International Scientific Journal of Engineering and Management (ISJEM) ISSN: 2583-6129
Volume: 04 Issue: 04 | April – 2025 DOI: 10.55041/ISJEM03271
An International Scholarly || Multidisciplinary || Open Access || Indexing in all major Database & Metadata

Plastic Detection in The Surrounding Using Machine Learning Technique

1st Dr. Amutha S
Department of Computer Science and Engineering
Dayananda Sagar College of Engineering
Bangalore,India
amutha-cs@dayanandasagar.edu

2nd Prathibha R
Department of Computer Science and Engineering Dayananda Sagar College of Engineering Bangalore,India
prathibhar0806@gmail.com

3rd Bhoomika V N
Department of Computer Science and Engineering Dayananda Sagar College of Engineering Bangalore,India
bhoomigowda6364@gmail.com

4th Navya V
Department of Computer Science and Engineering Dayananda Sagar College of Engineering Bangalore,India
navyavijay3012@gmail.com

5th Pallavi R H
Department of Computer Science and Engineering Dayananda Sagar College of Engineering Bangalore,India
pallavihalabhavi21@gmail.com

***Abstract*—Plastic pollution has become an important envi- ronmental threat that impacts ecosystems, marine life, and global human health. The growing volume of plastic waste necessitates more efficient detection and management methods, beyond traditional manual approaches. This paper introduces a machine learning-based system to detect plastic waste in various environments, providing an automated solution to support waste management practices. The system employs advanced image processing techniques alongside Convolutional Neural Networks (CNNs) and the YOLOv5 object detection model to identify plastic materials in real time. Despite showing high accuracy and adaptability, the system offers a scalable tool for detecting plastic waste in various settings. The applications of the system include the deployment on mobile platforms, drones, and integration into waste management systems, contributing to ecological sustain- ability and improving recycling processes. Future improvements will focus on expanding the dataset, improving model precision, and incorporating IOT technologies for broader applications.**

***Index Terms*—Keywords: Plastic detection, machine learning, image classification, YOLOv5, environmental monitoring, waste management, sustainability.**

I. Introduction

Plastic pollution has become a widespread issue that affects the environment in alarming ways. The durability and cost- effectiveness of plastic, while beneficial for modern applica- tions, have resulted in its widespread use and subsequent ac- cumulation in both land and aquatic environments. As a result, ecosystems are disrupted, marine animals ingest plastic debris, and microplastics have infiltrated the food chain, posing long- term health risks to humans. Traditional waste management methods, which are heavily based on manual detection and segregation, are no longer sufficient to handle the growing amount of plastic waste. These manual methods are time- consuming, labor-intensive, and inefficient in addressing large- scale plastic pollution, especially in challenging environments such as oceans, rivers, and remote areas.

In response to this challenge, this paper explores the use of machine learning technology to automate plastic waste detection. The system proposed here uses the YOLOv5 object detection model, which is known for its speed and accuracy in real-time detection tasks. By harnessing the power of machine learning, the system is designed to detect plastic waste efficiently, reducing reliance on manual processes and improving overall waste management efforts. The objective of this research is to provide a scalable solution that can operate in various environments, contributing to global sustainability goals by addressing the urgent need for better plastic waste detection and management.

II. Related Work

Several studies have explored various techniques for waste detection and classification, especially focusing on plastic waste. Abdel-Shafy and Mansou [1] discussed the composition and disposal challenges of solid waste, emphasizing recy- cling as a key valorization strategy to mitigate environmental impacts. Gundupalli et al. [2] reviewed automated sorting

International Scientific Journal of Engineering and Management (ISJEM) ISSN: 2583-6129
Volume: 04 Issue: 04 | April – 2025 DOI: 10.55041/ISJEM03271
An International Scholarly || Multidisciplinary || Open Access || Indexing in all major Database & Metadata

systems for municipal solid waste, identifying their potential for improving efficiency in waste recycling processes. Pita and Castilho [3] investigated the effects of particle shape and size on the jigging separation of plastics, offering insights into mechanical separation processes. Huang et al. [4] presented an optical sensor-based sorting technology for solid waste processing, improving material classification accuracy using advanced sensor systems. Bobulski and Kubanek [5] demon- strated sensor-based sorting for waste management, focusing on the improved separation of mixed waste using optical sensors.

