Plant Control for Fully Automated AI-Driven Product Type Recognition

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***Abstract*—The development of industrial automation has led to a transformation in manufacturing, with the advent of advanced production and measurement technologies driven by digitalisation, information, and communication applications. The integration of artificial intelligence (AI) and machine learning (ML) into industrial applications represents a pivotal shift in the evolution of advanced control systems. This article examines the development and implementation of an AI-driven control system into an automated process, with a particular focus on optimizing raw material recovery through the classification of recycling items. The system developed is a prime example of the interlocking of mechanics, electronics and AI, paving the way for a new era in recycling technology. In addition, this work contributes to research in the field of industry automation and underlines the transformative power of AI in promoting a sustainable circular economy.**

I. INTRODUCTION

In modern industrial automation, particularly in the recycling sector, the automatic recognition and classification of products using artificial intelligence (AI) is becoming increasingly important [1], [2], [3]. In recycling plants, the precise classification of objects is crucial in order to separate different materials efficiently and accurately. This not only increases the recycling rate, but also contributes significantly to resource conservation and environmental compatibility. AI systems, when combined with efficient control systems, significantly improve precision and efficiency in the sorting and classification of recycling materials [4]. In a world where new products and packaging materials are constantly being developed, the flexibility of AI systems is crucial. By expanding the data sets and retraining the neural networks, new product ranges can be integrated into the classifier. This ensures the sustainability of the classifier. Current research shows that AI-supported systems are able to handle complex classification tasks more reliably and faster than conventional methods, which is of great importance for the recycling industry [1], [2], [4], [5]. This article examines the development and implementation of an AI-driven control system into an automated process. Particular attention is paid to the integration of the system into existing recycling processes, with the aim of increasing the recovery rate and quality of the recycled material. In conclusion, the integration of AI in the recycling industry represents a crucial step towards more efficient, agile, economical and environmentally friendly waste processing and resource utilisation [6]. Therefore, this article not only outlines the technical aspects of AI applications in recycling, but also emphasises their importance in achieving global environmental goals and promoting a sustainable circular economy.

II. State of the Art

This chapter offers an overview of the existing methods for modern automation processes. The main focus is on the implementation of AI systems into these processes.

A. AI classification system in recycling applications

Traditional recycling methods often necessitate manual sorting, which is both labor-intensive and less efficient. In contrast, AI-based techniques offer faster processing, higher accuracy, and the ability to handle a larger variety of materials. However, AI systems require significant initial investment and technical expertise for implementation and maintenance [7], [2], [3], [8].

The utilisation of AI in the field of object detection offers a number of advantages over traditional methods. The capacity of AI systems to process and classify objects at a significantly faster rate, coupled with their consistent accuracy, represents a notable advantage over manual classification by a human. Additionally, AI systems are highly adaptable, readily adjusting to new types of materials. However, these systems are not without their own set of challenges, including substantial initial investment costs and a heavy reliance on the quality of training data. Furthermore, the intricacy of sustaining and enhancing AI systems necessitates the involvement of skilled personnel, a factor that is frequently overlooked during the initial planning stages [9], [7], [10], [3], [8].

In contrast, traditional methods, which are primarily reliant on manual sorting, benefit from human judgement, particularly in ambiguous cases. However, they are less efficient, slower, and less consistent than alternative methods. This is often due to human error and fatigue.

The process of object detection, which is a fundamental aspect of AI functionality, comprises two distinct stages. Firstly, the identification of objects is achieved, followed by the disassembly and localisation of different materials. In the context of the recycling industry, this translates into the ability to distinguish and locate various types of recyclable materials, including plastics, metals, and other components. The process involves the collection and annotation of a diverse range of images of recycled objects and the different materials present within them. The images thus obtained constitute the training data, which is meticulously labelled for each object, thus providing a foundation for the subsequent training process of the AI model [11].

The AI system employs advanced machine learning algorithms, particularly Convolutional Neural Networks (CNNs), to discern patterns and features specific to different materials. This training phase is both resource-intensive and critical, laying the groundwork for the system's accuracy. The model's performance is rigorously evaluated using separate test data, leading to continuous refinements until satisfactory accuracy is achieved. Once optimised, the model is deployed in recycling facilities to categorise objects in real-time, representing a significant leap from traditional methods [9], [11], [3].

In this approach, the initial phase of the recycling process, which involves the identification of the object, is carried out through an automated process [12].

