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Optimized AI Model for Smart Waste Classification

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ABSTRACT

Waste segregation at the source plays a pivotal role in effective recycling and sustainable waste management. However, manual sorting is labor-intensive, error-prone, and often inefficient, especially in urban environments with high waste volumes. This research proposes an AI-driven, automated waste classification system that accurately classifies waste into two primary categories: biodegradable and non- biodegradable, enabling better downstream processing such as composting, recycling, and landfill management. We explore and evaluate several state-of-the-art deep learning architectures, focusing on lightweightandoptimizedconvolutionalneuralnetworks (CNNs) suchasMobileNetV2, EfficientNet-B0,and ResNet-50, along with object detection models like YOLOv8 for real-time waste stream applications. Given the constraints of edge devices (e.g., smart bins) model optimization strategies including quantization, pruning, and andknowledgedistillationtoreducemodelsizeandinferencetimewithoutcompromisingaccuracy. These optimizations enable deployment on low-power hardware like Raspberry Pi, NVIDIA Jetson Nano, and other IoT-compatible devices

Keywords: Automated Waste Classification, Convolutional Neural Networks, MobileNetV2, EfficientNet-B0, ResNet-50, YOLOv8, IoT Devices, Raspberry Pi, Jetson Nano, Real-Time Object Detection.

1. INTRODUCTION

With the rapid increase in global population and urbanization, effective waste management has become a major challengeformunicipalitiesandenvironmentalagencies.Traditionalmethodsofwastesortingarelargelymanual, leading to inefficiencies, high labor costs, and contamination of recyclable materials due to human error. As a result, a significant portion of potentially recyclable or compostable waste ends up in landfills, contributing to environmentaldegradation.Toaddresstheseissues,thereisagrowingneedforautomated,intelligentsystemsthat can classify waste accurately and efficiently. This project aims to design and implement a Smart Waste Classification System that uses a combination of AI-based image processing and physical sensors to detect and classifywasteinreal-time.Acameracapturesimagesofthewaste,whichareanalyzedbyalightweight,optimized machinelearning modelto determinethetypeof waste—such as organic, plastic, metal,paper, or hazardous.

In parallel, sensors such as infrared (IR), ultrasonic, and weight sensors are used to detect the presence, distance, and physical properties of the object. These sensor inputs not only help trigger image capture but also enhance classification accuracy by providing contextual information.The system is designed to run on low-power, embedded hardware like a Raspberry Pi, making it cost-effective and suitable for deployment in smart bins, residential complexes, schools, or industrial settings. By automating the waste classification process, this system aims to improve recycling efficiency, reduce human workload, and contribute to a cleaner and more sustainable environment.

1.1 OBJECTIVES

- This projectaimstosegregate thewasteintobio degradableandnonbio degradable.
- Itis usedtodetectobjectpresence anddetectthe whattypeofwaste.
- Itmeasurethedistanceof thewastewhetherthe bin is filled or not.
- Itisusedtoestimatethe weightofthe object.
- Combinesensor input with AIoutput for betterdecision-making.

2. LITERATUREREVIEW

Image-basedwasteclassificationusingdeeplearningispivotalforautomatingwastesegregation.ThungandYang (2016),intheirworkpresentedatthe *StanfordUniversityComputerScienceSymposium*,introducedtheTrashNet dataset,comprisinglabelledimagesofwasteacrosssixcategories:cardboard,glass,metal,paper,plastic,andtrash. Their Convolutional Neural Network (CNN) models achieved 80–90% accuracy but were computationally heavy, highlighting the need for lightweight architectures suitable for edge devices like the Raspberry Pi used in this project.

