, such as mobile phones and laptops, which are no longer in use. E-waste is a concern due to the presence of toxic elements like PCBs (polychlorinated biphenyls) and various metals, posing environmental and health risks.

Biomedical Waste: This type of waste is produced by healthcare systems, including hospitals and clinics, and comprises materials such as chemicals, pharmaceuticals, bandages, and frequently includes discarded drugs. These components found in medical waste are often dangerous and poisonous, highlighting the potential hazards associated with the improper disposal of such waste.

Agricultural Waste: Agricultural wastes are byproducts of the production and processing of agricultural goods, which may contain some useful materials for mankind (Obi et al., 2016).

Construction Waste: This category includes waste generated during the construction phase. Examples of construction waste comprise concrete, plastic, wood, metals, and other materials, etc. (Amasuomo et al., 2016).

Industrial Waste: Industrial waste is defined as waste generated during the processing of raw materials for the development of new goods. Examples include waste generated by factories, mills, and mines, such as chemicals (Amasuomo et al., 2016).

Commercial Waste: This category refers to waste generated from commercial establishments such as restaurants, offices, service stations, etc.

Radioactive Waste: This type of waste contains radioactive materials. Examples of materials found in radioactive waste include uranium, cotton swabs, and other substances with radioactive properties.

1.2 Waste Management System and its challenges

Waste management is a set of processes involving collection, transport, processing, and disposal. To minimize the negative impact on the environment and human health, waste management must adhere to specific protocols. Proper waste management is achieved through handling waste in a productive manner.

Challenges of waste management

Improper Collection of Waste: Proper waste collection is a fundamental aspect of waste management. However, due to the excessive generation of waste, inefficient transportation, poor routing, and misuse of resources, the quality of waste collection is deteriorating and becoming increasingly challenging.

Limitations in Landfill Capacity: Urbanization, expanding cities day by day, has resulted in a shortage of land for landfilling waste, posing a challenge in the disposal process.

Impacts of Traditional Waste Management: Conventional waste management practices are time-consuming and less effective. These methods often rely heavily on manual labor, posing potential health risks to individuals involved due to the hazardous nature of the materials being handled.

Insufficient Infrastructure in Waste Processing Procedures: Procedures such as sorting for recycling require intelligent and effective machinery to accurately process and sort waste materials. This is essential for achieving smooth and efficient recycling processes.

1.3 Objective of the Research

The primary objective of this paper is to highlight the significance of integrating artificial intelligence into waste management systems. The focus is on addressing the challenges associated with inadequate waste management and demonstrating how effective waste management contributes to the development of smart cities. The paper reviews various applications of artificial intelligence in waste management, specifically highlighting subdomains such as machine learning and deep learning. Additionally, it covers concepts like genetic algorithms and Artificial Neural Networks. The emphasis is on utilizing robots for efficient waste sorting and recycling, contributing to a clean environment, and offering solutions to pollution problems.

Chapter 2

2. Literature Review

The issue of waste management poses a significant challenge worldwide, impacting both developed and developing countries. This paper aims to explore productive and efficient techniques for managing this major concern across different countries, with a specific focus on leveraging artificial intelligence. Recognizing that manual waste sorting is time-consuming and costly, scientists have developed and researched automated sorting methods to enhance the overall effectiveness of the recycling process (Bobulski et al., 2020). Urgent attention is required for addressing major environmental problems such as trash collection and disposal, and waste management emerges as a crucial subject warranting increased academic research investigation (Naserrn Banu et al., 2021).

A recent deep learning-based approach (Chowdhury et al., 2023) addresses solid waste management issues in Bangladesh. The researchers developed a model trained on diverse datasets capable of detecting 12 types of waste. The classification accuracy achieved was 73%, with an F1 score of 0.729. The custom dataset used for training included one-third of locally gathered and fully annotated images.

In another recent study (Thao and L.Q, 2023), a solution for precise waste sorting was presented. The system, incorporating a camera and Convolutional Neural Network (CNN), achieved an impressive 99% success rate in waste classification. Moreover, the system featured a robotic arm for physical waste sorting into respective bins, resulting in enhanced productivity and reduced human intervention.