B. Industry 4.0 in Plant Control applications

The current evolution of automation in industry is being shaped by a convergence of innovative developments in the areas of control technology, computing, communication, software, and materials. These advances are not only driving forces behind the evolution of industrial automation systems, but they have also paved the way for the implementation of more complex and efficient processes in product processing [13].

The integration of artificial intelligence (AI) and machine learning (ML) into industrial applications represents a pivotal shift in the evolution of advanced control systems. These systems, which are equipped with the capacity to learn and adapt to data, facilitate the performance of complex tasks with enhanced efficiency and precision. These applications are collectively referred to as Industry 4.0. In the recycling industry, the application of AI and ML has led to a significant improvement in the accuracy of material sorting and classification, which has contributed to an increase in recycling rates and the promotion of sustainability. Furthermore, AI-driven classification systems offer a high degree of flexibility [13].

The advent of Industry 4.0 has brought about a transformation in manufacturing, with the advent of advanced production and measurement technologies driven by digitalisation, information, and communication applications. This has led to a shift towards cost-efficient production with an increasing focus on product and process quality [3].

The advancement of automation in industry is significantly influenced by innovations in the areas of control technology, computing, communication, software, and materials. These advances are of paramount importance for the future development of industrial automation systems. Recent developments include factory automation, process control systems, and energy automation systems [14].

The integration of model-based control with industrial IT systems has the potential to enhance productivity and expand the scope of traditional automation systems. This integration enables more precise control and monitoring of processes [14].

The integration of artificial intelligence (AI) and machine learning in industrial applications is facilitating the emergence of novel automation possibilities. These technologies facilitate the development of sophisticated control systems that are capable of handling complex tasks in an efficient manner. Illustrative examples of this include model-based control and non-linear predictive control in industrial applications [13], [14].

C. Integration of AI based applications in production plants

The successful integration of an AI-driven control system into an existing production line is a challenge that requires detailed planning and customisation. The main goal is to achieve seamless communication and synchronisation between the new system and the existing production processes in order to maximise efficiency and accuracy. Research in this area emphasises the importance of careful analysis of existing production processes and potential interfaces for integration [13].

The synchronization of cycle times is of paramount importance in order to guarantee the efficient production of goods. The new system must be capable of adapting dynamically to the varying speeds of the production line. Empirical studies have demonstrated that the implementation of adaptive control mechanisms, which utilize real-time data from the production line, can result in a notable enhancement in overall efficiency.

Another crucial aspect is the transfer of products and related information between different segments of the production line. The system must be capable of capturing and transferring product data in an efficient manner to ensure uninterrupted and error-free production. Research on data integration in production lines emphasises the significance of standards and protocols that facilitate interoperable data transfer. One illustrative example of a widely utilised protocol between plant control systems is Modbus.

The integration of the system into a human-guided production environment also necessitates an examination of the human-machine interaction. Research indicates that the ergonomic design of interfaces and the consideration of safety aspects are crucial for the successful integration of the system [15].

In order to accommodate future requirements and technological developments, the system must be designed to be adaptable and expandable. Research on modular system design in production automation recommends designing interfaces and system components in such a way that they can be easily updated or replaced. Additionally, the identification and handling of faulty samples is a critical aspect. The system must be able to detect defects and take appropriate action, such as rejecting defective products. Research in this field is focused on the development of algorithms that enable the rapid detection and response to defects, with the objective of minimising downtime and ensuring product quality [16].

In conclusion, the optimal design of production lines necessitates the meticulous integration of sophisticated control technologies, including AI and ML. The advancements in automation technology, such as model-based control integration and real-time Ethernet solutions, play a pivotal role in enhancing production efficiency and accuracy. In the context of Industry 4.0, digital transformation represents a pivotal element in the pursuit of enhanced product and process quality. The integration of new technologies into existing production lines necessitates the seamless synchronisation of cycle times, the efficient transfer of products and information, the precise handling of faulty samples and the harmonious collaboration between humans and machines. In addition, the systems must be flexible, adaptable and expandable in order to meet future requirements and technological developments. This holistic approach not only promotes increased production output, but also makes a significant contribution to sustainability and long-term competitiveness.

III. IMPLEMENTATION

The development of a part of a production line for classifying objects necessitates meticulous planning and implementation. The subsequent chapter provides an overview of the automated image capture system. The implementation of the AI-based classification system, which classifies the captured objects, is elucidated in the given publications [6] and [8]. The innovation described in this paper is based on the automated detection of objects via a camera. The primary focus of the system is to capture high-quality images. For effective classification, it is essential that the detection is conducted without shadows and with uniform illumination.