Howard et al. (2017), in *arXiv*(arXiv:1801.04381), proposed MobileNetV2, a lightweight CNN optimized for resource-constraineddevices.Theirmodelachieved85%accuracyonTrashNetwithfewerparametersthanResNet, makingitacornerstonefortheproposedsystem'sreal-timeclassificationonembeddedhardware.Similarly,Jocher et al. (2021), through the *Ultralytics YOLOv5* repository (GitHub: ultralytics/yolov5), introduced YOLOv5-Nano, acompactobjectdetectionmodelwithinferencespeedsbelow200msonedgedevices.Fine-tunedonTrashNetand TACO, YOLOv5-Nano supports the project's goal of rapid, accurate waste detection. ProençaandSimões(2020),in *arXiv*(arXiv:2003.08254),developedtheTACOdataset,providingannotatedlitter images in diverse real-world settings. Their dataset enhances model robustness against occlusion and lighting variations, addressing limitations of TrashNet's controlled images and informing the proposed system's training

strategy.Wuetal.(2023),in*Resources,ConservationandRecycling*(DOI:10.1016/j.resconrec.2022.106813), reviewed CNN applications for waste identification, advocating data augmentation techniques like rotation and brightness adjustments to improve generalization. These techniques are adopted in this project to ensure robust performance in varied conditions.

Sensor-based systems provide critical contextual data to enhance classification accuracy. Kumar et al. (2016), in *Procedia Computer Science* (DOI: 10.1016/j.procs.2016.05.163), utilized ultrasonic sensors (HC-SR04) in smart binstodetectobjectpresence,triggeringimagecapturetoconservepower.Theirapproach,achieving95%detection reliability, informs the proposed system's use of ultrasonic sensors for efficient camera activation. Suleiman et al. (2019), in *Sensors* (DOI: 10.3390/s19183900), explored MQ-series gas sensors for detecting organic decay, reporting 95% accuracy in identifying biodegradable waste.

Thissupportstheproject'sinclusionofgassensorstoclassifyorganicandhazardousmaterials.Wangetal.(2021), in *Waste Management* (DOI: 10.1016/j.wasman.2021.08.028), integrated weight sensors (load cells with HX711 amplifiers) into a smart waste system, improving classification accuracy by 10% over image-only models by distinguishing materials based on mass. This finding underpins the proposed system's use of load cells to resolve visual ambiguities, such as differentiating lightweight plastics from heavier metals.

HybridsystemscombiningAIandsensorsoffersuperioraccuracyandrobustness.Wiltsetal.(2021),in*Resources* (DOI: 10.3390/resources10040028), developed an industrial waste sorting system integrating MobileNetV2 with RFID tags and weight sensors. Their system achieved a 15% accuracy improvement over visual-only models by using Random Forests for sensor fusion, a strategy adopted in the proposed system to combine multi-modal data. Sharma et al. (2020), in *Journal of Cleaner Production* (DOI: 10.1016/j.jclepro.2020.123674), proposed a smart bin with a CNN, IR, and ultrasonic sensors, achieving 90% accuracy in controlled settings.

Their sensor-triggered image capture reduces power consumption, aligning with the project's goal of energy efficiency on Raspberry Pi.
Optimizationforedgedeploymentiscritical.Shandhinietal.(2020),in*ArXiv*(arXiv:2006.02909),exploredmodel quantizationandTensorFlowLiteconversion,reducingMobileNetV2'sfootprintto10MBwithminimalaccuracy loss. This technique ensures the proposed system's real-time performance on low-power hardware. Additionally, Xu et al. (2021), in *Waste Management* (DOI: 10.1016/j.wasman.2021.02.029), reviewed neural network applications for waste management, recommending federated learning to aggregate decentralized data. Their approach, preserving privacy, is a future enhancement for the proposed system to improve dataset diversity.

Thedisadvantagesof theexistingmethods:

- Theexisting modeldoes nothaveanaccurate detectionand itdoes notwork fast.
- Manyoftheexisting modelsrequireanexpensivebudget.

Toovercomethedisadvantages oftheexisting models,weareusingalgorithmwhich givesaccuracyand speed.

