Development of an AI-Based Predictive Modeling System for Microplastic Pollution: Analyzing Pollution Sources, and Environmental Factors for Effective Management and Mitigation Strategies

Mr. Manikanta*[1], Mr. Jeevan K P*[2], Dr. P Sandhya*[3].
[1]Assiatant professor, Dept. of MCA, ATME College of Engineering Mysuru, Karnataka, India.
[2]Research Scholar, Dept. of CSE, VTU CPGS Mysuru, Karnataka, India.
[3]Associate Professor, Dept. of CSE, VTU CPGS Mysuru, Karnataka, India.

ABSTRACT:
Microplastics (MPs), defined as plastic particles ≤5 mm, have garnered global attention due to their detrimental effects on aquatic ecosystems and human health. Originating from fragmented microplastics or microbeads in consumer products, their pervasive distribution necessitates innovative detection methodologies. Traditional techniques for MP analysis are often labour-intensive, imprecise, and unsuitable for large-scale applications. This study introduces a novel AI-driven predictive modelling system for detecting, classifying, and analysing MPs using advanced camera sensors and deep learning methodologies. A comprehensive review of over 1,200 articles identified convolutional neural networks (CNNs), specifically the mobilenet_v3_large_100_224 model, as highly effective in feature extraction, achieving a classification accuracy of 92.5% across MP categories such as fragments, pellets, film, and fibres. Despite this success, existing research has yet to fully leverage CNNs for analysing real-time image data from open sewer systems. Our proposed approach integrates AI with real-time monitoring to enhance MP detection, classification, and size-velocity measurement capabilities. The results underscore the potential of AI-based systems to revolutionize environmental monitoring, offering scalable, efficient, and precise solutions to mitigate the ecological and health risks associated with microplastic pollution.

Keywords: Microplastics (MPs),convolutional neural networks (CNNs), Fourier transform infrared (FTIR), machine learning (ML) and computer vision (CV),

INTRODUCTION

Microplastics (MPs), defined as plastic particles ≤5 mm in size, have become a pressing global environmental issue due to their ubiquitous presence and detrimental effects on ecosystems and human health. Originating from the degradation of larger plastics and anthropogenic activities such as synthetic textile production, tire abrasion, and the use of microbeads in personal care products, MPs are now found in aquatic, terrestrial, and atmospheric environments. Their small size and complex composition make them challenging to detect and remove, posing threats to marine life, agriculture, and drinking water safety. Traditional methods for analyzing MPs, including microscopy, Raman spectroscopy, and Fourier transform infrared (FTIR) spectroscopy, are labor-intensive, costly, and often lack scalability for widespread monitoring. Moreover, these techniques are constrained by their inability to accurately analyze MPs in complex environmental matrices. As plastic pollution continues to grow, it is projected that without intervention, the weight of plastics in the ocean could surpass that of fish by 2050, highlighting the urgent need for effective solutions. Recent advancements in artificial intelligence (AI), specifically deep learning and computer vision, offer transformative potential in addressing these challenges. By enabling automated detection, classification, and characterization of MPs, AI systems can provide faster, more cost-effective, and scalable solutions. This study explores the application of convolutional neural networks (CNNs) in MP detection and classification, proposing a novel approach to improve waste management and mitigate the environmental and health risks posed by microplastic pollution. Deep learning has emerged as a powerful tool for addressing complex image classification tasks, with Convolutional Neural Networks (CNNs) being a particularly effective model. CNNs are multi-layer neural networks designed to analyze visual patterns directly from raw pixel data, making them well-suited for microplastic detection. Their efficiency, cost-effectiveness, and reduced reliance on human intervention have made CNNs increasingly popular in environmental research. Notably, prior studies have leveraged CNNs to classify microplastics in urban wastewater and other environmental samples, achieving promising results.Despite advancements, challenges persist in detecting microplastics in real-world environmental samples. Current datasets primarily feature isolated, pretreated microplastic images, limiting the applicability of trained models to raw, complex ecological scenarios. To address this, we propose integrating generative adversarial networks (GANs) to augment training data by simulating microplastic images in diverse environmental contexts. This approach seeks to improve the generalization capability of CNN models. This study aims to classify microplastics based on their morphological types—fragments, pellets, films, and fibers—using three state-of-the-art CNN architectures: EfficientNet-B7, InceptionV3, and MobileNetV3-Large. These networks were chosen for their proven success in image classification tasks and high accuracy rates. Additionally, the integration of deep learning with IoT-based systems and low-cost imaging solutions presents a scalable pathway for real-time microplastic detection.

