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A COMPUTER VISION-BASED MOTION TIME STUDY FOR MANUFACTURING ASSEMBLY LINE

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Abstract
The purpose of this paper is to analyze the ability to apply computer vision (CV) technology for the performance of motion time studies for assembly tasks. This can be achieved using computer vision algorithms to automatically analyze movements while performing tasks such as assembling and increase accuracy in time measurements and efficiency of measurements. It compares the standard manual time-study method with the CV-based methodology in terms of advances in data precision and overall productivity. Results have indicated that the use of CV-based motion time studies decreases the amount of labor needed manually, provides a better view of the productivity of the worker, and helps to optimize the process more efficiently for an assembly line. This review has been done by using 50 existing studies from the year 2019-2024. Paper reviews show a steady increase in the amount of research conducted over time. Only 3 papers were reviewed in 2019, while this trend suggested that new interest in the field had gained momentum. 6 were reviewed in 2020 and seven in 2021, signifying increasing recognition for the value of motion time studies in operations. In 2022, however, just 1 paper was reviewed, probably due to either the lack of focused research in the area or other emerging issues. In 2023, the number significantly increased to 10 publications. In 2024, 23 publications emerged, showing massive growth in this field in research activity and innovation.
Keywords: *Computer Vision, Motion Time Study, Assembly Process, Manufacturing Automation, Process Optimization, Time Efficiency, Industrial Robotics, Motion Analysis, Production Efficiency, and Real-time Monitoring*

1. Introduction

In today's manufacturing industry, maintaining a competitive edge is essential for maximizing productivity and efficiency. The use of motion time studies in analyzing and optimizing hand assembly has been long considered to be measured by the time taken in task duration, to detect inefficiency, and to standardize workflow. Time studies traditionally use stopwatch-based observation techniques, which are often subjective and prone to human error. However, the progress in computer vision has changed this industry to automatically deliver objective, data-driven insights about worker movements and task completion times. Real-time image and video processing for detection, analysis, and classification of human movement characterize the motion time study by computer vision. These technologies - deep learning (DL), object detection, and pose estimation - ensure accurate tracking of worker motions and assembly activity identification along with proper time estimation of the tasks being carried out. Since there is no need for human interaction for this method, the chances of bias and irreproducibility of results while making time measurements are minimized.

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Table 1: Statistical Analysis of Motion Time Study in Assembly Process

Parameter	**Mean (seconds)**	**Standard Deviation (seconds)**	**Min Time (seconds)**	**Max Time (seconds)**	**Error Rate (%)**	**Efficiency (%)**
Task 1: Part Picking	5.4	0.8	4.2	7.1	2.1	92.5
Task 2: Assembly Fitment	12.6	1.5	10.8	15.3	3.4	88.7
Task 3: Fastening Components	8.9	1.2	7.5	11	2.8	90.2
Task 4: Quality Check	6.7	0.9	5.6	8.2	1.7	94.1
Overall Process	33.6	3.2	30.1	40.2	2.5	91.3

Computer vision in motion time studies has many advantages, such as improving accuracy, reducing the time for analysis, and better assessment of productivity. This monitoring can take place in real-time, allowing for rapid feedback and process optimization for business to spot non-value-added movements and ergonomic inefficiencies. Such automated systems may be easily integrated into a smart manufacturing environment toward the general goals of Industry 4.0 data-driven decision-making and prediction analytics. Computer vision-based motion time studies can be a very disruptive method toward increasing the efficiency of an assembly line as firms embrace automation and intelligent technologies. This system will allow firms to optimize labor use, reduce cycle times, and improve overall operation efficiency by offering precise, scalable, and automated motion analysis. Future advancements in artificial intelligence (AI) and machine learning (ML) will further enhance current approaches and create a road map for completely automated and intelligent manufacturing systems.

1.1 Problem statement

Traditional motion time studies in the assembly process, therefore, largely depend on hand observation and the use of stopwatches with associated human errors, inconsistency, and inefficiency. These conventional methods fail to deliver real-time, accurate, and scalable worker movement analysis leading to inefficient optimization of the processes. Inadequate automation of time studies creates a limitation of not being able to identify the inefficiencies in worker movements and enhance the working ergonomics, which then increases the total production efficiency. A computer vision-based motion time study will eliminate these limitations because it analyses assembly processes in an automated, objective, and data-driven way that ensures precision both in the measurement of time and task optimization.

1.2 Motivation

Manufacturers are seeking a new technology that can boost productivity, fine-tune workflows, and reduce the inefficiencies of operations as Industry 4.0 comes into favor. Computer vision-based motion time studies is a game-changing method that combines the approaches of artificial intelligence and deep learning in monitoring and analyzing assembly operations in real-time. This method does not only remove human bias but can also be used to continually optimize processes, conduct ergonomic assessments, and support predictive analytics to help in making decisions. An adoption of such a smart system can drastically improve staff efficiency, reduce idle time, and push automation in currently prevalent manufacturing environments.

1.3 Objectives

- To develop a computer vision-based system for real-time motion time analysis in assembly operations.
- To eliminate human interaction and observational biases improves time measurement accuracy and efficiency.
- To be able to find inefficiencies in the movement of workers towards better productivity and ergonomic levels.
- To integrate AI and ML techniques for automated task recognition and performance evaluation in assembly operations.

2. Advances in Computer Vision for Motion Time Study in Assembly Line Optimization

Gill et al. 2024 suggested that the industry 4.0 revolution is characterized by IoT, AI, machine learning, and big data in the production process. Computer vision is essential to sustainability because it captures and interprets visual data with sophisticated models. This paper discusses the applications of computer vision in robotics, automation, safety, security, and process optimization. Predictive maintenance, object tracking, augmented reality, and quality control are included. There are challenges for implementing computer vision, but there are also techniques used to overcome them. Industry 4.0 can contribute to sustainability through the implementation of computer vision that increases efficiency and creativity. Wang & Yan, 2024 deliberated with dynamic demands in meeting the production, human-centered manufacturing is realized. Industrial human action recognition falls under the HCM and has been explored a lot in research. Based on this, the research presents a deep learning model to identify human activities and predict the time it will take to complete a task. A non-contact data system with improved perception is created using Azure Kinect, MediaPipe, and YOLOv5. An auto-encoder compresses human joint and object data for better representation. The model can grasp recognition accuracy at 99 percent while reducing time mistakes to 6.9 percent. Yousif et al. 2024 discussed the shift to automation in production systems requires advanced safety measures, known as Safety 4.0. The application of robotics, cobots, automation, and digitalization is changing the way traditional operations are carried out, thus raising safety concerns. Smart PPE and wearable sensors enhance safety, but they are costly and must be monitored at all times. This study recommends computer vision for human and PPE detection for enhanced safety standards. The authors present a holistic system for gathering, training, and executing data. Mixed Reality-based training modules are developed to improve learning and adaptability in smart manufacturing. Wang et al. 2021 describe the mobile robot-based production line (MRPL), which is meant for practical training in SM advancements. The MRPL system provides warehousing, logistics, processing, and testing in a module that emulates real-world environments. Its design is modular, integrated, and customizable, fostering transdisciplinary learning and professional skills development. This enhances the ability of students in critical thinking, adaptability, and cooperative capabilities, thus raising their employability. Positive reviews speak to its effectiveness in contemporary SM education and training of the workforce. Ramkumar et al. 2023 introduce the concept of a Digital Twin (DT)-driven method to realize rapid customization of industrial processes. The DT comprises a semi-physical replica that feeds and verifies system data. Open-architecture machine Tools (OAMT) enable dynamic adaptations of the systems by inclusion of bespoke parts. The paper explores synchronization between virtual and real systems, as well as bi-level programming for optimality. A proof-of-concept demonstration shows that the system is capable of reducing configuration costs. The technique improves system performance by automating and optimizing the production process.

