INFORMATIK

INFORMATIK JOURNAL, Volume 21, No 3, 2025

Developing Sorting Algorithm for SmartEdu Conveyor using Computer Vision Technology

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Article Info

Article history:

Received 07 Oct 2025
Revised 21 Oct 2025
Accepted 21 Oct 2025

Keywords:

Sorting algorithm
MQTT
Node Red
Raspberry Pi 4
YOLO v8

ABSTRACT

This study aims to develop a sorting algorithm for the SmartEdu Conveyor using computer vision technology to enhance accuracy and efficiency in automated sorting systems. The system integrates a Raspberry Pi 4 as the main processing unit and employs the YOLOv8 object detection algorithm to classify geometric objects moving on a conveyor belt. Images captured by an overhead camera are processed in real time, and the results are transmitted through the MQTT protocol using the Paho MQTT library. Node-RED functions as the Human-Machine Interface (HMI), while a Programmable Logic Controller (PLC) drives double-acting pneumatic cylinders to perform the sorting mechanism. Experimental tests conducted at three conveyor speeds demonstrate that the system achieves an average accuracy confidence of 89.38% at 1 cm/s, 78.57% at 1.7 cm/s, and 59.28% at 2.3 cm/s. Further performance evaluation using the Precision–Recall curve yields a mean Average Precision (mAP) of 0.993 at an Intersection over Union (IoU) threshold of 0.5, indicating highly accurate object detection capability. The proposed YOLOv8-based sorting system demonstrates reliable real-time operation, high precision, and robust communication between vision and control modules. It will be implemented as a SmartEdu teaching aid prototype to support automation learning and industrial training applications. This work contributes to educational automation by integrating an open-source vision algorithm with industrial control architecture.

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I. INTRODUCTION

Global trends, including just-in-time production, e-commerce, and containerization, have resulted in an increased volume of goods requiring shipment within stringent delivery timelines. Within numerous supply chains, the implementation of an automated conveyor system constitutes a fundamental component of the distribution process [1]. The accuracy and speed of goods distribution, particularly during the sorting phase in conveyor systems, are critical in distribution systems, especially within the industrial sector [2]. Sorting involves the selection of goods [3], which, in this context, refers to geometric objects or shapes. The automation of conveyor sorting systems seeks to optimize efficiency, defined as the average number of complex orders processed over an indefinite period [4]. The field of computer vision, particularly object detection, provides a foundational basis for sorting [5]. The application of computer vision in industrial contexts is experiencing significant growth over time [6]. Various methodologies are employed, including CNN, R-CNN, YOLO, SSD, among others [7][8][9]. Each method presents distinct advantages and disadvantages [10]. Consequently, it is imperative to comprehend the objectives of the research to be undertaken.

Numerous studies have investigated conveyor sorting systems. Study [11] employs a color sensor (TCS 34725 RGB) and a weight sensor (Strain Gauge Load Cell), with the system being controlled by Arduino. The findings indicate a 100% detection rate via the color sensor and a detection rate ranging from 85.80% to 99.813% through the weight sensor. Another study [12] utilizes computer vision based on HSV color filtering, achieving a 100% accuracy rate. Study [13] focuses on waste sorting using neural network image processing. Images captured by the camera are input into the neural network, which identifies the position and type of detected objects, utilizing a database comprising over 13,000 images of municipal solid waste. The Mean Average Precision (mAP) reported in this study is 64%.

This study, grounded in a comprehensive review of existing literature, aims to explore the design of a production control system utilizing computer vision to distinguish production outcomes based on geometric shapes. The system is composed of several integral components: a camera for capturing images, a Raspberry Pi 4 for system control, the YOLO v8 algorithm for image processing, MQTT for facilitating communication between the image and the PLC, and Node Red for the Human-Machine Interface (HMI).

The YOLO method [14] is recognized as the most rapid among object detection algorithms. In a study focused on pill detection, the mAP of Faster R-CNN achieved 87.69%, whereas YOLO v3 demonstrated a substantial advantage in detection speed, with FPS exceeding that of Faster R-CNN by more than eightfold. This indicates that YOLO v3 is capable of real-time operation with a high detection accuracy rate of 80.17% mAP. Additionally, the performance of the YOLO v3 algorithm was superior when comparing detection results on challenging samples. In contrast, SSD did not attain the highest scores in terms of either mAP or FPS [7]. Moreover, in YOLO v8, research findings [15] reported a mAP value of 95%, the highest in comparison to YOLO v3 at 87.36%, YOLO v7 at 81%, and other methods such as MobileNetV2 at 90%.