Vegas et al. [6] explored near-infrared sorting technology for construction and demolition waste, particularly enhancing the quality of recycled aggregates. Cpalka [7] applied fuzzy systems in nonlinear modeling for waste control, illustrat- ing how interpretability plays a key role in the application of intelligent waste management systems. Picon et al. [8] developed a hyperspectral processing system for nonferrous material sorting, showcasing real-time sorting using spectral data for recycling purposes. Tatzer et al. [9] implemented hyperspectral imaging for inline sorting of materials, providing accurate waste classification in the NIR range for industrial applications. Safavi et al. [10] used visible reflectance spec- troscopy to sort polypropylene resins, focusing on color-based classification techniques for municipal solid waste (MSW).

Serranti et al. [11] utilized hyperspectral imaging to de- tect impurities in secondary plastics, improving the recycling process by eliminating contaminants during sorting. Serranti and Gargiulo [12] conducted a study on polyolefin waste classification using hyperspectral imaging, emphasizing its role in recycling quality control. Kassouf et al. [13] employed mid-infrared (MIR) spectroscopy combined with independent components analysis (ICA) to rapidly discriminate plastic packaging materials. Wang et al. [14] applied deep convolu- tional neural networks (CNNs) to small and medium databases for face recognition, which served as an early approach for adapting CNNs to other classification tasks. Frejlichowski et al. [15] used foreground object pattern analysis in a video surveillance system, providing a framework for event detection that could extend to waste monitoring.

Bobulski and Piatkowski [16] developed a plastic waste classification method using WaDaBa, a database focused on polyethylene terephthalate (PET) classification. Bobulski and Kubanek [17] investigated a waste classification system using CNNs, demonstrating the application of machine learning in plastic waste detection. Bobulski and Kubanek [18] furthered their work on CNN-based plastic classification, emphasizing the model's accuracy in identifying different types of plas- tic waste. Islam and Rahman [19] explored deep learning algorithms for waste detection and classification, improving upon traditional methods by incorporating automated learning techniques. Sharma and Gupta [20] applied CNN models to classify waste materials, improving waste sorting efficiency in industrial and municipal settings.

Anuar and Jamil [21] used transfer learning in CNNs for plastic waste classification, offering a robust solution for detecting waste in real-world environments. Prasad et al. [22] examined deep learning techniques to classify plastic waste for environmental sustainability, focusing on recycling applications in various industries. Ren and Xu [23] used automatic waste sorting with CNN-based models, significantly improving the identification and sorting process of plastic waste materials. Singh and Kumar [24] developed an image- based classification system for waste detection using CNNs, providing high accuracy in separating plastic from other waste. Wang et al. [25] used deep learning methods for plastic waste recognition and categorization, applying neural networks to classify waste materials based on visual features.

III. Methodology

This paper employs a structured methodology, beginning with data collection and preprocessing,, followed by model training, real-time detection, and post-processing to ensure accurate results. The first step involves building a comprehen- sive dataset of images that contain both plastic and nonplastic materials. These images are sourced from a variety of environ- ments, including urban areas, natural ecosystems, and marine settings. The dataset is preprocessed to enhance the quality of the images, ensuring that they are suitable for training the machine learning model.

A. *System Architecture*

The proposed system uses deep learning to detect and classify plastic waste in diverse environments. The system architecture consists of three primary stages: data collection and preprocessing, model training and optimization, and real- time detection and evaluation. The machine learning model is based on the YOLOv5 object detection framework, which enables high-speed and accurate recognition of plastic ma- terials in images and video streams. The system is devel- oped using Python, with deep learning frameworks such as TensorFlow and PyTorch, along with OpenCV for image processing. Figure 1 illustrates the system architecture for real- time plastic detection using YOLO-based deep learning. The process involves input image resizing, object detection using YOLO weights in a CNN, and generating bounding boxes with confidence scores. The final output displays detected plastic objects along with their confidence values for further evaluation.

