Conveyor-Based IoT Platform for Machine Vision Tasks

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Abstract. The progress in conveyor belt automation and digitalization will revolutionize our classrooms, offering endless possibilities. Students can practice remotely by connecting through intuitive software and controlling the conveyor via Internet of Things technology. Experimentation can range from using classical control algorithms and monitoring real-time results through a built-in camera to leveraging an artificial vision system for applying both traditional algorithms and novel techniques to solve vision tasks. All this is possible without losing the option of physically interacting with the equipment, seamlessly switching between remote and manual control.

Keywords. IoT, automation, machine vision and artificial intelligence.

1 Introduction

In recent years, teaching techniques have been constantly evolving. The COVID pandemic made us change from in-person to virtual classrooms (Alvarez Aguilar & Habib Mireles, 2021). These challenges have made us improve our methods to access learning resources from anywhere. The Internet of Things (IoT) has appeared as a powerful tool that can be used to develop new platforms where knowledge is applied. As an example (Sutjarittham et al., 2019) makes use of IoT for classroom usage prediction, (Bento et al, 2023) report the effects of the use of IoT in an entire organization. As well, (Adhicandra et al., 2024) find out that technology in education has a significant impact on improving classroom management efficiency, and helps to personalize the learning experience.

In the current automation and digitalization era, innovations that make knowledge acquisition easier are required, (Revathi et al., 2020) conclude that "IoT based Cloud Integrated Smart Classroom for smart and a sustainable Campus will be an evolution in the educational environment resulting in high efficiency and effectiveness of classroom teaching methodology".

Nowadays, the application of those technologies is not involved in all areas, and here is where we found an opportunity to use new technologies in learning platforms by bringing remote access. This paper proposes the development of remote access to an automated belt conveyor and a computer vision system.

The development of this system comes with two gains: the first gives students the ability to experiment with control and automation. The second one is the deployment of algorithms and artificial intelligence for object recognition tasks.

In this paper, we exploit the integration of the vision system to the conveyor and explore the application of an algorithm, and AI systems for object detection in our platform.

2 Related Work

The integration of advanced technologies into industrial processes, particularly in the context of Industry 4.0, has been a focal point of recent research. The development of intelligent virtual assistants (IVAs) and their application in industrial settings, as explored by Hernández Figueroa et al. (2020), highlights the potential of artificial
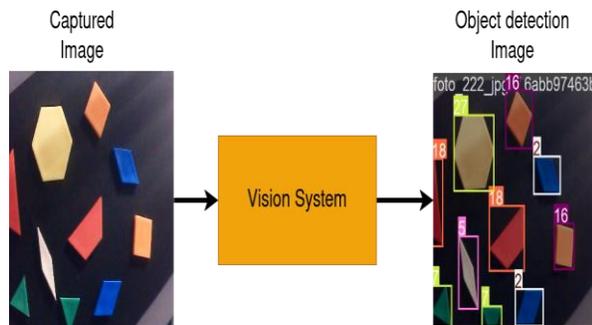
Fig. 1. Vision system overview

intelligence (AI) in enhancing human-machine interaction. Their work demonstrates how an IVA can be integrated with a robotic arm to streamline communication and control in industrial environments, offering a more intuitive and natural interface compared to traditional human-machine interfaces (HMIs). This research underscores the importance of AI-driven systems in optimizing industrial processes, particularly in scenarios where real-time decision-making and adaptability are crucial.

On the other hand, Sierra-Pérez and Legrá-Lobaina (2014) delve into the optimization of belt conveyor systems, focusing on the selection of optimal belt speeds to enhance energy efficiency and reduce operational costs. Their study provides a comprehensive methodology for determining the optimal speed of belt conveyors, particularly in the context of transporting lateritic ores.

By considering factors such as belt width, material properties, and energy consumption, their work offers valuable insights into the design and operation of conveyor systems. The authors emphasize the importance of minimizing energy consumption while maintaining productivity, a consideration that is highly relevant to the development of energy-efficient control systems for semi-commercial belt conveyors.