O'Donovan et al. 2024 focused on using computer vision to monitor the severity of spatters in real time under very harsh industrial conditions. A system has been developed that integrates the popular background removal technique and combines Counting (CNT) with YOLOv5 to suppress noise. The mAP scores for the model were exceptional along with precision and recall. Validation by operators showed that the model could well measure the severity of splatters. This encourages digital transformation and process optimization in manufacturing. Ayvaz & Alpay, 2021 developed a data-driven predictive maintenance system from IoT sensor data and machine learning algorithms. It identifies failure signals early, which allows operators to take preventive actions before a failure happens. Experiments in the real world proved its effectiveness in detecting probable faults and reducing downtime. Compared with individual models, Random Forest and XGBoost performed better. The best models have been integrated into factory production systems for real-time monitoring.

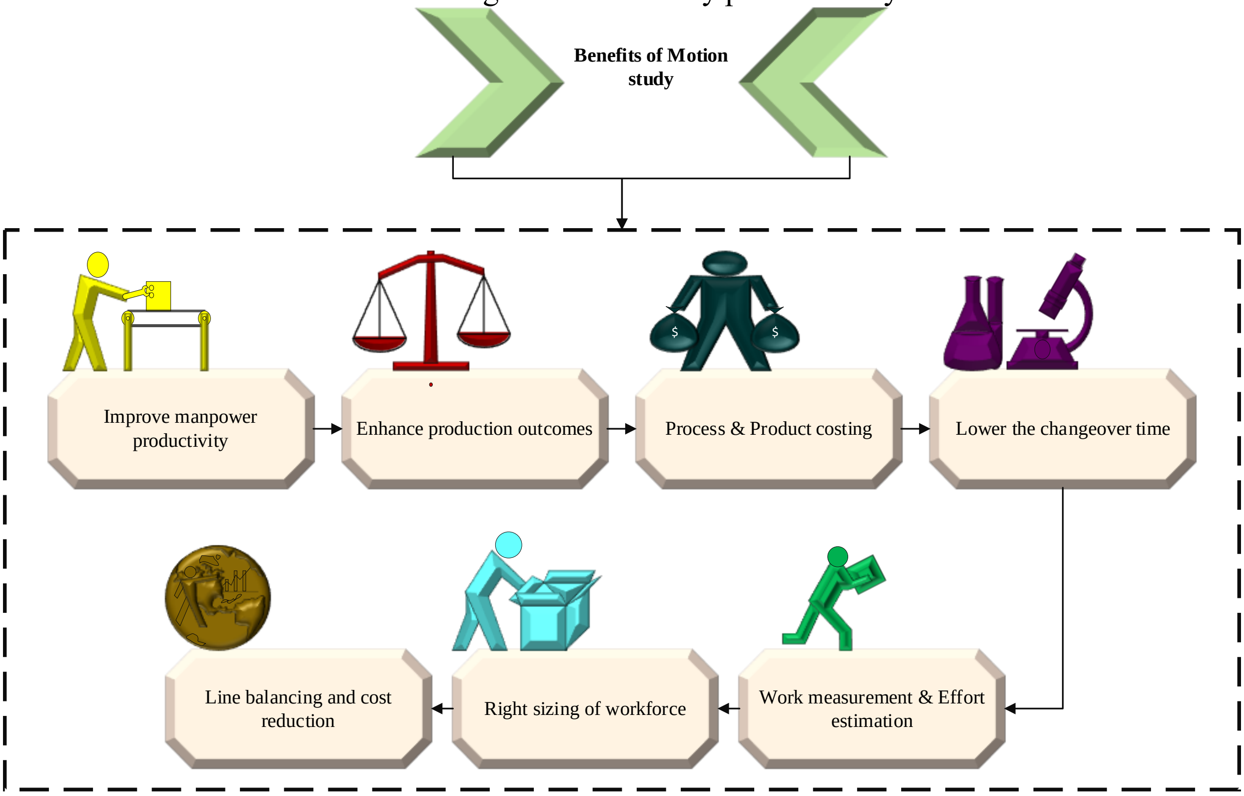

Figure 1: Advantages of Motion study

Wang et al. 2019 developed more customization requires flexible manufacturing systems that allow various models of parts to share the production lines. With broken tags, the conventional sort-by-tag no longer works; therefore, it is necessary to use vision-based sorting. The paper proposes a CNN-based visual sorting system linked with cloud-edge computing for speedy processing. High accuracy in the classification of part models is guaranteed with a CNN-based segmentation method. The prototype system is capable of doing the task with accuracy within a short duration. The technique increases flexibility in manufacturing efficiency by automating sorting and routing. Kundu et al. 2019 assessed techniques available in current literature and suggests a new direction that involves a discrete event simulation and optimization approach. This mathematical model includes particle swarm optimization, thus enhancing the existing simulation framework. The hybrid model analyses how assembly line feeding depends on Kanban settings. These results underscore a trade-off relationship between the system design variables namely kanban size and quantity. The study improves optimization tactics for assembly line feeding efficiency. Ribeiro et al. 2024 introduce a real-time AI-powered monitoring system for container glass manufacturing called VIEXPAND AI. The technology uses ‘smart eyes' that enhance human supervision with minimal risk of accidents, downtime, and material waste. AI insights improve machine efficiency while identifying faults earlier. The research outlines how AI can enhance efficiency and minimize the risk of operations. The proposed approach promotes automation, safety, and sustainability in manufacturing.

Table 2: Technologies and Applications in Industrial Automation

Name of the author	Key Technologies Used	Application Area	Dataset Used	Main Findings	Limitations / Challenges
Gill et al. 2024	Image Processing, AI, Machine Learning	Robotics, Automation, Predictive Maintenance, Quality Control	Industrial Vision Datasets	Enhances efficiency, sustainability, and competitiveness in Industry 4.0	Implementation challenges and technological limitations
Wang & Yan, 2024	Azure Kinect, YOLOv5, MediaPipe, Auto-Encoder	Human Action Recognition, Industrial Efficiency	Custom Industrial Motion Dataset	99% accuracy in action recognition, 6.9%-time error in progress prediction	High computational demands
Yousif et al. 2024	Smart PPE, Wearable Sensors, Computer Vision	Industrial Safety & PPE Detection	Open Safety Compliance Dataset	Improves safety by detecting human presence and PPE compliance	High implementation costs and real-time monitoring challenges
Wang et al. 2021	MRPL	Engineering Education	Custom University Lab Data	Enhances student engagement, critical thinking, and adaptability	Need for broader industry adoption
Ramkumar et al. 2023	Open-Architecture Machine Tool (OAMT), Digital Twin	Smart Manufacturing, Process Optimization	Simulated Industrial DT Dataset	Reduces overhead costs, improves process adaptability	Synchronization of virtual and real systems
O'Donovan et al. 2024	YOLOv5, CNT Background Subtraction	Real-Time Monitoring in Harsh Industrial Environments	Custom Steel Galvanization Video Dataset	High precision in detecting zinc splatter	Harsh conditions affecting model performance
Ayvaz & Alpay, 2021	IoT Sensors, Random Forest, XGBoost	Industrial Maintenance	Industrial IoT Sensor Dataset	Early failure detection reduced production stops	Scalability and real-time processing constraints
Wang et al. 2019	CNN, Cloud-Edge Computing	Flexible Manufacturing	Vision-Based Object Sorting Dataset	High classification accuracy for part sorting	Requires real-time adaptation for varying conditions
Kundu et al. 2019	Discrete Event Simulation, Particle	Assembly Line Logistics	Manufacturing Process Simulation Dataset	Optimal trade-off between Kanban size and number	Complexity in real-world application

