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RESEARCH PAPER

Real-Time Scheduling Approach in Internet of Things-Enabled Production Monitoring Systems

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ABSTRACT
The rapid advancement of the Internet of Things (IoT) has become a cornerstone in the evolution of Industry 4.0, particularly in the manufacturing sector. This technology presents a significant opportunity to enhance productivity on a production basis by enabling real-time monitoring of production processes. However, it is challenging for many companies to align production outcomes with their first plans, as consumer demands fluctuate, often leading to inefficiencies, delays, and increased operational costs. This study proposes designing and implementing a robust real-time production monitoring system using the IoT framework. The system's architecture integrates sensors into the production processes to identify and track product types as they progress through the production line. Data collected by these sensors are transmitted to a centralized web platform, disseminating the information to all relevant stakeholders in realtime. This method ensures that the manager's production can make immediate and appropriate decisions to adjust strategies as consumer demands change. Initial testing of the system has demonstrated its effectiveness in improving production agility, allowing companies to swiftly realign their production strategies with market dynamics, ultimately reducing downtime and enhancing overall efficiency.

KEYWORDS: Realtime production scheduling; Internet of Things; Production monitoring system; Smart manufacturing; Cyber-physical systems.

1. Introduction

Industrial value creation at the beginning of industrialization is currently shaped by developments towards the fourth stage of industrialization called Industry 4.0. Recently, this stage has developed and has a significant influence on the manufacturing industry. It is accompanied by the development of digital technology, which brings growth in industrial competition in each region and country in the world market. Technology and digitalization change how people live and interact, allowing all operations to be carried out quickly to connect all work and share information in the unit. Industry 4.0 adopts digital technology to collect and analyze data in real time, providing helpful information for manufacturing systems. According to the World Economic Forum by Klaus Schwab, the Industrial Revolution 4.0 is an era in which technology can replace less efficient human energy with more sophisticated robots that increase productivity and improve services and income.[1]. The Industrial Revolution 4.0 is a digital era in which all parts work together and communicate using real-time information technology. [2].

The concept of Industry 4.0 emphasizes Smart Manufacturing as its core element. It considers integrating factories with the entire product lifecycle and supply chain activities, transforming how people work. [3]–[5]. Implementing smart factories, products, and services embedded in the Internet of Things (IoT) realizes Industry 4.0. Market demands drive the production sector to embrace advanced technologies such as the Industrial Internet of Things (IIoT), focusing on

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interconnected and intelligent factories.[6]–[9]IIoT, smart factories, and intelligent manufacturing are IoT applications that connect factories inexpensively, competently, and in a low amount to enhance productivity and machine maintenance. More than just a single technology, IIoT combines various techniques like IoT, big data, cyber-physical systems (CPS), machine learning, and simulation to orchestrate intelligent operations in industrial environments.

The Industry 4.0 revolution, also known as Cyber-Physical Systems (CPS), involves computerization strengthened by the Internet's emergence and various systems' integration. CPS, controlled by computer-based algorithms, is closely integrated with the Internet and its users. This technology guides the planning of Industry 4.0 with principles such as interoperability, process virtualization, and decentralized decision-making in manufacturing industries. In virtualization, real-time vision and control of production lines through interactive dashboards, real-time error detection, and synchronization of data from production, quality control, and component warehouses become crucial. [10]–[18]. Industry 4.0 changes the production of goods or other productivity aspects, utilizing digital technology, integration, and automation to enhance production efficiency, reduce production costs, and quickly respond to rapid market demand changes.

Current manufacturing companies face uncertain market conditions that require them to respond quickly to market demand changes. To respond swiftly, companies must produce various product variations that consumers need [19]. The company's production system must have a high level of process flexibility. However, some issues arise when companies implement flexible production systems related to the efficiency of their resources. Inappropriate management of resources in a flexible production system can lead to significant production process inefficiency. In production inefficiencies, knowledge of the level of inefficiency is needed to understand the factors causing inefficiencies, enabling efforts to improve efficiency and increase the productivity of the production system. Several previous studies have discussed solutions to production process efficiency problems in fluctuating and uncertain market demands, including efforts to apply visual management concepts [20], development of production data recording using Radio-Frequency Identification (RFID) concepts [21], and enhancement information systems to improve information and visibility of production results. These studies aimed to improve production efficiency by using information technology to quickly record and realize production results.

In the Production Planning and Inventory Control (PPIC) section, real-time production information can be crucial in scheduling the production process. The fluctuating market demand requires the PPIC department to accurately plan production according to consumer demand to avoid stockpiling products, which can increase inventory costs. Therefore, real-time production data can assist the PPIC section in monitoring production results to ensure according to planned production. If there is a change in market demand, the PPIC section can quickly reschedule the show using real-time production information data. A common constraint faced by the PPIC section is the waiting time to obtain information related to production results. Manual input of the production monitoring system also affects production results, requiring considerable time for data collection.

In addition, the reliance on manual data input produces a susceptibility to errors, specifically human errors. Consequently, an urgent need arises for production data to be collected precisely and accurately to enhance operational efficiency and mitigate inaccuracies in the input of production data. A real-time production monitoring system can facilitate expeditious adjustments to production plans within the Production Planning and Inventory Control (PPIC) section, particularly in response to abrupt change in consumer demand. Moreover, real-time production monitoring systems afford production managers the capacity to supervise production outcomes without the need to wait for reports from department heads of the reporting period.