In addition to AI-driven interaction and energy optimization, recent studies have explored the integration of computer vision techniques in industrial automation.

Torres et al. (2021) present an approach for real-time object detection and classification using convolutional neural networks (CNNs) in conveyor belt systems. Their research demonstrates how CNN-based models can accurately segment and

identify objects of various colors and shapes, improving sorting efficiency and reducing manual labor. The use of vision-based techniques allows for a more precise and automated workflow, minimizing errors in material handling and increasing productivity.

Furthermore, Martínez-González and Rivera (2022) investigate the application of machine learning algorithms for defect detection in conveyor belt operations. Their study highlights the effectiveness of deep learning models in identifying irregularities in transported materials, enhancing quality control and predictive maintenance strategies. By integrating these vision-based methods into semi-commercial conveyor systems, industries can achieve higher levels of automation and accuracy in material processing.

Both studies contribute significantly to the understanding of how advanced technologies can be leveraged to improve industrial processes.

Hernández Figueroa et al. (2020) highlight the role of AI in creating more interactive and responsive systems, while Sierra-Pérez and Legrá-Lobaina (2014) provide a framework for optimizing the mechanical and operational aspects of conveyor systems.

Additionally, Torres et al. (2021) and Martínez-González and Rivera (2022) expand upon these foundations by demonstrating the potential of vision-based systems in object detection and quality control.

Together, these works form a solid basis for the development of a remote-control system for semi-commercial belt conveyors, integrating AI-driven interfaces, energy-efficient operational strategies, and computer vision techniques.

In the context of this article, the proposed remote-control system for a semi-commercial belt conveyor builds upon these advancements by incorporating a commutator for speed and direction control.

Additionally, it leverages computer vision techniques for segmentation and identification of objects based on color, improving automation and efficiency. By combining AI-driven interaction, energy optimization principles, and vision-based detection methods, the proposed system aims to offer a more efficient, user-friendly, and adaptable solution for controlling belt conveyors in semi-commercial settings.
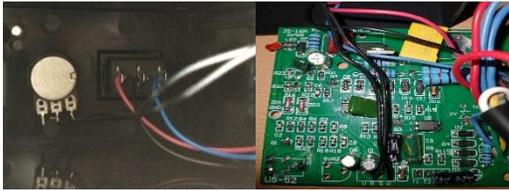
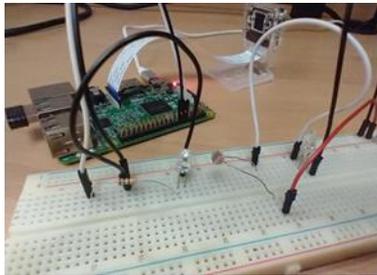**Fig. 2.** Conveyor belt control system for direction and speed

Fig. 3. PWM implementation for LED light intensity control

3 Experimental Procedures

A comprehensive evaluation of the conveyor belt control circuit, as shown in "Fig 2," was conducted to determine its feasibility for reuse or redesign. This analysis involved assessing controllers, sensors, and power modules to ensure compatibility with the proposed automation system. Functional tests verified compliance with speed and direction control requirements, while integration with remote and manual configurations was examined.

A preliminary schematic diagram was created to map the electrical connections, detailing power sources, control elements, and signal flow. This schematic provided a foundation for the final circuit design, optimizing layout and signal processing efficiency.

Technical documentation included the electrical schematics and motor specifications, outlining key parameters such as voltage, current, and control system configuration. The interaction between the control circuit and motor was analyzed, focusing on signal conversion for precise actuation.

A remote speed control system was designed using a Raspberry Pi, integrating photoresistors and high-precision LEDs for dynamic speed modulation, as illustrated in "Fig 3." The photoresistors detect light intensity variations emitted by the LEDs, adjusting resistance to modulate control signals. This system ensures accurate, real-time speed regulation through adaptive signal processing, with the Raspberry Pi acting as the core controller, interpreting sensor data and fine-tuning LED output to maintain optimal belt performance.

