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Research Paper

Progress of Industry 4.0 Technologies and Their Applications in Post-COVID-19 Pandemic: A Study on Image Processing AI

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Abstract: The COVID-19 pandemic has significantly impacted various industries, leading to the adoption of advanced technologies to address the challenges faced during and after the crisis. Industry 4.0 technologies have played a crucial role in reshaping business operations and enhancing resilience. This research paper focuses on the progress of Industry 4.0 technologies, with a specific emphasis on image processing AI, and explores their applications in the post-COVID-19 era. The paper presents an overview of Industry 4.0 technologies, highlights the role of image processing AI, discusses its relevance in the context of the pandemic, and provides insights into the implementation and future potential of these technologies.

Keywords: COVID-19, Coronavirus, image processing AI, Learning technologies, Industry 4.0

1. Introduction

1.1 Background and Motivation:

Two years have passed since the World Health Organisation designated COVID-19 a Public Health Emergency of International Concern. The virus has been linked to more than 18 million more deaths worldwide between Jan. 1, 2020, and Dec. 31, 2021, making it one of the main causes of mortality during this time. Beyond this staggering death toll, the COVID-19 epidemic also caused devastating social and economic damages. According to the most recent projections, the global gross domestic product (GDP) would decline by 3% in 2020 as a result shown in figure1. Globally, both high-income and low-income nations have reacted by implementing economic and social packages to lessen the effects of the public health measures put in place to control the pandemic. To achieve maximum development and sustainability, each sector, industry, and function will need to reinvent itself. For instance, procurement leaders are dealing with one of the most challenging market circumstances of their careers. Among other fundamental changes, procurement organisations need to take the lead in defending corporate profit and growth, invest in tried-and-true technology and process automation, and develop in-depth knowledge of supplier market dynamics. The CFO's function is increasing in breadth, needing new skills, and necessitating increased engagement with C-suite colleagues, according to two publications with McKinsey and independent experts. The need for CFOs to support capability building and talent development inside their organisations is one of the most important changes to the profession.

The COVID-19 pandemic has had a profound impact on global economies and industries, disrupting supply chains, halting operations, and challenging traditional business models. In response, organizations have accelerated their adoption of Industry 4.0 technologies to enhance resilience and adaptability. Among these technologies, image processing AI has emerged as a powerful tool for automating and optimizing various processes. This research paper aims to explore the progress of Industry 4.0 technologies, with a specific focus on image processing AI, and examine its applications in the post-COVID-19 era.

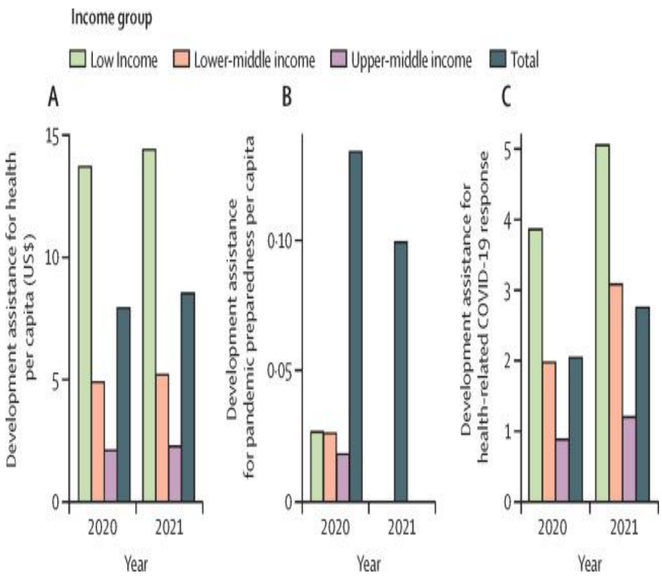

Figure 1. World Bank income groups' per-person COVID-19 development support for health spending, per-person

Importance of study:
The paper discusses the challenges faced by businesses during the pandemic, including supply chain disruptions, remote work, and contactless operations. It highlights the role of Industry 4.0 technologies, particularly AI-powered image processing, in overcoming these obstacles and facilitating recovery. The study emphasizes the importance of understanding the impact of these technologies on organizational operations, enabling decision-makers to optimize productivity and ensure business continuity. It also highlights the value of resilience and the future potential of image processing AI. The research paper's findings are universally applicable across various industries, making it a valuable resource for professionals seeking to harness these technologies. It also guides policy and investment decisions.
In essence, the research paper's comprehensive exploration of Industry 4.0 technologies, with a focus on image processing AI, provides a roadmap for businesses and policymakers to navigate the complexities of the post-COVID-19 landscape. It offers insights into overcoming challenges, optimizing operations, fostering innovation, and building resilience, while also advancing academic knowledge in the field. Artificial Neural Networks (ANNs) are a fundamental component of AI that can play a significant role in improving quality control and inspection processes in Industry 4.0. ANNs, particularly deep neural networks, are well-suited for tasks involving complex data patterns, such as image recognition and analysis.

