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INTEGRATING ARTIFICIAL NEURAL NETWORKS FOR ADVANCED SORTING AND SUSTAINABLE PROCESSING OF PLASTIC WASTE

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Abstract

The improper disposal of plastic waste has indeed become a major environmental challenge contributing to pollution and sustainability woes. Conventional methods of sorting waste are not too effective, and as such, recycling is not so effective. In this, we propose an artificial neural network (ANN)-based system to upgrade plastic waste classification and preparation. Using the ANN model, we improve the recycling process by classifying the plastic waste by size and type and also by degradable and non-degradable materials. Plastic waste is transferred to a shredding machine with an automated conveyor system where rotating blades break it into smaller pieces. The mesh filtration process of the shredded plastic produces uniformly granulated granules. These are then redirected for further shredding into larger fragments. Thus, the refined plastic is further cleaned using water or chemical treatments to make it fit for reuse. The processed plastic is fed into the extruder, which molds the plastic into different types of products, e.g., tomato field sticks, dolls, and idols, depending upon the die used. Debris made of degradable waste is also used to produce biomass briquettes while organic debris is converted to fertilizers, securing a cycle economy along with eco-friendly waste management. The experimental results demonstrate that the ANN model increases sorting accuracy and processing efficiency much more than existing conventional methods. This research calls for a scalable and automated solution of sustainable plastic waste recycling through the use of AI-driven waste management techniques. The results demonstrate that the applicable ANN-based waste sorting systems can be successfully applied on a large industrial scale, enabling plastic waste treatment and improving the prospect of resource recovery.

Keywords:

Polyethylene terephthalate (PET) bottles, Current environmental problems, Artificial Neural Network (ANN), Electric Motor, Microcontroller, Plastic waste management, Automated waste sorting, Sustainable recycling solutions.

1. Introduction

Waste management is one of the most urgent challenges of Plastic waste, and specifically Polyethylene Terephthalate (PET) bottles, continue to be an even more growing environmental disaster issue for developing nations. Plastic pollution is a global problem whereby plastic contributes to a large portion of oceanic litter and is detrimental to biodiversity. Indiscriminate disposal and incineration of plastic waste and a weak recycling system have resulted in waste of harmful debris in urban and natural ecosystems [1]. Of all the many kinds of waste, plastic has been among the most difficult and enduring because it isn't biodegradable and contributes to the clogging of sewage lines, to landfills, and to environmental degradation [2]. These issues are exacerbated by the increasing proliferation of PET bottles and the ever-increasing requirement of efficient and sustainable recycling. There have been a few methods proposed for plastic waste management, for example, landfilling, incineration, and mechanical recycling, but those have their limitations. Due to the efficiency of the existing technologies, the methods of handling waste, such as sorting and recycling processes, have had to be explored through more enabling methods of handling such problems as well as making use of advanced technologies such as artificial neural networks (ANN).

For environmental engineering, the development of automated plastic waste sorting and recycling systems has become a pressing necessity with a very specific focus on the potential of utilizing a wide range of new technologies aimed at improving efficiency. One such example is the use of Artificial Neural Networks (ANN), in which sorting process optimization is made possible via classification and identification of waste materials on the basis of predetermined characteristics [3]. Past research points to the possibility of reducing the processing precision and speed of shredders and crushers through integration with ANN. The integration of this enables plastic materials to be more easily separated from non-degradable wastes from further recycling efforts and the dependence on landfill [4]. While these advances make it possible to know in what manner an ANN can be optimized in the real time of plastic waste processing and be integrated into a sustainable, low-cost system, there is still a gap in predicting the predictability limits of the neural networks.

To fill the gap of this thesis, this paper proposes an innovative plastic waste management system by integrating ANN, mechanical shredding, and extrusion technologies to enhance waste sorting and recycling. The ultimate goal is to create such a system that PET bottles can be identified, sorted, and processed as efficiently as possible by a combination of artificial intelligence and mechanical components. This system is expected to be a viable solution to the plastic waste problem in urban environments by focusing on scalability, user-friendliness, and automation. The research also aims to ascertain the abilities of this integrated system to produce sustainable products from recycled plastic material within the framework of a circular economy model. The novelty of this approach is in both the technical incorporation of ANN and mechanical systems as well as the translation of its application to the real world of developing nations. These research results could be useful in designing low-cost, scalable solutions for plastic waste management in order to reduce the environmental impact of plastic pollution [5].