3.1 Bidirectional Control of the Conveyor Belt

To control the direction of motor rotation, a relay-based system was implemented. Two electromagnetic relays, were configured to activate either of the two possible rotation directions by inverting the polarity applied to the motor. This method enables precise and reliable management of conveyor belt movement, ensuring smooth operation in both directions. The relay system was chosen for its simplicity, robustness, and efficiency in handling motor direction control.

3.2 Remote and Manual Control Modes

The system incorporates a dual-mode control strategy, allowing the conveyor belt to be operated either manually or remotely:

− Manual Control: The operator can start, stop, and adjust the belt speed via a physical interface on the control panel.
− Remote Control: A Raspberry Pi acts as a programmable logic controller (PLC), enabling real-time monitoring and control through a custom software interface. This setup allows the operator to visualize operational parameters such as speed and system status, while also sending commands to modify operating conditions.

3.3 Mode Selection System Implementation

A DPDT (Double Pole, Double Throw) three-position toggle switch, was integrated to switch between manual and remote control modes. The switch operates as follows:

− Position 1: Direct connection between the manual interface and the conveyor motor, enabling local control.

− Position 2: Open circuit, disabling both control modes as a safety measure.
− Position 3: Connection between the Raspberry Pi and the motor, activating remote control functionality.

Speed Control and Performance Validation: A remote speed control system was designed using a Raspberry Pi, integrating photoresistors and high-precision LEDs for dynamic speed modulation, as illustrated in "Fig 3." The photoresistors detect light intensity variations emitted by the LEDs, adjusting resistance to modulate control signals. This system ensures accurate, real-time speed regulation through adaptive signal processing, with the Raspberry Pi acting as the core controller, interpreting sensor data and fine-tuning LED output to maintain optimal belt performance.

To validate system functionality, a temporary connection was established to test the integration between the control circuit and the conveyor belt. This phase included performance tests to measure the maximum achievable speed, allowing for system adjustments to ensure operation within the predefined speed ranges. The results confirmed the reliability of the control system and facilitated fine-tuning to optimize performance before full deployment.

By integrating these control and automation strategies, the developed system significantly enhances the efficiency, flexibility, and reliability of the conveyor belt, ensuring seamless operation across different industrial applications.

3.4 Interface

The interface features two dropdown menus that allow users to select the shape they want to detect as the conveyor belt moves the pieces. Additionally, there is an option to detect all available shapes from the menu.

Upon selecting an option and clicking "Accept," the detection visualization is displayed, allowing users to capture desired images

3.5 Yolo 11

You Only Look Once, better known as YOLO (Redmon et al., 2016), has emerged as a powerful

Fig. 4. Mode selector system (remote or local) and speed and direction of rotation control system for the conveyor belt
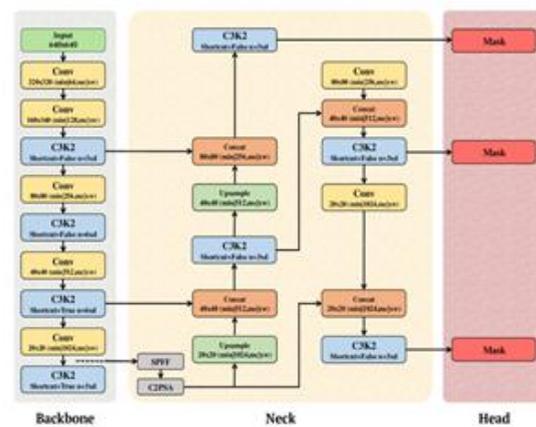

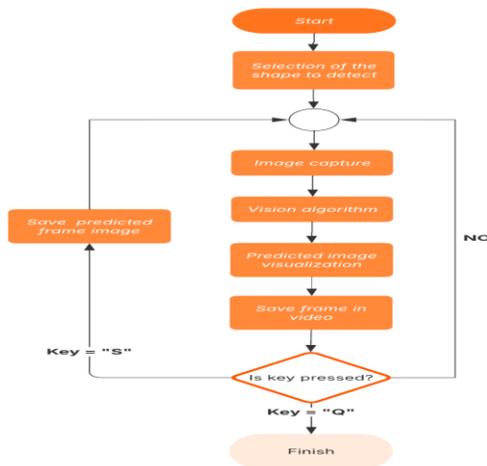**Fig. 5.** Interface functioning diagram