By leveraging deep learning models and addressing data limitations, this research provides a baseline for the automated classification of microplastics. The findings have the potential to inform environmental quality management strategies, support policy planning, and inspire future advancements in AI-driven microplastic analysis The increasing accumulation of waste and its impact on the environment has become a critical global concern. Poor material management practices contribute significantly to the excessive waste generated, which poses severe ecological and public health risks. Effective waste management strategies, such as recycling and adopting non-waste technologies (NWT), are imperative to mitigate these challenges. NWT emphasizes the prevention of waste and the complete utilization of raw materials through innovative technical processes, reducing environmental pollution while offering economic benefits such as lower operational costs and decreased reliance on energy-intensive disposal methods. In particular, plastics, which dominate household waste, are a key focus of waste management efforts. Common types such as PET, HDPE, PP, and PS are often recyclable but require advanced sorting technologies to ensure effective reuse. Artificial Intelligence (AI) offers a promising solution by combining computer vision and machine learning techniques to enhance waste classification and sorting. AI-powered tools, such as portable devices equipped with cameras and microprocessors, can identify waste materials in real-time, enabling users to sort and dispose of them efficiently. Within the broader scope of waste management, microplastics (MPs)—tiny plastic particles less than 5 mm in size—have emerged as a particularly pressing environmental issue. MPs are pervasive pollutants found in aquatic, terrestrial, and atmospheric environments. Their sources, transport mechanisms, and ecological impacts have garnered significant attention in recent years. However, traditional methods for detecting, collecting, and analyzing MPs are labor-intensive and time-consuming, often requiring weeks or months to achieve sufficient spatial coverage. The integration of AI in microplastic research has revolutionized the field, offering new avenues for efficient detection, characterization, and management of MPs. AI techniques, including machine learning (ML) and computer vision (CV), enable automated processing of large datasets, improving the accuracy and efficiency of MP identification. For example, autonomous drones and aquatic robots equipped with AI-driven systems can perform large-scale MP collection from diverse environments, including surface waters, beaches, and sea-beds. These technologies significantly reduce the time and labor involved in traditional sampling campaigns while increasing spatial and temporal coverage. Additionally, advancements in robotics, such as microrobots powered by external magnetic fields or UV light, present innovative solutions for targeted MP cleanup in aquatic environments. These devices are designed to navigate water bodies with precision, capturing MPs using bio-inspired adhesive surfaces or polymeric mechanisms. Such cutting-edge applications of AI and robotics have demonstrated their potential in real-world field trials, paving the way for scalable and efficient MP collection methods.

This study aims to provide a comprehensive review of the current state of AI applications in MP research, focusing on its role in detection, characterization, dynamic modeling, and management. By consolidating insights from existing studies, we seek to identify key challenges, knowledge gaps, and opportunities for future research. Furthermore, this review highlights the transformative potential of AI in addressing the life cycle of MP pollution, from collection to impact assessment and mitigation. The findings will not only advance our understanding of MPs but also inform strategies for effective environmental management.

