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Role of Artificial Intelligence, Automation, and Machine Learning in Sustainable Plastics Packaging markets: Progress, Trends, and Directions

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Abstract

The optimisation of manufacturing processes in terms of resource consumption, waste minimization, and pollutant emissions is gaining prominence, especially in small and medium-sized enterprises (SMEs). The advent of digital technology and the subsequent explosion in data volume is another key factor. There is great potential in the data collected from a wide variety of devices and systems, which is why even smaller businesses require access to clever, dynamic analytic models. Sustainable packaging solutions are gaining significance as the world struggles to address global environmental issues. These solutions are being developed with a growing contribution from artificial intelligence (AI). Artificial intelligence is being used to create sustainable and environmentally friendly packaging. Artificial intelligence (AI)-driven technology can be used, for instance, to determine which packing materials and designs are optimal for a given product. Artificial intelligence can also be used to determine the best methods of packaging, such as those that make the most of recyclable materials or that optimise packaging lines. The term "plastic production automation" refers to the use of automated systems and machines in the production of plastic goods. Computer-aided design (CAD), robots, and other cutting-edge technologies are used to automate and optimise production. In this article, we describe the findings of a study that aimed to determine whether or not small and medium-sized enterprises (SMEs) in the plastics processing industry may benefit from the use of machine learning methods in order to optimise energy consumption and reduce the number of wrongly made plastic parts. The machine data in a plastics manufacturing facility for the automobile industry were recorded and analysed in terms of the material and energy fluxes for this purpose. To find areas for optimisation, these data were trained using machine learning techniques. The project also sought to solve the challenge of analysing manufacturing processes with significant non-linearities and time-invariant behaviour by employing Big Data techniques and self-learning controls. Machine learning can help with this if there is enough data to train the system.

Key words: Artificial Intelligence, Automation, Machine learning, Sustainable Plastic Packaging.

1. Introduction

Polymer production is currently exceeding breakdown, making plastic waste one of humanity's most pressing challenges. According to the current plastics consumption trajectory, annual global plastic trash might increase from 260 million tonnes in 2016 to 460million tonnes in 2030, a 75 percent increase in only 14 years (Pohjakallio, 2020). Even thoughplastic recycling rates vary widely between countries, just 16% of the plastic gathered by humans has been recycled. Over 75% will be disposed of in landfills, while the remaining 25% will be incinerated (Hahladakis et al., 2018). More than 8 million tonnes of plastic aredumped into the oceans annually, resulting in the suffering and death of countless marineorganisms (Recycling, 2020). As a result of improper plastic management, plastic pollution has spread throughout the oceans, posing threats to marine life, marine ecosystems, human health, and the global climate. The carbon dioxide emissions from their production add to the environmental damage caused by plastics, which are nearly impossible to degrade. Since polymers are derived from fossil fuels like gas, coal, and oil, a sizable amount of carbon dioxide is released during their extraction and transportation. Most polymers

are made from fossil fuels including oil, gas, and coal, all of which produce substantial amounts of carbon dioxide (CO2) during their extraction and distribution. M.M. Cencer et al. (2022) estimate that in the United States alone, 12.5–13.5 million metric tonnes of carbon dioxide are released from the combustion of natural gas used in the production of plastic. One tonne of plastic recycled can prevent about two and a half tonnes of greenhouse gas emissions, five thousand seven hundred and seventy-four kilowatt hours of energy, sixteen and a half barrels of oil, twenty-four million calories, and twenty-three cubic metres of landfill space (Recycling, 2020).

Artificial intelligence (AI), virtual reality (VR), the Internet of Things (IoT), robotics, and nanotechnology are all poised to revolutionise the packaging industry by facilitating the development of automated, connected, environmentally friendly, and individually tailored packaging solutions that better engage customers with product content and immersive buying experiences. Smart labels, QR codes, RFID tags, NFC chips, and augmented reality are challenging conventional packaging by providing consumers with up-to-the-moment details about items and facilitating two-way communication. Sustainable packaging is gaining popularity as people become more aware of the harmful effects of packaging made from plastic. One pioneer is replacing plastic milk cartons with sugarcane-based packaging, and another is providing aluminum-free aseptic cartons packs for oxygen-sensitive items like fruit juices. The use of plastics, waxes, and other non- biodegradable materials in packaging is being reduced by the use of nanotechnology to the creation of a renewable, cellulose-based packaging material.

Three-dimensional printing and nanotechnology, for example, allow for highly individualised product packaging. For instance, 3D printers using stereolithographic photopolymer materials are expanding therange of possibilities in terms of product design, colour, and packaging. Hygiene in food transit and storage, as well as protection of vegetable products, consumables, or immunisationsagainst viral agents, can be ensured by the use of expanded polystyrene (EPS) packaging with an active protective layer using nanotechnology.