Suppose the production output does not reach the target per hour. In that case, the department head may hamper the effectiveness of the manufacturing company's coordination process and control system, thereby initiating immediate process improvements. Given the various challenges of manufacturing entities and the inherent market volatility, this research aims to offer an innovative and integrative solution. Applying the Industry 4.0 paradigm is expected to enable companies to achieve a harmonious balance between the production process's adaptability and resource management's efficiency, thereby encouraging increased response to market demand fluctuations.

The development of production systems in the current era combines the concepts of Industry 4.0 and the Lean Production System. [12]. Lean production is the basis for designing the current production system based on information technology. The fundamental concept of lean production is integrating all company-owned resources to reduce waste in the production system, thereby increasing the company's profit. [22]. One of the commonly used lean production concepts in manufacturing companies is the Just In Time (JIT) concept. The JIT production system requires continuous production processes in its activities. This concept requires producing products according to the specified quantity and location. [15]. Some JIT activities related to production in the lean production concept ([12], [23],[24])

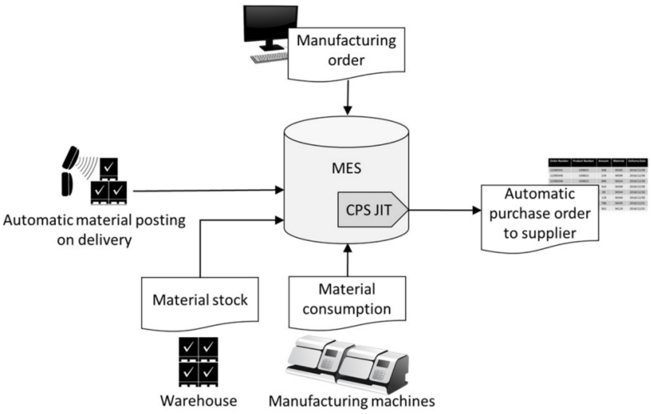

Fig. 1. Cyber-physical system in JIT [24]

Fig.1 shows that all activities in the lean production concept are interconnected, so data and information connectivity will improve the performance of the poor production system. Therefore, the use of information technology will assist in optimizing the applied strategy. One of the production systems based on the JIT concept is the conveyor production system. This system has been widely used in several manufacturing industries due to its ease of material handling and operational simplicity. However, one common issue the production department faces is the manual input of production data. Sometimes, inaccuracies occur between the input results and the actual conditions of the production process. [12], [24].

2. Experimental Procedure

2.1. Research framework

Some problems in the production section that require speed for decision-making and changes in production schedules due to uncertain demand can be solved with a production system that can monitor production results and provide fast production results to meet consumer demand.This research will discuss how the production system is built with the Internet of Things approach and how the production monitoring system is used for production scheduling. The stages of the study are explained in the fig. 2 below.

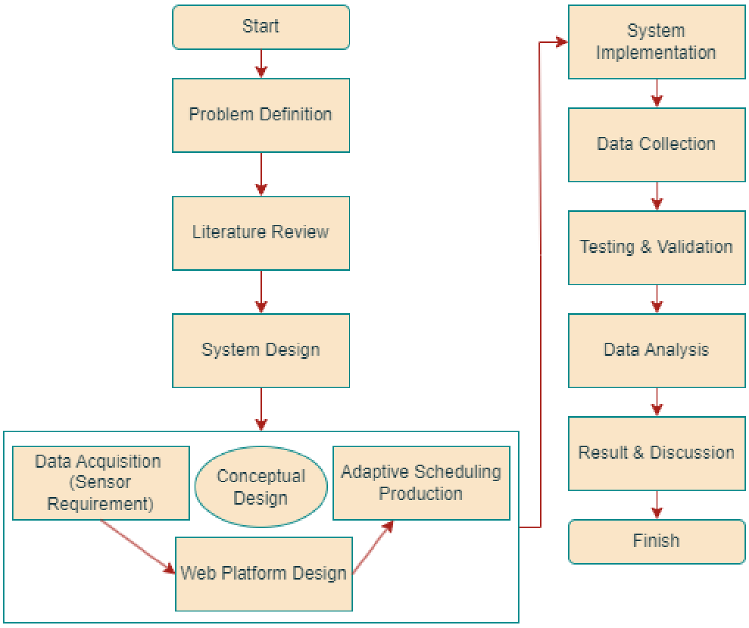

Fig. 2. Flowchart research

2.2.System design

In the System Design phase, the main focus was creating a comprehensive framework to address the identified issues. The system was designed to support real-time data acquisition through sensors selected as needed, allowing for rapid analysis and immediate adjustments in the production process. The design also integrated adaptive scheduling, allowing the system to adjust its operations based on the data received, ensuring efficiency and flexibility in changing conditions. In addition, the system was equipped with a web platform that served as the main interface, allowing for centralized monitoring and management of the system. This modular approach in design ensured that each part of the system could operate independently yet remain integrated, providing easy access and control from multiple devices to support better decisions in dynamic production.

2.2.1. Data acquisition

Data acquisition using object detection enables automatic data collection by utilizing object recognition technology through images or videos. In this context, the object detection system will identify and track relevant objects in the production environment, such as machine components, finished products, or materials moving on the production line. This system can detect and classify objects accurately, even in complex conditions, using machine learning algorithms, such as Convolutional Neural Networks (CNN). We can use the data from the detection process for various purposes, such as production performance analysis, quality monitoring, or even adaptive scheduling, in which the system can adjust the production process based on actual conditions detected in the field. Thus, data acquisition using object detection increases data collection efficiency and improves the overall production system's adaptability and responsiveness. The concept of data acquisition design can be seen in the fig. 3.