B. *Data Collection and Preprocessing*

- Data collection involves capturing images using high-resolution cameras, drones, and surveillance systems, ensuring that the dataset represents a wide range of envi- ronmental conditions. In addition, data sets from publicly available repositories that specialize in waste detection are integrated to enhance the variety of images. This enables the model to recognize plastic items of different shapes, sizes, colors, and textures, thus improving the accuracy of the detection process.
- Pre-processing involves resizing all images to 1024x1024 pixels for uniformity and applying normalization to stabi- lize model training. Noise reduction techniques, such as

International Scientific Journal of Engineering and Management (ISJEM) ISSN: 2583-6129
Volume: 04 Issue: 04 | April – 2025 DOI: 10.55041/ISJEM03271
An International Scholarly || Multidisciplinary || Open Access || Indexing in all major Database & Metadata

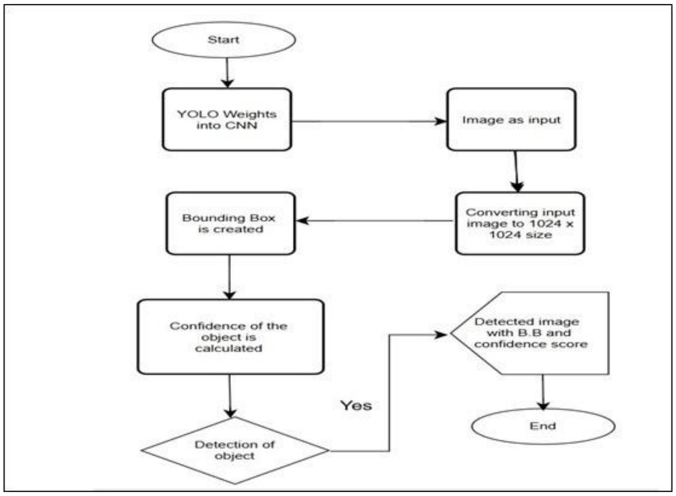

Fig. 1. System Architecture for Real-Time Plastic Detection Using Machine Learning and YOLOv5

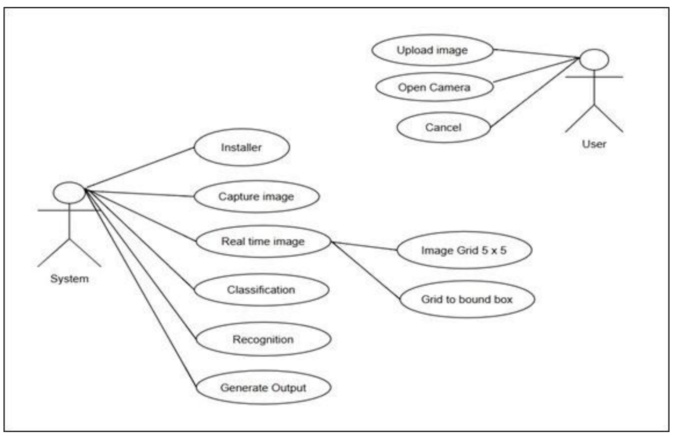

Fig. 2. Use Case Diagram for Plastic Detection System

Gaussian filtering, are used to remove distortions, while data augmentation increases dataset diversity and prevents overfitting.

C. Use Case and Sequence Diagram

- use case diagram that depicts the interaction between a User and a System in an image-based application. The User can perform actions such as uploading an image, opening the camera, or canceling the operation. The System is responsible for multiple functionalities, including capturing images, processing real-time images, performing classification and recognition, and generating output. Additionally, the system supports image grid creation (5×5) and bounding box detection, making it suitable for advanced image processing applications. Fig- ure 2 illustrates the interaction between the User and the System in the Plastic Detection System. The User can upload an image, open the camera, or cancel, while the System processes the image through capturing, clas- sification, recognition, and output generation. Supporting