The goal of every nation is making its metropolitan cites smarter. Smarter city needs very strategic and proper waste management which has to good at the more important fields like prediction of generation of waste, collection of waste, treating of waste materials. In study (Rajalakshmi et al., 2023) proposed the AI based waste management system using Earth Worm Optimization and Deep Learning (AIEWO-WMC) for smart cites which is featuring a Retina Net-based object detection module and Adagrad optimizer to identify the presence of waste objects in the images, with experimental results showing superior performance (99.15%) compared to other techniques.

A proper waste management system requires a well-planned approach to waste collection, which is greatly facilitated by intelligent route recommendations. Optimized routings offer numerous benefits, including reduced wastage of resources such as fuel and time.

In a recent study (Ghahramani et al., 2021), an intelligent approach is proposed for optimizing waste collection routes in IoT-enabled smart cities. The study utilizes AI-based methods and multi-level decision-making to effectively manage waste collection while taking spatial constraints into consideration.

In the case study conducted by (Diaz et al., 2022), the utilization of machine learning techniques is proposed for predicting four critical variables in the urban solid waste collection process. These variables include total route time, kilometres travelled, the number of compactions performed, and tons collected. The study employs eleven regression-based machine learning techniques and achieves a correlation coefficient R2 higher than 0.7.

In recycling, sorting plays a pivotal role, as the effectiveness of subsequent recycling procedures hinges on efficient sorting. The paper by (Satav et al., 2023) addresses the significance of garbage sorting in waste management and explores how robots can enhance the sorting process by reducing worker health hazards while improving accuracy and efficiency. The paper highlights the benefits of employing robots equipped with automation, computer vision, and artificial intelligence systems for garbage sorting, thereby enhancing recycling efforts and promoting resource conservation. The study reviews current research on robotic garbage sorting, comparing gripper designs and algorithms, and outlining developments in the field. It also discusses key challenges to global deployment and explores potential future advancements.

In study (Liu et al., 2018) proposed the sorting system having two subsystems including hardware system which is based on the core module Raspberry Pi and the software one is based on image processing algorithm SURF-BoW and multi-class SVM classifier. This study succeeds with 100% accuracy for batteries and 83.38% for other categories when it is tested on 5 different types of wastes.

3. AI applications in waste management

3.1 Waste Wizard Robot

In the research paper by (Jacobsen et al., 2020), the authors present the Waste Wizard, a waste sorting robot designed to investigate public waste sorting practices and explore how such machines could contribute to this process, alongside other waste sorting robots. The Waste Wizard features two waste bins inside the robot designated for specific types of waste. The waste disposal process involves users dropping waste into the waste chute, which is situated directly on the conveyor belt. Subsequently, users are prompted to guess which bin the waste will be directed to. While the user is making their selection, asynchronous blinking lights on both buttons indicate ongoing processing. Regardless of the user's choice, the waste is directed into the appropriate bin based on the model's response.

Constructed with a wood lathe skeleton and covered with MDF panels, the Waste Wizard comprises four main components: the waste chute, conveyor belt, control box, and two rail-mounted waste bins. The waste chute includes side panels made of plywood, and cardboard panels for the front and rear, ensuring proper waste positioning when the lid is opened. The conveyor belt, repurposed from a caterpillar robot vehicle, is inverted on top of the control panel, and its motor positions are reversed using an Arduino Mega 2560 controlled by C++ programming and an L293d motor drive shield. The conveyor belt, with two motions, effectively sorts garbage into one of the two trash bins. The wooden control box houses electronic components, including a Raspberry Pi 3, capable of managing four tasks: taking an image using a NoIR Camera V2 after a user's guess, uploading the image to a cloud-hosted image categorization model, providing user input while awaiting model classification results, and sending commands to the Arduino Mega through USB-serial to operate the conveyor belt appropriately. The image classification model, implemented as a neural network using TensorFlow Machine Learning, is based on Google's Inception model. The classification model is encapsulated in a Python flask server wrapped in a

Docker container, enabling efficient processing of waste sorting based on visual recognition.

3.2 Waste robot

In the work by (Taho and LQ 2016), the authors developed a robotic system for waste detection and classification utilizing a camera, a robotic arm, a Raspberry Pi board, and the SSD_lite-MobileNetV2 model. The SSD (Single Shot MultiBox Detector) method proposed by (Liu et al., 2016) was employed for rapid waste detection. The study focused on waste items such as bottles, nylon, and scrap paper. A dataset was created containing images of these waste items, which were resized for the convolutional and pooling layers in the neural network. LabelImg software was utilized to annotate the images.