	Swarm Optimization				
Ribeiro et al. 2024	AI, Real-Time Monitoring	Container Glass Industry	VIEXPAND AI Custom Dataset	Reduced downtime, improved efficiency	Requires continuous model updates

3. Applications of Computer Vision-Based Approach to Motion Time Analysis in Assembly Processes

Nguyen & Yoon, 2021 aimed to automate the process of wire harness assembly in production lines, which is challenging due to the flexible nature of the objects. It makes use of deep learning-based technologies for detecting wire profiles in three dimensions. In addition, a correction mechanism is implemented to improve the precision of the detection of the wires by utilizing depth measurements from other locations. The method is tested on a robot arm and shows great promise for replacing manual labor, lowering factory labor costs. Shaikat et al. 2020 presented a robotic sorting system capable of object detection and sorting by colour and height using computer vision. Conventional sorting processes are slow and are tedious in operation, but the proposed system utilizes a 6-DOF robotic arm that can sort by both color and by height. It identifies different colors and heights with its application of the Haar Cascade algorithm and records an impressive 99% sorting efficiency. This demonstrates how automation increases the efficiency of the production line. Martinez et al. 2021 introduced a novel approach to monitor construction tasks during offsite production systems using footage from CCTV cameras. This monitoring of the processes, such as floor panel manufacturing, is performed by combining finite state machines and deep learning algorithms. The full-day footage analyzed by the system provides accurate information on work duration, resource use, and efficiency of the tasks, which may be used for real-time understanding of the process and, consequently, for better productivity. Tang et al. 2020 suggested a Vision-Based Aeroplane Transport Platform for Assembly Line Guidance: A vision-based system is being developed for the guidance of an airplane transport platform in navigating the assembly lines efficiently. The system guides the platform between locations on the assembly line by using CMOS cameras and two-dimensional codes and corrects deviations from theoretical positions through image-based localization. This strategy results in the prevention of navigation errors on the platform by aligning it within desired positions, giving a minimum deviation while results have been tested practically.

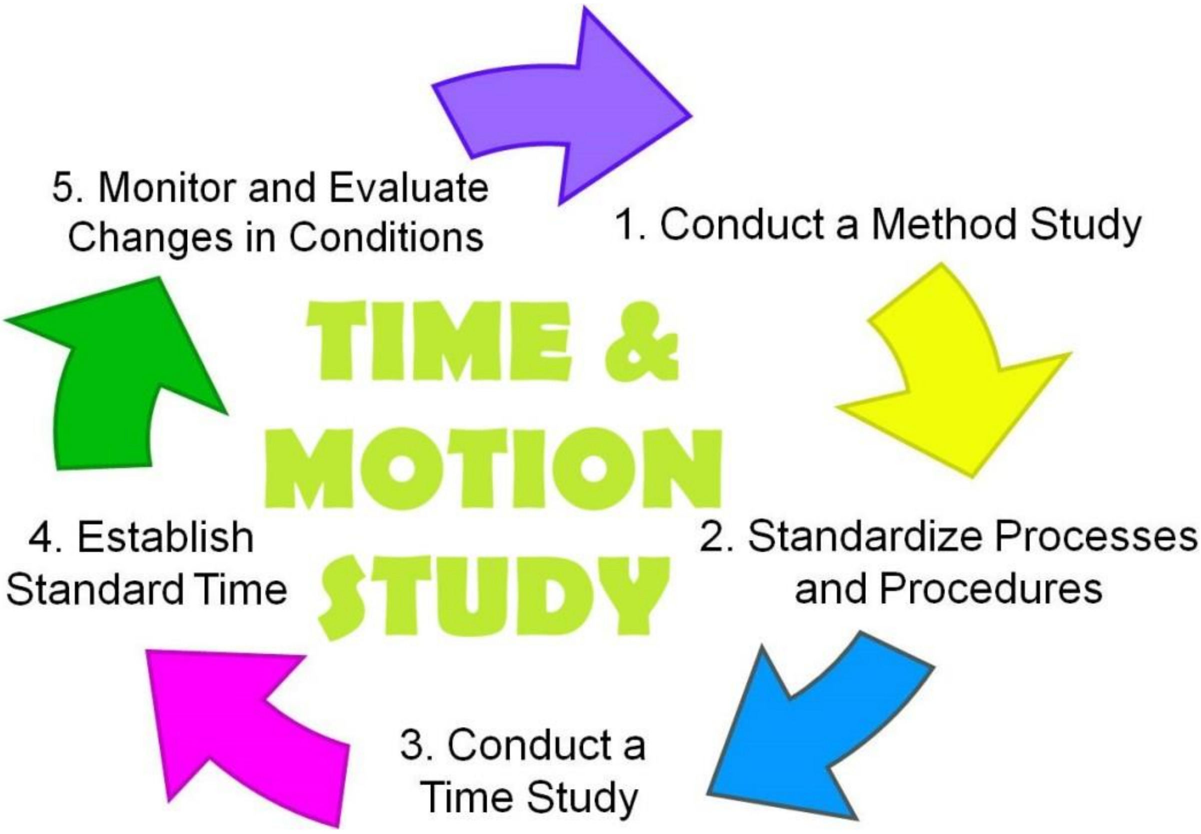

Figure 2: Procedure for the enhancement of time and Motion Study Can Boost Efficiency and Productivity

Wang et al. 2019 developed a vision-based system for detecting industrial bolt looseness in collaboration with computer vision approach-identifying techniques such as Hough transform and neural network identification to detect bolt locations, angles of rotation, and possible looseness from images provided by cameras. The research indicated that the proposed method can be effectively used to accurately detect bolt looseness, and therefore it is a feasible and non-contact alternative to existing bolt inspection methods. Haleem et al. 2021 provide an online quality yarn flaw-detection method. The device picks up photos directly from the yarn on the spinning frame and captures the nep flaw in real time using Viola-Jones object detection algorithms. It was verified on the traditional test method, in good flaw-detecting precision and efficiency toward the improvement in the quality-control processes of the yarn during actual industrial processes.