The production line is divided into several sections, each of which is responsible for one part of the recycling process. The section for object classification is conceptualised below. Once the object has been transferred to the object recognition sector, it is transported to the object classification section via a conveyor belt. A photo box is used for object classification, which records and analyses the object and then forwards it to the next section of the line. The photo box consists of light panels that ensure optimum lighting from every side. The object is captured by a camera and classified using AI, for details see [6] and [8]. If the classification is successful, the object is transported to the end of the sector and passed on to the next section. In cases where a clear assignment of the object is not possible, the object is returned to the beginning of the line section for sorting. This ensures that the quality level remains consistent throughout the entire line.

A. Hardware configuration

The technical implementation of the object classification section of the production line is elucidated below.

The system is controlled centrally via a Siemens SPS (programmable logic controller), which processes signals from the sensors and controls the actuators. The objects are transported through the system via a carriage on a conveyor belt. A stepper motor is employed to ensure precise control of the movement sequences. This enables the position of the carriage to be tracked after calibration, as the distance traveled can be precisely determined by the stepper motor. This implies that previously configured positions can be approached automatically and reproducibly. A position sensor is employed to calibrate the stepper motor. This is utilized to set the starting point of the conveyor belt. The information about the starting position is crucial for the calibration of the other positions within the system, thus ensuring that the positions of the conveyor belt are approached with precision. The classification is implemented in a photo box with a camera. The photo box doors are opened via controllable pneumatic pistons. It is necessary to close the photo box in order to allow illumination from all sides of the object. The walls and ceiling consist of dimmable light panels that guarantee uniform and shadow-free illumination for image capture. The formation of shadows must be prevented to achieve a high quality of classification. The status of the doors can be read out via a sensor. This checks whether the gates are in the desired position. This is necessary to prevent collisions. Figure 1 shows an image of the camera in the photo box. Additionally, information about the classification of the object is displayed above the photo.

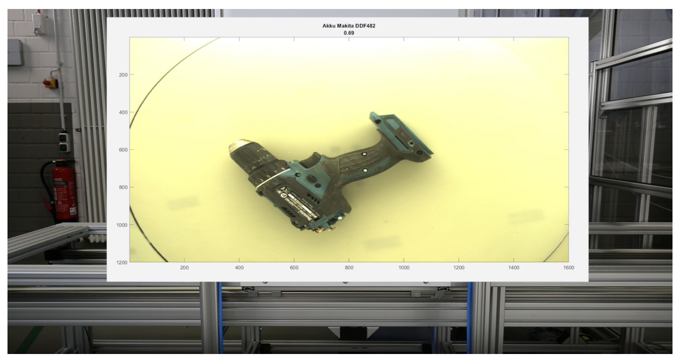

Fig. 1. Object Classification of the Recycling Process.

1) Implementation in MATLAB: The implementation in MATLAB employs Modbus communication (based on a client/server architecture) for a standardised interface for data exchange with the Siemens SPS. MATLAB's support for Modbus facilitates the implementation and integration with industrial control systems. The existing libraries enable straightforward implementation of data exchange between the SPS and the computer. Furthermore, MATLAB's App Designer facilitates the expedient and lucid development of user interfaces, which were employed for the front-end to permit the user to manually regulate various aspects of the production line and initiate the automation process. MATLAB's comprehensive integrated development environment (IDE) provides access to a suite of sophisticated tools for mathematical calculations, data analysis and visualisation, which is particularly advantageous for the development and debugging of control software. This enables automation process sequences to be analysed and verified for correctness after the fact.

When implementing the controller in MATLAB, particular attention must be paid to the following aspects:

1. Modbus communication with the SPS must be handled correctly. It is important to ensure that no requests are lost. If used incorrectly, instructions can be lost due to collisions of commands on the Modbus. This is prevented by an upstream queue, which processes requests to the SPS cyclically.

2. SPS memory addresses used should be properly configured and documented. Incorrect configuration of the memory addresses does not result in compilation errors. Therefore, it is essential to verify the configured memory addresses for correctness in all states prior to use.

Another crucial aspect is the creation of an intuitive and user-friendly graphical user interface (GUI) design for efficient operation. This is crucial for preventing incorrect operation by the user. This encompasses the generation of system status information and the implementation of robust error handling, in addition to the incorporation of safety measures such as emergency

B. Development of the Automation Control Software

The software of the automation system is responsible for controlling the automation process and manual mode of the production plant. It is divided into two sections: the frontend and the backend. The software is implemented in MATLAB and communicates with a Siemens SPS in order to control the actuators and obtain measurements from the sensors.