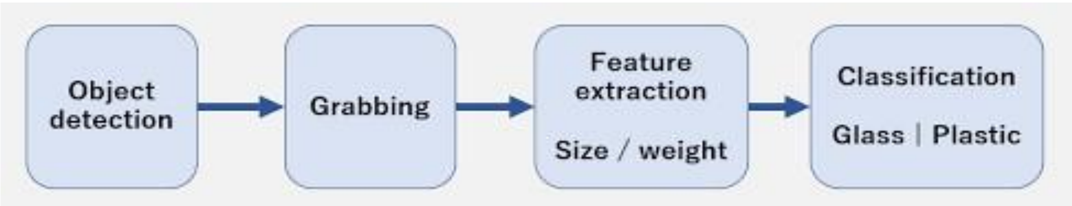

Figure 1: Classification of Plastic through CNN

The primary danger to environmental protection comes from solid waste. It poses a significant threat from plastics. Considering how rarely these polymers are reused and how quickly they are produced. Plastic may stay in landfills for hundreds of years, decomposing into ever-tinier fragments known as micro plastics because it does not degrade or soak back into the environment. The best way to prevent plastic from entering landfills and the ocean is to eliminate single-use plastic and reduce the quantity we use of it. With an average daily production of 24,500 tonnes of plastic garbage, Indonesian is the second-largest producer of plastics pollution in the environment. Strong waste creation is mostly caused by irrational material management. Some plastics, such as those used in our mobile phones, autos, and other items, are single-use plastics and may be avoided, while others are more difficult to do without. If we can't reduce our usage of plastic, we should consider ways to recycle it. The 3R Initiative seeks to increase resources and material efficiency by promoting the "3r concept" (reduce, reuse, and recycle) on a global scale to build a sustainable material-cycle civilization.This 3Rs philosophy primarily emphasises resource reuse, trash reduction, and regeneration. Making thoughtful decisions while purchasing items helps limit waste production. Reusing trash entails using the created things more than once. Utilizing garbage as a raw material to create new products is known as recycling. The main goals of non-waste technology (NWT) are to minimise waste and maximise the utilisation of raw resources. This involves a variety of technical procedures that result in comprehensive trash management and disposal without harming the environment. Garbage disposal should not be done using this method. Financial justification exists for its deployment. One can cut back on energy-intensive waste disposal processes to use less electricity, heat, or technologies.

The main idea behind it is to lower the cost of manufacturing the same resources while maximising their reuse. Items are often recycled in two locations. Is the one at the level of production, another is at the level of post-consumer. From the consumer's perspective, we prepare the material then use it a second time as a raw material in the creation of a different product. Advanced technologies must be used to identify the kind of material in each category since not all the materials in each group are recyclable. the plastics recycling process. We described a method for garbage recognition that may be applied to portable devices since it is time- and money-consuming to separate recyclable products from municipal solid waste [7].

At least 8 million tonnes of plastic enter our seas each year, where they become contaminants that harm the ecosystem. Therefore, handling this sort of mass-produced material is required. Plastics may be categorised into seven main groups [8]. Each of them stands apart from the rest in some way. Some are recyclable, while others may leak dangerous chemicals if subjected to high heat. Some materials may be recycled with ease, while others need more intricate and sensitive processing in order to be recycled. Recycling programmes mostly accept Polyethylene Terephthalate (1-PET) and High-Density Polyethylene (HDPE), even though scientists are currently working to discover the best method and strategy for recycling all those types of plastic (2-HDPE).

To prevent the greenhouse gasses and the ozone layer being depleted, plastics must be categorised for recycling, reuse, or reduction, which is a challenging task to do with human labour. The major goal is to cut the cost of producing the resources while reducing waste, recycling, and encouraging reusing of the same materials. As a result, consumer trash can be recycled by mixing their condition and composition alteration with the secondary use of raw resources. The creation of an automated method for classifying plastic garbage is the main problem this essay addresses [8, 1]. To do this, garbage must be divided into categories apart from metals, biological, plastics, papers, & glass.Advanced processes should be used to identify the kind of materials for each category since not many of the elements in each category are now appropriate for reuse. It can sort into the PS, PP, PE-HD, and PET categories, and it may be utilised at a sorting plant or at homes by households.

1. LITERATURE REVIEW

1.1 Deep Learning Overview

Deep learning represents a sophisticated subset of machine learning, utilizing Artificial Neural Networks (ANNs) to address complex problems like image classification, object detection, and motion analysis (Chan et al., 2020). Its ability to handle diverse data types such as text, images, and videos (Moen et al., 2019) has made it indispensable in various domains, including environmental monitoring and waste management. Algorithms like Deep Neural Networks (DNNs), Recurrent Neural Networks (RNNs), and Convolutional Neural Networks (CNNs) form the backbone of deep learning advancements.

1.2 Convolutional Neural Networks (CNNs)

CNNs, a specialized type of deep neural network, are highly effective for analyzing visual data. Inspired by the biological structure of the human visual cortex, CNNs process image data through layers of neurons connected via convolutional filters (Chauhan et al., 2018). The architecture typically includes convolutional, ReLU, pooling, and fully connected layers, enabling CNNs to identify intricate patterns in images.