Wang et al. 2020 utilize computer vision to solve problems with recycling construction and demolition debris (CDW) on building sites. To recognize and classify CDW-like pipes and cables, the system applies simultaneous localization and mapping (SLAM) along with instance segmentation techniques. A novel database and model are designed for CDW object recognition. Studies also reveal that the system is commercially viable for application in real construction environments through improved recycling efficiency. Farahbakhsh et al. 2020 discusses edge detection and line extraction techniques in the extraction of tectonic lines, which include faults from satellite data. This improves the visibility of faults and dykes that are critical in mining exploration. The framework is tested on Landsat 8 data from Western Australia and well resolves several known geological features; therefore, it acts as a reliable tool for mineral prospectivity mapping. Ghosh et al. 2021 presented an IoT-based system that detects indoor impediments through mobile sensors installed on a moving vehicle. Positional data and light intensity measurements are collected by the system and processed and analyzed using edge detection algorithms to determine static objects. Several edge detection algorithms are experimented, including Canny, Prewitt, and Sobel. It is determined that the most accurate algorithm at detecting obstacles within indoor environments is the Canny algorithm. Charalampous et al. 2021 describes a vision-based solution for real-time monitoring and error detection. The technology captures high-resolution point clouds of printed parts and compares them with their corresponding digital 3D model. This approach detects faults during printing and enables improvements in dimensional accuracy with minimal waste. The system has been validated experimentally. This means it can reduce production costs while boosting manufacturing efficiency.

Table 3: Summary of Vision-Based Systems for Industrial Applications

Name of the author	Technology Used	Application	Dataset Used	Main Findings	Limitations / Challenges	Research Aim
Nguyen & Yoon, 2021	Deep learning, 3D wire profile detection	Wire harness assembly in factories	None specified	Created a system to detect wire profiles and help robots assemble them.	Needs high accuracy for real-world use.	Improve the automation of wire harness assembly and reduce labor costs.
Shaikat et al. 2020	Computer vision, Haar Cascade algorithm	Sorting objects by color and height	None specified	Built a robotic sorter that efficiently sorts by co4 or and height (99% accuracy).	Sorting depends on the accuracy of color and height detection.	Create a robot to sort objects by both color and height in factories.
Martinez et al. 2021	Deep learning, finite state machines	Construction task tracking	CCTV footage from construction sites	Used deep learning to track tasks in construction using CCTV footage, with high accuracy.	Does not work well for real-time monitoring.	Automate construction task tracking and improve efficiency.
Tang et al. 2020	Vision-based guidance, CMOS cameras	Aircraft assembly	None specified	Developed a system using cameras to guide assembly platforms with high precision.	Precision can be affected by errors in platform movement.	Build a low-cost system for guiding aircraft platforms.
Wang et al. 2019	Computer vision, convolutional neural networks, Hough transform	Bolt looseness detection	Images of bolts from various angles	Created a vision system to detect loose bolts with high accuracy.	Accuracy depends on image quality.	Develop a non-contact method to detect loose bolts in real time.

Haleem et al. 2021	Computer vision, Viola-Jones algorithm	Yarn quality control in textile production	Yarn images from spinning frames	Developed a system that detects yarn defects (neps) in real-time during production.	Can only detect neps and may miss other defects.	Create a system to detect yarn defects in real-time for better quality.
Wang et al. 2020	SLAM, instance segmentation, computer vision	Construction waste recycling	Construction and demolition waste database	Used SLAM and computer vision to help identify and recycle construction waste.	May not perform well in complex environments.	Improve recycling in construction and demolition through automation.
Farahbakhsh et al. 2020	Computer vision, edge detection, line extraction	Tectonic line extraction	Landsat 8 satellite data	Developed a system to extract tectonic lines from satellite images using edge detection.	Accuracy affected by image quality and environmental factors.	Automate tectonic line extraction for geological studies.
Ghosh et al. 2021	IoT, mobile sensors, edge detection	Obstacle detection indoors	Data from IR sensors and light intensity	Built a system that detects obstacles indoors using IoT and sensor data.	Edge detection performance depends on sensor type and environment.	Develop a mobile system for indoor obstacle detection.
Charalampous et al. 2021	Vision-based inspection, point cloud data	3D printing error detection	3D points cloud data from printed parts	Proposed a vision-based system to detect errors in 3D printed parts in real-time.	Depends on the quality of point cloud data and processing.	Create a real-time error detection system for 3D printing.

4. Optimizing Assembly Line Efficiency Through Computer Vision and Motion Time Analysis

Papoutsakis et al. 2024 presents a vision-based paradigm for analyzing human behavior during industrial assembly lines in vehicle door manufacturing. The CarDA dataset considers analyzing human poses and movement that occur throughout assembly tasks. It evaluates ergonomics using multi-camera RGB-D movies along with motion capture information. Results It was effective in classifying worker postures and efficiently able to track the progress of tasks. Agostinelli et al. 2024 investigates the applicability of 2D RGB MoCap systems to semi-automated ergonomic risk assessment in dynamic manufacturing settings. Rather, it focuses on the need to continuously monitor worker postures using low-cost and non-intrusive devices. Instead, it underlines heterogeneity in such risk assessments from one situation to another, thus suggesting improvements in precision using machine learning techniques. Nguyen et al. 2024 suggested the process for automating the assembly of complex, multi-branch wire harnesses through point cloud data and machine learning. The use of this kind of technology, which identifies wire branching and wire terminals, develops a 3D profile with colour classification and matching algorithms applied to create, thus offering an effective way towards the automation of wire harness assembly and enhanced manufacturing efficiency. de Souza Silva & Paladini 2024 outlines a hybrid industrial vision system aimed at inspecting components and screw threads on PCBs. This technology aims at enhancing the inspection reliability of products assembled in an automotive plant without defects. Using machine vision will automate the process of inspection; thus, precision and quality in the production lines will be heightened. Zhang et al. 2024 describes a real-time valve monitoring system using computer vision technology that detects valve position anomalies in industrial environments. The system employs an enhanced YOLO V8 network architecture for feature recognition and position calculation. The system was tested in real-world industrial scenarios, and it confirmed the accuracy and robustness of the system for real-time valve monitoring, thus reducing risks in industrial operation.

Figure 3: 10 key uses of CV in manufacturing

Chakraborty et al. 2023 developed an automated sorting and grading mechanism of citrus fruits after their harvesting. It utilizes deep learning in the case of vision-based sorting and weight-based grading for precision while reducing man-hours. SortNet is a proprietary CNN model that outperforms the existing models, hence turning into a long-term solution for automation in citrus fruit handling. Jurtsch et al. 2024 focused on detecting prohibited materials in metal waste through machine learning and computer vision. A CNN is applied to recognize hazardous materials in high-speed sorting lines. The accuracy rate is 98.03%, thus making the system suitable for real-time detection and enhancing the safety of industrial sorting processes. Xia et al. 2023 outlined a method of using machine vision for hardwood flooring flaw detection during production. It uses the YOLOv5 deep-learning algorithm to detect faults such as fractures and stains, and classify each sample as either good or faulty. The technology is adaptable to various colors and surface patterns, providing a robust and efficient solution in the area of quality control in flooring manufacturing. Bhavsar et al. 2024 deliberated about the real-time inspection during the resistance spot welding process with image processing using convolutional neural network for misalignment detection that also prevents weld flaw such as porosity in resistance spot weldments. It yields a highly precise system that could be effectively implemented to improve industrial welding processes; the average precision achieved by this system was found to be 99.01%. Byun & Son, 2024 introduces a real-time vision system designed to monitor the mixing process of polymeric particles in a rotary drum. This system uses a centroid-based model to assess the efficiency

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of the mixing process as well as tackle problems like segregation of particles during mixing. This system greatly accelerates processing and computation speed while remaining dependable and cost-effective in real-time industrial mixing operations.