Previous studies on conveyor-based sorting systems using computer vision have primarily focused on improving detection accuracy under controlled industrial conditions [2], [4], [7]. However, most of these systems rely on high-end computing platforms and lack adaptability for resource-limited environments such as embedded processors. In addition, existing methods often face challenges in maintaining detection reliability at varying conveyor speeds, particularly when motion blur or limited frame capture reduces image clarity. Integration between computer vision modules and industrial controllers is also rarely optimized, as data transmission is often handled by separate interfaces rather than a unified IoT-based protocol. These limitations highlight the need for a compact, low-cost, and real-time sorting system that can operate effectively on embedded hardware while maintaining consistent detection performance across different operating speeds.

This study aims to assess the accuracy and precision of geometric object detection outcomes within a conveyor sorting system employing computer vision technology. The research is expected to provide a solution for the rapid and precise sorting of geometric objects on a conveyor and is intended to serve as a reference for future studies. Although numerous studies have investigated object detection for automated sorting systems using deep learning models such as Faster R-CNN, SSD, and YOLOv5 [2], [4], [7]–[9], most of these implementations are optimized for industrial-scale hardware with high computational capacity. However, limited research has focused on the development of real-time object detection systems that function effectively on low-cost embedded platforms such as the Raspberry Pi, particularly in educational or small-scale automation environments. Existing works often prioritize either speed or accuracy, rather than achieving a balanced trade-off suitable for constrained systems. Furthermore, few studies have integrated computer vision with Internet of Things (IoT) communication protocols—such as MQTT—for seamless interaction between the detection module and programmable logic controllers (PLCs). Therefore, this study addresses these gaps by developing an embedded, real-time sorting system named SmartEdu Conveyor, which utilizes the YOLOv8-s model to achieve reliable detection performance while maintaining efficient hardware utilization and network integration.

II. RESEARCH METHOD

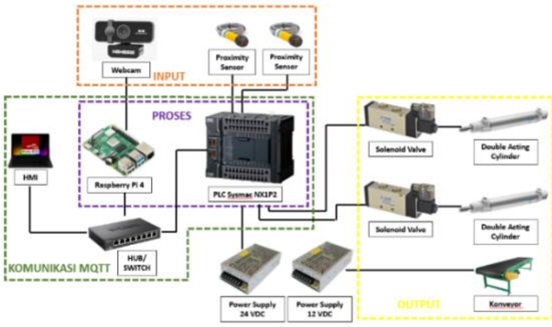

Fig. 1. Overview of the Entire System

This study employs the Raspberry Pi 4 as the primary processing unit to manage data acquisition from a camera or webcam utilizing the YOLO v8 algorithm within the framework of conveyor sorting. The procedure commences with the camera capturing images of objects positioned on the conveyor. The Raspberry Pi 4 is tasked with processing these images for the purpose of object identification and classification, employing the YOLO v8 methodology.

Upon completion of the identification process, the processed data is transmitted to the PLC and Node-Red HMI utilizing the MQTT communication protocol. The PLC functions as the primary controller, receiving data from the Raspberry Pi 4 via MQTT. This data is interpreted by the PLC to operate actuators, specifically double-acting pneumatic cylinders in this context. Node-Red HMI functions as the human-machine interface, enabling users or operators to visually monitor and control the sorting process through the graphical interface provided. The system is comprehensively designed to enhance efficiency and automation in the sorting of geometric objects by employing computer vision technology and the Internet of Things (IoT).