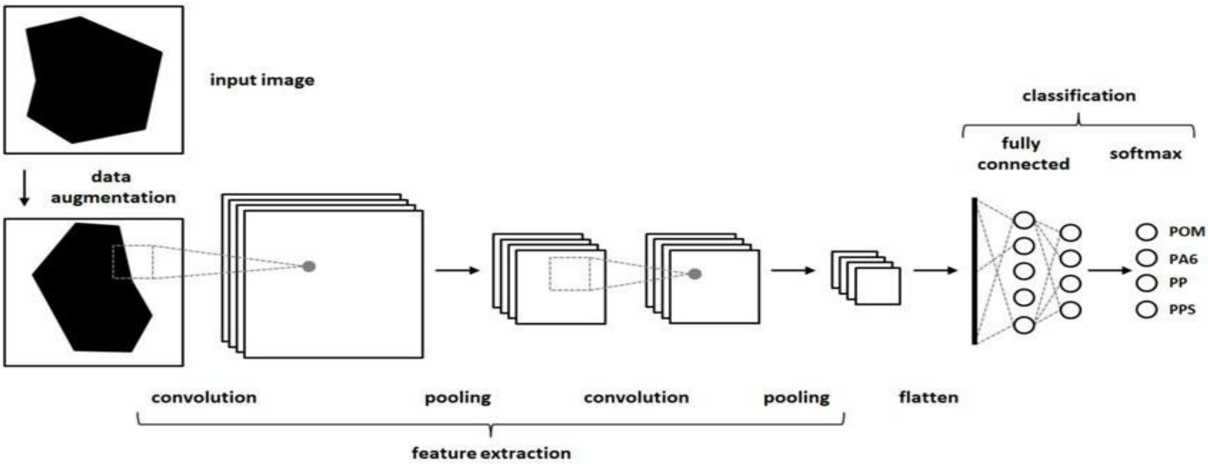

Figure 2: Convolutional Neural Networks Layers CNN

Key features of CNNs:

- **Convolutional Layers**: Use filters to extract spatial features from images.
- **Pooling Layers**: Reduce dimensionality while preserving critical information.
- **Fully Connected Layers**: Perform classification based on extracted features.

These capabilities have proven crucial for applications in environmental monitoring and waste management, particularly in automating the detection of microplastics and sorting of waste materials.

1.3 AI in Microplastic Detection

Recent studies, such as Zhang et al. (2023), highlight the role of AI, specifically deep learning models like CNNs, in identifying and quantifying microplastics across diverse environments. These methods have shown significant promise in automating complex tasks, improving both accuracy and efficiency. However, challenges remain, particularly the need for robust and accessible labeled datasets for model training. Efforts like Yurtsever et al. (2019), which used multiple water sources to train CNNs for microbead detection, underscore the importance of dataset diversity and international collaboration.

Integrating AI with technologies such as Unmanned Aerial Vehicles (UAVs) offers potential for large-scale environmental monitoring, providing cost-effective solutions for detecting microplastic pollution.

1.4 Waste Sorting Technologies

Efficient waste sorting is critical for recycling and waste management. Traditional methods, including magnetic and eddy current sorting, have limitations in handling diverse waste streams (Huang et al., 2010). Emerging technologies like hyperspectral imaging, optical sensors, and deep learning-based systems are addressing these challenges:

- **Hyperspectral Imaging**: Effective for identifying material impurities in waste streams (Wolf et al., 2005; Serranti et al., 2012).
- **Optical Sensor-Based Sorting**: Automates the classification of solid waste based on attributes like color, shape, and texture (Vegas et al., 2015; Masoumi et al., 2010).
- **Deep Learning in Waste Management**: CNNs have been employed for tasks like recognizing recyclable materials and automating sorting lines. For instance, Bobulski and Piatkowski (2018) developed a database for object recognition in municipal waste sorting, enhancing efficiency through computer vision.

Challenges and Future Directions

While deep learning and AI have revolutionized environmental monitoring and waste management, challenges persist:

1. **Dataset Limitations**: Lack of standardized, high-quality datasets limits model performance and generalizability (Zhang et al., 2023).
2. **Interdisciplinary Collaboration**: Greater collaboration among researchers and institutions is needed to address data-sharing and methodological gaps.
3. **Scalability**: Many solutions remain in the research phase and require scaling for real-world implementation.