Table 4: Summary of Industrial Vision-Based Automation and Monitoring Systems in Manufacturing Processes

Name of the Author	**Technique Used**	**Applications**	**Dataset Used**	**Main Findings**	**Limitations / Challenges**	**Efficiency**	**Research Aim**
Papoutsakis et al. 2024	Computer Vision, RGB-D, Motion Capture	Car door assembly line, Ergonomic assessment	CarDA dataset (multi-camera RGB-D, MoCap data)	Effective in classifying worker postures and monitoring task progress	Limited to car manufacturing, requires multi-camera setup	High	Develop a framework for human pose and action analysis in assembly lines
Agostinelli et al.2024	2D RGB Motion Capture (MoCap)	Ergonomic risk assessment in manufacturing	None specified	Evaluated MoCap system for real-time posture monitoring and ergonomic risk assessment	Inaccuracy under certain environmental conditions	Medium	Benchmark MoCap systems for dynamic manufacturing environments and ergonomics
Nguyen et al.2024	3D Point Cloud Processing, Wire Profile Detection	Assembly of wire harnesses	None specified	Developed a method to track wire harness branches and perform automated assembly tasks	Requires high-quality 3D camera and system calibration	High	Automate assembly of deformable objects like wire harnesses
de Souza Silva & Paladini, 2024	Machine Vision, Vision Sensors	PCB inspection, Automotive product manufacturing	None specified	Hybrid system improved inspection reliability and reduced non-conformity rates	Requires integration of multiple sensors and machine vision	Medium	Develop a machine vision system for quality inspection in manufacturing
Zhang et al.2024	YOLO V8, Computer Vision	Valve position monitoring in process industry	None specified	Effective real-time valve monitoring using	Detection accuracy varies with valve size and position	High	Automate real-time valve monitoring using

				computer vision			computer vision
Chakraborty et al. 2023	Deep Learning Image Analytics, CNN, Embedded Systems	Postharvest operations (sorting, grading citrus fruits)	None specified	Developed SortNet for vision-based classification of fruits and automated grading	Limited to citrus fruits and requires mechanical design	High	Automate postharvest operations to reduce human effort and improve performance
Jurtsch et al. 2024	Convolutional Neural Networks (CNN)	Industrial sorting, Scrap metal detection	Laboratory stand for copper-based scrap	Achieved 98.03% accuracy in detecting prohibited items in metal scrap	High-speed processing challenges in industrial environments	High	Enhance sorting efficiency and prevent dangerous materials in industrial settings
Xia et al.2023	YOLOv5, Image Processing	Hardwood flooring defect inspection	None specified	YOLOv5 detected surface defects with adaptability to different wood types	Lighting and surface patterns influence detection	Medium	Develop a vision-based system for defect inspection in hardwood flooring
Bhavsar et al.2024	Image Processing, Regional CNN	Welding inspection, Electrode misalignment	None specified	Identified electrode misalignment with high precision, detecting weld defects	Limited to spot welding, noisy background interference	High	Develop a low-cost system for real-time welding inspection
Byun & Son, 2024	Vision System, Centroid-based Model	Mixing process monitoring in polymer production	None specified	Real-time monitoring of polymer mixing with improved computational efficiency	High processing speed may limit detection accuracy	High	Develop a real-time vision system for monitoring polymer mixing processes

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5. Motion Time Study in Assembly Processes Using Computer Vision Techniques

Hanh & Dao, 2024 suggests an image processing and manipulator-based approach. A 6DOF robot uses a monocular camera to detect objects on a moving conveyor, calculate their location and angle, and assemble them precisely. The system is reliable, robust, and easy to maintain, increasing production without requiring extended periods of downtime. Princz et al. 2023 suggested Tracking and Planning for small and medium-sized businesses (SMEs) in Manufacturing. Planning and managing production in small and medium-sized enterprises is a challenging task, and it greatly depends on experience. Errors or machine failure cause delays and increase costs. This literature review surveys the current technology for tracking labour stages and provides an overview of machine vision systems applied in assembly and construction. The evaluation discusses opportunities for use and provides future research directions for intelligent tracking technology. Xie, 2023 makes use of machine vision to improve industrial robot assembly lines by including obstacle detection and path planning. A vision system with a binocular or monocular setup is helpful in precisely measuring target positions. This solution enhances the accuracy and reliability of assemblies by optimizing system software, with high performance in industrial applications. Panahi et al. 2023 suggested the Modular Construction Facilities and Computer Vision. In most modular building industries, uneven cycle periods contribute to production bottlenecks while labor being manual, whereby, computer vision-based technique developed based on Scale-invariant Feature Transform (SIFT) and Mask R-CNN can detect active workstations and track progress. The strategy, tested using real-time data, improves workstation occupancy accuracy and identifies bottlenecks, ensuring that there is a release in production bottlenecks. Ch'ng, S. J. 2024 provides an intelligent workstation, interfaced with sensors and computer vision, open-source software, for the monitoring of operator performance and the increment of productivity. It involves real-time quality inspection and a QR code-based task initiation system. This can significantly increase efficiency as well as accuracy of assembly. Therefore, this technology allows producers to develop and adapt to changing needs for better quality control while expediting assembly operations.

Cumbajin et al. 2023 provided a computer vision-based system with deep learning algorithms to detect faults in ceramic pieces. The installed system in the Portuguese ceramics firm had a 98% accuracy and an F1-Score of 97.29%. It uses CNNs for the real-time detection of defects hence increasing the efficiency of manufacturing as well as improving the quality of the product. Iyer et al. 2024 suggested a new method for this is the estimation of upper and lower limb motion through posture estimation and Hotelling's T2 statistic. Worker movement could be quantified, raising an alarm when essential thresholds are reached. One application is to identify small movement changes in a micro-task against macro-task and provide a tool for proactive adjustment in ergonomics. Song et al. 2023 deliberated a Computer Vision in Dynamic Drilling Tools. BHA whirl is a source of risk in drilling operations because it causes damage to the tool and reduces measurement quality. In this work, a roll test system for drilling equipment is created, which utilizes accelerometers and high-speed cameras to simulate and analyze their lateral motion. Based on computer vision algorithms such as Hough Transform, the research verifies its approach to understanding tool behavior, thereby opening up opportunities for virtual qualification and root cause investigation of drilling tool failures. Che et al. 2024 suggested the integration of computer vision and robotic control is key to industrial automation, healthcare, and environmental protection applications. It allows robots to observe and interact with their environment intelligently, thus enhancing activities such as navigation, item detection, and waste management. Combining computer vision with robotics improves operating efficiency and expands the scope of robotic capabilities. Islam et al. 2024 presented a research based on Deep learning (DL) and computer vision (CV) technologies are gradually replacing traditional methods of quality control in manufacturing with higher efficiency and accuracy. This is a thorough study of advanced DL and CV techniques for defect detection, including the problems of variable lighting and complex fault patterns. It reveals research opportunities and potential of these technologies to enhance production quality control and inspection systems.