Key strategic challenges faced in thepackaging sector

Creating a memorable first impression on consumers and mitigating the environmental impact of plastic consumption are two of the many obstacles that traditional packaging must overcome. Some of the biggest problems in the packaging industry are:

As e-commerce and last-mile delivery continue to grow in popularity, manufacturers are under increasing pressure to provide packaging that can be mass-produced without compromising product security or compliance with safety regulations.

Because of the importance that customers place on first impressions, retailers are increasingly prioritising factors such as customer connection, ease, and ergonomics when designing packaging.

Packaging prices go up in tandem with the price of raw materials, therefore finding new ways to cut back on production expenses is essential.

Compliance with ever-evolving regulatory norms is essential for businesses in today's climate, as the globe works towards a more sustainable future through combating climate change.

To keep their products safe in the face of rising consumer awareness, businesses must offer compelling value propositions in the forms of sturdy products and reputable brands packagedin high-quality containers.

Key use cases of emerging technologies inthe smart packaging sector value chain

Production of packaging materials, packaging converters, filling and packing, wholesale, distribution and logistics, retailers, and consumers are all links in the value chain. To maximise output, minimise risk, and maintain cost control, new technologies are increasingly being applied at every stage of the packaging value chain.

Production of packaging materials: Internet of Things (IoT) and 3D printing are becoming more important technologies for reducing production time and improving the robustness of packaging materials. In order to increase their goods' adaptability and efficiency, leading package suppliers are turning to 3D printing. In terms of design and development, 3D printers provide a wide range of possibilities, including material, colour, and efficiency. Celwise, a technology firm based in Sweden, and ExOne, a machine industry company based in Pennsylvania, have teamed up to create environmentally friendly packaging. Utilising ExOne's 3D-printed metal tools made of 316L stainless steel, Celwise modifies wood and other cellulose fibres into long-lasting moulded fibre goods that can substitute for disposable plastics. Additive manufacturing, such as ExOne's binder jetting technology, is essential to Celwise's proprietary production method for creating the novel form of moulded fibre product.

For packaging converters, the optimisation of design and production is being driven by technological advancements including 3D printing, artificial intelligence, and augmented reality. Goglio, a producer of packaging systems, has included conventional 3D printed parts into its packaging equipment. The equipment improves the production of flexible laminates, plastic parts, and packing machines. By enhancing production, Goglio hopes to attract and retain clients over the long term andincrease sales. Robotics is one of the most promising new technologies, and it is already being put to use in a number of industries, including filling and packing, labelling and palletizing, and quality control inspection. In order to increase product traceability and maintain the quality consumersexpect, packaging companies are increasingly turning to artificial intelligence and robotics forautomated inspection. The Italian conglomerate Stevanato has introduced a robotic inspection device called the "Vision Robot Unit" (VRU) that is controlled by artificial intelligence. To improve the dependability of the control process, it is built to meet and adapt to the requirements of automated inspection in themodern smart factory. Vaccines, lyophilized pharmaceuticals, and monoclonal antibodies (mAbs) are just some of the biotech goods that benefit from VRU's ML capabilities, which automate the examination of applications across the pharmaceutical development and production landscape [1].

2. The role of automation in plastic production

The United States is a leading global manufacturer of plastic, demonstrating the importance of this sector of the economy. However, producers confront various hurdles, including keeping production efficient, cutting costs, and improving worker safety, due to the rising demand for plastic items.

Automating the plastics manufacturing processis one way to address these issues. Production times, efficiency, and worker safety are all boosted by automation technology.

The United States is projected to be the largest market for automation technology, with the global market for industrial automation, including robotics, predicted to reach $350 billion by 2025.

Automation in plastics production is essential since it raises efficiency, boosts output, andreduces production costs for businesses.
Incorporating automation into plastics manufacturing processes can improve product quality and uniformity, leading to more reliableand efficient end uses.

The high upfront costs, the necessity for specialised labour to operate and maintain automated systems, and worries regarding job displacement are just a few of the obstacles that stand in the way of the widespread adoption of automation despite its many advantages.

The good news is that manufacturers may reduce the impact of these problems by doing things like investing in staff training programmes and developing initiatives to reduce job displacement brought on by automation technology.

Figure 1: The Role of Automation in Plastic Production

3. The role of ai in sustainable plastics

A plastic disaster is currently affecting the entire planet. Millions of tonnes of plastic garbage are created annually, contributing to environmental pollution and animal suffering. As a result, a growing number of businesses and nonprofits are relying on AI to aid in the fight against plastic pollution.