2. EXISTING SYSTEM

Artificial Intelligence (AI) is transforming the battle against plastic pollution, offering innovative solutions across monitoring, detection, recycling, and biodegradation. AI-driven systems, like The Ocean Cleanup's Interceptor, are specifically designed to identify and capture plastic waste in rivers, using predictive models to detect accumulation zones in polluted waterways worldwide. Similarly, projects like Plastic Tide utilize AI to analyze drone and satellite imagery, enabling large-scale mapping and tracking of plastic waste on coastlines and in oceans. These advancements make it possible to detect and mitigate plastic pollution more effectively.In the realm of recycling and waste management, AI is proving to be a game-changer. Companies like ZenRobotics have developed advanced AI and robotics solutions to efficiently sort waste in recycling centers. These systems can distinguish various types of plastics, significantly reducing contamination in recycling streams and improving the quality of recycled materials. AMP Robotics takes a similar approach by deploying AI-powered robotic systems in recycling facilities, enhancing the efficiency and speed of separating plastics from other waste materials. These innovations not only increase recycling rates but also reduce the overall environmental footprint of waste management processes. AI-powered predictive models are another promising area of application. For instance, researchers at the University of Exeter have developed AI models that use environmental data, such as ocean currents and wind patterns, to predict the movement of microplastic pollution in oceans. This predictive capability enables clean-up efforts to be targeted more effectively. Likewise, The Ocean Cleanup employs forecasting models to track the movement of oceanic plastic, optimizing the deployment of clean-up technologies like autonomous vessels and floating booms. These models not only improve the efficiency of clean-up operations but also help prevent further pollution by anticipating its pathways. Microplastic detection is another critical challenge that AI is addressing. The Norwegian Institute for Water Research (NIVA) has created AI-based systems that use spectroscopic analysis for real-time detection of microplastics in water samples. This technology improves the speed and accuracy of monitoring pollution levels. Similarly, IBM Research utilizes AI algorithms to analyze data from water sensors, providing valuable insights into microplastic contamination across various water bodies. These advancements are critical for understanding and mitigating the impact of microplastics on ecosystems and human health. AI has also been integrated into clean-up efforts. RanMarine's WasteShark, an autonomous drone, uses AI to collect plastic waste from polluted harbors, rivers, and lakes, targeting areas with high pollution density to prevent plastics from reaching oceans. While not fully AI-driven, systems like the Seabin Project are effective in collecting floating debris in marinas and harbors. With the integration of AI, these systems could become even more efficient by predicting pollution hotspots for more strategic deployment.

In addition to clean-up technologies, AI is advancing research in biodegradation. Researchers at the University of Portsmouth are using AI models to design and optimize enzymes capable of breaking down plastics like PET. These enzymes represent a potential breakthrough in addressing the massive volumes of plastic waste that cannot be easily recycled. However, challenges remain in acquiring sufficient datasets for training AI models, as capturing diverse images of plastic waste is complex and resource-intensive. Additionally, deep learning models often require vast amounts of data for effective feature extraction, which can limit their performance when data is scarce. Despite these advancements, existing systems still face several limitations. Monitoring progress and evaluating performance can be challenging, particularly in remote or large-scale operations. Many systems lack automation, relying heavily on manual processes, which reduces their efficiency. Additionally, current processes often involve extensive paperwork and manual computations, which are time-consuming and error-prone. Another major challenge is the difficulty in collecting diverse datasets needed for training AI models to accurately identify plastic waste. Without sufficient data, feature extraction and model generalization become limited, hindering the overall effectiveness of these technologies.

To address these challenges, further advancements are necessary. Automating systems to enhance efficiency and reduce dependency on manual processes is crucial. Developing larger, more diverse datasets can significantly improve the performance of AI models in identifying and analyzing plastic waste. Integrating predictive AI with physical clean-up systems can further optimize the removal of plastic waste from polluted environments. Finally, leveraging AI to accelerate research in plastic biodegradation can pave the way for sustainable solutions to the global plastic pollution crisis. By addressing these limitations, AI has the potential to play a transformative role in reducing plastic pollution and protecting our planet.