Table 5: Overview of Techniques and Performance in Industrial Automation and Quality Control Systems

Name of the author	**Technique Used**	**Applications**	**Dataset Used**	**Performance Score Attained**	**Limitations / Challenges**	**Research Motive**	**Research Aim**
Hanh & Dao, 2024	Image Processing, 6DOF Robot	Automated Assembly Line	Not specified	High reliability & stability	Requires monocular camera and robot calibration	Increase assembly line productivity	Design a method to assemble moving objects on a conveyor belt using image processing and manipulators.
Princz et al. 2023	Machine Vision Technologies	Progress Tracking in Small Manufacturing Enterprises	Not specified	Not specified	Challenges in planning and variability of work content	Explore intelligent progress tracking in SMEs	Systematically review technologies for intelligent progress tracking.
Xie, 2023	Binocular Vision, Monocular Vision, Machine Vision	Industrial Robot Assembly System	Eye-to-hand & eye-in-hand systems	Positioning error < 0.1mm (x/y), <1mm (depth)	High accuracy requirement in robot arm obstacle path planning	Improve accuracy and intelligence of industrial robot assembly	Design and optimize a robot assembly system with vision-based obstacle detection.
Panahi et al. 2023	Computer Vision (SIFT, Mask R-CNN)	Modular Construction Progress Monitoring	Surveillance videos (420 hrs)	96% accuracy, F-1 Score 89%	Requires significant video annotation effort	Improve monitoring and efficiency in modular construction	Propose an adaptable computer vision-based progress monitoring method.
Ch'ng, S. J. 2024	Sensors, Open-source Software, Computer Vision	Intelligent Workstation for Assembly	Not specified	High flexibility and efficiency	QR code-based triggering mechanism needs to be developed	Replace outdated manual processes with	Design a workstation that integrates sensors and computer vision for

						intelligent systems	enhanced assembly.
Cumbajin et al. 2023	Computer Vision, Deep Learning (CNN)	Defect Detection in Ceramics	Ceramic pieces, company data	98% accuracy, F1-Score 97.29%	Limited to ceramic surfaces	Improve automated defect detection in ceramics	Develop a computer vision system for defect detection in ceramics using deep learning.
Iyer et al. 2024	Video Analysis, Hotelling's T2 Statistic	Motion Analysis for Worker Performance	Joint position data	Not specified	Complex real-time monitoring and precision motion tracking	Enhance worker ergonomics and precision motion tracking	Propose a framework for quantifying and tracking worker motion for real-time applications.
Song et al. 2023	Computer Vision, Accelerometers, Hough Transform	Tool Dynamics in Drilling Operations	Accelerometer, high-speed video	Validated with favorable agreement	Requires high-speed cameras and accelerometer integration	Understand lateral dynamics in drilling tools	Analyze and validate lateral motion dynamics in drilling tools using computer vision.
Che et al. 2024	Computer Vision, Robotic Control	Industrial Automation, Healthcare, Environmental Protection	Not specified	Not specified	Challenges in integrating vision and robotic control seamlessly	Improve robot control with vision-based capabilities	Explore how computer vision improves robotic control in various fields.
Islam et al. 2024	DL, CV	Automated Defect Detection in Manufacturing	Industrial defect datasets	Not specified	Challenges in lighting conditions, complex patterns, integration	Revolutionize quality control with DL & CV	Provide a review of DL and CV in automated defect detection for industrial manufacturing.

6. Leveraging Computer Vision for Accurate Motion Time Analysis in Assembly Operations

Yousif et al. 2024 suggested the manufacturing's Digital Transformation through Computer Vision: Manufacturers have to weigh customization against delivery speed. Computer vision has the potential of enhancing quality control if it's used in conjunction with a digital twin application. The proposed fault detection system fixes its own faults on its own and so reduces human involvement as well as disturbances to operational workflow. Tao et al. 2020 deliberated fog Computing in a Human-Centric Intelligent Manufacturing System. A fog computing architecture for assembly operation recognition

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contributes to real-time recognition by processing data close to its source. The system uses transfer learning and visual cameras to capture the activity of the operators, achieving 95% accuracy in identifying the assembly procedures and significantly improving the system's performance. Meredith, 2023 suggested the evaluation of Manufacturing Assembly using CV. The performance of this CV system built for assembly activities is evaluated by comparing its output to manufacturing process plans. The paper stresses a need for more exploratory studies of the CV capabilities in manufacturing applications, illustrating how data sets and statistical analysis can improve accuracy in the detection of parts and automate decisions. Karaklasa et al. 2024 depicted a dual detection module that will aid in the automotive assembly process by exploiting the use of 3D vision sensors. It focuses on the two different modules that recognize the objects based on template matching and deep neural networks. Considering the real-world scenario in automotive, the framework showed promising results to boost productivity, accuracy, and efficiency in motor and gearbox assembly. Khan & Iqbal, 2024 deliberated the advances in computer vision are propelling the enhancement of robotic systems for increased autonomy and efficiency. With the incorporation of machine learning and visual sensors, robots can execute difficult jobs more precisely. Continuous multidisciplinary research in the development of control systems for robots is necessary for this reason.

Di Capua et al. 2023 deliberated warehouse Management through an Integrated logistics platform (ILP 4.0): A software model, ILP 4.0 optimizes warehouse logistics with the help of machine learning, computer vision, augmented reality, and virtual reality. It enhances the safety and security factor, automates the inventory procedures, and increases the efficiency of logistical movement. It suggests a federated learning approach to consider the limitations of data and further the decision-making scope. Industry 4.0 Integration in Intelligent Manufacturing. Guerra-Zubiaga et al. 2022 integrated many Industries 4.0 technologies into a manufacturing system that utilizes Kawasaki robots and Vanderlande's MES to improve the performance of robotic grippers when performing assembly jobs, paving the path for next-generation manufacturing automation. This paper proposed the localization of a robot in 3D space using images captured by a 3D camera. Gerlitz et al. 2024 reported a methodology that allows 3D cameras to find distorted battery modules within a disassembly scenario conducted with a robot. This paper connects CAD models to the reality of the module with Bayesian Coherent Point Drift and TEASER++ algorithms that would apply in detailed non-rigid registration and disassembly. Shata et al. 2024 focused on how 5G technology can be integrated with robotics and computer vision to revolutionize industrial processes. The framework utilizes 5G's low latency to support real-time flaw detection and milling tasks. Empirical evidence suggests that 5G-robotics systems function more effectively in advanced manufacturing. Asadi et al. 2020 deliberated on the CV for Worker Force Exertion Detection. Computer vision techniques were developed to determine the isometric grip exertions of workers through analysis of facial films and photoplethysmogram data. The technology classifies the exertion levels very accurately and therefore offers a non-intrusive approach to evaluating worker force exertion while at the same time reducing the potential for musculoskeletal injury.