Convolutional Neural Network (CNN) is described as a two-, three-, or n-dimensional array of largely identical dynamical systems, referred to as cells. It fulfills two requirements: all state variables are signals with continuous values, and most interactions occur locally within a defined radius T. CNN is known for providing more accurate image classification (Chua et al., 1993). Its two fundamental components are feature extraction and classification. Feature extraction involves multiple convolution layers followed by max-pooling and an activation function, while the classifier typically comprises fully connected layers (Khoshdeli et al., 2017). The image is then transformed into a feature layer, converted into a single 1D vector, and sent to fully connected layers, determining the accuracy of the bounding box.

SSD, an object detection model using the Mobile Net architecture, exports position vectors into a matrix. It consists of two types of convolutions: Depth wise convolution, where each input channel is filtered separately, and pointwise convolution, which linearly combines the outputs of depth wise convolution. The feature is then imported into the SSD model, and cross-entropy classification is employed, measuring the difference between two probability distributions. The cross-entropy classification loss value is determined using an equation that incorporates regression loss. A 4-DoF robotic arm is used for waste manipulation, grasping, and placement into bins based on inverse kinematics calculations derived from bounding box coordinates post-detection.

Table 1. Comparision between models made by different authors

Author	Model	Accuracy
Ku et al.	Auto encoder CNN	90%
Ruiz et al.	VGG-16	76.94%
Ruiz et al.	VGG-19	79.32%
Ruiz et al.	Inception	87.71%
Ruiz et al.	ResNet	88.66%
Ruiz et al.	Inception-ResNet	88.34%
Mao et al	DenseNet121	95%
Shi et al	MLH-CNN	92.6%
Adedeji et al.	ResNet-50	87%
Proposed Model	SSD_lite-MobileNetV2	99%

The messaging protocol MQTT (Message Queuing Telemetry Transfer) is described as a straightforward and lightweight messaging protocol designed for devices with limited resources. The MQTT protocol consists of two primary components: the server and the client. The client is further divided into the information feedback machine and the sending communication machine. The 4-DoF robotic arm functions as the server, the sending communication device comprises the camera, and the feedback machine involves three trash bins.

3.3 Leather waste

The authors developed a model for sorting leather products in industrial waste using artificial intelligence (AI), employing a machine learning network architecture to create a detection model (Ghahramani et al., 2021). Their objective is to initiate the development of an automated waste detection system, offering significant benefits to the industry in garbage control. The authors utilized public datasets, namely Trash Net and Waste Picture, and employed software such as

Visual Studio Code, TensorFlow framework, LabelImg for data annotation, and RoboFlow for data modification.

Table 2. Results of the different scenarios

Scenario	Batch Size	Step	mAP	Accuracy	Presicion	Recall
Scenario1	8	20k	0,7418	0,6014	0,9610	0,6103
Scenario2	16	20k	0,7691	0,7791	0,9593	0,7795
Scenario3	32	10k	0,7611	0,8292	0,9628	0,8288
Scenario4	32	20k	0,8716	0,9211	0,9832	0,9201
Scenario5	64	10k	0,8813	0,9795	0,9985	0,9693
Scenario6	64	15k	0,6598	0,7195	0,8502	0,7195
Scenario7	100	15k	0,7114	0,7501	0,9698	0,7328
Scenario8	100	20k	0,7013	0,6514	0,9301	0,6421

The model implementation involves five stages. Firstly, data is collected, studied, and categorized into labels, with the determination of garbage coordinates. Subsequently, in the image repair stage, the image quality is enhanced and adjusted using a specified formula. The SSD (Single Shot MultiBox Detector) architecture is then employed to train the model. Lastly, the performance of the created model is assessed through two distinct evaluation methods: detection evaluation and classification evaluation. The detection evaluation involves measuring the mean average precision (mAP), while the classification evaluation assesses the accuracy, recall, and precision levels.