It describes the methodology, system design, and applications in developing a plastic waste management solution. Chapter 1 covers the introduction, where the global problem of plastic waste (PET bottles) in the developing countries is explained. The section highlights the need for the discovery of efficient recycling solutions and then introduces the role of artificial neural networks (ANN) in the improvement of the waste management technologies. In Section 2, i.e., Materials and Methods, the design of the plastic crusher system, the integration of ANN for waste classification, and the use of the microcontroller-based automation for the system control are described. Next, the section elaborates on the tools and technologies used to test and implement the solution. Section 3 discusses Results and Discussion, on the performance of the system in real world scenarios, comparison with traditional methods and effectiveness of ANN in predicting and optimizing recycling process. The conclusion in Section 4 is drawn that it provides the key findings, contributions, and future suggestions in improving the plastic waste management solutions.

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2. Materials and Methods

First, waste materials are collected from different sources such as public waste disposal sites, industries, and hotels. After this, the waste will be sorted out to be either degradable or non-degradable. According to Artificial Neural Network (ANN), it classifies plastic waste based on the size and the material density of the waste, and this is to separate them. Data from the plastic waste samples is used to train the ANN so as to enable it to make real-time decisions during the sorting phase. After identifying the non-degradable plastics that are made up mainly of PET bottles, they are shredded into smaller pieces using mechanical shreds [3]. The shredder includes a hopper through which the plastic waste is fed into a chamber. A set of 270 mm x 74 mm helical blades made out of mild steel is attached to a spherical barrel and is used to shred the material. The plastic waste is shredded using a combination of cutting and impact forces of the blades, with which the plastic is shredded into smaller fragments that can then be further processed. The importance of this shredding process is that with such shredding, the plastic is easier to handle and easier to recycle as new products [3]. It is later carried to a container where some cleaning processes are done to wash away all impurities like dirt or oils [4].