Object detection (OD) is a tool that supports real-time system monitoring used as input for the scheduling process (fig.3.). OD will provide data to the PPIC section to quickly control the process and production schedule. One of the core tasks in computer vision is object identification, which is recognizing and finding something in an image or video frame. TensorFlow's deep learning framework provides solid tools and resources to help create reliable and effective object identification models. TensorFlow allows developers to build models that recognize items and precisely localize them with bounding boxes by fusing convolutional neural networks (CNN) with methods such as region proposal networks (RPN) and anchor boxes. Many domains use this model, including medical image analysis, retail inventory management, autonomous driving, and surveillance. TensorFlow is the preferred option for solving object detection problems and facilitating sophisticated computer vision solutions due to its adaptability, pre-trained models, and broad community support.

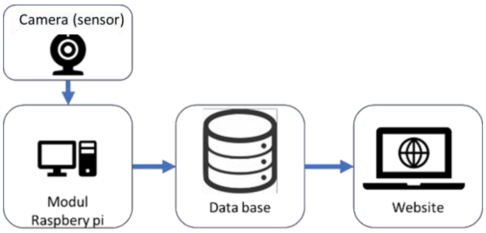

Fig. 3. Design data acquisition use camera (object detection)

The algorithm for object detection is explained through several stages in Fig 4, including:

Step 1: Import Dependencies
The task at hand is to import the required Python libraries and modules. We are importing the operating system module for file operations, the time module for introducing delays during image capture, the Universally Unique Identifier (UUID) for creating unique IDs, and OpenCV (cv2).

Step 2: Define Images to Collect
In this stage, we define the labels (like "block", "cube", "tube", and "cone") for the items we want to detect and indicate how many photographs (like "five images per label") we want to collect.

Step 3: Setup Folders
The code creates the directory structure to gather the photographs in this stage. It constructs the requested directory structure if it does not already exist and tests to see if it does. It makes a subdirectory in every label’s 'collected images' directory.

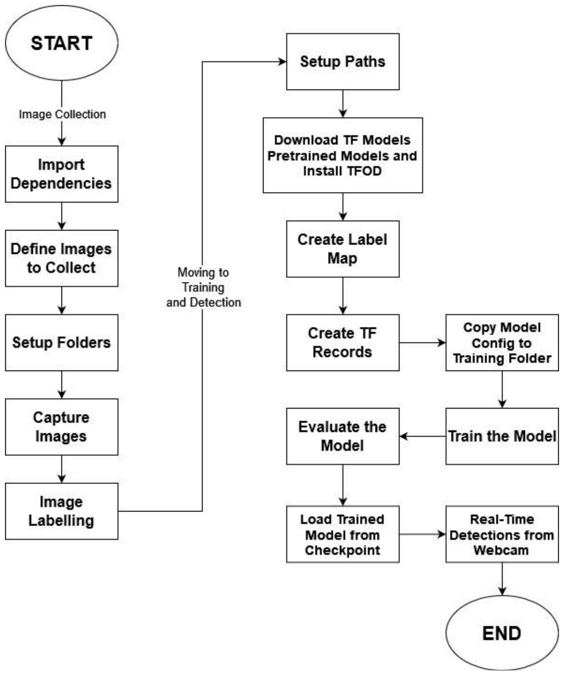

Fig. 4. object detection flowchart

Step 4: Capture images
During this phase, we take pictures with our camera using OpenCV. The code initializes the camera capture (cap) to collect photos and then iterates through each label and image number. Every assembled frame is saved as an image file and given a distinct filename created using UUID, stored in the label's folder. Pressing 'q' will end the picture-capturing loop. The code further shows the recorded frame. It releases the camera and closes the OpenCV windows once it has taken the necessary pictures for each label.

Step 5: Image labelling
In this step, we actively set up the "labeling" program for labeling or annotating the collected photos. We begin by installing the necessary dependencies, including pyqt5. Subsequently, if the 'labelImg' directory is not present, the 'labelImg' GitHub repository is cloned. Additional setup procedures for "labeling" are then performed and tailored to the specific operating system,

Windows or Linux. Lastly, it launches the 'labeling' tool, which enables us to manually create bounding boxes around each object in the gathered photos and annotate them with the appropriate class.

With the aid of these strategies, we can collect and annotate a set of photos to construct an object identification model. This annotated dataset enables the model to find and identify objects of interest within photographs.

Fig. 5. Result of object detection

2.2.2. Web platform production monitoring system

Data and information are crucial in determining the effectiveness and efficiency of the company in the manufacturing production system. The company might achieve production efficiency and accuracy by utilizing available resources more effectively. Production results should be shown quickly and accurately to identify problems in the production[25] [26]. The constraint commonly found in the production is manual data recording, leading to less accurate and delayed production information. Users who need quick and precise production information require an information system that connects real-time with easily accessible information. Real-time monitoring technology facilitates understanding of sensitive and stigmatized conditions that are invisible in research or clinical settings. Technological advancements can enhance efficiency in the production system. [20], especially by monitoring production processes automatically to detect production results and enable quick corrections.