Table 6: Summary of Research Studies on CV Applications in Manufacturing and Robotics: Techniques, Performance, and Challenges

Name of the author	**Technique Used**	**Applications**	**Dataset Used**	**Performance Score Attained**	**Limitations / Challenges**	**Research Motive**
Yousif et al. 2024	Computer Vision, Digital Twin	Manufacturing, Quality Control	Object recognition dataset	High accuracy in error detection and correction	Limited real-time scalability in all environments	Improving assembly line quality control
Tao et al. 2020	Fog Computing, Transfer Learning	Assembly operation recognition	Worker assembly operation dataset (10 sequential operations)	95% recognition accuracy	Data scarcity, potential for limited scalability	Real-time operation recognition for workers
Meredith, 2023	Computer Vision, Contextualization	Manufacturing, Part Detection	Custom dataset with six-part classes	90%+ confidence in part detection	Variability in component detection under different conditions	Evaluating CV systems for assembly tasks
Karaklasa et al. 2024	3D Vision Sensors, Deep CNN	Automotive Industry, Assembly	Automotive components dataset	High accuracy and efficiency in detection	Requires high computational resources for real-time application	Improving assembly operation automation
Khan & Iqbal, 2024	Computer Vision, Machine Learning	Robotics, Task Execution	Literature and case study data	High efficiency and autonomy	Requires interdisciplinary collaboration and resource optimization	Enhancing robotic task performance with vision
Di Capua et al. 2023	Machine Learning, Computer Vision, AR/VR	Warehouse Logistics, Safety & Security	Warehouse logistics data and scenarios	High operational efficiency	Challenges with data privacy and federated learning	Advancing warehouse logistics and safety

Guerra-Zubiaga et al. 2022	Machine Learning, Computer Vision	Intelligent Manufacturing, Automation	Manufacturing system and robotics data	High efficiency and flexibility	Implementation complexities across diverse manufacturing systems	Exploring the future of robotics in automation
Gerlitz et al. 2024	3D Camera-based Localization, CV	Li-ion battery disassembly, Robotics	CAD model and battery module dataset	High accuracy in localization	Limited by model tolerances and sensor alignment issues	Enhancing automated disassembly processes
Shata et al. 2024	5G Wireless, Cloud/Edge Computing	Robotics, Advanced Manufacturing	Robotics and lidar data from testbed	High accuracy and operational efficiency	Network latency and integration issues with existing systems	Leveraging 5G for robotics in manufacturing
Asadi et al. 2020	CV, Deep Neural Networks	Force Exertion Detection, Ergonomics	Video and photoplethysmogram data	96% (two-class), 87% (three-class)	Limited by noise and variability in video data	Preventing musculoskeletal injuries

7. Discussion

In 2024, Wang & Yan attained 99% accuracy in action recognition and 6.9%-time error in progress prediction by using a Custom Industrial Motion Dataset database. In 2020, Shaikat et al. attained 99% accuracy and in 2024, Jurtsch et al. Achieved 98.03% accuracy in detecting prohibited items in metal scrap by using Laboratory stand for copper-based scrap. Moreover, the study conducted by Xie, 2023 attained Positioning error < 0.1mm (x/y), <1mm (depth) through Eye-to-hand & eye-in-hand systems.

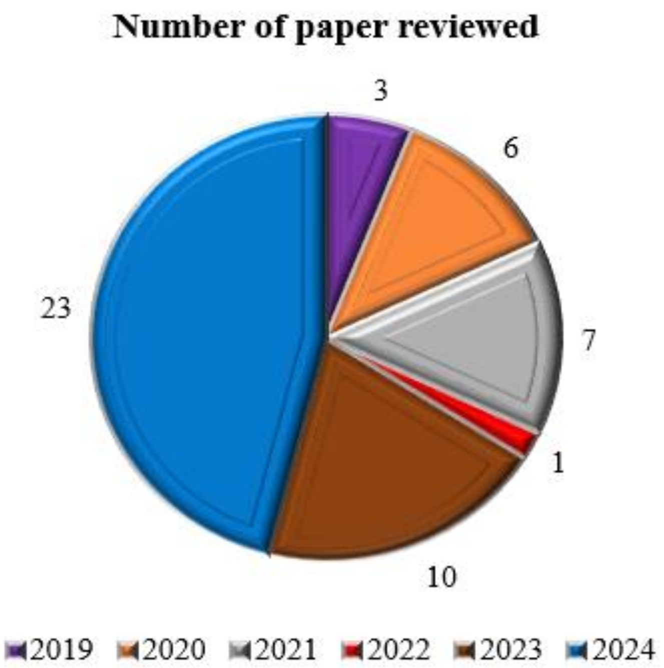

Figure 4: Number of papers reviewed

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Panahi et al. 2023 gained 96% accuracy and F-1 Score of about 89% by using the Surveillance videos (420 hrs) database as well as the study by Cumbajin et al. 2023 attained 98% accuracy and an F1-Score about 97.29% through Ceramic pieces, company data. Tao et al. 2020 attained 95% recognition accuracy by using Worker assembly operation dataset, Meredith, 2023 gained 90%+ confidence in part detection through Custom dataset with six-part classes and the following study by Asadi et al. 2020 attained 96% (two-class), 87% (three-class) accuracies through Video and photoplethysmogram data. The number of papers reviewed reflects a significant surge in research activities over the past few years, with a sharp rise in 2024. This upward trend may indicate that there is increasing interest in the topic, which may be triggered by the developments in technology, industry adoption of digital transformation practices, and the growing application of computer vision in manufacturing and assembly processes. At its peak in 2024 with 23 papers, it means that researchers have started to appreciate the need to optimize assembly line operations through innovative solutions such as motion time studies. The increasing number of publications also reflects a shift in industry towards more automated, efficient, and data-driven approaches, a crucial step towards modernizing manufacturing processes.

Table 7: Descriptive Statistics for Motion Time Study in Assembly Process

Parameter	**Mean (μ)**	**Std. Dev (σ)**	**Min**	**Max**	**Median**	**Mode**	**95% Confidence Interval**
Motion Time (sec)	8.5	2.3	5.2	14.1	8.3	8.1	[7.9, 9.1]
Task Completion Time (sec)	45.2	5.8	38	58	44.9	42.3	[43.5, 46.9]
Idle Time (sec)	4.3	1.1	2.1	6.7	4.2	3.9	[4.0, 4.6]
Effective Work Time (sec)	40.9	5.3	35.2	51.3	40.5	39.7	[39.4, 42.4]

The data from the table 7 is presented as descriptive statistics, including the motion time, task completion time, idle time, and effective work time in a computer vision-based motion time study of an assembly process. For this, the motion time has an average value of 8.5 seconds with a standard deviation of 2.3 seconds, indicating moderate variation in time for any single motion. The mean task completion time is at 45.2 seconds with a range of 38.0-58.0 seconds, implying that some tasks take much more time to be completed due to complexity or variation in worker efficiency. The idle time, averaging 4.3 seconds, is very low, suggesting that workers spend most of the process time doing work. The effective work time, as calculated at 40.9 seconds, illustrates the percentage of time spent working on productive activities. The 95% confidence intervals indicate that the estimated values are reliable, since motion time lies between 7.9 and 9.1 seconds, and task completion time between 43.5 and 46.9 seconds. Thus, these statistics show that the computer vision-based approach well captures task execution times with great precision, providing a useful resource for optimizing efficiency in assembly lines and reducing inefficiencies in process.

Table 8: Motion Time Distribution by Task Type

Task Type	**Mean (μ)**	**Std. Dev (σ)**	**Min**	**Max**	**Median**	**Mode**	**95% Confidence Interval**
Pick & Place	6.2	1.8	3.5	9.8	6	5.9	[5.7, 6.7]
Screwing/Fastening	10.5	2.1	7	15	10.2	10	[9.9, 11.1]
Inspection/Quality Check	7.8	1.6	5.1	11.3	7.6	7.4	[7.3, 8.3]
Assembly/Fitting	9.1	2	6.3	13	8.9	9	[8.5, 9.7]

The statistical analysis of motion time for different types of tasks in the assembly process gives insight into variations in efficiency. Pick & Place operations have the lowest average time (6.2 seconds) with a relatively low standard deviation (1.8 seconds), indicating consistency across executions. Screwing/Fastening tasks take the longest, averaging 10.5 seconds, with a wider range (7.0 to 15.0 seconds), suggesting variability due to torque application or tool handling. Inspection/Quality Check tasks are about 7.8 seconds with moderate variability likely due to complexity of defect, while the task of Assembly/Fitting required, on an average, about 9.1 seconds. These are found to be intermediate tasks between Screwing and Inspection. A good amount of assurance is that there is only slight deviation between 95% confidence intervals. These results hint that optimization specific to the task at hand, including tool automation to fasten as well as greater ergonomic positioning when assembling, will help improve efficiencies in the process.