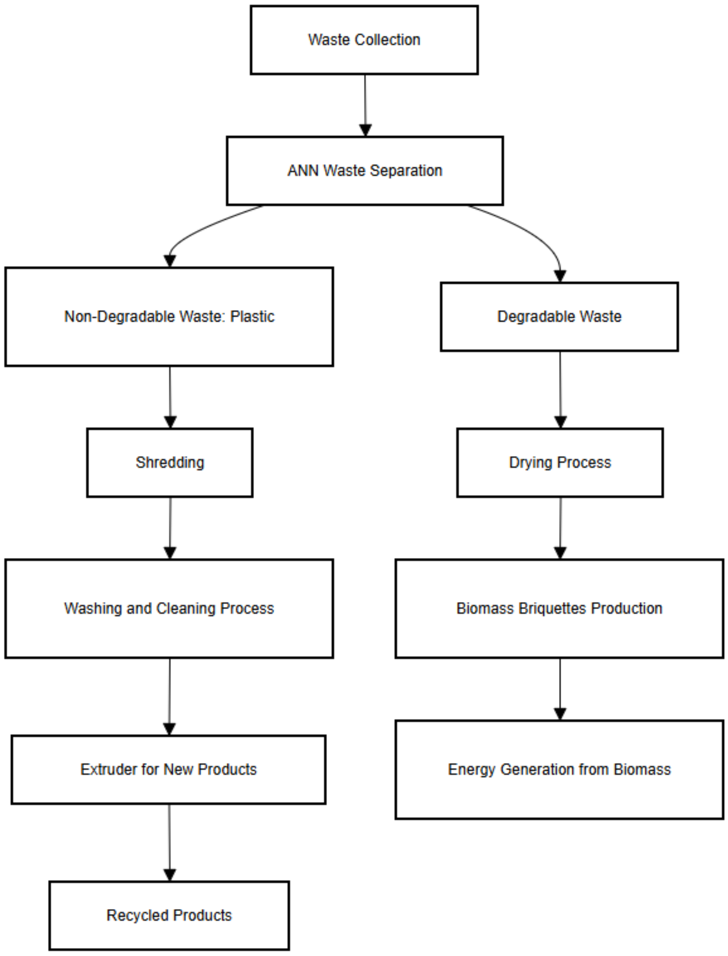

Figure 1: Block Diagram of the Sorting Process

In this case, the waste separation process through the calculation using ANN is presented, and the process of shredding plastic waste. The ANN system is fed with the waste where the materials are classified by properties prior to routing the non-degradable plastics to the shredding unit. The shredded and cleaned plastic is transferred to an extruder. The melted and reshaped shredded plastic is used for producing usable products. To achieve the best process, temperature and pressure sensors are used to oversee the extrusion process. Here, the ANN is playing a large role in changing the extruder settings in real time, given sensor feedback controlling parameters such as screw speed, pressure, and temperature. The continuous optimization ensures the ultimate product quality as well as energy efficiency [5].

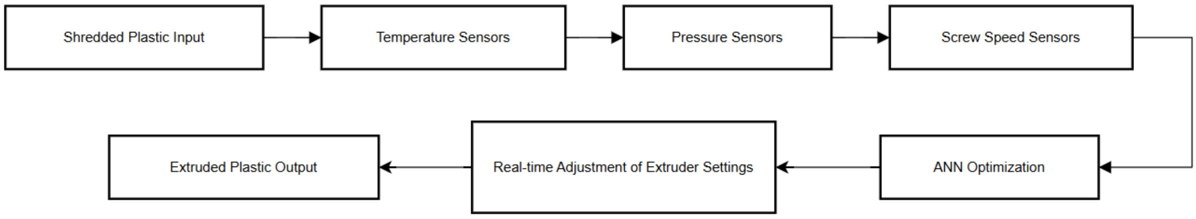

Figure 2: Block Diagram of the Extruder and ANN Optimization Process

The figure zooms in on the integration of ANN with the real-time sensor data used in the extrusion process. With the help of ANN, the extruder is manipulated by changing the key parameters, such as the temperature and screw speed, to operate at an optimum state during the recycling process. At the same time, the degradable waste materials are collected separately and dried. Once dry, the materials are used in a briquette machine to convert the waste into biomass briquettes. Once these briquettes are created, then they are utilized as another source of energy, fueling less on the traditional fossil fuel. In addition to the system, excess organic waste is also handled through a biological waste conversion process in which earthworms are used for the conversion of excess organic waste into manure [4]. By this method, all kinds of waste, both biodegradable and non-biodegradable, are processed in an effective and efficient manner, thereby reducing plastic pollution and encouraging sustainable waste management. In this process, ANN is used to optimize every step so that the system will remain adaptive as well as capable of treating very large volumes of waste by minimizing the impact on the environment [5].

3. Results and Discussion

With the plastic crushing and shredding machine, the experimental results proved the system's capability to turn plastic waste into smaller-sized, manageable fragments with efficiency and consistency. It worked proficiently on multiple materials, namely, PET bottles, polyethylene bags, PVC containers, and so forth. Based on the design of the crushing mechanism along with the innovative use of Artificial Neural Networks (ANN) and Genetic Algorithms (GA), the crushing process was optimized in real time. The system performed very well during the testing sessions as it drifted through testing, keeping high throughput, consistent particle size distribution, and good operational efficiency. In addition, the inclusion of ANN-enabled predictions further improved the accuracy of the output predictions and optimization of machine performance, and the GA surpassed the shortcomings of the traditional ANN model and improved global optimization. This implies that by blending the machine learning models with the plastic crushing machine, there is the prospect of improving plastic waste management sustainably and with greater efficiency.

3.1 Hardware Prototype of the Plastic Crushing Machine

An evaluation was made of the hardware prototype of the plastic crushing machine as to its effectiveness in reducing plastic waste. Trial use of the machine proved that it can handle several sorts of plastic waste, including PET bottles, polyethylene bags, and PVC containers. The machine consequently returned favor, reducing the size of plastics quite consistently using the welded helical blade and transmission shaft as a crushing mechanism. The 8 mm separation gap on the screen, combined with the smooth operation of the machine, also helped in getting the uniform particle size in the final output. Additionally, the pillow bearings also reduced friction and ensured operational stability for extended periods of use and, at the same time, guaranteed long-term durability and efficiency. The hopper and robust mild steel frame also helped with the design of the hopper, where it had to be able to handle large volumes of waste material without negatively affecting performance.