Image Recognition and Classification: ANNs, especially Convolutional Neural Networks (CNNs), are highly effective for image recognition tasks. They can learn to recognize specific patterns, textures, and features in product images, enabling them to classify products as defective or non-defective.: ANNs can identify defects in products by analyzing images or sensor data. By training on a dataset of images containing various defects, ANNs can detect even subtle deviations from the expected appearance.

1.2 Literature Review:
Industry 4.0, a paradigm shift typified by the integration of cutting-edge technology and intelligent systems across numerous industries, has caused the industry to alter. This literature review aims to provide a comprehensive overview of Industry 4.0's applications in healthcare, particularly in response to the challenges caused by the COVID-19 outbreak. Javaid M. et al. (2019) underline the significance of Industry 4.0 in the medical sector, with its range of technologies, functions, and research status [1]. The incorporation of smart factories and cutting-edge technology has increased the effectiveness and affordability of the production of specialized implants, instruments, and equipment. Ienca M et al. (2020) underline the importance of big data and astute analytics in the fight against infectious diseases like COVID-19 [2]. Complex computer models based on machine learning can anticipate the spread of illnesses, and forecasting during epidemics is facilitated by the use of digital data sources like cell phone data. Manogaran G et al. (2017) propose a secure Industrial IoT architecture for health care applications. Sensor data from medical equipment attached to patients' bodies is gathered and stored utilizing the Meta Cloud-Redirection (MC-R) architecture [3]. Key management security approaches are used to safeguard big data in the industry 4.0 environment. Zeng J et al.'s (2020) paper discusses the COVID-19 pandemic's implications on the detection and treatment of acute myocardial infarction (AMI) [4]. The high contagiousness of COVID-19 has an influence on how cases of AMI are handled. The study suggests that COVID-19 mortality may be associated with fulminant myocarditis or virus-induced "cytokine storm syndrome".

In the framework of quality improvement and industrial engineering, Antony et al. (2023) examine organizational readiness characteristics for adopting Quality 4.0 [5]. The focus of Singh et al. (2020) is on AI-based supply chain management optimization techniques [6]. Mani and Patvardhan (2009) propose a novel hybrid constraint management approach for adaptive algorithms [7]. In 2021, Katiyar et al. will discuss defect detection using deep learning models and image processing [8]. Maggipinto et al. underline the importance of anomaly detection in production systems in their 2019 research [9]. Cho et al.'s (2019) discussion on external wall insulation and energy efficiency [10]. Schmitt et al. (2015) develop a real-time quality control system for textile samples [11]. In their study on image-based cell/colony analysis for regenerative medicine, Hoshikawa et al [12]. An algorithm for segmenting pancreatic islets in microscopic pictures is created by Habart et al. (2016) [13]. A machine vision system for bearing fault inspection is described by Shen et al. (2012) [14]. Manish et al. (2018) research image processing methods for machined surface polish and flaw inspection [15]. A low-cost machine vision system for use in industrial manufacturing processes is created by Manzano et al. in 2020 [16]. A framework for defect prediction in continuous-flow manufacturing is put out by Jun et al. (2020) [17]. Zero Defect Manufacturing (ZDM) and its implementation in quality improvement are examined by Psarommatis et al. (2022) [18]. The use of product-oriented machine learning algorithms for defect identification is covered by Powell et al. in 2023 [19]. A model for thermal signal reconstruction and fault identification is presented by Shepard in 2003 [20]. Förstner (2000) explores feature extraction pre-processing methods for digital phot [21].

A 2023 study by Vaishali Sarde et al. explores five machine learning techniques - K-Nearest Neighbours, Support Vector Machine, Decision Tree, Naive Bayes, and Artificial Neural Network - for diabetes prediction, evaluating their performance using metrics like accuracy, precision, recall, F1-score, and Support [22].

Mukul Kumar's 2023 paper explores recommender systems in various fields, highlighting their benefits and challenges [23]. He introduces a hybrid approach combining content-based filtering and collaborative filtering techniques for improved movie recommendations. Ashok Sharma et al.'s 2022 research explores data mining in healthcare, highlighting the potential of AI in diagnosing diseases, treating disorders, and drug discovery [24]. Both studies highlight the transformative potential of AI in healthcare.