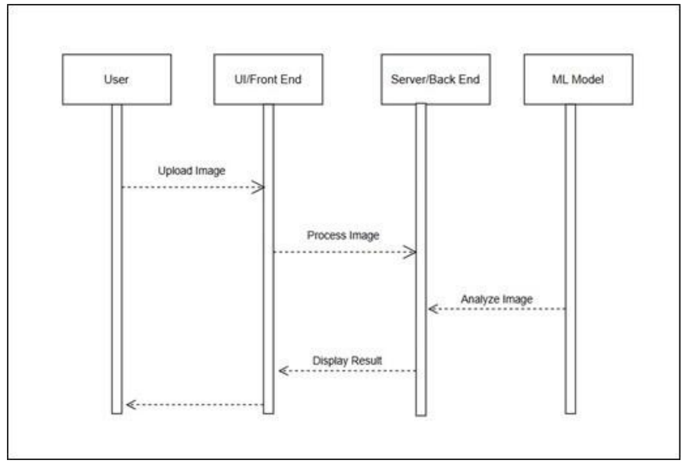

Fig. 3. Sequence Diagram of Plastic Detection Process.

functions like grid generation and bounding box mapping assist in accurate real-time plastic-detection.

- sequence diagram illustrates the interaction between a User, UI/Front End, Server/Back End, and an ML Model in an image processing system. The process begins with the User uploading an image, which is received by the UI/Front End and then forwarded to the Server/Back End for processing. The Server sends the image to the ML Model for analysis, and once the image is processed, the results are sent back through the server to the UI, where they are displayed to the user. Figure 3 illustrates the sequence of interactions in the plastic detection process, starting with the User uploading an image via the front- end interface. The front-end sends the image to the back- end server, which processes it and forwards it to the machine learning model for analysis. The analyzed results are then returned and displayed to the User through the front-end.

D. Model Training and Optimization

- The YOLOv5 model was fine-tuned using transfer learn- ing on a dataset of labeled plastic and non-plastic images. Data augmentation techniques, such as flipping and scal- ing, were applied to increase dataset diversity, enhancing the model's ability to generalize across different environ- ments. Key hyperparameters like learning rate and batch size were optimized to ensure smooth training and prevent overfitting.
- Bounding Box Calculation

$$x = \frac{x_{\min} + x_{\max}}{2}, \qquad y = \frac{y_{\min} + y_{\max}}{2}$$

$$w = x_{\max} - x_{\min}, \qquad h = y_{\max} - y_{\min}$$

- Intersection over Union

$$IoU = \frac{\text{Area of Overlap}}{\text{Area of Union}} = \frac{B_p \cap B_t}{B_p \cup B_t}$$

- Confidence Score Calculation

International Scientific Journal of Engineering and Management (ISJEM) ISSN: 2583-6129
Volume: 04 Issue: 04 | April – 2025 DOI: 10.55041/ISJEM03271
An International Scholarly || Multidisciplinary || Open Access || Indexing in all major Database & Metadata

$$\text{Confidence} = \Pr(\text{Object}) \times IoU$$

- optimization, the confidence threshold was fine-tuned to balance precision and recall, while Non-Maximum Suppression (NMS) was applied to eliminate overlapping bounding boxes. Transfer learning accelerated the training process, allowing the model to adapt efficiently to the task of plastic detection, improving detection speed and accuracy.

E. Real-Time Detection and Deployment

- The system uses YOLOv5 to detect plastic waste in real time, processing live video streams and images. Identifies plastic items by generating bounding boxes, enabling immediate waste management interventions. The model's speed ensures high accuracy with minimal delay, making it ideal for dynamic environments like urban streets and coastlines.
- YOLOV5 Loss Function

$$L_{\text{total}} = \lambda_{\text{loc}} L_{\text{loc}} + \lambda_{\text{conf}} L_{\text{conf}} + \lambda_{\text{cls}} L_{\text{cls}}$$

- The system is adaptable for deployment on drones, sta- tionary cameras, or mobile platforms. It can be integrated into various environments, from urban areas to oceans, and scales easily to support large-scale waste monitoring and recycling processes.