Artificial intelligence (AI) fueled eco-friendly polymers are on the rise. Sustainable polymers powered by artificial intelligence are crafted from non-depletable resources. Compared to conventional plastics, which are derived from fossil fuels and hence not renewable, these materials are more eco-friendly.

There are multiple ways in which AI is helping to lessen plastic waste. To begin, AI may be used to determine the various forms of plastic trash and organise them accordingly. As a result, businesses will have an easier time sorting plastics for recycling. The second way AI may help cut down on plastic use is by optimising the manufacturing process. Finally, AI may be utilised to create environmentally friendly plastics that are stronger and endure longer.

The sustainable polymers fueled by AI have many advantages. Production costs can be lowered and environmental effect mitigated if plastic waste is reduced. Sustainable polymers powered by AI can also be utilised to make items that endure longer and are less likely to break. As a result, less plastic garbage will be sent to landfills and the ocean.

Sustainable plastics powered by AI can help alleviate the waste problem. Businesses may contribute to a more sustainable future by usingAI to cut down on plastic usage.

4. Role of machine learning in psasticpackaging

A strong economic foundation is more crucial than ever in this era of rapid industrialization and rapid digitalization.

Companies' CO_2 balances are a key factor in this. Plastics, used by many factories, contribute to environmental degradation and must be phased out if we're to make any progress.

It's not easy to create a sustainable economy. They call for the application of proper remedies. In the context of IT, one subfield receives a disproportionate amount of attention, namely that of AI and ML. Small and medium-sized businesses are more reticent to adopt machine learning than their larger competitors, who often have dedicated teams to the task. There are obstacles for SMEs in the digitization space. The majority of small and medium-sized enterprises (SMEs) view digital transformation as too difficult and expensive to justify. When an initiative fails, it can have a much more significant impact on a small business than it would on a huge corporation. Federal Ministry of Economics and Energy- commissioned research on the "Potentials of artificial intelligence in the manufacturing industry in Germany" found that a lack of internal competence in the manufacturing industry is one of the biggest barriers to the useof AI technologies. In Germany, just 15% of SMEs now use AI in their value-adding processes. Artificial intelligence (AI)-based process control automation is likewise at a very early stage at the moment [7]. Workers' academic and professional preparation in the area of AI is likewise only at a basic level. Currently, only 15% of organisations allow their staff to gain AI-relevant degrees, according to a study conducted by the University of Saarland across 200 SMEs in 8 EU nations. Only 19% of businesses surveyed said they currently use AI applications [8]. KfW Research even projected that by 2020, SMEs will only benefit by 5% from using AI applications [9].

This paper details the process of creating a prototype for utilising machine learning to track and improve waste reduction and energy savings at a small to medium-sized plastics manufacturer. Engineering science and cognitive science come together to form artificial intelligence. The purpose is to create a technological solution that mimics human performance and perception in terms of cognitive abilities. As a result, we need to createapps for situations that required human intervention in the past [10]. Understanding algorithms, data structures, and combinatorics are, thus, prerequisites for AI study; this placesAI within the realm of theoretical computer science [11] and statistics. One of the mostcutting-edge approaches to data analysis and processing is machine learning, a branch of artificial intelligence [12]. The very concept of technology is implied by the link between computers (machines) and humans (learning): to acquire knowledge and make forecasts through analogy with the human mind. In order to create predictions, machine learning seeks tolearn from data, build a model, and employ thismodel. Machine learning's ability to generate knowledge from massive volumes of data in order to develop a picture of reality [14] and enable the system to solve issues on its own is one of its primary applications. In the realm of machine learning, we can categorise our approaches as either supervised, empowered, orunsupervised. To build a model in supervised learning, "trained data sets" are used. Promoting learning helps a system evolve in response to its surroundings. The goal of unsupervised learning is to discover patterns with little to no oversight from the instructor. Learning methods are selected in light of the given situation and problem [15].

Data without labels can be processed via unsupervised learning. However, the entries here have already been sorted. Because of the failure to take into account what is already known, an incorrect outcome is to be anticipated. There is also a well-defined end point in mind, which is to cut down on wasteful output while simultaneously decreasing energy usage. It's possible that a clustering analysis will group together things that are related but don't help answer the study issue. Some outcomes could be obtained with careful interpretation, but the other forms of machine learning have a better chance of success because they take advantage of all the available information, including the labels. Reinforcement learning is one approach that could be used to do this. However, this is not possible because a crucial condition, environmental interaction, was not satisfied. In this case, data had already been obtained. Algorithmically modifying the machine's parameters based on the outcomes was required for this approach [16]. The financial investment

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required to acquire even theoretically promising outcomes is out of proportion to the potential savings that may result from the research. All of the conditions for supervised learning to take place here are present.