DRAWBACKS OF EXISTING SYSTEM

- Tough to Evaluate Progress – It can be challenging for managers to keep track of their employees' development and performance when they are not physically present in the same workplace.
- The system must be better automated in order to get around all of these restrictions and improve functioning accuracy.
- Gobbles up a lot of papers. involves manual computations.
- If the job position necessitates many "background tasks" that cannot be tracked on a work's system, this is significantly heightened. The world's debt is a burden, mortalities and morbidities between persons mental and social separation.

3. PROPOSED SYSTEM

In our research, we focus on newer Convolutional Neural Networks (CNNs) that are built on the same principles as traditional ones. With grid-structured data such as photographs, the CNN algorithm proves to be robust, yielding effective and accurate results. Unlike classic machine learning algorithms like **SVM** and **KNN**, CNN performs exceptionally well on large datasets. However, we also demonstrate that with transfer learning methodologies, CNN can operate efficiently on small databases. For our study, we used two challenging and small datasets: one for waste texture and another for plastic trash items. The layered architecture of CNNs is meticulously structured, and the system's software employs image processing methods for picture preparation. The primary component is a classifier designed for object categorization using convolutional neural networks and deep learning. The plastic detection module in our study applies a simplified approach to plastic identification. A key step in this method involves the preparation of input images for validation and learning. Using layers such as the convolutional layer, max-pooling layer, activation functions, drop-out layer, and SoftMax layer, the system extracts features and sends them to subsequent layers. Each layer contributes to the identification of features in the image. The overall system performs data analysis, identifies critical decision points, synthesizes multiple components, and provides an optimized solution for plastic identification.

STEPS IN THE PLASTIC DETECTION MODULE

1. Processing of Data: We encountered several challenges in data collection. Certain types of data were not readily available online, so we gathered information from local retailers, plastic trash, and other sources. A total of 720 images of plastic items were captured using mobile phones on a white background, followed by necessary pre-processing steps. These images were divided into four labels across four data classes to minimize data bias. The trash analysis and classification process utilized these images. After data collection, an advanced processing phase was conducted to clean up and prepare the data for the network. Since real-world data is often unstructured and noisy, initial data cleaning is a critical step to ensure the system can process the images effectively.

2. Extraction of Characteristics: The feature extraction process identifies relevant features from new samples. We utilized a pre-trained network's convolutional layer, added new data, and trained a new class on the model. During this phase, the last three layers of the pre-trained network were removed, and fully connected layers were added to train our database. We applied fine-tuning, where all layers except the last were frozen, and a custom layer was created to refine the outputs. This custom layer incorporated two layers with RELU activation functions and a final SoftMax layer. By combining the convolutional layer and the phase divider, we enhanced the model's performance after fine-tuning. Our study showed that Convolutional Neural Networks (CNNs) in Deep Learning are highly effective for identifying features in pictorial images. The same algorithm was applied to identify features of microplastics from photographic images captured in open sewer systems. Our findings revealed that microplastics exist in significant quantities and pose a severe threat to the environment and ecosystem, particularly affecting water bodies like oceans, lakes, and rivers.

APPLICATION AND DRAWBACKS

The proposed system uses real-time images of water captured and classified through a convolutional neural network. The system can identify the presence of microplastics in water, helping mitigate the threat to organisms caused by consuming contaminated water. One limitation of the system is its occasional misidentification of other substances, such as glass particles, as microplastics. However, this misidentification could still be beneficial in detecting other harmful materials. By providing a larger dataset, the system's classification accuracy can be further improved, leading to better results.

Our research highlights the necessity of using AI-driven solutions to address microplastic pollution, which is a significant environmental menace. While traditional techniques such as physical and chemical methods have been used to identify microplastics, they are often costly and challenging to implement on a large scale. Our system offers a cost-effective solution, emphasizing the role of AI and deep learning in solving real-world problems like plastic pollution