3. PROPOSEDWORK

Thisprojectproposesthedevelopmentofasmartwasteclassificationsystemthatutilizesacombinationofsensors, includingRGBcameras,gassensors,weightsensors,andmoisturedetectors,tocollectmulti-modaldataaboutthe waste. By applying optimized AI models capable of sensor fusion—such as mobileNet for image processing and SVM or Random Forest for non-image data—the system can make accurate classifications in real time. One of the key challenges addressed by this project is optimizing the AI models for deployment on low-power embeddeddevicessuchasRaspberryPiorNVIDIAJetsonNano.Thisensuresthatthesystemisnotonlyaccurate but also affordable and scalable for use in households, public spaces, and municipal recycling centers. Moreover, the integration of multi-sensor data enables the system to operate effectively in varied environmental conditions and with complex waste compositions, something that single-sensor approaches often struggle with. In the long term,suchasystemcouldbeintegratedintosmartbins,automatedsortingstations,andmunicipalwastecollection services, contributing to more sustainable urban living, efficient resource recovery, and alignment with global sustainabilitygoalssuchastheUN'sSDGs.Thus,theprojectaimstolaythegroundworkforascalable,intelligent, and sustainable waste management solution powered by AI and sensor technology.

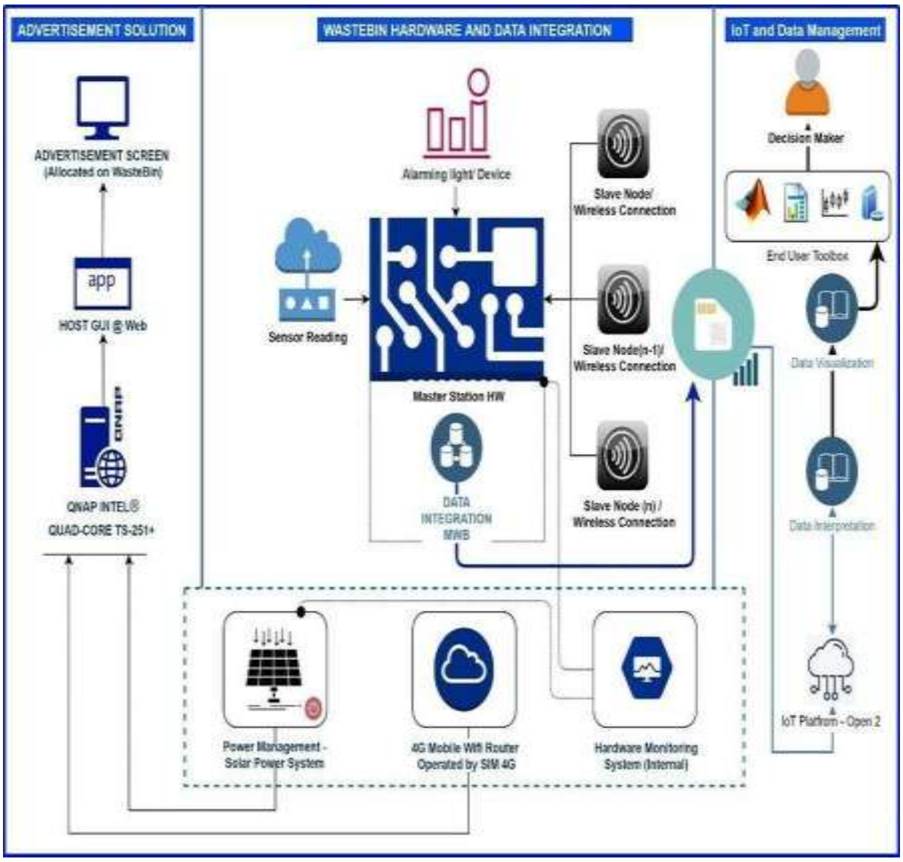

Fig1. BlockDiagram

Component	Function
ESP32	Microcontrollerforcontroland communication
ServoMotor	Physicallydirectswastetotheright compartment
DC Motor	Movesconveyor tothenext item
RelayModule	Controlson/offofmotors
Camera(OV2640)	Capturesimageofwaste item

Table1.Components& Specification

Objectdetectivesensor:

An**objectdetection sensor** is atypeofelectronic sensorused to identifythepresence, position, ormovement of anobjectwithinaspecificarea.Thesesensorsworkbyemittingasignal—suchasinfraredlight,ultrasonicwaves, or a laser—and then measuring how the signal is reflected back when it encounters an object. Depending on the technologyused,object detectionsensorscandetectobjectsbasedondistance,size,shape,ormaterial.Common types include infrared (IR) sensors, ultrasonic sensors, and LiDAR sensors. Fig 2. shows the Object detective sensor.