3.4 IOT based agent

The authors developed an Internet of Things (IoT)-based model in Dockland, Dublin, Ireland, integrating algorithms such as Genetic Algorithms (GA) and Artificial Neural Networks (ANN). Genetic Algorithms, introduced by Holland in 1975, emulate evolutionary processes and have found broad applications in various scientific and technological domains (Krol et al., 2016; Ghahramani et al., 2021). The GA employed in this study comprises phases such as parent selection, crossover, mutation, and the creation of a final population. To enhance the selection process, the authors introduced a hybrid roulette tournament pick operator. This modification adjusts the exploration-to-exploitation ratio by recombining crossover operators, influencing the generation of individuals in the mating pool. The model focuses on optimizing the collection of garbage by dispatching garbage collectors to locations based on the status of bins. Information about bins is gathered by querying the Application Programming Interface (API) of a waste management company, with HTTP requests and responses containing spatial and non-spatial data, including bin coordinates and status parameters. Spatial analysis, a critical aspect of the study, involves methods for areal data such as K-nearest neighbors, which is an instance-based algorithm suitable for situations with little or no prior knowledge about data distribution (Chua et al., 1993). The authors also employed graph neighbor approaches, specifically Delaunay triangulation and Gabriel graph methods, to address limitations in their spatial analysis. Given the NP-hard nature of the optimization problem and the computational cost of finding the shortest path, the authors adopted two metaheuristic techniques based on population-based models coupled with metaheuristic search algorithms. GA played a central role in creating a suitable algorithm, with two variants implemented: continuous and discrete. The discrete space model aimed to demonstrate superior performance. In both variants, bins were treated as bit strings, or chromosomes in GA terminology. The model utilized an initial population and genetic operators, such as crossover and mutations, to generate new generations by recombining population chromosomes. Fit individuals were selected based on the objective function.

Operators are employed to explore and exploit the search space, with a focus on finding the optimal solution through a crossover operation that traverses the input space. Mutation operators are also introduced to prevent premature convergence of the algorithm. These steps are iteratively repeated until specific termination criteria are met. The best solution, defined as the solution with the least cost at the end of the algorithm, is then selected.

A discrete Genetic Algorithm (GA) is implemented, coupled with a spatial objective function, where an initial population is randomly generated. Cost-effective chromosomes are classified and selected from the population. The parent selection phase creates a new population at each iteration, utilizing permutation crossover and permutation mutation operators in the regeneration phase. These procedures are repeated until the termination criteria are met.

The integration of an Artificial Neural Network (ANN) is crucial in this model. An ANN is an artificial intelligence technology that simulates the neural connections found in the human brain. In this context, the ANN is utilized to calculate the cost of each solution, and the parent selection phase selects two solutions. The Boltzmann selection method and Roulette Wheel mechanism are employed for diversity maintenance and sampling, respectively. After parent selection, a crossover operation is executed, creating new offspring through permutative crossover. To achieve permutative crossover, two cut points on each pairwise parent is considered, ensuring no conflicting bits and guaranteeing that each chromosome is a permutation without repetition. Mutation operators (insertion, inversion, and swap) are considered to prevent local minimum traps and maintain diversity. The ANN is integrated to reduce the cost function, measuring corresponding cost values in various iterations.

In a continuous context, GA is applied, encoding solutions with random keys. Unlike the previous method, where the order of bin visitation is represented by a stream of integers, each solution here consists of an integer part (pertaining to the permutation used) and a fractional part (indicating random key numbers assigned to bit strings). The starting population is created with n chromosomes, and various operators are used in an elitist manner to transfer the best solutions to the following generation. The reproduction phase generates new individuals based on predefined crossover and mutation rates. The reproduction phase involves parent selection after the initial population is generated, aiming to select solutions with the lowest possible cost, consistent with the ANN and cost function mentioned earlier. Bits are passed down to the newly added children based on a probability metric to maintain a diverse population. A mutation operator is incorporated to ensure diversity. A parameterized single crossover is explored to produce two new offspring when two parents are chosen. The algorithm's termination criterion is set to a maximum of 1000 iterations.

3.5 Smart Trash bin

In their work (Liu et al., 2016), the authors developed a smart waste sorting system utilizing image processing algorithms, specifically the SURF-BoW algorithm and a multi-class SVM classifier. Initially, the authors categorized the garbage into recyclables, large-size refuse, compostable garbage, hazardous waste, combustible waste, and hazardous waste. These categories were further divided into batteries, bottles, cans, paper-balls, and paper-boxes.