2.2.3. Framework scheduling based on the internet of things

The Internet of Things (IoT) is a network that uses intelligent sensors to connect items so they may communicate wirelessly without human involvement. Applications of IoT can be found in the transportation, automotive, and healthcare sectors. Issues infrastructure, connectivity, interfaces, protocols, and standards are all part of the IoT development process. We aim to identify key study areas and plans for IoT and provide an overview of the research progress made thus far in IoT technology's development, standardization, and security. Distributed Data Service (DDS), a recently proposed IoT data management architecture, works effectively for gathering, combining, and retrieving data from IoT middleware systems. With the introduction of metadata modules and particular communication protocols, DDS can process massive amounts of data from several sources. However, all existing frameworks for data acquisition concentrate on specific problems rather than the still difficult task of gathering and storing industrial big data. According to recent research, industries are moving toward digitization to increase performance, productivity, and competitiveness. In addition, additional research into the data collection methods is required to solve current and upcoming issues.

An IoT-based framework for the Industrial Data Management System (IDMS) was to manage large amounts of industrial data, facilitate online monitoring, and regulate smart manufacturing. The framework's five fundamental levels comprise the physical, network, middleware, database, and application layers, providing users access to a service-oriented architecture. According to experimental results from an intelligent factory case study, this framework can handle routine and urgent event data from different factories. It is equipped in a distributed industrial environment through improved communication protocols and effectively manages various physical and virtual data.

In factory devices, the collected data is translated into valuable information that forecasts the production path and increases productivity to meet manufacturing goals and regulate the production path. [27], [28].

Uneven production flow is a common problem in companies, affecting the mismatch between production quantity and customer demand. The use of software aims to analyze production process performance and improvement efforts. Software that assists high-efficiency production systems can facilitate smooth process flows on each production line and maximize the company's spatial and temporal benefits. One use of the software is to determine optimal production scheduling and reduce the makespan value (the total time to complete work from the first job in sequence to the last position in line), which is too large for production scheduling. Optimal production scheduling should not result in additional working hours or days, avoiding customer dissatisfaction due to production exceeding predetermined limits.

2.3. System implementation

In the system implementation stage, start with a conveyor system equipped with a camera sensor and Raspberry Pi as a microcontroller. The camera sensor is installed on the conveyor to identify the type of product passing through the production line. When the sensor detects a product, the camera takes a picture, and the Raspberry Pi immediately processes the data. The Raspberry Pi then analyzes this image data to classify the product type, allowing real-time production monitoring automatically. The product classification data is then uploaded to a central database, where the information is stored for further analysis and decision-making.
Furthermore, the data stored in the database is accessed and displayed on a previously developed web platform. This web platform serves as the primary interface for production managers to monitor production results directly. With this system, the company can schedule production faster and more adaptively, adjusting operations based on actual data received from the conveyor. This technology allows for a faster response to changes in market demand, ensuring production runs efficiently and on time. This implementation also paves the way for further developments, such as integrating more sophisticated analytics and higher automation.

2.4. Data collection

At the data collection stage, the developed conveyor system is equipped with camera sensors to implement object detection technology and to identify product types in real time. The data generated from this identification process is then automatically stored in a database designed to store information structured and efficiently. This process involves integrating hardware and software, and the camera sensor is the primary tool in data collection. At the same time, object detection ensures accurate product recognition. All collected data is stored in a format that allows quick and easy access for further analysis. This information will be used for production scheduling. The process supports the research objective of creating an adaptive and responsive production system.
Furthermore, we focus on reading the object detection system for produced products. The data taken is accurate since we read the product types by considering system conditions that affect the production process, namely conveyor speed and camera height. This activity will significantly affect the accuracy of data storage, which involves the adaptive scheduling process.

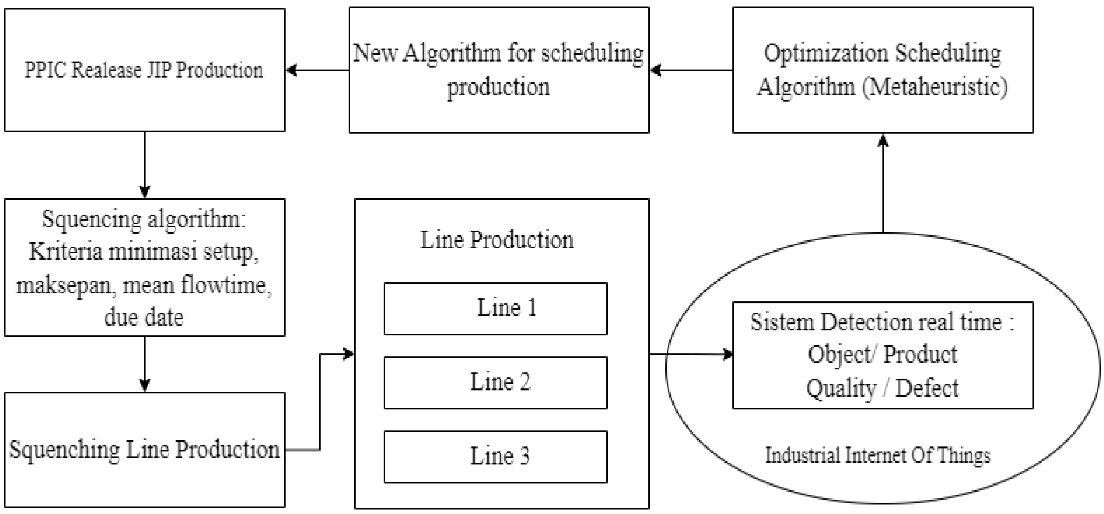

Fig. 6. Framework scheduling with the internet of things

Tab. 1. The notations of multiple regression analysis and analysis of variance (ANOVA)