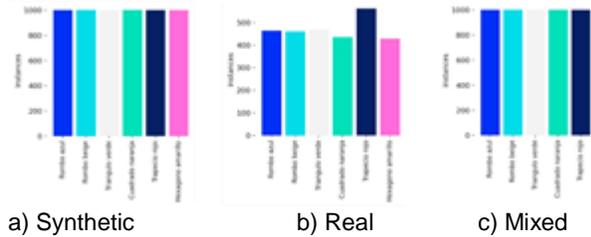**Fig. 6.** YOLO11 architecture overview. Image taken from (Khan & Jensen, 2025)

a) Synthetic   b) Real   c) Mixed

Fig. 7. Datasets

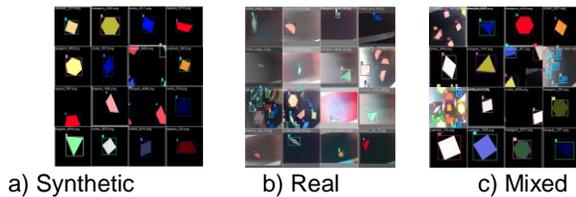

a) Synthetic   b) Real   c) Mixed

Fig. 8. Dataset instance distribution

Fig. 9. Results of applying object recognition algorithms with different forms and colors

tool of AI, solving different tasks of computer vision such as instance segmentation, classification, object detection, and pose prediction. Over the years this method has been improved to achieve better performance (Nazir & Wani, 2023).

In our experiment we use the YOLO version 11, YOLO11 onwards, proposed by (Jocher & Qiu, 2024), which at the time is the most recent architecture. Yolo11 is composed in three main blocks named as backbone, neck and head, as shown in figure 6.

The backbone is designed in a cascade architecture, providing multiscale features on three levels. These features are fed later in the neck block, where the features are upsampled. Then,

multiscale masks are created to make object detection of different scales in the head block.

3.6 Datasets Description

The goal of the vision task is to detect objects of different shapes and colors (Fig. 7). To achieve the proposed goal, three datasets were done: one with synthetic data (It contains 6000 images divided into: 2000 images for train data, 2000 images for validation data and 2000 images for test data), real data(it has 942 images divided into: 400 images for train data, 400 images for validation data and 142 images for test data), and mixed data(with a total of 6942 divided into: 2400 images for train data, 2400 images for validation data and 2142 images for test data).

The synthetic dataset is ideal and provides good images of the different classes with one thousand instances per class (Fig 7a and 8a). The real dataset contains captured images on the conveyor with multiple cases: in operation, static, lights on, and off. To produce a robust solution to these perturbations (Fig 7b and 8b).

Finally, we explore mixing the datasets, following the idea that synthetic data provides good features, while real data introduces possible perturbations that may occur when deployed on- site.

The data distribution for the datasets is shown in Fig. 8. We have six different classes of objects. In mixed and synthetic images, we balanced datasets, while in real data we wanted to add multiple objects in an image, and the perturbations were impossible to create a balanced dataset. In addition, the mixed dataset uses all the real data, and the missing elements are synthetic data.
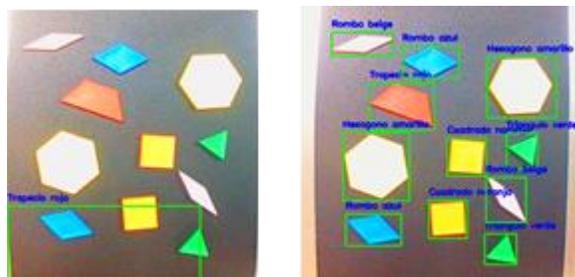
4 Results

In this section we present quantitative results of the proposed methods for the vision system in the IoT platform. All the validation experiments are conducted on a Raspberry Pi 5 with 64-bit OS. For the YOLO11 training a computer equipped with an Intel Core i5-10400F CPU, NVIDIA GeForce RTX 3060 with 12 GB VRAM GDDR6 and 16 GB of RAM.