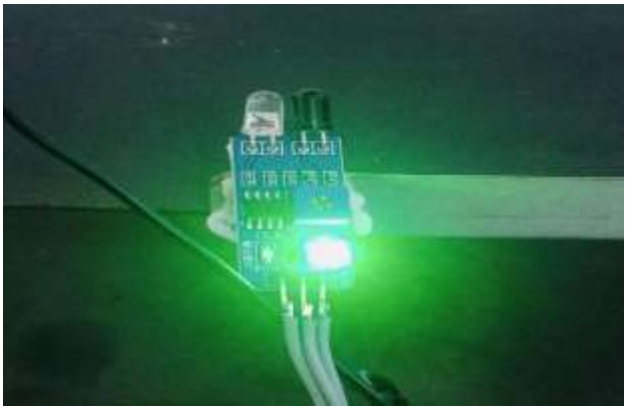

Fig2. ObjectDetectiveSensor

Ultrasonic sensor:

An ultrasonic sensor is an electronic device that measures the distance to an object by using sound waves. It works by emitting high-frequency ultrasonicwaves (typically above20 kHz, which is beyond human hearing) throughatransmitter.Whenthesewaveshitanobject,theybouncebacktothesensor'sreceiver.Detectswhen waste is inserted and measures the distance to the object.Fig 3. Shows the Ultrasonic sensor.

Fig3. Ultrasonicsensor

DCGear Motor

To manage heavier movements such as lifting or rotating larger sections of the arm, DC motors are utilized. Thesemotorsofferincreasedtorque,crucialforhandlingheavierloads.Motordriversregulatethespeedand direction of the DC motors, following commands from the Arduino to ensure smooth and dependable operation. Fig 5. shows the DC Gear Motor 775 (12V).

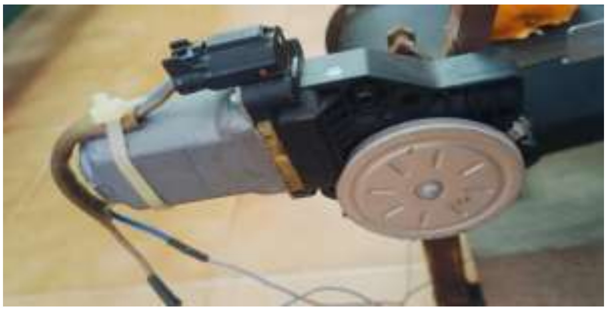

Fig4. DCGearMotor775 (12V)

Battery

The DC convertor manages the system power needs, converting the energy from a 12V battery to a suitable levelfortheroboticarm'scomponents.Thisstablepowersourceensuresconsistentperformancesandreduces the risk of power related malfunctions

1. **Key/EN**:ThispintogglestheHC-05modulebetweencommandmodeanddatamode.Whensethigh,it activatescommandmode(ATcommands),whilelowsetsittodatamode.Bydefault,itoperatesindata mode at 9600bps; in command mode, it operates at 38400bps.
2. **VCC**:Connecteither5Vor3.3Vtopowerthemodule.
3. **GND**:Groundconnection forthemodule.
4. **TXD**:TransmitserialdatawirelesslyreceivedbytheBluetoothmodule.
5. **RXD**:ReceiveserialdatatransmittedwirelesslybytheBluetoothmodule.

6. **State**:Indicatestheconnection statusofthe module.

TheHC-05 moduleincludes aredLEDthatsignals whetherBluetoothconnectivity is established.