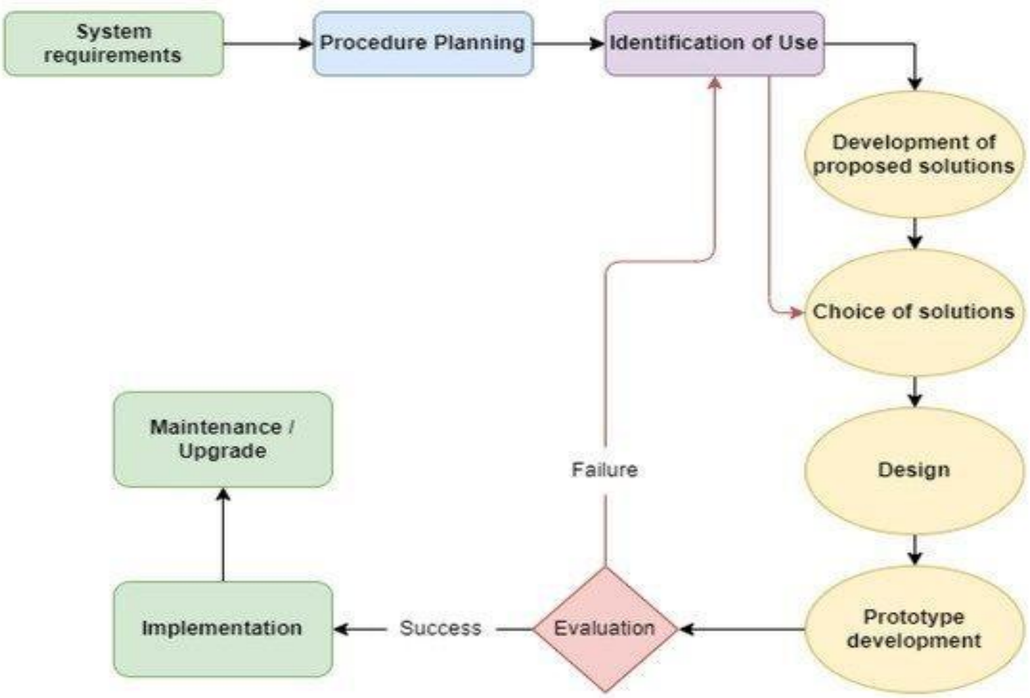

Figure 3: Flowchart of classification

4. COMPARATIVE STUDY

Based on past research, we will utilise a convolutional neural network (CNN) architecture to recognise Plastic objects. CNN is a deep learning technology idea that is commonly used for image and video processing, pattern recognition, object identification, and object recognition from digital pictures.

- **Image and video processing digital**

For digital photograph processing, computer algorithms are used [18]. It's useful for image classification, feature extraction, multi-scale signal analysis, sample recognition, and projection. Digital image processing is used in clinical diagnosis and treatment, system/robotic vision, image transmission and encoding, remote sensing, and several more applications. Spatial low bypass, spatial excessive bypass, Fourier representation, Fourier low bypass, and Fourier high bypass filtering are used to blur and sharpen digital images. Spatially linear affine image transformations include scaling, rotation, translation, mirroring, and shearing.

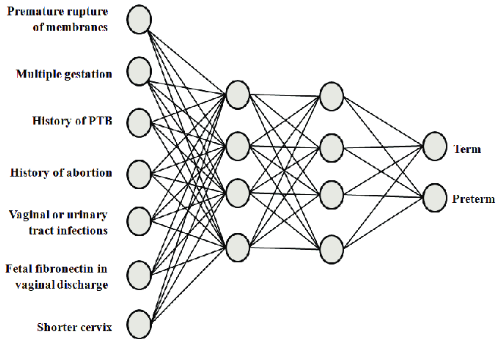

Figure 4: Image Classification using Deep Learning Approach

- **Deep Learning**

Deep processing is a type of machine learning that can categorise pictures, recordings, or sounds. Deep learning is frequently accomplished through the use of a neural network structure. The term "deep" refers to the number levels within the network; the more layers, the deeper the network. Deep learning networks will include tens to hundreds of layers. Deep learning may be employed for facial recognition, optical person recognition (OCR), speaker identification, key components navigation, and recreation recognition [18, 3].