1.3 Research Objectives:
The main objectives of this research are:
- To provide an overview of Industry 4.0 technologies and their key components.
- To explore the concept, applications, and advancements of image processing AI.
- To analyse the impact of COVID-19 on industries and the need for technological transformation.
- To investigate the role of Industry 4.0 technologies, particularly image processing AI, in addressing the challenges posed by the pandemic.
- To identify and evaluate the applications of image processing AI in the post-COVID-19 era.
- To discuss implementation challenges, ethical considerations, and workforce training requirements.
- To assess the future potential, opportunities, and benefits of image processing AI in Industry 4.0.
- To present case studies and success stories showcasing the application of image processing AI in different industries.
- To summarize the findings, provide key takeaways, and offer recommendations for future research.

1.4 Research Questions:
The research paper will address the following questions:
- What are the key components and benefits of Industry 4.0 technologies?
- How does image processing AI fit into the concept of Industry 4.0?
- What are the recent advancements and innovations in image processing AI?
- What are the challenges and limitations associated with image processing AI?
- How has the COVID-19 pandemic impacted industries, and what is the role of Industry 4.0 technologies in addressing these challenges?
- In what ways can image processing AI be applied in the post-COVID-19 era?
- What are the implementation challenges related to image processing AI, such as data privacy, security, ethics, and workforce training?
- What are the future potential, opportunities, and benefits of image processing AI in Industry 4.0?
- Can case studies and success stories demonstrate the practical applications of image processing AI in various industries?
- Based on the research findings, what are the key takeaways and recommendations for future research in this field.

2. Definition and Concept

Industry 4.0, also known as the Fourth Industrial Revolution, involves integrating digital technologies into manufacturing processes, transforming them into interconnected, smart systems. This shift enables data-driven decisions in real-time, enabling collaboration between machines, processes, and humans. AI image processing enhances visual perception, enhancing efficiency, precision, and productivity. Combining IoT, robots, and big data analytics with AI can create networked systems that detect and respond to their surroundings in era (figure 2).

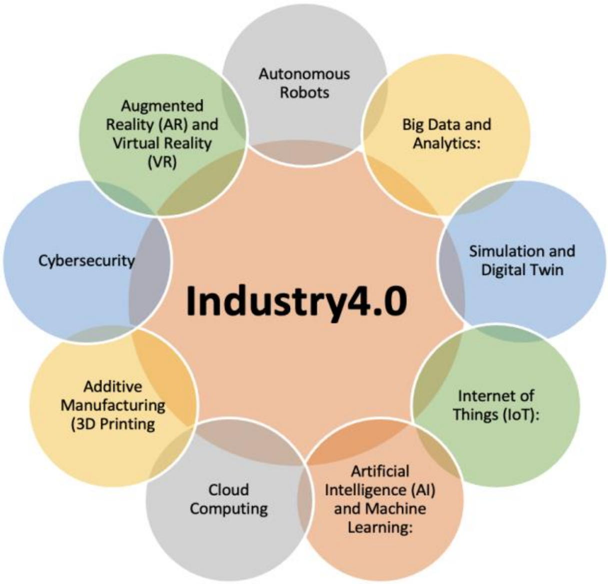

Figure 2. Key Technologies and Components of Industry 4.0

2.1 Benefits and Challenges:
Implementing Industry 4.0 technologies offers several benefits to industries, including (figure3):

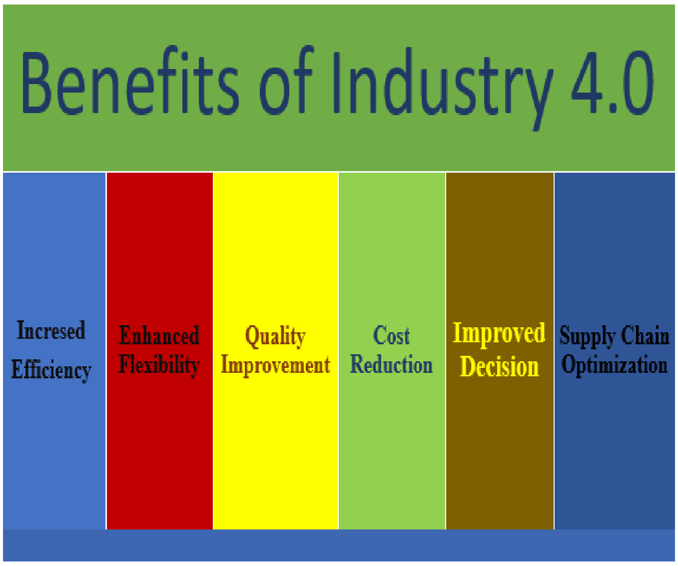

Figure 3. Benefits of Industry 4.0

However, the adoption of Industry 4.0 technologies also presents challenges:
- High Implementation Costs: Implementing advanced technologies requires substantial investments in infrastructure, equipment, and skilled personnel.
- Security and Privacy Concerns: Interconnected systems are vulnerable to cyber threats, necessitating robust security measures to protect sensitive data and operations.