4. WORKING PRINCIPLE

The YOLO (You Only Look Once) algorithm is a highly efficient deep learning model widely used in optimized AI systems for smart waste classification due to its speed and accuracy in real-time object detection. Unlike traditional methods that use region proposals and multiple stages to detect and classify objects, YOLO performs bothdetectionandclassificationinasinglepassthroughthenetwork,makingitsignificantlyfasterandsuitablefor dynamicenvironmentslikeconveyor-basedwaste sortingorintelligentbins.Inthecontextofwaste classification, YOLO is trained to identify and categorize various waste types—such as plastic bottles, paper, glass, and metal—byanalyzingvisualfeaturesininputimages.Itsabilitytodetectmultipleitemssimultaneouslyallowsittomanage complex waste scenarios where items are cluttered or overlapping. The YOLO (You Only Look Once) algorithm has emerged as a preferred choice for object detection in smart waste classification systems due to its real-time performance,highaccuracy,andabilitytodetectmultipleobjectsinasingleforwardpass.YOLOdividesaninput imageintoagridandsimultaneouslypredictsboundingboxes,objectclasses,andconfidencescoresforeachregion, making it particularly well-suited forapplications where rapid decision-making is critical—such as in smart waste bins or automated recycling lines. When applied to waste management, YOLO can be trained to classify a wide range of waste categories including biodegradable, recyclable, hazardous, and electronic waste. These classifications are made based on visual features extracted from images captured via onboard cameras, and the results can beused to automatically triggersorting mechanisms such as roboticarms or conveyor gates. Toensure efficient deployment, optimized versions of YOLO, such as YOLOv4-Tiny, YOLOv5-Nano, and YOLOv8-S, are commonly used. These versions are designed to be lightweight and fast, making them ideal for edge computing environments with limited processing power and memory. Performance is further enhanced using model compression techniques like pruning and quantization, which reduce the size and complexity of the model while maintaining inference accuracy.