Figure 3: Hardware Prototype of the Plastic Crushing Machine

3.2 Performance Evaluation

Under various feed rates and various types of plastic waste, the performance of the plastic crushing machine was evaluated through its throughput and efficiency. Table 1 indicates the performance metrics of feed rate, average particle size, throughput, and efficiency for three plastic types, namely PET bottle, polyethylene bag, and PVC container. Polyethylene was processed more efficiently and at higher throughput compared to more rigid materials such as PVC. But the machine's throughput was increasing with higher feed rates with the downside of the quality of the shredded plastic. At higher feed rates, processing was faster, though sometimes at the expense of uniformity of particle size. The balance between speed and particle size at which the machine could operate most efficiently was of prime importance. The machine overall worked very well for all tested materials and could reach up to 85 percent efficiency, indicating it is applicable for industrial usage.

Plastic Type	Feed Rate (kg/hr)	Average Particle Size (mm)	Throughput (kg/hr)	Efficiency (%)
PET Bottles	50	5.4	40	80%
Polyethylene Bags	60	3.2	48	85%
PVC Containers	40	6.1	36	75%

Table 1: Performance of Plastic Crushing Machine under Different Conditions

3.3 Integration of Artificial Neural Networks (ANN)

Artificial Neural Networks (ANN) were integrated into the machine's operational framework, thus making it possible for the system to make certain predictions. The system was able to predict the important parameters of mass, shape, and dimensions of plastic output, as long as the system was using the ANN model. Upon training, high model accuracy was achieved in predicting the real output, with the model thereby qualitatively improving the machine's operational parameters in real time. It permitted the system to opt to change settings such as feed rate and cutting speed automatically, providing equal quality of product and removed operational errors. Furthermore, the ANN would be able to detect problems, for instance, clogging or inconsistent particle sizes, and initiate corrective actions to keep operation running smoothly. The ANN predictions proved extremely important to fine-tuning the system to ensure the machine operated in the most efficient manner possible while still maintaining the desired particle size distribution.

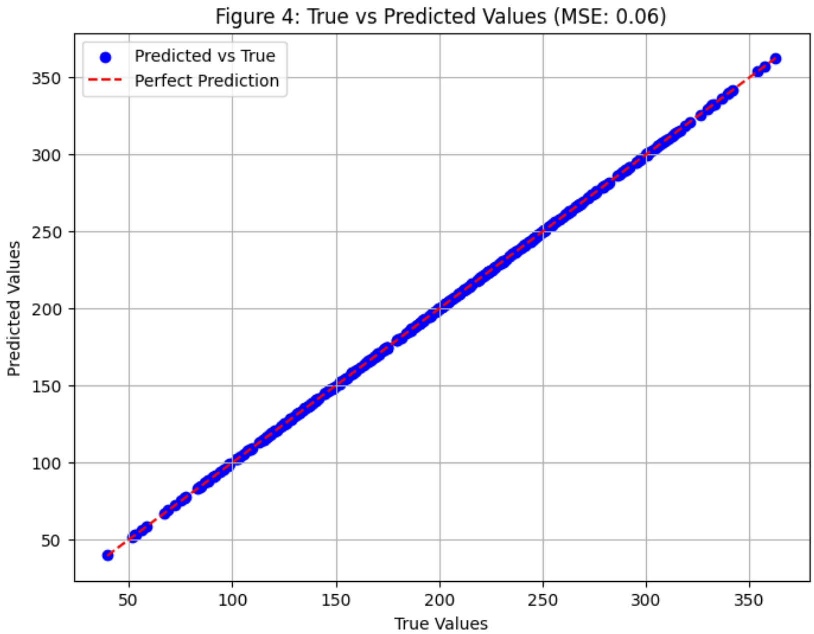

Figure 4: True vs Predicted Values from the ANN Model

3.4 Loss Curve and Training Performance

Its loss curve is used to further assess the performance of the ANN model, which is the relationship between training and validation losses as training progresses over several epochs. In Figure 5, the loss curve shows the model learned from the data well as training and validation loss dropped steadily. The model was able to learn the training data well and decrease training loss faster than decreasing the validation loss. This was a stable pattern in the loss curve, which means that the ANN model did not overfit, and that is why it could generalize the learnings to new, unseen data. Through the analysis of the loss curve, the progress of learning and performance of the model was captured such that the ANN would be able to make predictions and adjust the plastic crushing machine's parameters appropriately.