- Workforce Transformation: The integration of automation and AI may require upskilling or reskilling the workforce to adapt to changing job roles and requirements.
- Data Integration and Interoperability: Integrating data from disparate sources and legacy systems can be complex, requiring standardized protocols and interfaces.
- Ethical Considerations: The ethical use of AI and automation, including issues related to job displacement and bias, must be addressed.
- Regulatory and Legal Challenges: The implementation of Industry 4.0 technologies may require compliance with regulations concerning data privacy, intellectual property, and safety.

3. Overview and Applications

Image processing AI refers to the use of artificial intelligence techniques to analyse, interpret, and manipulate digital images or visual data. It involves algorithms and models that can extract meaningful information from images, recognize patterns, and perform various tasks such as image classification, object detection, segmentation, and content-based retrieval (figure 4).

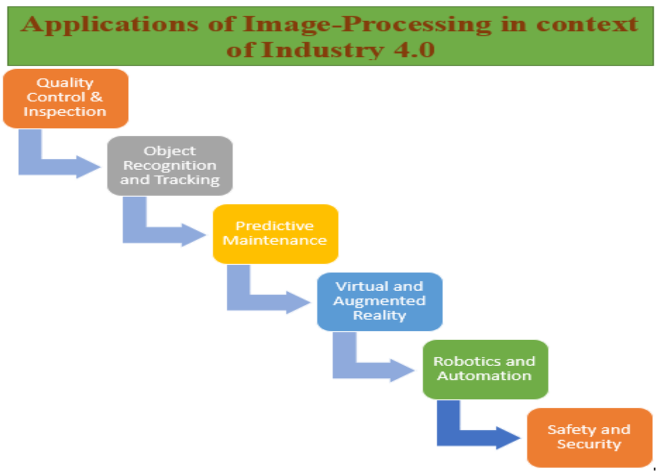

Figure 4. Applications of Image Processing in context of Industry 4.0

3.1 Advancements and Innovations

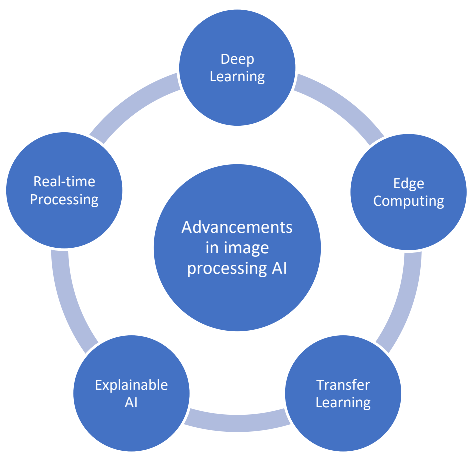

Figure 5. Advancements in Image Processing

3.2 Challenges and Limitations:

Despite the progress, image processing AI still faces several challenges and limitations:

Data Quality and Quantity: Image processing AI models heavily rely on large, high-quality labelled datasets. Acquiring and annotating such datasets can be time-consuming, expensive, and prone to bias.

Generalization: AI models trained on specific datasets may struggle to generalize to new, unseen data or handle variations in lighting, angles, or environmental conditions.

Computational Requirements: Complex image processing AI models require significant computational resources, making deployment on edge devices or resource-constrained environments challenging.

Ethical Considerations: Image processing AI raises ethical concerns regarding privacy, bias, and fairness, particularly in sensitive domains such as facial recognition or surveillance.

Interpretability: Deep learning models used in image processing AI are often regarded as black boxes, lacking transparency and interpretability in their decision-making process.

Addressing these challenges and limitations through ongoing research and development efforts is crucial to fully leverage the potential of image processing AI in Industry 4.0 applications.

3.3 Challenges Faced During the Pandemic:

The COVID-19 pandemic faced unprecedented challenges for industries worldwide, including disrupted supply chains, labour shortages, shifts in consumer demand, remote work and collaboration, and strict health and safety measures. These challenges required industries to adapt to changing consumer behaviours, adapt to digital infrastructure, and implement strict protocols to protect employees and customers. Ensuring worker safety and compliance with health guidelines was a top priority.