The YOLOv8-s (small) model was employed in this study due to its balanced trade-off between accuracy and processing speed, making it well-suited for the Raspberry Pi 4 platform. The training dataset consisted of 300 labeled images of geometric objects—circles, squares, and triangles—captured under various lighting and positioning conditions. YOLOv8 was chosen for its superior efficiency compared with earlier models such as Faster R-CNN, SSD, and YOLOv5. Unlike the two-stage Faster R-CNN, which requires high computational power, YOLOv8 uses a one-stage detection framework that supports real-time processing. It also improves feature extraction through the CSPDarknet backbone and employs an anchor-free detection mechanism that reduces false positives. Compared to YOLOv5, YOLOv8 introduces a decoupled head and dynamic input scaling, increasing accuracy while remaining lightweight and fast. These advantages make YOLOv8 ideal for the SmartEdu Conveyor, which requires reliable, real-time detection under limited hardware conditions.

The training process was executed over 100 epochs, utilizing a batch size of 16, a learning rate of 0.001, and an image resolution of 640×640 pixels. The model was developed using the Ultralytics YOLOv8 framework on a workstation equipped with an NVIDIA RTX 3060 GPU, and subsequently deployed to a Raspberry Pi 4 for inference.

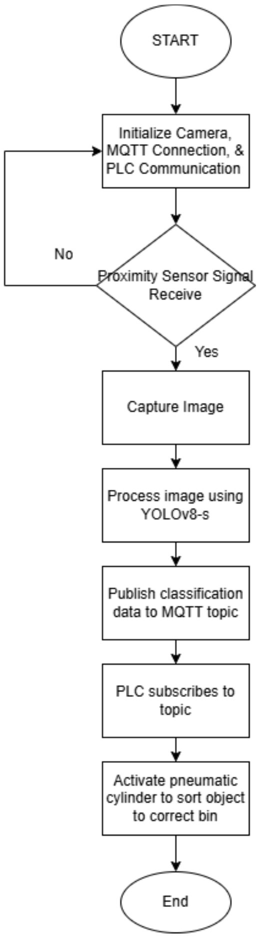

Fig. 2. SmartEdu Shorting Algorithm

The sorting algorithm developed for the SmartEdu Conveyor follows a structured sequence of sensing, computation, and actuation steps to achieve real-time classification and sorting. The process begins with system initialization, where the camera, MQTT connection, and PLC communication are set up to ensure seamless integration between modules. When the proximity sensor detects an object on the conveyor, the overhead camera captures an image of the object at the detection area. The captured image is then processed on the Raspberry Pi 4 using the YOLOv8-s model to recognize object shapes (circle, square, triangle) and generate confidence scores.

If multiple objects are detected simultaneously, the system selects the object with the highest confidence score for sorting first. The system then computes the actuation delay based on conveyor speed to ensure precise timing for the pneumatic cylinder. Classification data, including the object label and calculated delay, is published to the MQTT broker. The PLC subscribes to this topic, interprets the received message, and activates the corresponding pneumatic cylinder to direct the object to the correct sorting bin. After actuation, the system returns to standby mode, waiting for the next object to repeat the process.

III. RESULT AND DISCUSSION

The prototype of the developed conveyor sorting system for geometric objects is shown in Figure 3 that illustrates the prototype of the SmartEdu Conveyor system, which has been engineered for the automatic detection and sorting of geometric objects utilizing computer vision technology. The prototype comprises a conveyor belt, camera, gearbox, pneumatic cylinders, and proximity sensors, each of which plays a pivotal role in the system's operation and synchronization.

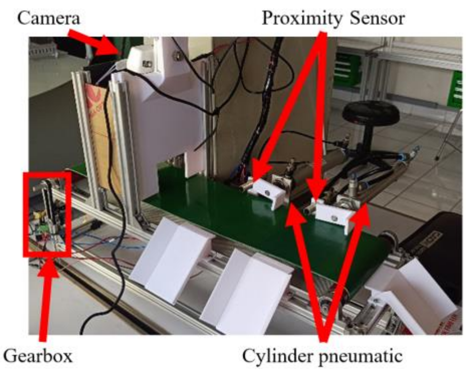

Fig. 3. The Prototype of System

The conveyor functions as the primary mechanism for transporting objects through the inspection area. It is powered by a DC motor and coupled with a gearbox, which provides adjustable and stable speed control, ensuring that each geometric object consistently passes under the camera's field of view. The gearbox regulates motor torque and speed, preventing slippage and maintaining smooth motion during operation. A camera mounted above the conveyor acts as the visual sensor, capturing images of passing objects and transmitting them to the Raspberry Pi 4 for real-time processing using the YOLOv8 detection algorithm. The camera's position and lighting are optimized to minimize glare and shadow, thereby enabling accurate classification of objects based on their geometric shape and size.