1) Frontend development: The frontend enables users to control each step of the production line and initiate the automation process. This facilitates the debugging of the production plant in isolation, allowing for the testing of new functionalities and objects with greater ease, thereby reducing costs. Figure 2 depicts the front end of the system. It is divided into four main areas: “Linear Drive”, “Rotation Table”, “Doors” and “Automation”.

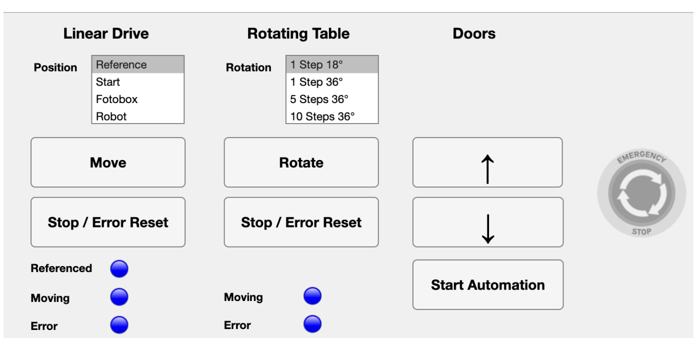

Fig. 2. Frontend GUI Controlpanel.

The “Linear Drive” area is used to control the carriage for moving the object. A desired position can be selected from a list of options (“Reference”, “Start”, “Fotobox”, “Robot”) and then the movement to the desired position can be arranged using the “Move” button. Additionally, a display is provided to indicate the current status of the conveyor belt. The movement sequence can be aborted by pressing the “Stop/Error Reset” button. The “Referenced” display indicates whether the conveyor belt has been calibrated. The “Moving” display indicates that the carriage is currently in motion. The “Error” display is active when an error occurs. The statuses are read from the SPS registers.

The “Rotating Table” area offers the user the option of manually controlling the rotation of the table by angles of 18°, 36°, 180° and 360°. This is intended to allow the object in the photo box to be viewed from several sides. However, this functionality is not yet mapped in the automation process. The “Stop/Error Reset” button allows the user to cancel the current movement. The “Moving” and “Error” status displays indicate the current status of the rotation table.

The “Doors” area contains arrow buttons that permit the photo box doors to be opened and closed manually.

The automation process is initiated by selecting the button “Start Automation” in the interface.

2) Backend Development: The backend processes the incoming signals from the frontend. The incoming commands are converted into specific Modbus commands in order to facilitate communication with the SPS. These commands are queued prior to Modbus transfer in order to guarantee the prevention of information loss. The actuator functionalities are configured in the Siemens SPS and are triggered by a value in a reconfigured register, which is controlled via Modbus.

The following section describes the automation process, which controls the automatic sequence of the production line. Figure 3 shows the corresponding automation flow chart.

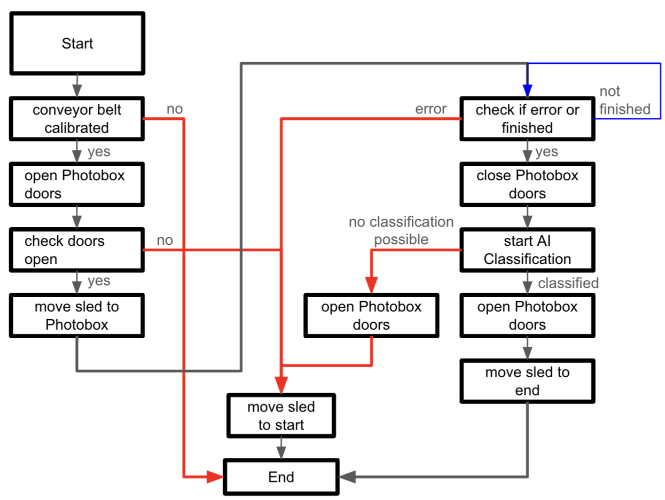

Fig. 3. Flow Chart of the Software Implementation.