The hardware components used to create the smart trash bin include a Raspberry Pi3 Model B for the core module, a 720P webcam for the image acquisition module, BYGH40 stepping motor, motor controller, 12V DC power supply for the Stepping motor module, a wireless mouse, a 10-inch LCD monitor for the Auxiliary operation module, and a frame with stainless metal plates for the Mechanical framework module.

The SURF algorithm is employed to extract feature points, and a classic Bag-of-Words (BoW) model is combined with SURF to create a novel image feature extraction algorithm called SURF-BoW. For waste image classification, a multi-class SVM classifier is utilized. The SURF algorithm follows several steps, including the generation of an integral image, building the Hessian Matrix, establishing a scale pyramid with different sizes of box filter templates, and extracting feature descriptors.

The BoW model, commonly used in text analysis, is adapted for image classification. In the construction of SURF-BoW, a database called SURF is created, encompassing all images extracted by the SURF algorithm. Next, a dictionary (Dict kx64) is built based on K-Means clustering, and BoW is constructed for training images.

Support Vector Machine (SVM), a supervised machine learning algorithm based on statistical learning theory, is employed for training the model. The steps include inputting training data, calculating support vectors, obtaining parameters, and testing the training model. To effectively address multi-class problems, the authors chose to use a multi-class SVM for classifying waste images.

4. Transportation and Recycling

4.1 Transportation

Transportation means the transfer of waste from the source to the destination such as recycling centers through transportation. Transportation plays an important role in the waste management system because it provides the proper waste collection, transportation, and disposal of waste. Waste collection and transportation from the point of origin to disposal facilities are critical elements in ensuring public health and environmental sustainability. To transfer waste items safely and in line with regulatory standards, many means of transportation, Road Transport such as specialized trash collecting vehicles like trucks, Rail Transport which is used for long-distance Transportation, and water transport, are used. Transportation route optimization and the development of proper vehicles are very important for decreasing the environmental impact, fuel consumption, and overall operating expenses. Furthermore, the use of technology, such as route optimization software and GPS tracking, usage of Artificial Intelligence improves the accuracy and efficiency of garbage transportation, assuring prompt and dependable service. Sustainable waste transport techniques contribute to a cleaner environment and encourage responsible resource management throughout the waste cycle.

Nowadays the cost associated with transportation increases due to unorganized collection plans, and fewer vehicles. For this Artificial intelligence-based solutions have been developed and applied to optimize trash logistics and transportation operations. This artificial intelligence will decrease waste transportation and logistics from four perspectives such as travel distance, travel cost, travel time, and efficiency (Frang et al., 2016). One of the researchers stated an ant colony optimization algorithm-based vehicle routing solution. First, get 110 points for a certain Turkish city. After that, the point coordinates are converted and entered into a file. To generate a distance matrix, plot these locations on a map. Finally, the path with the least distance matrix is found by the ant colony optimization technique. The researchers found that to get the ideal result, the ant colony optimization method's tenth iteration may need to lower the transit distance by 13%. Additionally, several research has demonstrated that reducing trash transportation distance can be achieved by utilizing Dijkstra and Tabu search methods. Travel distance can be cut by 28% with the use of the Dijkstra and Tabu search algorithms. The ant colony optimization approach reduced waste transit lengths by 13% on average. Also, utilizing the Dijkstra-Tabu search algorithm reduced the distance travelled by waste by 28% (Frang et al., 2023).

Another innovative trash management concept is the intelligent dumpster, which is outfitted with AI programs and IoT sensors. The sensors on these dumpsters monitor the waste levels of the rubbish put inside and send this data to the main disposal system via intermediary servers for processing (Sharma et al., 2021). Garbage trucks, and vans can move in response to the alert and collect rubbish from the overflowing bins. Another one of the researchers has proposed a law called Genetic Algorithm which will optimize the vehicle routing, optimized garbage collection routes using GA and GIS. The study employed an altered Dijkstra algorithm in GIS to determine the best route alternatives and then applied the findings in GA to select the optimum route. The proposed technique reduced travel time, operational distance, and fuel consumption by 28, 8, and 3%, respectively (Sharma et al., 2021).in conclusion using artificial intelligence in waste logistics can reduce transportation distance by up to 36.8%, cost savings by up to 13.35%, and time savings by up to 28.22% (Frang et al., 2023).