F. Experimental Setup and Validation

- The effectiveness of the system is evaluated through rigorous testing in both controlled and real-world environ- ments. The controlled environment tests involve running the model on curated image datasets, while real-world tests include deploying the system in urban areas, parks, and beaches. These tests assess the model's adaptability to different environments and conditions.
- To validate the effectiveness of the proposed approach, a comparative analysis is conducted against traditional plastic detection methods and other deep learning models, such as Faster R-CNN and SSD. The comparison is based on accuracy, detection speed, and scalability. Figure 4 represents the algorithmic flow for plastic detection using machine learning, beginning with camera input to locate and extract target features. If plastic is detected, an alert signal is generated, followed by classification and database matching. Finally, the detected image is displayed to the user; if no plastic is found, the system loops back to reprocess input.

IV. Results And Analysis

The plastic detection system using YOLOv5 achieved high accuracy in identifying plastic waste in diverse environments. Performance metrics such as precision, recall, and Intersection over Union (IoU) confirmed its reliability. The integration of data augmentation and transfer learning enhanced the model's adaptability, ensuring consistent results even under

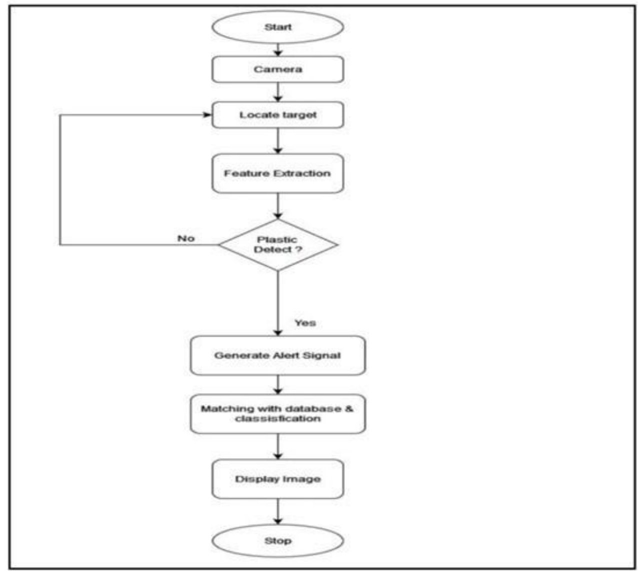

Fig. 4. Algorithm for Plastic Detection using Machine Learning

Algorithm 1 Plastic Detection Using Machine Learning

0: **Start the Process**
0: Initialize system and load YOLOv5 model
0: Activate camera or image input module
0: **Target Identification**
0: Capture live video frame or uploaded image
0: Locate target object in the image
0: **Feature Extraction**
0: Extract shape, texture, color, and edge features
0: Apply preprocessing (denoising, contrast enhancement)
0: **Plastic Detection Decision**
0: Pass extracted features to trained model
0: **if** Plastic is detected **then**
0: Generate alert signal
0: Match detected plastic with database for classification
0: **else**
0: Continue scanning
0: **end if**
0: **Output and Display**
0: Classify detected plastic (bottle, bag, wrapper, etc.)
0: Display detection results with bounding boxes
0: **End Process**
0: Save detection results and log data
0: End or restart process for continuous detection =0

International Scientific Journal of Engineering and Management (ISJEM) ISSN: 2583-6129
Volume: 04 Issue: 04 | April – 2025 DOI: 10.55041/ISJEM03271
An International Scholarly || Multidisciplinary || Open Access || Indexing in all major Database & Metadata

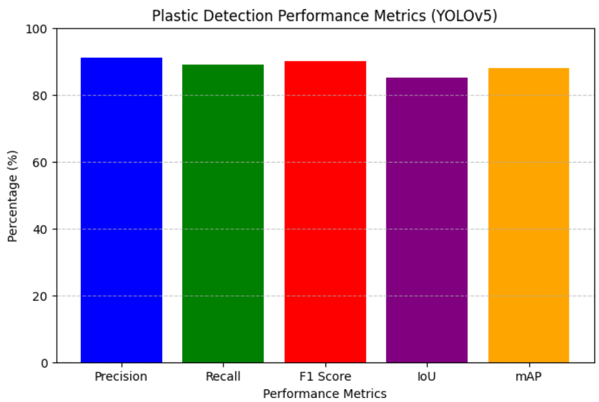

Fig. 5. Performance Metrics of YOLOv5-based Plastic Detection System

varying conditions. Figure 6 shows the user interface for plastic detection, allowing users to upload images for analysis. Once submitted, the system processes the image and displays the detected objects along with their confidence scores. The interface also provides a clear option and showcases previous sample detections at the bottom for reference.