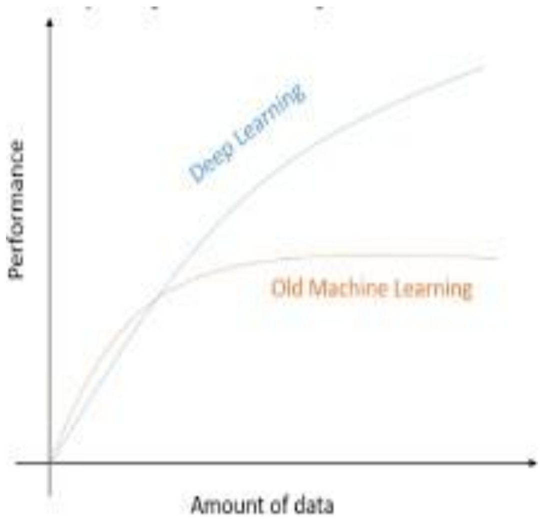

Figure 5: Comparison between Proposed and existing algorithms

5. CONCLUSION

Model concepts and performance vary depending on several external factors. To make informed and specific decisions, it is essential to understand the elements of the model. Currently, there is a significant need for interpretability research in plastic waste detection models, as it can address critical gaps in this field. Deep learning models, such as CNNs, have shown potential in detecting and classifying different types of plastic waste. Enhancing the transparency and interpretability of decision-making algorithms will foster user trust and security. Interpretability research can help mitigate biases induced by artificial intelligence and enable audits, while also contributing to legal, moral, and philosophical frameworks for transparent AI systems. Our research assessed various image recognition and classification techniques, particularly their application in detecting and sorting plastic waste, such as empty containers. Among the models tested, AlexNet CNN initially produced the most accurate results. However, after several modifications, the LeNet model achieved comparable accuracy. The findings demonstrated that image pre-processing and the improvement of training and testing sets play a critical role in boosting recognition accuracy. Additionally, a Convolutional Neural Network (CNN)-based system was developed for plastic waste separation, capable of categorizing plastic types and identifying associated risks. This system has the potential to autonomously separate waste, thereby minimizing the need for human intervention and reducing risks of infection and contamination. With an expanded dataset, the system's accuracy can be further improved. Our study also highlights the effectiveness of CNNs in detecting and classifying microplastics from photographic images. The system processes real-time images, identifies microplastics in water bodies, and provides actionable data, significantly mitigating the threat posed to the environment and ecosystems. By leveraging deep learning methodologies and fine-tuning techniques, the system demonstrates robust performance, even with small datasets, showcasing its scalability and adaptability.

6. FUTURE SCOPE

The future scope of this research lies in expanding the system's capabilities to handle larger and more diverse datasets, which will enhance the accuracy and robustness of plastic waste detection. By integrating advanced deep learning models and transfer learning techniques, the system can be adapted to detect various types of plastic and other pollutants across different environments, such as oceans, rivers, and urban areas. Moreover, the development of IoT-enabled devices equipped with real-time image processing capabilities will enable autonomous plastic detection and sorting systems. This will not only improve efficiency but also reduce manual intervention and associated risks. Additionally, incorporating hyperspectral imaging and multi-modal data analysis could further refine the system's ability to differentiate between microplastics and other materials. The application of this technology in recycling centers**,** waste management facilities, and environmental monitoring initiatives will play a pivotal role in addressing the global plastic pollution crisis.

REFERENCES

[1]. Monitoring Area. Available online: https://www.ospar.org/documents?v=7260 (accessed on 22April 2020).

[2]. Real-Time Detection of Microplastics Using an AI Camera Md Abdul Baset Sarker 1 , Masudul H. Imtiaz 1 , Thomas M. Holsen 2 and Abul B. M. Baki 2,

[3]. Rapid Classification of Microplastics by Using the Application of a Convolutional Neural Network Pensiri Akkajit1, Arsanchai Sukkuea2

[4]. PLASTIC MATERIAL DETECTION AND CLASSIFICATION USING CNN Vavilala Sushma, Electrical and electronics engineering, CVR college of engineering, Hyderabad

[5] MICROPLASTIC DETECTION IN WATER USING IMAGE PROCESSING NEETHA K1 , LINSA MARY VARGHESE2 , MAMBULLY RADHAKRISHNAN HARSHITHA2.

[6]. Microplastic Identification Using AI-Driven Image Segmentation and GAN-Generated Ecological Context Alex Dils Sequoia High School alexarthurdils@gmail.com David Raymond Sequoia High School davidraymond1081@gmail.com Jack Spottiswood Sequoia High School 813667@seq.org.

[7]. Advancing microplastic analysis in the era of artificial intelligence: From current applications to the promise of generative AI Bu Zhao,1 Ruth E. Richardson,1 and Fengqi You2,

[8]. LeCun Y., Bottou L., Haffner P., Gradient-based learning applied todocument recognition. Proceedings of the IEEE, 86(11):2278-2324.