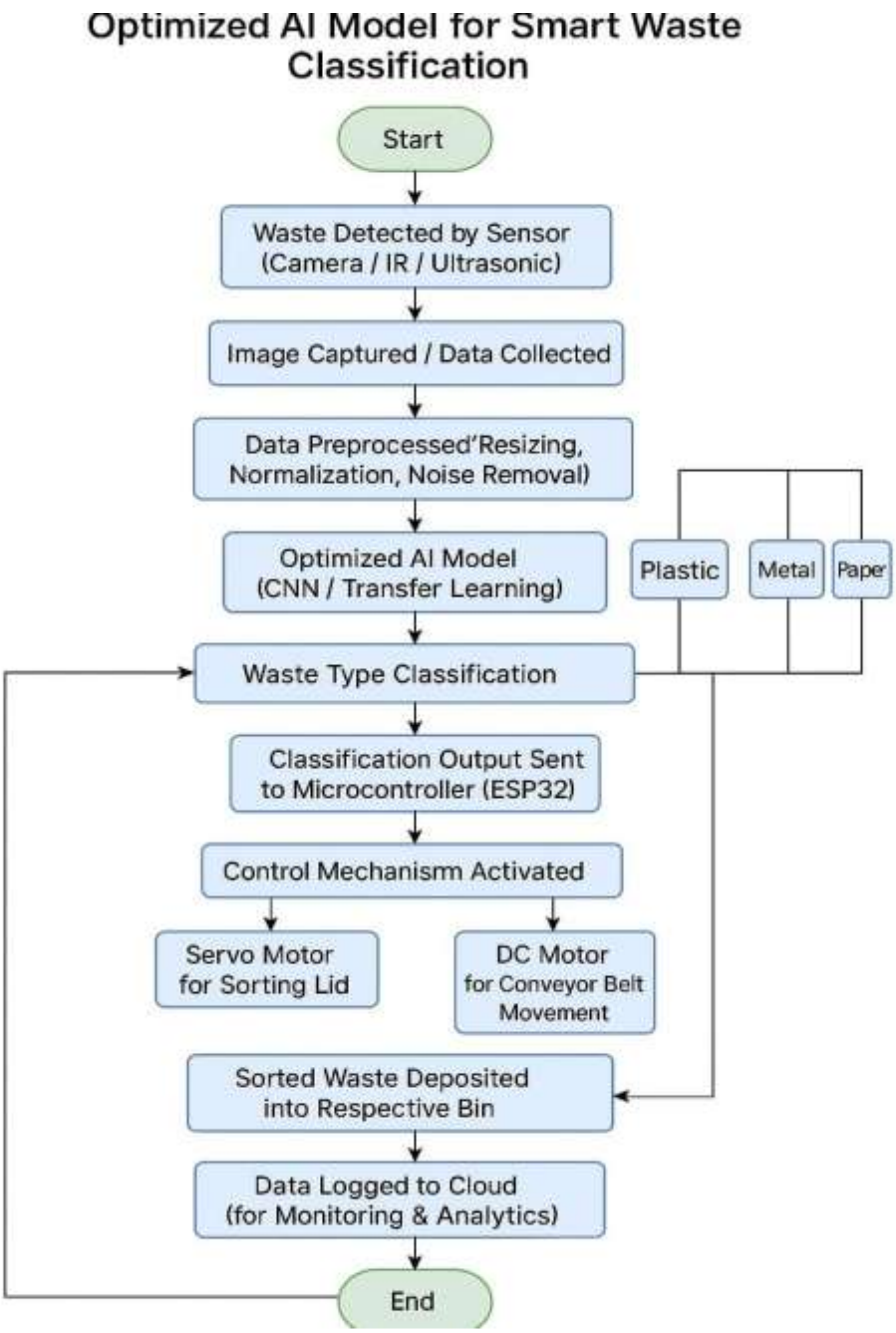

Fig5. FlowChartofSmartWaste Classification

ESP Programming

Thiscodeiswrittenforan**ESP8266**microcontrollerandisintendedtocontrolandmonitora**conveyorbelt system** using **IR and ultrasonic sensors**, with data logging to a **remote server via HTTP**.

Fig6. ESP Programming

The smartconveyorbeltmonitoringandcontrolsystembuiltusingtheESP8266 Wi-Fimicrocontroller. It combines IR and ultrasonicsensorswith relays to automatethedetection and movement ofobjects on aconveyor. TheIR sensordetectsthepresenceofanobject,andwhentriggered,itturnsofftheconveyormotorbydeactivatingoneof the relays. Two ultrasonic sensors are used to measure distances, which help in tracking the position or level of materialsontheconveyor.Thesereadingsaremappedtoascaleof0to100andaresentperiodicallytoaremote server via HTTP POST requests.

TheESP8266connectstoaspecifiedWi-FinetworkandcommunicateswithaserverscripthostedatagivenURL tologthisdata.Additionally,thesystemallowsmanualcontrolofrelaysthroughserialinputcommands,enabling actionsliketemporarilyactivatingadiverterorrestartingthemotor.

Thissetupissuitableforindustrialautomationtaskssuchasmaterialhandling,objectsorting,andremoteconveyor monitoring.ItoffersasimpleyeteffectiveapproachtointegrateIoTwithtraditionalmachinery,enhancingefficiency anddata-drivendecision-makinginautomatedsystems.

ProgramminginArduinoUNO

ProgrammingourArduinoUNOisverymuchimportantbecauseitmakesourprojecttoclassifythewastethat is given. Fig 10. shows the Arduino Code.