5. Materials and methods

Data Exploration and Data Validation

The prototype was developed using information from four machines in a factory with more than sixty machines. Not only were the data gathered and trained in a non-production environment, but they were also gathered in real-time. [17-18] Indirect issues (such as service schedules and mechanical breakdowns) were also considered. The data was gathered using OPC interfaces created for the project and Modbus RTU protocols specified by the ISO. The IT department has to be set up in a methodical fashion to do this. The information is stored in a SQL database. The data are first inspected and preprocessed. A model is developed and evaluated after the best machine learning algorithm has been chosen. Over the course of four months, over 800,000 data sets are examined. In the first stage, we take a look at the dataset and pick the necessary paramet

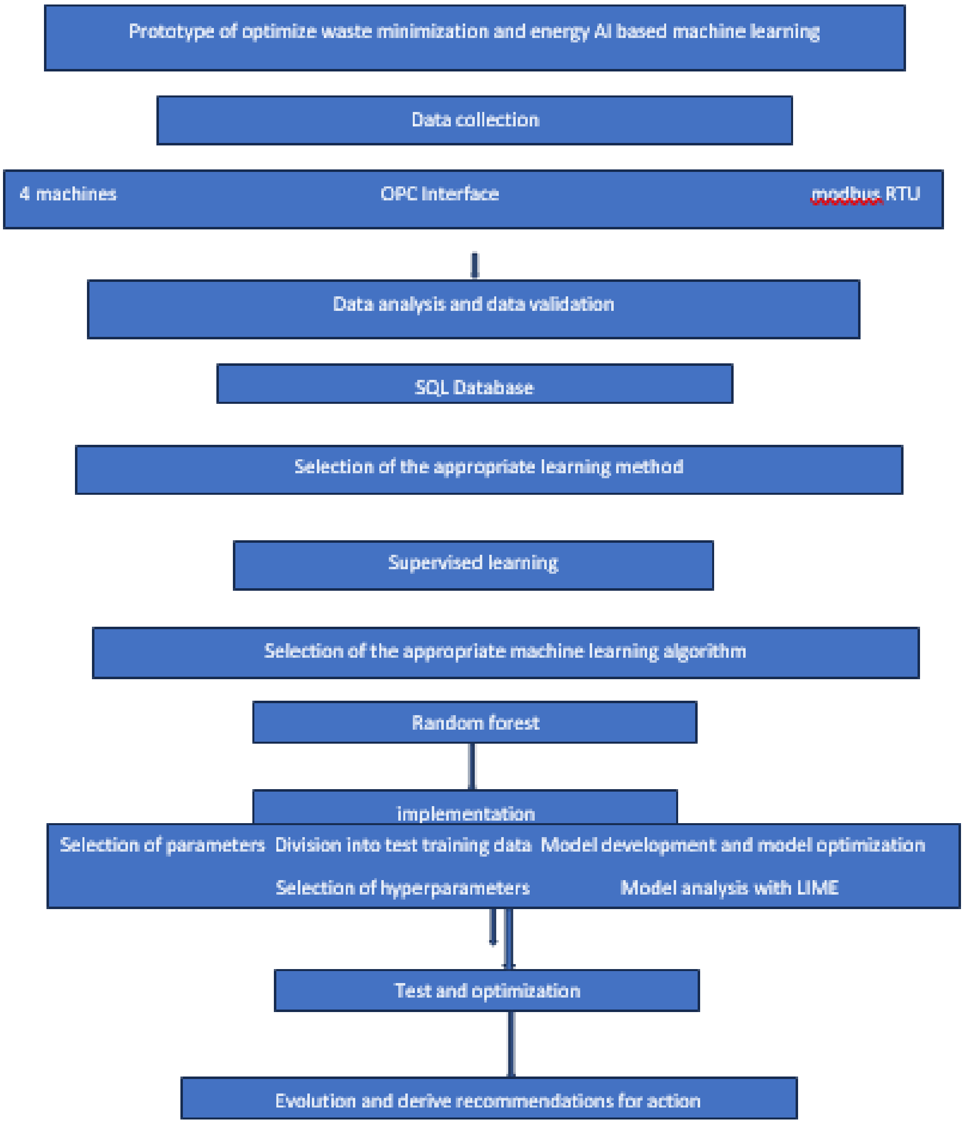

Figure 2. Study procedure.

Figure 2 provides a summary of the research. To slow down the model's computation, it discards data that adds no value to the analysis. Tool, substance, and software are all appropriate descriptors here. The data can be used for machine learning overall, but because to the gaps in data collecting, more time and effort must be spent filtering and preparing the data for use. The machine data is stored in the database and is displayed in Table 1.

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Table 1. Description of the database columns.