The pneumatic cylinders function as actuators that physically sort detected objects based on classification outcomes. Detection data from the computer vision module are transmitted via the MQTT protocol to the PLC, which governs the double-acting pneumatic cylinders to direct objects into their designated bins. Proximity sensors installed along the conveyor detect the presence of objects and synchronize the timing between image capture and actuator movement. This integrated configuration ensures coordinated mechanical motion, accurate detection, and precise sorting, thereby forming a compact and effective platform for computer vision-based automation within the SmartEdu teaching aid system.

The SmartEdu Conveyor's electrical setup combines different parts into one automated system. It uses computer vision, MQTT for data sharing, and PLC for control. The system runs on 220 VAC power, which is changed into 24 VDC, 12 VDC, and 5 VDC to meet the needs of each device. The 24 VDC powers the Omron Sysmac NX1P2 PLC and other control parts. The 12 VDC powers the DC motor through a BTS 7960 motor driver, keeping the conveyor moving smoothly. The 5 VDC powers the Raspberry Pi 4, which handles image capture and real-time object detection. As shown in Figure 4, this power setup uses energy well and keeps high- and low-voltage parts separate, improving system stability, communication, and safety.

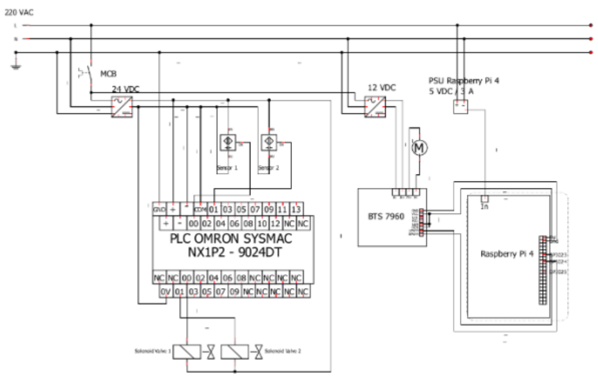

Fig. 4. The Electrical of The System

This configuration ensures stable power distribution, reduces noise interference, and enhances the reliability of communication among control components. The integration of electrical and data networks enables the system to execute object sorting in real time while maintaining high synchronization accuracy between image detection and actuator response.

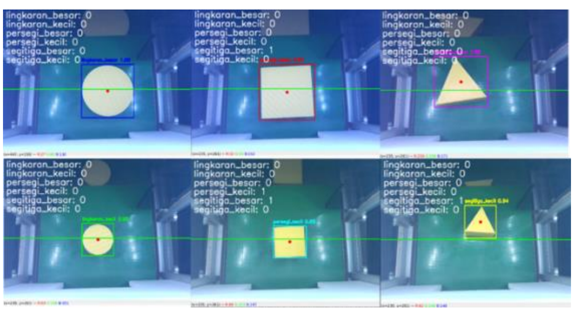

Fig. 5. The Result of Computer Vision

The results of the object detection process using the YOLOv8 algorithm are illustrated in Figure 5, where each bounding box color represents a distinct geometric class and size category. Large circular objects are outlined in blue, large squares in red, and large triangles in purple. In contrast, small circular, square, and triangular objects are marked in green, turquoise, and yellow, respectively. These visual outcomes demonstrate the model's ability to accurately detect geometric features even under moderate lighting variations. The color-coding scheme also enhances object differentiation in the Node-RED HMI interface, enabling clear and responsive real-time monitoring during conveyor operation.

A. Computer Vision Accuracy Test Result

Accuracy testing entails evaluating the extent to which the results obtained from a measurement instrument or system align with actual or established reference values. In this study, 60 trials were conducted. Each data entry consists of six test results, corresponding to each shape of the object: Large Circle, Small Circle, Large Square, Small Square, Large Triangle, and Small Triangle. Regarding speed, three distinct variations of conveyor speed were employed in the tests. The first variation, designated as low speed, is set at 1 cm/s. The second variation, termed medium speed, is set at 1.7 cm/s. Lastly, the third variation, referred to as high speed, is set at 2.3 cm/s.