Parameters	
y	Dependent variable (the variable you are trying to predict or explain)
β_0	Intercept term (the value of y when all predictors are 0)
β_1	Coefficient for the first independent variable
x_1	First independent variable (predictor or explanatory variable)
β_2	Coefficient for the second independent variable
x_2	Second independent variable (predictor or explanatory variable)
R^2	Coefficient of determination (measures the proportion of the variance in the dependent variable that is predictable from the independent variables)
k	Number of independent variables (predictors)
ε	The error accounts for the variability in the data that the regression model does not explain.
x_{1i}	Value of the first independent variable
x_{2i}	Value of the second independent variable

2.5. Data analysis

During the data analysis, we tested the object detection accuracy of products by reading the conveyor system. This analysis aims to evaluate the influence of two main variables, conveyor speed, and camera height, on the accuracy of the results by reading the collected data. We used Multiple Regression Analysis(MRA) and variance analysis (ANOVA) to demonstrate the relationship and impact of the two variables. This analysis will provide in-depth insight into how conveyor speed and camera height changes can affect the system's performance in accurately detecting and reading products, which will later become the basis for optimizing production scheduling.

Multiple regression analysis is used to analyze the influence of two independent variables, namely conveyor speed (x_1) and camera height (x_2), on object detection accuracy (y). The mathematical formula is as follows eq (1) :

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \varepsilon \tag{1}$$

we assume that the value of E (ε) = 0, β_1 and β_2 Re-partial regression coefficients. β_1 measures the expected change in y per unit change in x_1 when x_2 is held constant, and β_2 measures the expected change in y per unit change in x_1 when x_2Is held constant.

Stages in working on multiple regression:

a. Finding the value of β_0 , β_1 and β_2
b. Find the simultaneous correlation value (R) and the coefficient of determination (R^2)
c. Performing the F test

Additionally, ANOVA is a powerful statistical tool to evaluate the significance of differences in detection accuracy across different variable levels. This method lets us identify which parameters significantly contribute to the object detection system's performance variability. By meticulously conducting these tests using MRA and ANOVA, our research aims to quantify the accuracy of the object detection system and elucidate the intricate interplay between critical parameters. This thorough analysis is instrumental in refining and optimizing the system for robust and reliable performance in real-world applications in manufacturing environments.

ANOVA hypothesis from the data analysis system using ANOVA (F test) can be described as follows:

$\boldsymbol{H_0}$: Variable Independent (conveyor speed (x_1) and camera height (x_2)) does not significantly affect the dependent variable (object detection accuracy (y).

$\boldsymbol{H_a}$: Variable Independent (conveyor speed (x_1) and camera height (x_2)) significantly affect the dependent variable (object detection accuracy (y).

When using the F count

- If the calculated F value > F table value, then $\boldsymbol{H_0}$ **i**s rejected; Ha is accepted.
- If the calculated F value < the F table value, we accept $\boldsymbol{H_0}$ and reject Ha.

3. Results and Discussion

3.1. Results

The designed production monitoring system can provide real-time production information due to the use of a web server to display readings from sensors/cameras. The design production monitoring system allows users, particularly in the production department, to control or adjust if the results do not meet the planned targets. The system that has been built can also provide fast and precise information about production results to be used as a reference in designing the next day's production. The data collection produced by this system is automatic, so operators no longer need to input production results. To enhance the functionality of this system, integration with other production floor-related components is necessary. This integration aims to optimize costs related to the process, storage, and delays caused by production system errors.

3.1.1. System conveyor with object detection

The design of a production monitoring system with object detection uses replacing analog sensor input with a camera to detect the type of product that has been produced. The following is an overview of a conveyor system for production with object detection cameras (Fig.7).

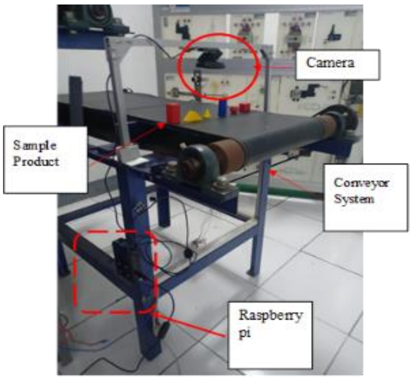

Fig. 7. Conveyor system with object detection

Accuracy data were obtained from the created system using two controlling variables: conveyor speed and camera height. The results of this data will be subjected to regression analysis related to the accuracy influence of the two variables. The measurement data can be seen in Tab. 2. The operating system of the conveyor object detection goes through several stages, including:

1. Prepare a PC, conveyor, products (cone and cube), camera, height measurer, and Raspberry Pi module.
2. Prepare the pre-designed algorithm and adjust the conveyor speed according to the measurements.
3. Adjust the camera height according to the measurements to be performed.
4. Capture the accuracy of the results displayed on the PC.
5. Repeat the process 20 times.