4.2 Recycling

Recycling is a crucial component of waste management systems aimed at mitigating the environmental impact of garbage and conserving resources. The process involves reusing materials that were previously discarded. Waste materials, categorized as recyclable items and non-recyclable items, are collected to initiate recycling. Recyclable items, including paper, glass, plastics, and metals, are separated from general waste at the source. These materials are then transported to recycling centers where a combination of manual labor and automated machinery is used for sorting and separation. Following this, recyclables undergo cleaning and processing to transform them into raw materials suitable for the manufacturing of new products. The processed materials are subsequently sent for use in the production of new items. Recycling plays a significant role in preserving the environment and conserving resources by diverting materials from landfills and repurposing them. This approach fosters a more sustainable and eco-friendly method of waste management.

Various recycling methods exist, encompassing operations that aim to transform discarded materials into new goods. Examples of recycling methods include glass recycling, plastic recycling, agricultural recycling, textile recycling, E-waste recycling, hazardous recycling, among others. Each of these methods contributes to resource sustainability and environmental conservation, highlighting the importance of adopting diverse recycling practices in waste management systems.

5. Sorting Mechanisms

5.1 Automated waste sorting techniques

Automated trash sorting approaches leverage technology, including sensors, robots, and artificial intelligence, to streamline the sorting and recycling of waste products. These methods aim to enhance efficiency, increase recycling rates, and mitigate the environmental impact of waste disposal. In contrast, manual rubbish sorting conducted by human workers relies on visual inspection to identify different categories of waste.

The efficacy of manual sorting is influenced by factors such as the dimensions of the objects to be identified, the volume of mixed waste on the conveyor, and the speed of the conveyor. To automate the separation of recyclable waste, various sensors and technologies are employed depending on the materials involved. For instance, a specific automated waste sorting system has been designed to segregate metal, dry, and wet rubbish. In this system, a parallel resonance impedance device is utilized to separate metallic waste, while capacitive sensors distinguish between moist and dry waste. A novel method for recognizing nonferrous waste metals combines an electromagnetic sensor and a dual-energy X-ray transmission sensor, potentially replacing traditional ferro-silicon-based dense media systems (Satav et al., 2023). A mechanical separation procedure using a compressed air nozzle in an indirect sorting method, guided by a camera sensor to identify features, forces target items out of the mainstream. The sensor identifies the locations, colors, sizes, and shapes of each trash particle, utilizing these characteristics as sorting criteria. In managing plastic waste, three fundamental approaches are employed: mechanical recycling, feedstock recycling, and chemical recycling (Satav et al., 2023). These automated trash sorting processes can be integrated into recycling facilities, sorting centers, and waste management systems to enhance recycling efforts and reduce the amount of waste sent to landfills. The combination of these technologies holds the potential to improve overall efficiency and contribute to more sustainable waste management practices (Satav et al., 2023).

5.2 Waste sorting using robotic systems and AI

Intelligent robot technology for waste sorting has made significant strides in recent decades. Numerous studies have explored the application of robots equipped with sensors, computer vision, and robotic arms for the recognition and sorting of various types of waste. Examples include a robot vehicle and arm utilizing infrared, metal, ultrasonic, and moisture sensors to separate dry and damp garbage. Another robot arm was designed to sort plastic, biological, and metallic waste, with remote operation facilitated by Mobile Java software. Various robotic machines, such as an integrated system featuring an electronic robotic arm with sensors for sorting garbage into biodegradable and non-biodegradable categories, a modular Cartesian robot for sorting cardboard, and a robotic arm with five servomotors and a mechanical gripper for sorting multi-materials, have been developed. An additional application involves a robot arm with a two-finger gripper and a location and grasping AI system to separate opaque plastic containers, paperboard boxes, transparent plastic bottles, cans, and plastic bottles (Satav et al., 2023).

A new robot technology called SamurAI, developed by Machinex, is designed to sort recyclable materials faster than humans. This filtering robot employs Artificial Intelligence (AI) to recognize items on a moving belt, focusing on recyclable objects like bags, plastic bottles, and containers. The robot identifies objects, utilizes a suction file to remove them, and deposits them into the appropriate container (Ahmed et al., 2021).