Description of Database Columns
Date and time of shot
Unique identifier of DB
Name of the machine
Applied tool
Program name used during operation
Applied thermoplastic material
Quality per shot, 1: error-free piece 3: erroneous piece
Shots since program restart
Duration of production of the piece
Compensating mass for contraction on cooling of the piece
The process is switched over from this volume value (repressing)
Pressure for repressing
Maximum pressure of the process
Duration of filling in the mold
Duration of the melting process for the next process
Heating zones for granulate melting
Control of the temperature of the tool
Water temperature to control the tool heating circuit
Cumulative pressure over time
Energy meter reading of the corresponding machine

Figure 3 provides an aggregate view of the machine and parameter data. Existing entries are denoted in black, and blank spaces are represented by white. The parameters are listedin the top bar, the names of the associatedmachines are listed on the left, and the total number of records for each machine is listed on the right. You can observe that every machine has several properties with completely blank rows. These are not gaps in the data; rather, they are not measured because of variations in construction techniques, such as the lack of a cylinder heating zone. In most cases, a whole data set can be obtained. The holes in machine M69's cylinder heating zone K2 (3, 4, 5].

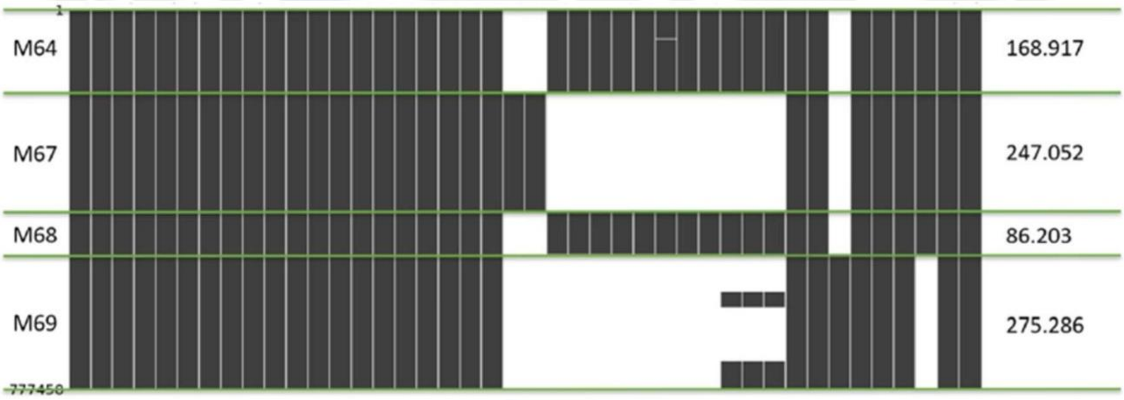

Figure 3. Data amount per machine.

Selection of the Appropriate LearningMethod

To achieve these two goals of improved efficiency and decreased error rate, it isnecessary to select the most suitable learning approach at this time. Data without labels can be processed in unsupervised learning. In this scenario, though, the data is already organised. This means that prior knowledge is disregarded, leading to a flawed conclusion. In addition, thegoals have been stated in detail. It's possible fora clustering study to produce clusters whereby members share similar traits but offer nothing towards answering the research questions. Applying techniques from reinforcement learning could be one method to accomplish this. However, the most fundamental requirement, namely engagement with the surrounding world, is not provided. Data from the project's previous phases are available. In order to employ this technique, the algorithm would have to perform physical manipulations on the apparatus and then analyse the resulting changes to fine-tune the settings. All of the conditions for supervised learning to take place here, including the availability of pre-labeled data and the specification of an optimal analysis and application of that data, are met. Using these details, reliable models may be built and evaluated. As a result, we employ supervised learning.

Selection of the Appropriate Algorithm

The requirements must be specified before any individual algorithms can be considered. There is a massive amount of data to analyse, with almost 600,000 whole data sets. Since the model cannot assume anything, non-linear correlations must also be taken into account. To solve it, we need a technique that not onlyaccurately predicts the future but also can justify its choices. Since there is a time constraint on the study and lengthy calculationsover multiple days can quickly slow down progress, it is ideal if the model can be developed in a short amount of time. Discrete- classification explanations of quality and continuous-estimation regressions of energy use are also part of the mission. The development time and cost can be minimised by making the algorithm compatible with both types. Additionally, it would be helpful to havea minimal risk of over-adaptation in order to obtain a general model.

Support Vector Machines

Classifications can be linear or non-linear, and both are possible with Support Vector Machines. Additionally, a classification and regression analysis are performed. Having only their support vector to go on, the classifiers are less likely to suffer from excessive customization. However, this feature is inherentto kernel functions, which moves the focus away from choosing appropriate hyper parameters and onto choosing an appropriate kernel. Moreover, as SVMs were originally developed for much lower quantities, they do not scale accurately enough for massive data sets. The algorithm wasn't chosen for this particular task because of its low level of interpretability.