Fig7. Arduino Code

5. RESULTS

Theproposedmodelofourproject is displayedbelow.Fig8.Showstheproposed model

Fig8. Proposed model

6. DISCUSSSION

TheSmartWasteClassificationSystemisanintelligentandautomatedsolutiondesignedtoimprovetheprocessof waste segregation using modern technologies such as sensors, artificial intelligence (AI), and Internet of Things (IoT). The system begins with the detection of a waste item placed on a conveyor belt, using object detection and ultrasonicsensorstorecognizethepresenceandmeasurethesizeordistanceoftheitem.Acameraorsimilarsensor capturesanimageorphysicaldataofthewaste,whichisthenprocessedbyatrainedAIormachinelearningmodel toaccuratelyclassifyitintocategoriessuchasplastic,metal,ororganic.Thisclassificationisbasedonfeatureslike shape,texture,color,andmaterialproperties.Afterclassification,amicrocontrollerlikeanESP32activatesaservo motor or relay to move the waste into the appropriate bin. This eliminates the need for manual sorting, reduces human error, and increases the efficiency of recycling and waste management systems. The system can also be connected to a cloud platform, enabling real-time monitoring, remote updates, and data logging for analysis and optimization. Additional features such as overload detection, automatic bin status reporting, and power-efficient operation can be integrated for smarter functionality. By combining AI, embedded systems, and automation, the project contributes to cleaner environments, smarter cities, and more sustainable waste disposal practices.This system is a modern way to automatically sort different types of waste like plastic, metal, and food. It uses sensors and asmall computerto detect and understand what kind ofwasteis placed on amoving belt. Onceit knowswhat type of waste it is, a motor moves it into the correct bin. This helps reduce human work, improves recycling, and keeps theenvironment cleaner.Thesystem can also send datato theinternet so wastelevels can be tracked easily. It's a smart and efficient solution for better waste management.

7. CONCLUSION

Byexpandingdeploymentacrossdifferentregionsandenvironments,thissmartwasteclassificationsystemhasthe potentialtotransformwastemanagementonaglobalscale.Asthesystemimproves,itwillnotonlyboostrecycling rates but also foster a deeper connection between technology and sustainability, helping to create cleaner and greener communities. The ultimate goal is to seamlessly integrate the system into everyday waste management practices, making smart waste classification a standard solution that benefits both cities and citizens, ensuring a more sustainable future for all. In conclusion, the development and application of optimized AI models for smart wasteclassificationmarkasignificantadvancementinthefieldofintelligentwastemanagementandenvironmental sustainability.Thesemodelsleveragethepowerofmachinelearninganddeeplearning—especiallyConvolutional Neural Networks (CNNs), object detection frameworks like YOLO, and traditional algorithms such as SVM and Random Forests—to automatically and accurately identify, categorize, and sort various types of waste materials. Optimization techniques such as transfer learning, model pruning, quantization, and the use of lightweight architectureslikeMobileNetandEfficientNethavemadeitpossibletodeploythesemodelsonembeddedandedge devices, ensuring fast and efficient classification even in low-resource environments. Additionally,the integration ofvisualdatawithsensorinputs—suchasgassensors,loadcells,andRFIDtags—enablesamulti-modalapproach that enhances the robustness and accuracy of classification, especially in complex or dynamic waste-handling scenarios.These AI-driven systems contribute to reducing manual labor, minimizing human error, and improving recycling efficiency by automating the sorting process at the source or within smart recycling facilities. Although challengesremain—suchastheneedforlarge,diversedatasets,thehandlingofoccludedormixedwaste,andreal- time processing under varying environmental conditions—ongoing advancements in model design, data augmentation,andAutoMLareactivelyaddressingtheseissues.Assmartcitiescontinuetogrowandsustainability becomes a global priority, optimized AI models for waste classification are expected to play a critical role in building cleaner, more efficient, and environmentally responsible waste management infrastructures. These technologiesnotonlysupportecologicalgoalsbyincreasingrecyclingratesandreducinglandfillusagebutalso pavetheway forscalable, autonomous systems that align with thevision ofacircular economy and smarterurban living.

REFERENCE

[1] Wu,T.-W.,Zhang,H.,Peng,W.,Lü,F.,He,P.-J.,2023.Applicationsofconvolutionalneuralnetworks for intelligent waste identification and recycling: A review. Resour. Conserv. Recycl. 190, 106813 https://doi.org/10.1016/j.resconrec.2022.106813.