Another innovative robot technology, Trashbot, is crucial for automatically separating recyclables from garbage. Equipped with an AI-powered robot garbage can system, Trashbot uses sensors and machine learning to determine the type of object when dropped into its tank. With an impressive accuracy rate of 90%, Trashbot efficiently categorizes items, allowing any fluids to be deposited in the appropriate tank. This technology is particularly suitable for large and dense waste-producing regions, such as retail malls, stadiums, railway stations, and airports (Ahmed et al., 2021).

Before the widespread application of Artificial Intelligence (AI) in recycling, the recycling sector faced numerous challenges, including inefficient sorting, inconsistent quality, maintenance issues, and limited innovation. Manual sorting, dependent on time-consuming and inaccurate techniques, led to inefficient sorting and high levels of contamination in recycling streams. Manufacturers were reluctant to use recycled materials due to inconsistent quality control. Recycling procedures and collection routes were often planned without data-driven decision-making, resulting in inefficient resource allocation and excessive operational costs. The sector encountered challenges related to efficiency, quality, contamination, and the inability to leverage data and technology for improved operations.

The introduction of artificial intelligence (AI) has played a vital role in overcoming these difficulties and enhancing recycling processes, incorporating advanced sorting technologies, real-time data analysis, contamination reduction, and environmental impact assessment. In conclusion, the evolution of artificial intelligence (AI) has brought automation, efficiency, and data-driven decision-making to recycling. This has substantially improved the sorting, processing, and management of recyclable materials, making recycling more sustainable and ecologically benign. AI has also facilitated the development of new waste management and recycling concepts and technologies.

6. Illegal Dumping and Waste Disposal

Illegal dumping refers to the unauthorized disposal of waste and garbage in both public and private areas, resulting in adverse effects on the surrounding ecosystem and potential health problems for the public and private individuals. The increasing rate of waste generation has become a significant issue globally. For example, South Korea has implemented the use of cameras in locations where illegal dumping is concentrated; however, the positive outcomes are limited despite the significant investment in materials and resources. Various waste disposal techniques, including physical, chemical, and pyrolysis gasification methods, aim to reduce waste volume and expedite waste purification. Human-generated waste needs to be collected, processed, and recycled to remove hazardous elements and decrease waste volume through composting organic matter. Landfilling, a common method for trash disposal, involves pouring garbage into deep trenches or depressions, followed by air-guiding, drainage, and anti-seepage measures. Despite its widespread use, landfills pose challenges related to odors, leachate, and siting. Researchers have proposed different methods, such as support vector machine regression time series techniques, multilinear perceptron's, and artificial neural networks, to predict leachate formation rates in landfills. Among these, the artificial neural network-multilinear perceptron approach with double hidden layers demonstrated superior performance.

Factors like socioeconomic status, demography, accessibility of trash collection services, recycling locations, and spatial features can influence illegal dumping in developing nations. Spatial regression analysis, incorporating geographically weighted regression (GWR) and ordinary least squares (OLS) techniques, reveals that elevation and population density are significant determinants of illegal trash disposal activities. Improper solid waste management techniques, such as burying, open burning, and illegal disposal, are prevalent in many developing nations, especially in rural areas with inadequate waste management infrastructure. The improper disposal of waste can release short-lived climate pollutants (SLCPs) and greenhouse gas (GHG) emissions, contributing to climate change. Poor waste management infrastructure, low income, lack of knowledge, and education levels are identified as causes of illegal dumping behavior.

The issue of illegal dumping extends to construction and demolition waste (CDW), where clean-up operations are expensive. Research on CDW dumpsites aims to increase awareness and understand the dynamics of these occurrences. Monitoring CDW dumpsites reveals insights into their characteristics and the factors driving them. The findings emphasize the importance of local solutions in managing CDW and provide valuable information for decision-making processes in less developed nations, addressing data gaps on the illicit disposal of CDW at a local level.