Artificial Neural Networks

The future of artificial neural networks seems bright. This technique, even at its most basic level, requires a substantial amount of data. In addition, a sophisticated model can be developed, allowing for the representation of nonlinear connections. Classifications and regressions are two examples of tasks that can be represented by neural networks. However, for proper operation, a significant number of hyper parameters must be calculated. Thesehyper parameters reveal the fundamental structure of the neural network. Training the neural network is computationally intensive in comparison to other machine learning algorithms.

5.2.4. Random Forest Algorithm

With the Random Forest Algorithm, you may create a single model that can map a wide variety of data sets and parameters. Its interpretability stands out from that of competing approaches because it provides unique visibility into the decisions made at the branch level. The LIME algorithm also works with Random Forest, so you can get the full picture. Additionally unique is the minimal pre-processing required. There is no need to normalise or standardise the data before using it. The algorithm is also resistant to the effects

Table 2. Selected hyper parameters per machine

Parameter	M 1	M 2	M 3	M 4
min_samples_leaf	100	80	200	100
n_estimators	20	70	50	40
min_samples_split	1000	800	1100	900
max_depth	3	3	6	4
max_leaf_nodes	20	30	30	20

6. RESULTS AND STUDY

of incomplete input. But its ability to tolerate overfitting is one of its greatest virtues. This situation occurs infrequently because data sets are chosen at random. For both regression and classification, the models are applicable. In this case, either the random forest or the neural networks would work. The random forest approach is employed because it generates models quickly and provides better insight into the selection criteria for classifications.

Analysis of the Model

There is now a model that can reliably categorise data sets. The anticipated research outcome, however, is more nuanced. Therefore, not only should an answer for a specific

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data setbe provided, but the model itself should beexplained. There needs to be a clear indicator of where the machines function at their best in order to cut down on trash, plastic, and carbon dioxide emissions.

For this, we employ Ribeiro, Singh, and Guestrin's LIME explanation algorithm, which makes use of the local Brutforce technique. Local Interpretable Model-Agnostic Explanations is the name of the tool's creators, who coded it in Python and R. It is possible to gain an approximative knowledge of complex models in machine learning with the help of LIME, which is used to generate the explanation of the prediction of any classifier or regressor based on text, tables, or images. The LIME methodology is founded on the idea thatsimple local models can be fitted to the predictions of a complicated model. The optimum settings for each machine are listed inTable 2.

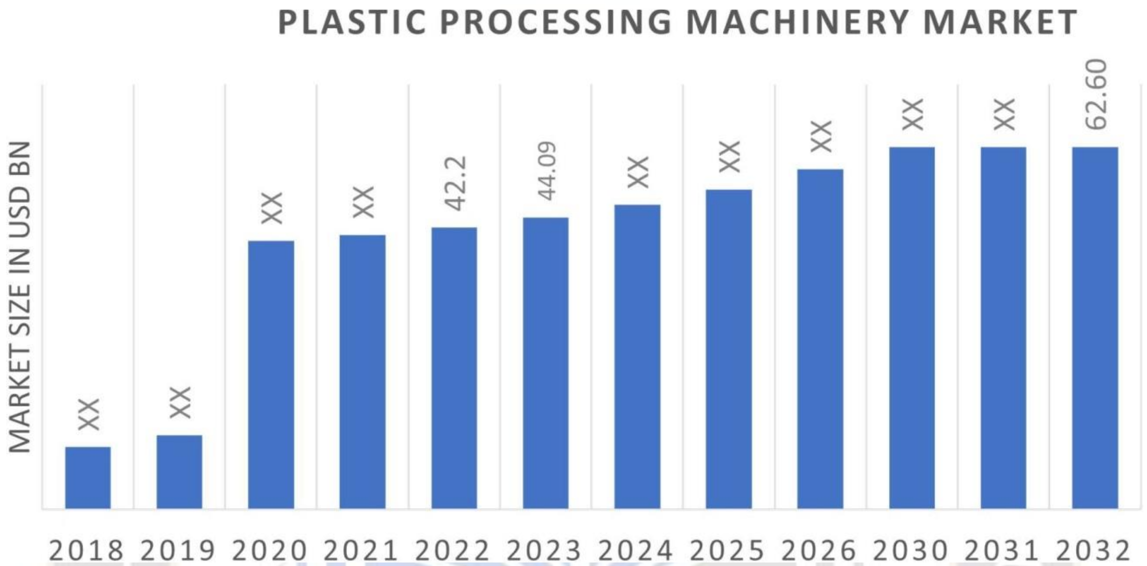

Figure 4: Plastic processing machinery market

Figure 4 depicts a rise from 2023's expected value of USD 44.09 billion in plastic processing gear sales to 2032's value of USD 62.60 billion.