Table 1. Comparison on YOLO11 over three proposed datasets

Metric/ Dataset	Synthetic	Real	Mixed
Box loss	**0.036**	2.295	0.038
Cls loss	0.055	3.078	0.055
Dfl loss	**0.760**	3.611	0.761
Precision	0.999	0.340	0.999
Recall	1	0.480	1
mAP50	0.995	0.227	0.995
mAP50-95	0.995	0.0963	0.995

Table 2. Comparison on YOLO11 and Algorithm

Metric/ Method	YOLO 11	Algorithm
Time	**120 ms**	230ms
Detected objects	**25/30**	10/30

a) Synthetic database   b) Mixed database

Fig. 11. YOLO11 validation results

4.1 Algorithm Results

Figure 13 shows the results of the object detection classical algorithm, detecting multiple instances in an image. It is appreciated that the result is given by the analysis of the number of vertices the figure is determined. In the case of the quadrangle it is determined from the length of its sides. While the color is defined using the HSV values of the pixels, since this approach makes use of HSV to approach the color it becomes difficult to detect objects when those are not.

4.2 YOLO11 Results

In this subsection, we present the YOLOv11n training and validation results. The objective is to ensure successful object detection while the conveyor operates. To achieve this, the training was conducted using three different datasets: synthetic data, captured data, and mixed data.

4.3 Transfer Learning with YOLOv11

Initially, to develop the project, the necessary libraries were installed on the 64-bit Raspberry Pi OS.

Since we are working with cameras and aim to achieve the best results while optimizing performance, calibrating the camera became essential. This was done using a computer vision-based method to enhance accuracy and efficiency in the processing tasks.

Next, the classes for the neural network were defined, along with the labels that will be used for their identification. Modifications were then made to the model.yaml and data.yaml files, which define the network structure and training paths.

These modifications specify the number of classes, the corresponding labels, and the directory paths for the data required for training and validation.

After modifying the files, the model was loaded and trained for 60 epochs freezing the backbone and applying a data augmentation by tuning the following hyperparameters:

freeze=10, flipud=0.5, fliplr=0.5, degrees=30.0, translate=0.2, scale=0.3, shear=5.0, perspective=0.005, hsv_v=0.4, mosaic=0.3

4.4 YOLO11 Training Results

Fig. 10 shows the transfer learning results of all three datasets. It shows that

The results are summarized in Table 1. Results show what was expected, noisy or perturbed data makes object detection difficult for YOLO11, while the synthetic data makes the task better solved.

4.5 YOLO11 Validation Results

We present validation results with the best performing model and the algorithm, to make a fair comparison we compare them in terms of inference time and how many objects they can detect while the conveyor is in operation, Table 2 summarizes our comparison.

As it was expected the perturbations added in the mixed dataset makes YOLO11 perform better in validation, despite that in training the synthetic database show better results, see Fig. 15.

5 Conclusions

The development of a remotely controlled conveyor belt system integrated with a computer vision module represents a significant advancement in automation and remote learning applications. The implementation of a dual-mode control system, leveraging both manual and remote operation through a Raspberry Pi, ensures flexibility and adaptability in different industrial and educational environments.

The integration of relays for bidirectional motor control has proven to be an efficient and reliable solution for managing conveyor belt movement. Additionally, the use of photoresistors and high-precision LEDs for speed modulation enhances control accuracy, allowing real-time adjustments to optimize performance.

The inclusion of a computer vision system using YOLO11 further expands the capabilities of the conveyor belt, enabling real-time object detection and classification. Experimental results demonstrate that synthetic datasets enhance recognition accuracy, while real-world perturbations pose challenges that can be mitigated through mixed dataset training.

This work highlights the potential of integrating IoT-based automation and AI-driven vision systems into conveyor belt applications, providing valuable insights for both industrial optimization and educational platforms. Future work will focus on refining the vision model for increased robustness in dynamic environments and expanding the system's connectivity to integrate with cloud-based monitoring solutions for enhanced remote accessibility.

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