Tab. 2. The results of accuracy object detection system

Speed (x1)	High (x2)	Value of accuracy (y)																			
		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
200	**20**	99	98	97	100	99	98	100	99	96	97	99	98	97	96	99	97	98	99	99	100
200	**25**	99	95	96	98	97	97	98	96	98	97	97	97	98	96	99	97	99	97	95	99
200	**30**	90	87	91	87	92	94	94	93	94	93	92	95	94	92	85	96	96	91	94	91
220	**20**	97	99	100	98	99	100	99	100	99	98	97	99	100	97	99	100	97	100	99	98
220	**25**	93	95	94	91	92	92	95	94	90	91	97	96	89	99	90	97	96	97	100	99
220	**30**	84	82	89	83	92	87	85	89	86	82	87	91	88	93	91	91	89	85	91	87
255	**20**	99	98	97	99	99	98	96	99	97	96	94	99	97	98	99	100	99	98	97	100
255	**25**	99	94	91	94	93	94	99	100	94	96	98	97	99	98	97	98	95	99	96	97
255	**30**	91	93	86	94	87	90	91	92	93	87	92	92	93	94	91	96	95	96	97	98
227	**20**	99	100	97	98	97	98	99	97	98	96	99	98	97	100	100	96	98	100	99	97
227	**25**	97	96	99	98	94	97	98	99	99	98	94	97	96	94	97	99	98	96	95	99
227	**30**	90	92	94	90	92	96	97	91	95	94	96	90	91	93	95	94	93	95	94	96
188	**20**	100	98	97	99	100	98	97	99	99	99	100	100	99	98	97	98	96	99	100	99
188	**25**	95	93	94	97	96	98	97	95	96	96	99	98	98	99	100	99	98	97	98	99
188	**30**	93	94	96	97	95	98	97	98	97	93	96	97	98	98	99	95	97	98	96	96

3.1.2. Model regression analysis (MRA)

After testing the object detection system 20 times, we obtained accurate data on product reading results using the object detection system. The following is the data from the system test results.

Describe the dood of the model's fit.

Based on the results of data processing using multiple regression statistics, the results showed that the contribution of the variable speed (x_1) and camera height (x_2) Simultaneously, the accuracy of product reading in the object detection system with a coefficient of determination value of 0.666, which means that variable x_1 and variable x_2 simultaneously influences object detection accuracy of 66.67%. These results can be seen from the MRA calculation results in Fig. 8 below.:

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.816[a]	.666	.610	1.96877

a. Predictors: (Constant), High, Speed

Fig. 8. Model MRA

Significance in statistics

The results of the ANOVA table (fig.9) show that the regression model is a good fit for the data that has been tested. The table ANOVA illustrated the test data F (2,12) = 11.962, whose value is greater than the table test of 3.82, which means that H_0Is rejected. The result indicates that the independent variable's conveyor speed (x_1) and camera height (x_2) have a significant effect on the dependent variable of the object detection accuracy (y). Apart from that, the significance of the model can also be seen from the p-value .001 < 0.05, which means that the regression model formed is significant.

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	92.733	2	46.367	11.962	.001[b]
	Residual	46.513	12	3.876		
	Total	139.246	14			

a. Dependent Variable: Accuracy

b. Predictors: (Constant), High, Speed

Fig. 9. Resume table of ANOVA

Estimated model coefficient

The prediction model is formed from two independent variables: conveyor speed (x_1) and camera height (x_2), which influence accuracy in product reading and will later be used as basic information for production scheduling. The regression model can be seen in the following Fig.10:

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	115.270	5.734		20.103	<,001
	Speed	-.021	.022	-.161	-.968	.352
	High	-.597	.125	-.800	-4.795	<,001

a. Dependent Variable: Accuracy

Fig. 10. Model multiple regression

The basic form of model estimation to predict accuracy based on conveyor speed (x_1) and camera height (x_2) can be written as

$$y = 115{,}270 - (0{,}021\ x\ X_1) - (0{,}597\ x\ X_2)$$

The formed prediction model can estimate the accuracy value of two variables, conveyor speed, and camera height while detecting the type of product used on the production. Object detection technology based on the Internet of Things will help production operations, especially scheduling activity. This system will also encourage efficiency in the production process.

3.1.3. Production monitoring systems

The production monitoring system operates in real time, allowing access to updated data anytime. The system's design uses analog data as input, representing the type of product being produced. The object detection results will be recorded in a database, which will later be posted on the web to make it easier for users to determine the production produced on that day. The steps involved in the process, in which analog sensor input is posted to the database using Raspberry programming, are detailed as follows:

The database designed for real-time production monitoring serves several functions and criteria:

a. Database for logins in the company: This database manages login information for various core parts of the company to access the system. The following is a database design for the login system

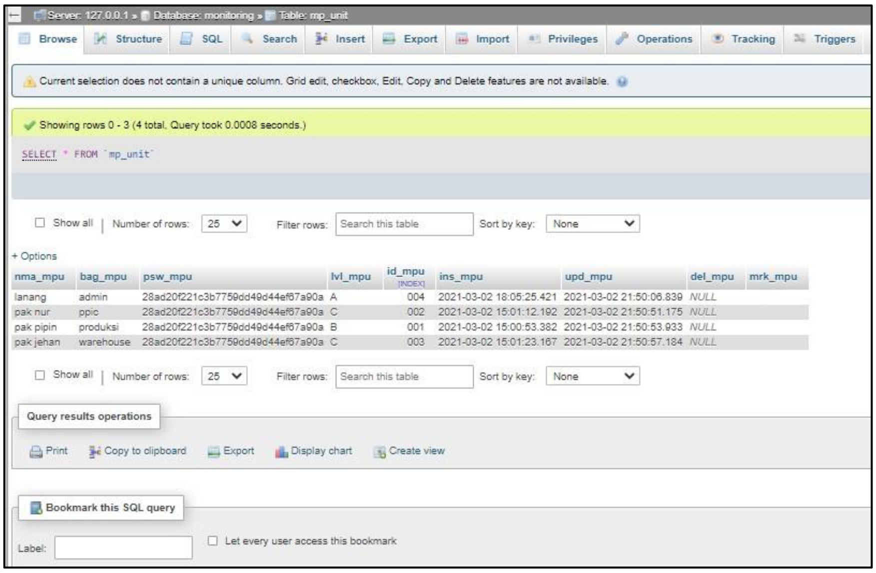

Fig. 11. Database login structure for operator

b. Product database: This database stores data input from the camera module for display on the website.