7. Case Studies

7.1 Case studies 1

The research worked on Efficient Waste collection optimization during covid -19 pandemic (with help of Genetic Algorithms in AI)

Genetic algorithms are a type of optimization algorithm, belonging to the class of heuristic algorithms inspired by natural evolution. They prove to be particularly valuable in addressing challenges related to waste management, such as waste collection. The COVID-19 pandemic posed significant challenges for waste management, with a shortage of trash collectors leading to uncollected trash on roads. Strategic planning of trash collection routes became essential to optimize resource utilization. In response to this, a proposed method actively involves users in generating and scheduling waste collection requests during the pandemic, focusing on hot spots and sealed areas within a city. This approach aims to optimize routes, resulting in 1.85 times increase in service time, which can have positive implications for various factors. The method utilizes Geographic Information System (GIS) technology to provide critical information about road conditions and routing areas for waste collection vehicles. A recent research study successfully combined genetic algorithms with Geographic Information Systems to optimize vehicle routing. The study focused on route optimization calculated through the GIS Dijkstra algorithm.

The solution demonstrated an 8% increase in operational space, a 28% reduction in traveling time, and a 3% decrease in fuel consumption (Rubab et al., 2022).

7.2 Case study 2

The research worked on Artificial Neural Networks in sorting in E-Waste

The integration of Artificial Neural Networks (ANNs) into recycling procedures significantly enhances the sorting precision. Traditional visible range image sensor (VIS) processing techniques encounter challenges in distinguishing between different e-plastics that share the same color. In a recycling process, as waste pieces enter the sorting machine, it is crucial for the machine to identify the types of plastics and separate them into their respective bins. To achieve this objective, three essential subsystems are required: advanced sensors capable of capturing spectral information, sophisticated algorithms that rapidly determine the types of materials based on the sensor-provided information, and mechanical actuators to effectively separate the materials into their designated bins. ANNs have proven to be a highly effective technique in accurately identifying materials, achieving an impressive success rate of 99% (Ruabab et al., 2023).

7.3 Case study 3

Napa waste Recycling company in California

The Napa Waste Recycling company, operating in California, specializes in recycling services. Historically, the company employed a traditional sorting methodology that heavily relied on manual labor in recycling procedures. However, this approach encountered several challenges. The human limitations, despite well-trained workers, made it difficult to consistently detect and collect recyclables, especially given the constantly changing material stream. Additionally, the manual sorting process faced limitations in terms of speed, hindering the workers' ability to process materials at a pace aligned with the company's revenue generation needs. To address these challenges, the company adopted an innovative approach by introducing AI-based classification machines. These machines are specifically designed to handle distinct types of recyclable waste. This strategic shift resulted in significant improvements, including a reduction in processing time and an increase in accuracy. Importantly, rather than laying off workers, the company reassigned them to different tasks. This transition to AI-based technology not only improved operational efficiency but also allowed the skilled workforce to contribute to other aspects of the company's operations (Thien-An Tran Luu, 2018).

7.4 Case study 4

Emmet county's Michigan Material Recovery Facility (MRF)

Before implementing AI-based sorting systems, the facility encountered several challenges, including issues related to line velocity—referring to the speed at which recyclables are sorted—and accuracy, particularly precision. In response to these challenges, the facility invested $800,000 USD to construct three functional AI-based waste sorting systems. The implementation of these AI systems resulted in significant improvements. Processing time saw a remarkable reduction of 60% compared to previous methods. Additionally, there was a 40% decrease in workload, showcasing the efficiency gained through AI technology. Notably, the AI-based systems led to an 11% increase in the amount of recyclable waste processed compared to previous techniques (Thien-An Tran Luu, 2018).

8. Conclusion

The conducted research underscores the imperative need to incorporate Artificial Intelligence (AI) techniques in waste management systems. Improper waste management poses detrimental effects on the environment, emphasizing the importance of addressing it through smooth, optimized, and efficient means. AI techniques, including Genetic algorithms, Artificial Neural Networks, Convolutional Neural Networks, etc., offer valuable tools for enhancing waste management processes. Illegal dumping, a significant contributor to pollution and improper waste management, highlights the urgency of effective solutions. The key determinants leading to illegal dumping include factors such as waste generation per capita and the quantity of waste collection facilities. Addressing these factors through the integration of AI techniques can play a pivotal role in improving waste management practices and mitigating the negative environmental impacts associated with improper waste disposal.

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