TABLE I. Accuracy Test Results at Low Conveyor Speed (1 cm/s)

No	*The number of test data*	*Avg. Accuracy Confidence (%)*	*Error(%)*
1	6	97	3
2	6	81	19
3	6	98.5	1.5
4	6	81.67	18.33
5	6	98.33	1.67
6	6	96	4
7	6	97	3
8	6	81	19
9	6	82	18
10	6	81.33	18.67
Average		89.38	10.62

The accuracy test results for the SmartEdu Conveyor operating at a reduced conveyor speed of 1 cm/s are summarized in *Table I.* Six geometric objects of varying shapes and sizes—large and small circles, squares, and triangles—were tested in ten repeated trials to verify detection consistency. The system achieved an average accuracy confidence of 89.38%, with an average error rate of 10.62%, reflecting stable and reliable performance under low-speed conditions. Most trials recorded confidence levels above 95%, confirming the system's capability to capture and classify objects effectively when motion is minimal and the camera has sufficient exposure time. Minor deviations in accuracy, particularly in the 81–82% range, are likely due to slight inconsistencies in object positioning, illumination variations, or partial occlusions within the camera's field of view.

TABLE II. Accuracy Test Results At Medium Conveyor Speed (1.7 cm/s)

No	*The number of test data*	*Avg. Accuracy Confidence (%)*	*Error(%)*
1	6	61.67	38.33
2	6	95.67	4.33
3	6	94.33	5.67
4	6	74.83	25.17
5	6	97.17	2.83
6	6	87	13
7	6	61,83	38.17
8	6	81	19
9	6	82.33	17.67
10	6	49.83	50.17
Average		78.57	21.43

Table II delineates the outcomes of the accuracy assessment conducted when the SmartEdu Conveyor functioned at a medium velocity of 1.7 cm/s. Consistent with the preceding evaluation, each trial encompassed six geometric objects with ten repetitions to ensure reliable assessment. The system attained an average accuracy confidence of 78.57%, accompanied by an average error rate of 21.43%, indicating a discernible decline in accuracy relative to operation at a lower speed. Several test iterations sustained high accuracy levels exceeding 90%, whereas others experienced a substantial reduction to approximately 50–60%. This variability suggests that as the conveyor speed escalates, the image capture duration per object diminishes, potentially leading to motion blur or incomplete object detection within the camera's field of view.

TABLE III. Accuracy Test Results at High Conveyor Speed (2.3 cm/s)

No	*The number of test data*	*Avg. Accuracy Confidence (%)*	*Error(%)*
1	6	9.83	90.17
2	6	32.83	67.17
3	6	86.33	13.67
4	6	64.67	35.33
5	6	82.33	17.67
6	6	58.33	41.67
7	6	61	39
8	6	65.83	34.17
9	6	49.67	50.33
10	6	82	18
Average		59.28	40.72

As summarized in *Table III*, when the SmartEdu Conveyor operated at a high conveyor speed of 2.3 cm/s, the detection accuracy declined substantially. The system recorded an average confidence of 59.28% and an error rate of 40.72%, reflecting degraded performance relative to lower-speed trials. The majority of test results ranged from 50% to 65%, with only a few instances surpassing 80%. This decline can be attributed to limited exposure time, motion blur, and frame loss within the camera's capture cycle. Furthermore, higher operational speeds disrupted synchronization between the camera, Raspberry Pi computation, and PLC actuator control, resulting in reduced classification stability.

The analysis of the three test results reveals a distinct correlation between conveyor speed and detection accuracy. At a low speed of 1 cm/s, the system achieved an average accuracy confidence of 89.38%, which decreased to 78.57% at a medium speed of 1.7 cm/s, and further declined to 59.28% at a high speed of 2.3 cm/s. This trend indicates that increased conveyor speeds adversely affect detection stability and classification precision. As the conveyor accelerates, the camera's exposure time diminishes, heightening the likelihood of motion blur and incomplete frame capture, thereby impairing the YOLOv8 model's capacity to accurately identify object boundaries. Consequently, optimal system performance is attained at lower speeds, where image clarity, synchronization, and actuation timing remain well-coordinated.