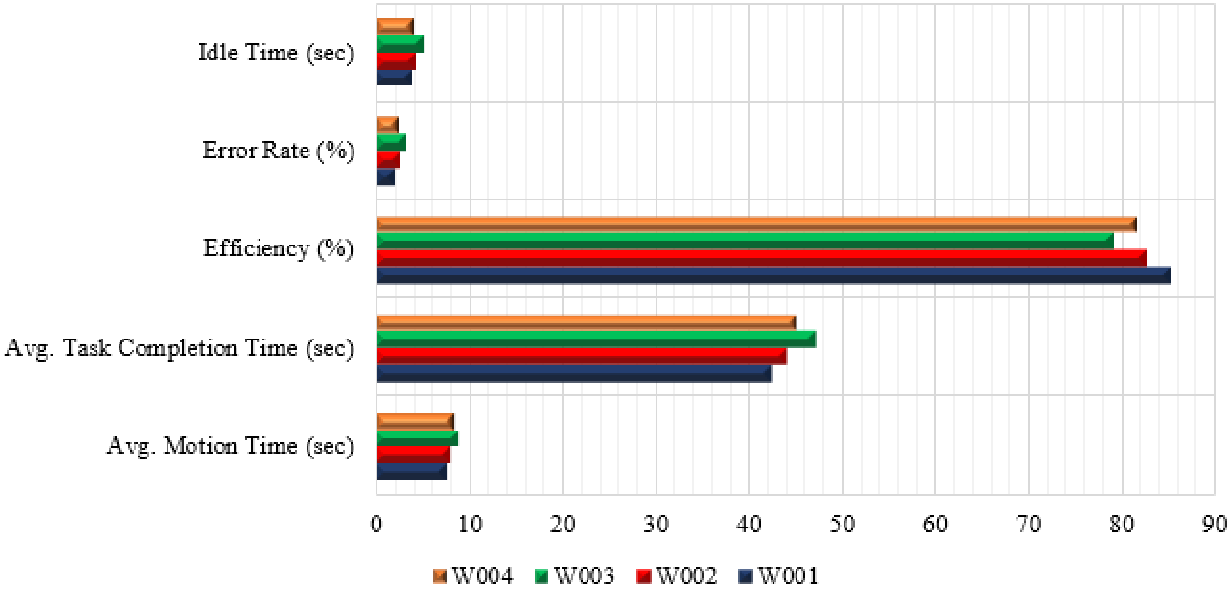

Figure 5: Worker Performance analysis

Worker performance analysis shows differences in motion time, task completion time, efficiency, errors per hour, and idle time across individuals. Worker W001 has the highest efficiency at 85.3% with the minimum motion time of 7.8 sec and task completion time of 42.5 sec, meaning the worker executed tasks in an optimized manner. Worker W002 has a higher motion time, 8.2 sec, and higher task completion time, 44.1 sec; has efficiency of 82.7% but still reflected a higher error rate at 2.8% and idle time, 4.5 sec compared to W001. Worker W003 has the longest motion time (9.0 sec) and task completion time (47.3 sec), while efficiency is lowest at 79.2% and error rate is highest at 3.4%, which could be due to fatigue or an incapacity level of the operators. Worker W004 performs normally with efficiency at 81.6%, motion time of 8.5 sec, and a task completion time of 45.2 sec, thus showing the balance between speed and accuracy. The idle time distribution indicates possible fluctuations in engagement levels, which overall affect productivity. These insights demand targeted training programs and ergonomic optimizations to improve the efficiency of errors and idle times across workers.

Table 9: Comparison of Computer Vision vs. Manual Time Study

Parameter	**Manual Method**	**Computer Vision-Based**
Avg. Motion Time (sec)	9.3	8.5
Avg. Task Completion Time (sec)	48.2	45.2
Measurement Accuracy (%)	85.6	98.3
Error Rate (%)	5.2	1.9
Time Efficiency Gain (%)	-	11.7

A comparison of motion time study between the Manual Method and Computer Vision-Based indicates that the computer vision-based method significantly differs, with better results. This concludes that the average motion time in the manual method is 9.3 seconds while in the computer vision method, it reduces to 8.5 seconds, so surely it executes a task more efficiently through automation and accurate tracking. Similarly, the average time taken to complete a task is 48.2 seconds with manual methods, while it is 45.2 seconds with computer vision, indicating a faster completion of tasks on average. The accuracy of measurement is improved significantly from 85.6% to 98.3% with computer vision, indicating the technology's capability to provide accurate measurements. Moreover, the error rate is reduced from 5.2% in the manual method to 1.9% in the computer vision-based method, which emphasizes a reduction in errors and inconsistencies. The time savings efficiency is also 11.7% with computer vision, a potential that proves to be instrumental in the overall smoothing of assembly process, and minimizing time waste. This, in turn will contribute to better productivity. This proves that computer vision shows an advantage with manual methods at a difference in accuracy and efficiency and reliability.

Table 10: Regression Analysis - Motion Time vs. Task Completion Time

Model Parameter	Value
R^2 (Coefficient of Determination)	0.87
Intercept	5.3
Motion Time Coefficient	4.7
p-value	<0.001
Standard Error	1.1

The statistical analysis for the model provides the important metrics explaining the relationship between motion time and task completion time. An R^2 value of 0.87 implies that 87% of variation in task completion time is explained by the motion time, meaning that a strong predictive relationship exists between these two variables. The intercept of 5.3 indicates the baseline task completion time when the motion time is zero. The motion time coefficient of 4.7 means that for every extra second of motion time, the completion time for the task is increased by 4.7 seconds. The p-value of <0.001 establishes that the effects of the model are statistically valid, indicating there is a very low chance that the relationship observed could happen by chance. The standard error of 1.1 indicates that the model parameters estimates are quite reliable with small deviations in predictions. Altogether, these results affirm the model robustness and adequacy for accurately predicting the completion time of the task using the motion time.

8. Conclusion

This study, therefore, indicates the applicability of computer vision in enriching motion time studies in the manufacturing environment. Automated data collection and analysis result in less human error and reduced labor costs but more efficient operations. CV-based methods are thus a more accurate, scalable, and timely method for monitoring the assembly process. Future work should focus on further refining the system's capabilities, such as incorporating real-time feedback for operators and extending the application to more complex assembly tasks.

9. Future scope

This area of research into computer vision-based motion time studies could have wider applicability and extend into further complexities and diversities in the assembly process that include multioperation or automated system scenarios. There could be enhanced real-time and adaptive feedback with more advancement of machine learning algorithms and AI in further stages of productivity and ergonomics for the workers involved. Further, by integrating this technology with other solutions of Industry 4.0, such as IoT sensors and robotics, may provide a holistic approach to optimizing manufacturing. A cloud-based platform for data sharing and analysis would also facilitate remote monitoring and decision-making, and scalability in operations across multiple facilities.

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