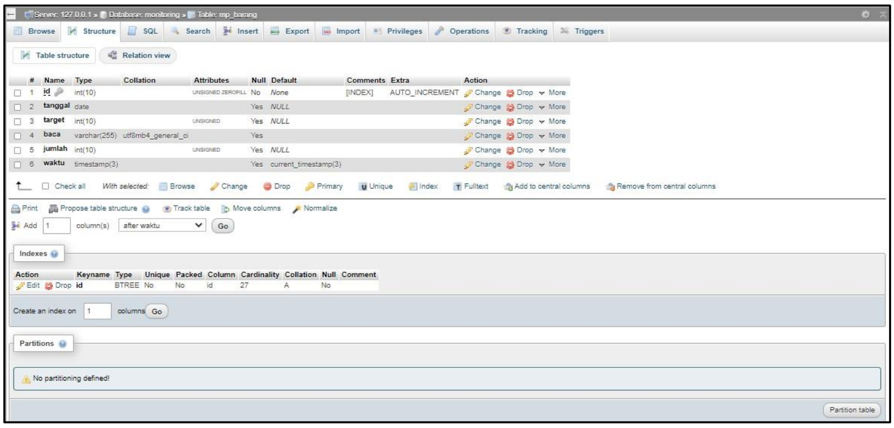

Fig. 12. Data based on the production monitoring system

The results of the sensor input from the camera will be displayed on a production information website accessible by various departments for production information. The production monitoring website interface includes several pieces of information, such as production achievements for each product, production achievement graphs for each product, and an Excel download feature that facilitates users in processing the acquired production data. Fig.13 below is the designed interface of the production monitoring website.

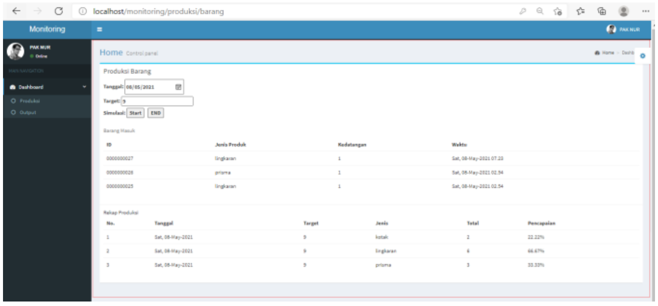

Fig. 13. The result of production monitoring system

3.1.4. Adaptive scheduling production

Implementing an IoT-based adaptive scheduling system in the conveyor-driven production process significantly improved operational efficiency and quality control. The system could automatically detect product mismatches and quality defects by integrating real-time data from object detection and quality inspection cameras. For example, in the case of Product A, the quality detection system identified two defective units during production. These units will immediately diverted for repair without disrupting the flow of non-defective products. As a result, the production monitoring system (PMS) dynamically updated the schedule to prioritize defect-free units for packaging, ensuring minimal delays and preventing congestion.

Additionally, the object detection system identified an instance when the wrong product (Product A) was placed on the conveyor during a scheduled production run for Product B. The PMS responded by adjusting the schedule in real time, redirecting the product to the correct line, and ensuring that production continued efficiently. These adaptive scheduling adjustments, triggered by real-time IoT data, resulted in a more agile production process utilizing resource and reduced downtime. Overall, the system enhanced the responsiveness of production scheduling and significantly improved quality assurance by solving production errors. For further explanation regarding the scheduling system considering IoT, an in-depth study will be carried out to evaluate IoT-based scheduling. However, the scenario and scheduling concept can be seen in Tab. 3 and Tab. 4.

Tab. 3. Scenario implementation scheduling

Section	Description
Conveyor Setup	- Products (A and B) move along a conveyor system. - Station 1 (Object Detection): Identifies the product type. - Station 2 (Quality Inspection): Detects defects and ensures product quality. - Station 3 (Packaging): Packages non-defective products.
IoT Cameras	- Placed at Station 1 and Station 2, the cameras detect product types and inspect quality in real-time. - Detected issues (e.g., mismatches or defects) are recorded and sent to the Production Monitoring System (PMS).

Tab. 4. Adaptive scheduling

Time Frame	Production Flow and Adjustments
10:00 - 11:00	Product A Production Resumes - Object Detection: Correct product detected. - Quality Inspection: All units pass inspection. - Adaptive Scheduling: The conveyor continues to operate as planned. Non-defective products move to packaging.
11:00 - 12:00	Mixed Production for Products A and B - Object Detection: Products A and B are scheduled for this period.

Time Frame	Production Flow and Adjustments
	- Adaptive Scheduling: Production for Product A is prioritized after the rerouting delay in the earlier period. This ensures balanced output. - Quality Inspection: One defective Product B unit is detected. It is automatically removed and rerouted for rework.
12:00 - 13:00	Increased Demand for Product B - Demand Surge: Real-time consumer data indicates increased demand for Product B. - Adaptive Scheduling: The system increases the priority of Product B production, adjusting the conveyor to focus on Product B during this time. - Object and Quality Detection: No defects were detected, and products were routed directly to packaging.
13:00 - 14:00	Rework Handling for Defective Units - Rework Scheduling: The defective units from earlier periods are now prioritized for rework. - Adaptive Scheduling: The system reserves a time slot in the production schedule to address previously defective units (from 11:00 - 12:00). These reworked products are inspected to ensure quality before being sent to packaging.
14:00 - 15:00	Product A Production Resumption - Object Detection: Product A is reintroduced into the production line. - Quality Inspection: No defects detected. - Adaptive Scheduling: Production continues smoothly, and non-defective products are sent to packaging as per the original schedule.