B. Computer Vision Precision Test Result

The precision test was conducted to assess the consistency and reliability of the computer vision system in identifying geometric objects under controlled conditions. While the accuracy test evaluates the overall correctness of detection outcomes, the precision test specifically examines the consistency with which the YOLOv8 algorithm can accurately identify objects without generating false positives. This parameter is crucial for validating the model's robustness in distinguishing between different geometric shapes when the conveyor operates at varying speeds.

In this study, six categories of geometric objects—namely, large circle, small circle, large square, small square, large triangle, and small triangle—were employed as test samples. Each category underwent ten detection trials at varying conveyor speed settings to examine the impact of object size and motion on the system's detection accuracy. The findings from this experiment offer insights into the YOLOv8 model's capability to sustain stable recognition confidence levels and to identify the optimal operational conditions for achieving reliable detection performance within the SmartEdu Conveyor system.

TABLE IV. Precision Test Results at Low Conveyor Speed (1 cm/s)

Object Shape	Test Data	Avg. Accuracy Confidence (%)	Error (%)
Large Circle	10	99.9	0.1
Small Circle	10	76.9	23.1
Large Square	10	88.1	11.9
Small Square	10	85.4	14.6
Large Triangle	10	99.2	0.8

Object Shape	Test Data	Avg. Accuracy Confidence (%)	Error (%)
Small Triangle	10	86.5	13.5

At a reduced conveyor speed of 1 cm/s, the computer vision precision test results are presented in *Table IV*. Each geometric object was tested in ten trials to evaluate the YOLOv8 model's consistency in identifying shapes under stable motion conditions. Precision in this context refers to the system's ability to correctly recognize objects within the captured frame with high confidence while minimizing false detections. The results reveal that larger objects yield higher precision levels than smaller ones, with the large circle achieving 99.9% confidence and the large triangle reaching 99.2%. In contrast, smaller objects—particularly the small circle—produced the lowest precision at 76.9%. This discrepancy occurs because larger shapes occupy more pixels, enabling YOLOv8 to capture their edges and contours more accurately, whereas smaller objects are more affected by lighting fluctuations and limited camera focus. Overall, the high precision values across all object classes confirm that under low-speed conditions, the SmartEdu Conveyor can deliver reliable and accurate object detection with minimal classification errors.

TABLE V. Precision Test Results at Medium Conveyor Speed (1.7 cm/s)

Object Shape	Test Data	Avg. Accuracy Confidence (%)	Error (%)
Large Circle	10	90	10
Small Circle	10	62.8	37.2
Large Square	10	98.1	1.9
Small Square	10	56.9	43.1
Large Triangle	10	99.2	0.8
Small Triangle	10	64.4	35.6

As summarized in *Table V*, when the SmartEdu Conveyor operated at a medium speed of 1.7 cm/s, the precision of object detection decreased compared to the low-speed tests. Larger objects—large triangle (99.2%), large squareoloyoyo (98.1%), and large circle (90%)—maintained high accuracy, whereas smaller objects—small square (56.9%), small circle (62.8%), and small triangle (64.4%)—showed lower precision. The reduction stems from reduced camera exposure time and motion-induced blurring, which hinder YOLOv8's ability to extract clear edge and contour features. Nonetheless, detection stability for larger objects confirms the model's adaptability, with size and frame duration remaining key determinants of recognition quality at moderate conveyor speeds.

TABLE VI. Precision Test Result at High Conveyor Speed (2.3 cm/s)

Object Shape	Test Data	Avg. Accuracy Confidence (%)	Error (%)
Large Circle	10	69.9	30.1
Small Circle	10	42.9	57.1
Large Square	10	88.5	11.5
Small Square	10	43.6	56.4
Large Triangle	10	60	40
Small Triangle	10	28.8	71.2

Table VI delineates the precision test outcomes of the SmartEdu Conveyor system when operating at an elevated conveyor speed of 2.3 cm/s. The data indicate a notable reduction in detection precision relative to lower and medium speeds, suggesting that increased motion dynamics adversely impact the accuracy of object recognition. Larger shapes, such as the large square (88.5%) and large circle (69.9%), exhibit relatively higher precision, whereas smaller objects, including the small triangle (28.8%) and small circle (42.9%), demonstrate a pronounced decline due to reduced exposure times and heightened motion blur within the camera's field of view. The diminished detection confidence at this speed further implies that the YOLOv8 model encounters challenges in capturing distinct geometric features when objects yolotraverse the frame rapidly. Despite this limitation, the system retains the capability to detect object presence, albeit with diminished reliability for classification. These findings underscore that optimal system performance is achieved at lower conveyor speeds, where frame capture, feature extraction, and actuation synchronization are more effectively aligned for precise real-time sorting.