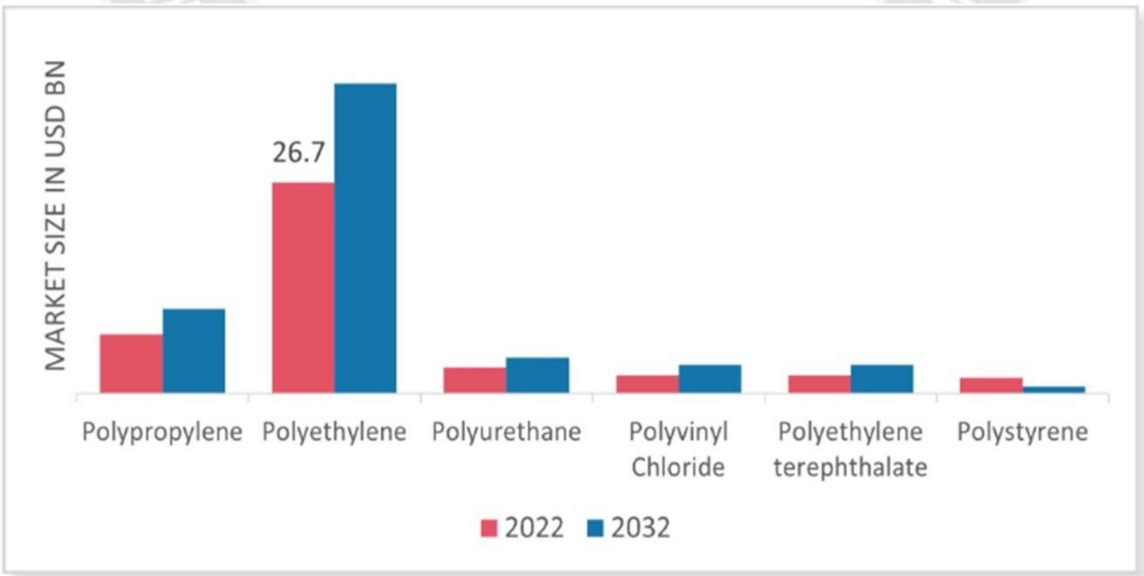

Figure 5: Global Processing machinery maket by product type, 2022 & 2032 (USD Billion).

Polypropylene, polyethylene, polyurethane, polyvinyl chloride, polyethylene terephthalate,and polystyrene are just some of the plastic types shown in Figure 5 of the Global PlasticProcessing Machinery Market.

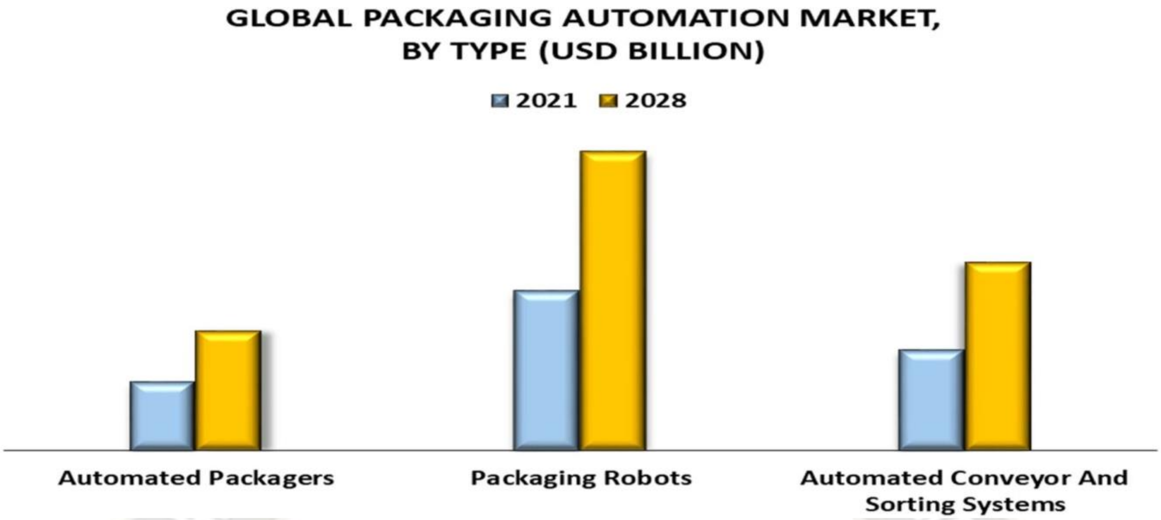

Figure 6: Global Packaging automation market by type (USD BILLION).