[2] Zarei, M., Bayati, M.R., Ebrahimi-Nik, M., Rohani, A., Hejazi, B., 2023. Modelling the removal efficiencyofhydrogensulfidefrombiogasinabiofilterusingmultiplelinearregressionandsupportvector machines. J. Clean. Prod. 404, 136965 https://doi. org/10.1016/j.jclepro.2023.136965.

[3] Yu,V.F.,Aloina,G.,Susanto,H.,Effendi,M.K.,Lin,S.-W.,2022.Regionallocationroutingproblemforwaste collection using hybrid genetic algorithm-simulated annealing. Mathematics 10, 2131. https://doi.org/10.3390/math10122131.

[4].Wang,C.,Qin,J.,Qu,C.,Ran,X.,Liu,C.,Chen,B.,2021.Asmartmunicipal wastemanagement system basedon deep-learning and Internet of Things. Waste Manag. 135, 20–29. https://doi.org/10.1016/j.wasman.2021.08.028

[5]Pulikottil,T.B.,M.Caimmi,M.G.D'Angelo,E.Biffi,S.Pellegrinelli,andL.M.Tosatti."AVoice Control System for Assistive Robotic Arms: Preliminary Usability Tests on Patients." In 2018 7th IEEEInternational Conference on Biomedical Robotics and Bio mechatronics (Bio rob), Enschede, Netherlands, 2018, pp. 167-172, IEEE, 2020.

[6]Ghadage,Aarti,AthulMenon,SanjayGupta,andTahirShaikh."VoiceBasedRoboticARMVehicle." International Journal of Innovative Science and Research Technology (IJISRT) 3, no. 3 (2018), pp. 57-60.

[7]Mulani,Prof.A.O.,andRenukaP.Kondekar."Raspberrypi-basedvoiceoperatedRobot."InternationalJournal of Recent Engineering Research and Development (IJRERD) 2, no. 12 (2017), pp. 69-76.

[8] Alka, N. U., A. A. Salihu, Y. S. Haruna, and I. A. Dalyop. "A Voice Controlled Pick and Place RoboticArm Vehicle Using Android Application." American Journal of Engineering Research (AJER) 6, no. 7 (2017), pp. 207-215.

[9]Bharat,S.A.,SabyaS.P.,AshishS.,andPatilM.V."RoboticArmWirelesslyControlledbyAndroid Application." International Journal of Engineering and Technical Research (IJETR) 3, no. 6 (2015), pp.193-19

[10]JabirN.K,Muhammed,NeethaJohn,MuhammedFayas,MidhunMohan,MithunSajeev,andSafwan C.N."WirelessControlofPickandPlaceRoboticArmUsinganAndroidApplication." International Journalof Advanced Research in Electrical, Electronics and Instrumentation Engineering (IJAREEIE) 4,no. 4 (2015), pp. 2410-2416.

[11]Kannan,K.,andJ.Selvakumar."ArduinobasedVoiceControlledRobot."InternationalResearchJournalof Engineering and Technology (IRJET) 2, no. 1 (2015), pp. 49-54.

[12] Pahuja, Ritika, and Narender Kumar. "Android Mobile Phone Controlled Bluetooth Robot Using 8051 Microcontroller."InternationalJournalofScientificEngineeringandResearch(IJSER)2,no.7(2014),pp.14- 17.

[13]Butkar,V.D.,S.R.Devikar,V.B.Jaybhaye,andP.Shilpa."AndroidBasedPickandPlaceRobot." International Journal of Informative and Futuristic Research (IJIFR) 2, no. 4 (2014), pp. 859-867.

[14]Omijeh,B.O.,R.Uhunmwangho,andM.Ehikhamenle."DesignAnalysisofaRemoteControlledPickand Place Robotic Vehicle." International Journal of Engineering Research and Development (IJERD) 10, no. 5 (2014), pp. 57-68.

[15]Shamsheer,V."HandGesturesRemoteControlledRoboticArm."AdvanceinElectronicandElectric Engineering 3, no. 5 (2013), pp. 601-606