The findings from the three precision tests conducted at varying conveyor speeds reveal a distinct correlation between object velocity and detection performance. At a low speed of 1 cm/s, the SmartEdu Conveyor exhibited the highest levels of precision and accuracy, with large objects such as circles, squares, and triangles consistently identified with confidence levels exceeding 95%. As the speed increased to 1.7 cm/s, detection precision experienced a moderate decline, particularly for smaller objects, attributable to reduced exposure time and limited frame capture. At the maximum speed of 2.3 cm/s, precision diminished significantly across all object types, with smaller shapes experiencing the most pronounced decline due to motion blur and insufficient feature extraction. Overall, these results substantiate that conveyor speed directly influences computer vision performance, with slower speeds facilitating optimal image clarity and detection stability. The YOLOv8-based SmartEdu Conveyor system demonstrates optimal performance under low to moderate speed conditions, rendering it suitable for educational demonstrations and controlled automation environments that prioritize detection accuracy over operational throughput.

C. Confusion Matrix analysis

The Confusion Matrix is a well-established analytical tool employed to evaluate the performance of classification models. It offers a structured representation of prediction outcomes across four categories: True Positive (TP), False Positive (FP), True Negative (TN), and False Negative (FN) [16]. By analyzing these components, researchers can assess the model's efficacy in distinguishing between correct and incorrect classifications. In the context of object detection using YOLOv8, the Confusion Matrix aids in quantifying detection accuracy and identifying potential sources of misclassification among geometric object classes.

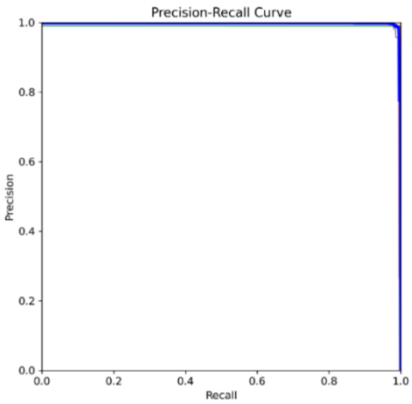

Fig. 6. Precision-Recall Curve

The Precision–Recall (PR) Curve, depicted in Figure 5, elucidates the relationship between precision (the accuracy of positive predictions) and recall (the model's sensitivity in correctly identifying all relevant instances). This evaluation method is particularly advantageous for object detection tasks, where the equilibrium between precision and recall determines the overall robustness of the detection algorithm. In contrast to the Confusion Matrix, which summarizes discrete prediction outcomes, the mean Average Precision (mAP) is derived from the area under the Precision–Recall curve, offering a singular quantitative measure of detection performance. Based on this analysis, the proposed YOLOv8 model achieved an mAP value of 0.993 at an Intersection over Union (IoU) threshold of 0.5, demonstrating excellent object recognition capability and confirming the model's effectiveness in high-precision, real-time detection applications.

IV. CONCLUSION

The development of a YOLOv8-based conveyor sorting system has been successfully accomplished to classify and sort geometric objects in real-time. At conveyor speeds of 1 cm/s, 1.7 cm/s, and 2.3 cm/s, the system achieved average accuracy confidence levels of 89.38%, 78.57%, and 59.28%, respectively. These findings indicate that conveyor speed significantly influences detection accuracy. Precision analysis reveals that larger objects result in higher precision compared to smaller ones. The system attained a mean Average Precision (mAP) value of 0.993 at 0.5 Intersection over Union (IoU) based on the Precision–Recall curve, affirming the high performance of the model. The integration of Raspberry Pi 4, MQTT communication, Node-RED Human-Machine Interface (HMI), and Programmable Logic Controller (PLC) offers a functional, low-cost, and modular solution for educational conveyor automation (SmartEdu Conveyor). Future work will focus on optimizing model inference speed on embedded hardware and expanding dataset diversity.

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