Prior to initiating the automation process, it is necessary to calibrate and adjust the conveyor belt in order to enable it to move to the configured positions. The calibration status is stored in a Boolean variable and can be queried via the Modbus in MATLAB. At the commencement of the process, the system verifies that the conveyor belt has been correctly calibrated. If this is the case, the gates of the photo box open to prevent the object from colliding with the gates during the movement process. Subsequently, the object is conveyed into the photo box on a carriage that is connected to the conveyor belt. In the photo box, the object is classified by a trained neural network, which has been trained in advance with a database of the objects to be recognised. The neural network returns the type and confidence value of the classification of the analysed object as output.

The confidence value is a key indicator of the reliability of the classification by the AI. This value indicates the degree of confidence with which the AI identifies and categorises the analysed object. A higher confidence value signifies that the features of the object are clearly discernible and correspond to an existing class within the AI's learning base. The AI compares the sensory data of the object, for instance visual patterns or shapes, with its trained model and derives from this how closely the object corresponds to the learned features of a class. This results in the confidence value.

If the confidence value is above 65%, the classification is deemed successful and the process is continued. Conversely, if the confidence value is below 56%, the process is aborted. This protects the process from errors that could be caused by uncertain or incorrect classifications and ensures that only objects with a trustworthy classification are forwarded through the system. In this case, the object is moved back to the beginning of the conveyor belt section for further processing. Prior to each conveyor belt transport, the gates of the photo box are opened to prevent the object from colliding with the gates.

Should the classification result be successful, the object is moved to the end of the conveyor belt section. There, it is transferred to the subsequent section of the system.

IV. Evaluation

The system was subjected to testing in a variety of scenarios involving different electronic devices, including smartphones and cordless screwdrivers. It was integrated into a real-world setup within the circular digital economy laboratory of the Prosperkolleg [12], where it was tested on a range of automated scenarios. The results of the AI driven object recognition is evaluated in the publication [8].

A. System Integration

In the demonstration plant existing production processes and product designs are analysed and compared. Based on the results, the processes and product designs are optimised and operational technical solutions are developed [17]. The system developed represents a significant advance in the integration of mechanics, electronics, and AI, thereby paving the way for a new era in recycling technology. The intelligent control and classification not only enhance work performance, but also improve environmental compatibility and resource efficiency [7].

B. Results

The automation process is capable of sorting the processed objects as intended. Unidentified components are redirected to the initial stage of the classification plant control unit. Subsequently, the identified components are directed to the end of the process, where pertinent data regarding the object is reported for disassembly in the subsequent control segment.

The automation recognizes hardware errors of the production plant as intended. The system utilises sensors to ascertain if the pneumatic doors of the photobox are opening correctly, thereby preventing collisions with the object on the conveyor belt. Furthermore, the system ensures that parts are accurately recognised, passing only objects with a certainty above a configured threshold in the classifier [8]. Moreover, it verifies the calibration of the conveyor belt, ensuring that the allocated positions of the conveyor belt are accurate. All of these safety functionalities have been tested and are fully functional.

V. Summary

The integration of this AI-controlled control system into existing recycling processes is of crucial importance. It enables a significant increase in efficiency and accuracy in the sorting of recycling materials. The flexibility of the system allows for the rapid adaptation to new products and materials by expanding and retraining the neural networks.

In the modern circular economy, this system is an essential component for increasing efficiency and protecting the environment simultaneously. This research serves to emphasise the significance of AI systems in attaining global environmental objectives and in fostering a sustainable circular economy. Furthermore, this work contributes to the field of industrial automation, thereby demonstrating the transformative potential of AI in promoting a sustainable circular economy.

VI. Future Work

A. Advanced object recognition through multi-perspective analysis

A significant enhancement to the current system could be the implementation of a rotation mechanism for the scanners that captures objects from different perspectives. This would result in the acquisition of multidimensional data, which would significantly increase the accuracy of the classification system, reduce misclassifications and expand the variety of identifiable materials.

B. Automated material separation

A further area of future research will be the development of an AI-based system for the automated decomposition and sorting of classified objects. Information from a database can be used to implement the optimum disassembly process by classifying the object. Such a system would increase the recycling rate of the objects. In addition, the purity of the recovered materials would be enhanced, as different raw materials could be specifically separated, which would not be possible using standard recycling processes.

C. Big Data Analysis for Process Optimization

Another research approach that has the potential to further increase the efficiency and effectiveness of the system is the use of big data analysis to continuously optimise the recycling process. This is achieved through precise analysis of operating data and feedback loops. Collected data can be used to identify bottlenecks in the system, and the cycle time of the automation process can be accelerated by eliminating them. In addition, the collected data can serve as training data for future AIs.

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