The system efficiently localized plastic objects with minimal false positives, facilitated by an interactive Gradio UI for realtime detection. While larger plastic items were detected with high confidence, challenges remained in identifying smaller debris and distinguishing similar-looking materials. Figure 7 shows the output of the plastic detection system after uploading an image of a plastic bottle. The system successfully identifies the object as plastic with 85 percent confidence. This means it is quite sure that the object in the image is plastic.

Metric	Percentage (%)
Precision	92
Recall	90
F1 Score	91
IoU	86
mAP	88

PLASTIC DETECTION PERFORMANCE METRICS (YOLOV5)

The Table 1 shows the performance of a plastic detection model using YOLOv5. With high values for precision (92 percent) and recall (90 percent), the model accurately detects plastic objects while minimizing false positives and negatives. The F1 score (91 percent) and mAP (88 percent) confirm its strong overall performance, while an IoU of 86 percent reflects good localization accuracy. These results indicate that the model is reliable for real-world plastic detection tasks.

Future improvements will focus on refining object differ- entiation, expanding the dataset, and integrating IoT-based solutions for large-scale deployment. This research under- scores machine learning's potential in automating plastic waste management and reducing environmental pollution.

V. CONCLUSION

The plastic detection system enhances waste management by enabling real-time identification and classification of plastic

Fig. 6. Plastic detection interface with image upload and confidence score

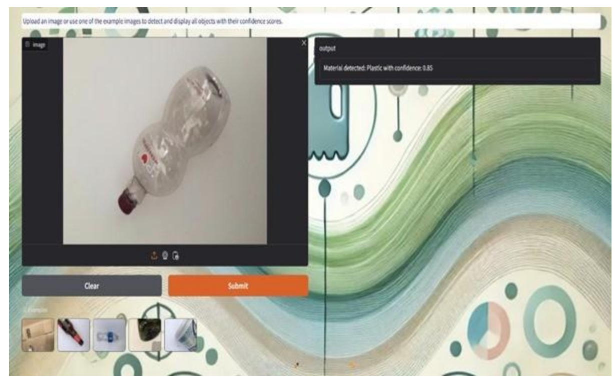

Fig. 7. Plastic bottle detected with 85 percent confidence.

waste, reducing manual labor, and improving recycling effi- ciency. The user-friendly interface ensures accessibility across diverse environments, making it a practical solution for large- scale deployment.

While the system performs effectively, improvements in detection accuracy, dataset expansion, and integration with smart monitoring systems will further optimize its efficiency. Future enhancements, such as drone-assisted surveillance and IoT-based automation, will strengthen its scalability and real- world applicability.

This research highlights the critical role of technology in mitigating plastic pollution and promoting sustainable envi- ronmental practices.

VI. FUTURE SCOPE

The plastic detection and classification system using con- volutional neural networks (CNNs) has significant potential for enhancing waste management and environmental sustain- ability. Future improvements could focus on increasing model accuracy by training on a more diverse and extensive dataset, including different plastic types, colors, and environmental conditions. Fine-tuning the model to handle real-time inputs, such as camera feeds under varying lighting conditions, will make it more reliable in real-world applications, ensuring better generalization across different settings.

Integrating the system with Internet of Things (IoT) devices, such as smart waste bins, could streamline waste sorting and

International Scientific Journal of Engineering and Management (ISJEM) ISSN: 2583-6129
Volume: 04 Issue: 04 | April – 2025 DOI: 10.55041/ISJEM03271
An International Scholarly || Multidisciplinary || Open Access || Indexing in all major Database & Metadata

recycling processes. These IoT-enabled bins, equipped with sensors and cameras, could automatically identify and classify plastic waste at the source. This would not only reduce manual labor but also allow real-time tracking and data analysis, enhancing the efficiency of waste management systems and providing valuable insights into waste trends for optimization.

REFERENCES

[1] Solid waste issue: Sources, composition, disposal, recycling, and val- orization" 2018 By panelHussein I.Abdel-ShafyaMona S.M.Mansou.