The concept above illustrates how an IoT-based adaptive scheduling system operates within a conveyor-driven production line. Production proceeds as scheduled at the beginning with object detection and quality inspection ensuring that non-defective products are moved to packaging. When defective products are detected, the system immediately reroutes them for rework, while non-defective products continue along the production line uninterrupted. In some instances, such as a real-time surge in demand for Product B, the system dynamically adjusts production priorities, shifting focus to Product B to meet market demands. Time slots are then allocated for reworking previously detected defective units, and once the rework is completed, the products are rechecked to ensure quality before packaging. The adaptive scheduling system ensures that production can return to the first schedule well after rework. It can optimize operational efficiency and respond to real-time demand fluctuations.

3.2. Discussion

Any variable's accuracy from earlier study performance traits and important innovations are the variables under investigation. We aim to provide an in-depth analysis of the most popular object detection methods and their development and use across various industries. We highlighted the advantages and disadvantages of each technique as we reviewed conventional feature-based methods and examined the most recent developments in deep learning-based object detection. We also examined performance evaluation metrics, speed and accuracy comparisons, and how well these approaches hold up to object size, orientation, and occlusion changes. Ultimately, obstacles and future possibilities in this field are revealed by highlighting object detection's potential to spur innovation across various industries. [30], [31].

The conclusion from other research on object detection is to compare and evaluate object detection algorithms. It is crucial to consider various factors such as performance metrics, trade-offs of speed and accuracy, and robustness to variations in size, orientation, and occlusion. This section comprehensively compares these aspects to different object detection approaches. Different object detection algorithms offer various levels of speed and accuracy, so it is crucial to consider the conveyor when choosing a strategy for a specific object application. [27].

Using an Internet of Things (IoT) based on a real-time production monitoring system is a big step toward the manufacturing sector's Industry 4.0. This research aimed to develop a resilient system that promotes flexibility in production scheduling and management in line with the market's ever-changing demands. This section covers the main conclusions, ramifications, and comparisons with previous studies, focusing on how well the suggested approach solves problems that manufacturing organizations confront.

1. Integration of iot in production monitoring

The integration of IoT in real-time production monitoring is in line with the Industry 4.0 paradigm, which emphasizes the seamless connectivity of manufacturing processes. The sensors embedded in basis production play a crucial role in discerning product types, enabling an elaborate understanding of the production process. This argument aligns with the works of [24] and [1], who highlight the transformative potential of Industry 4.0 in enhancing productivity through digital technology.

2. Comparative analysis with previous studies

Several previous studies have addressed challenges related to production efficiency in meeting fluctuating market demands. Efforts such as visual management concepts [20], RFID-based data recording [21], and information system enhancements have been explored [32]. The critical difference between our approach is the utilization of IoT for real-time data collection and dissemination. Unlike manual input systems, our IoT-based solution minimizes errors, providing accurate and timely production data. It contrasts with the time-consuming manual data collection highlighted in our study.

3. Enhancing production planning and inventory control (PPIC)

The real-time production data in the PPIC section is essential to monitor production results in real time and facilitates agile planning and scheduling, ensuring alignment with consumer demand. The proposed IoT-based solution effectively addresses traditional production monitoring systems’s manual input constraints and waiting times. This condition aligns with the findings, emphasizing the importance of process flexibility in responding to changes in market demand. [19].

4. Mitigating human errors and improving operational efficiency

One critical advantage of our proposed system is the mitigation of human errors in data input. This is a common concern in manual data collection systems, as highlighted by Steenkamp et al. (2017). The real-time nature of our IoT-based solution reduces the susceptibility to errors and empowers production managers with immediate oversight of outcomes, allowing for prompt adjustments to production plans.

5. Industry 4.0 as a solution for market volatility

This research applies Industry 4.0, mainly the IoT-driven approach, as a solution to the challenges posed by market volatility. The ability to harmonize adaptability and efficiency in resource management is crucial for manufacturing entities facing uncertain market conditions. Companies can enhance their responsiveness to market fluctuations by utilizing IoT for real-time monitoring, as Industry 4.0 and Cyber-Physical Systems (CPS) principles suggested.

4. Conclusion

In conclusion, the findings of this study emphasize the transformative potential of an IoT-based real-time production monitoring system in addressing the challenges faced by manufacturing companies in the Industry 4.0 era. The comparative analysis with previous studies highlights the unique contributions of our approach, emphasizing the efficiency, accuracy, and agility afforded by integrating IoT into production processes. This research contributes to the broader discourse on intelligent manufacturing and Industry 4.0, offering practical insights for companies seeking innovative solutions to enhance their production capabilities in facing dynamic market demands. Finally, we draw several conclusions as follows:

a. The information system currently being designed is expected to enable real-time monitoring of production results. The real-time system is the developed program that utilizes an internet-connected application, allowing production results to be recorded in real time and used quickly.
b. The developed information system can also swiftly detect various types of products. This information system is realized because the designed program/application utilizes image processing technology to distinguish between several developments in the

production conveyor system.

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