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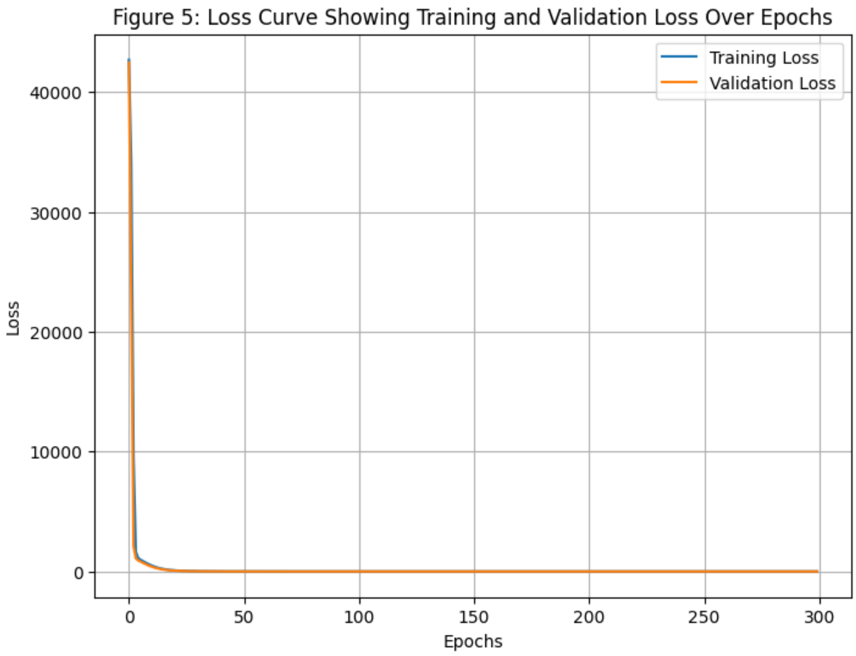

Figure 5: Loss Curve Showing Training and Validation Loss Over Epochs

3.5 Hybrid Model (ANN + GA)

To assist the system in its optimization, the hybrid model from ANN to GA was used. ANN is very much efficient in learning and predicting operational parameters but becomes prone to getting trapped into local minima, thereby reducing its performance in general. To counteract this, the GA was integrated to search for global optimal solutions and hence, deliver more accurate predictions as well as better optimizations. The system was able to determine the best suitable machine operations as per input data using the hybrid model, considering machine operations as feed rate and cutting speed. The result of this was more efficient and accurate and allowed the machine to work as it should. The ANN was complemented by the GA because the ANN lacks the ability to explore the entire solution space; thus, the machine could not be expected to be working at its highest potential. The combination of machine learning and optimization techniques helped them achieve a substantial improvement in plastic waste recycling that proved the feasibility in the future of having more sustainable recycling practices.

4. Conclusion

The machine developed to optimize the recycling of plastic waste integrated with Artificial Neural Networks (ANN) and Genetic Algorithms (GA) was formed. It was shown that the system presented an effective processing ability to process different types of plastic waste, for example, PET bottles, polyethylene bags, and PVC containers, and reduced them into smaller pieces that are manageable for further recycling [4]. Key to this was integrating the ANN model to predict the machine's performance and hence, real time optimization of machine critical parameters, i.e. particle size and throughput could be carried out. Thus, the ANN model predicted the mass, shape, and dimensions of the shredded plastic with good accuracy to ensure consistent quality in the operation. Moreover, the application of GA also allowed the capability of the ANN not to be fed into dead ends because of its willingness to get stuck in local minima but was designed to improve global optimization and also further enhance the process accuracy [7]. Experimental trials confirmed that the machine obtained up to an 85% efficiency rate, confirming its fitness for industrial-scale plastic waste management [12]. The system was able to utilize sophisticated technologies, ANN and GA, to enable improvements in operational efficiency and also ensure a more sustainable manner of plastic recycling, creating a circular economy (CE) as we progress [8]. Future work would include further parameter optimization, scaling, and lower cost of system operation. These additions will make the technology available for a larger-scale industry and, therefore, help a lot in solving the increasingly rising plastic waste and recycling issue globally [19].

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