[2] A review on au tomated sorting of source-separated municipal solid waste for recycling" 2016 By Sathish Paulraj Gundupalli 1, Subrata Hait 2, Atul Thakur 3.

[3] Influence of shape and size of the particles on jigging separation of plastics mixture," 2015 Fernando Pita 1, Ana Castilho 2.

[4] Intelligent solid waste processing using optical sensor-based sorting technology," 2010 Jiu Huang; Thomas Pretz; Zhengfu Bian All Authors.

[5] Advanced waste-splitting by sensor-based sorting on the example of the MTPlant oberlaa," 2020 Janusz Bobulskia and Mariusz Kubanekb.

[6] Upgrading the quality of mixed recycled aggregates from construc- tion and demolition waste by using near-infrared sorting technology," 2015 InigoVegas,Kris Broosb,Peter Nielsenb, Oliver Lambertz,Amaia Lisbonaa.

[7] Case study: interpretability of fuzzy systems applied to nonlinear mod- elling and control," 2017 Krzysztof Cpalka.

[8] Real-time hyperspectral processing for automatic nonferrous mate- rial sorting,2012 Artzai Picon, Aranzazu Bereciartua, Jone Echazarra, Ovidiu Ghita, Paul F. Whelan, Pedro M. Iriondo.

[9] Industrial application for inline material sorting using hyperspectral imaging in the NIR range," 2005 Petra Tatzer,Markus Wolf,Thomas Panner.

[10] Sorting of polypropylene resins by color in MSW using visible re- flectance spectroscopy," 2010 S. M. Safavi, H. Masoumi, S. S. Mirian, and M. Tabrizchi.

[11] utilization of hyperspectral imaging for impurities detection in secondary plastics," 2012 S. Serranti, A. Gargiulo, G. Bonifazi, A. Toldy, S. Patachia, and R. Buican.

[12] Characterization of post-consumer polyolefin wastes by hyperspectral imaging for quality control in recycling processes," 2011 S. Serranti, A. Gargiulo.

[13] Rapid discrimination of plastic packaging ma terials using MIR spec- troscopy coupled with independent components analysis (ICA)," 2014
A. Kassouf, D. N. Rutledge, H. Chebib, and V. Ducruet.

[14] Deep: convolutional neural network applies to face recognition in small and medium databases," 2018 M. Wang, Z. Wang, and J. Li.

[15] Application of foreground object patterns analysis for event detection in an innovative video surveil lance system," 2015 D. Frejlichowski, K. Go´sciewska, P. Forczmanski, and ´ R. Hofman.

[16] PET waste classification method and plastic waste database - WaDaBa," 2018 J. Bobulski and J. Piatkowski.

[17] Waste classification system using image processing and convolutional neural networks," 2019 J. Bobulski and M. Kubanek.

[18] CNN use for plastic garbage classification method," 2019 J. Bobulski and M. Kubanek.

[19] I. Islam and A. Rahman, "Waste detection and classification using deep learning algorithms," International Journal of Environmental Science and Development, vol. 10, no. 4, pp. 265–272, 2020.

[20] D. K. Sharma and P. Gupta, "Deep learning approach for waste material classification using CNN," Proceedings of the IEEE International Con- ference on Computational Intelligence and Computing Research, 2019.

[21] M. J. Anuar and N. Jamil, "Plastic waste classification using transfer learning and convolutional neural networks," International Journal of Advanced Computer Science and Applications, vol. 11, no. 2, pp. 1–6, 2020.

[22] S. Prasad et al., "Recycling plastic waste using deep learning techniques for environmental sustainability," Journal of Cleaner Production, vol. 258, 2020.

[23] J. Ren and L. Xu, "Automatic waste sorting using CNN-based models for plastic detection," Journal of Materials Processing Technology, vol. 276, pp. 1–7, 2019.

[24] A. K. Singh and R. Kumar, "An image-based waste classification system using CNN," Proceedings of the International Conference on Sustainable Technologies for Industry 4.0, 2021.

[25] X. Wang et al., "Plastic waste recognition and categorization using deep learning methods," Neural Computing and Applications, vol. 33, pp.