Packaging Automation Market, By Type

- Automated Packagers
- Packaging Robots
- Automated Conveyor and SortingSystems

Figure 6 displays the global market split into different types, such as automated packagers, packaging robots, and automated conveyor and sorting systems. As they are used to ensure product safety and quality all the way through the value chain and to create energy-efficient, low-impact "green" equipment, packaging robots have quickly become the industry standard. Since automated conveyors and sortation systems allow for greater adaptability,higher shipping accuracy, and more frequent shipments, they are in high demand in the e- commerce sector.

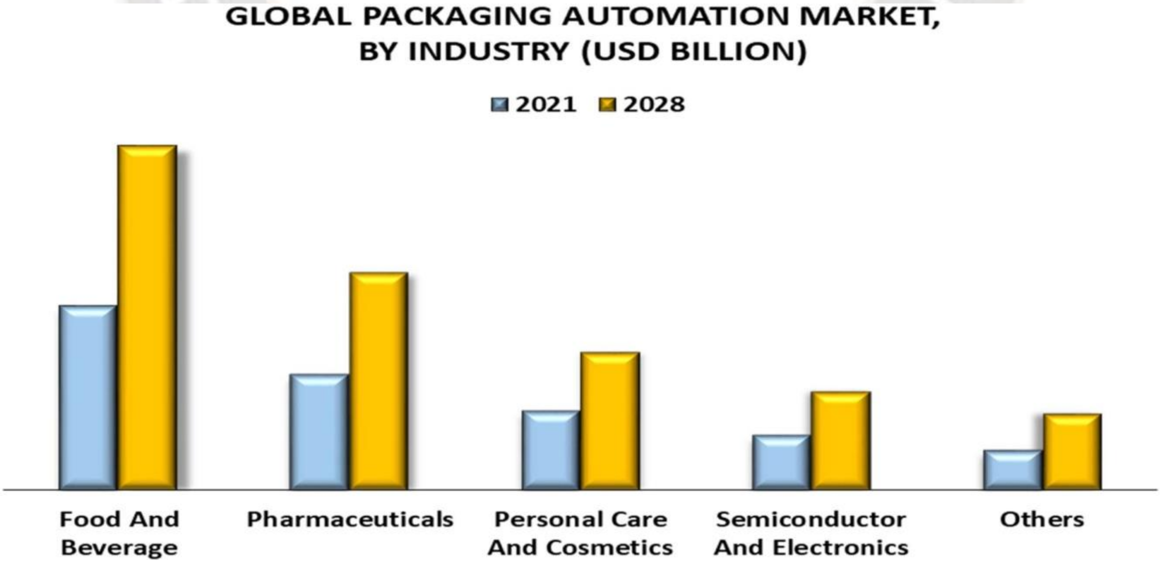

Figure 7: Global Packaging automation market by Industry (USD BILLION).

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The global food and beverage, pharmaceutical, personal care and cosmetic, semiconductor and electronics, and others sectors make up the many submarkets that make up the overall market. As a result of rising demand for rigid packaging solutions like filling and palletizing equipment, the food and beverage industry has become the undisputed leader in the worldwide Packaging Automation market. The need for adequate packaging to safeguard healthcare and pharmaceutical products from the elements is anticipated to drive the market forward over the forecast period. Figure 7 also shows that blisterpacks, plastic bottles, caps & closures, medical speciality bags, pouches, strip packs, pharmaceutical tubes and cartridges are all employed in Packaging Automation to keep their chemical qualities stable.

CONCLUSION

Many potential future scenarios for the digitalization of the plastics processing industry under study exist. Various opportunities can arise if the material flow management system and the necessary data sources include the entire operation. Intelligent monitoring of the entire production cycle may reveal additional chances for optimisation in the areas of resource efficiency, machine utilisation, and operating resource use. It is reasonable to suppose that there are savings and optimisation possibilities outside of manufacturing as well. Procuring materials is one potential growth area: Predicting the demand for raw materials and doing a market research can help optimise the purchasing process. Repairs and maintenance can be scheduled and performed ahead of time, preventing further harm. Logistics (fuel or electricity expenses) and production (machine use, personnel planning, etc.) can also contribute to enhanced productivity. Distribution of individual segment and subsegment market values (in US Dollar billions). Identifies the area and market subsector forecasted to expand quickest and dominate the industry. An examination of the product's or service's regional demand and the variables shaping that demand across different regions. The competitive landscape includes a rating of the top players in the market, as well as any recent developments in the companies profiled, such as the introduction of new services or products, the formation of strategic alliances, or the completion of large-scale expansions or acquisitions.

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