Table 1. Problems and their elements that were documented during pandemics and epidemics.

Serial No.	Facing Challenges	Effective Components
1.	Flexibility issues	delivery of healthcare is delayed, throughput time increase and sluggish reaction to illness test results
2.	**Social control issues**	Poor self-hygiene knowledge, government SOP adherence, misleading social media information, disease spread guidelines, country's population, cultural sensitivity, and tradition contribute to health issues.
3.	Lack of disease	government policy, and health

	forecasting & Surveillance	data Lack of openness in recording and disseminating pandemic data to inform the public of the effects and pace of spread rise, number of visits to the emergency room, Admission and attendance each day. a contagious illness genesis of the illness, performing disease testing, Contact tracing and illness notification
4.	Lack of assistance from the government	incentives, a cost-sharing agreement, financial assistance for the general public, and the state of the economy.
5.	Communication gap	a lack of communication between the federal, state, and local administrations, sharing of information between organisations and governmental entities, Guidelines for the transmission of infection, educating the general public about the disease
6.	Failure to Diagnose and Treat the Disease	Clinical signs, complexity and knowledge of illness management, and global readiness to deal with pandemic situations.
7.	Insufficient supply chain	Decreased supply, increased demand, the development of new pharmaceuticals, a delay in the supply of such drugs, and the timely delivery of goods and medicines
8.	Infrastructure deficit	Testing facilities, rigid storage, bed and medical equipment capacity limitations, preventing disease-related deaths, and inadequate training of health experts and professionals on how to handle pandemic situations and take preventative steps.
9.	Manpower shortage	Lack of doctors and medical personnel, timely treatment, and reducing disease-related deaths
10.	Tracking patients	safety, preventing the spread of disease, population group (Age), ethical & privacy issue. inadequate information about elderly people, people with impairments, and locations.

3.4 Need for Technological Transformation:
The pandemic has highlighted the need for technological transformation in industries, focusing on resilience, adaptability, remote operations, collaboration, supply chain optimization, safety, and data-driven decision-making. Resilience and adaptability are crucial, while digital technologies and automation enhance agility and adaptability. Remote work requires robust digital infrastructure, collaboration tools, and cloud-based systems. Safety measures, contactless operations, and data-driven decision-making are essential for responding to changing market dynamics.

3.5 Role of Industry 4.0 Technologies:
Industry 4.0 technologies played a significant t role in addressing the challenges posed by the pandemic. Some notable contributions include (figure 6):

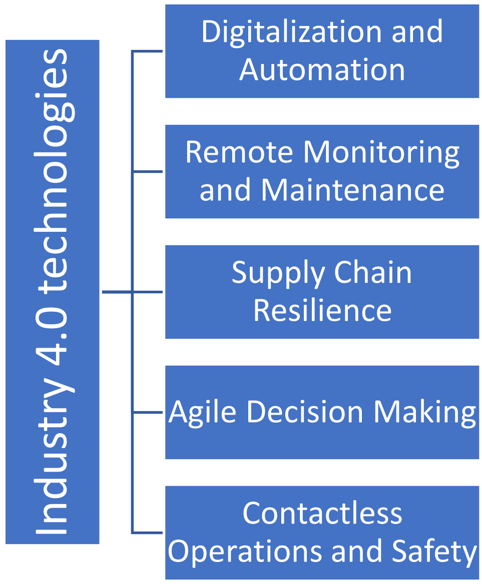

Figure 6. Role of industry 4.0

Industry 4.0 technologies enhance resilience, agility, and efficiency in industries, demonstrating their value in navigating post-COVID-19 challenges.

Table 2. Algorithmic methodology's effectiveness in automating product defect detection and contactless quality control.

Step 1	Camera Calibration and Occlusion Assessment	1. Capture the initial image of the product using the calibrated camera. 2. Analyse the image for occlusion using suitable techniques (e.g., object detection, contour analysis). 3. If occlusion is detected, prompt for a new image and recalibrate the camera. 4. If occlusion is not detected
Step 2	Fuzzy Image Segmentation	Apply fuzzy image segmentation algorithms to separate the product from its background, enhancing the accuracy of subsequent analysis
Step 3	Image Component Segmentation	Segment the image into distinct components using

		image segmentation techniques
Step 4	Machine Learning Classification	1. Train a machine learning model (e.g., neural network, random forest) using MI (Multiple Instance) learning to categorize individual components as defective or non-defective. 2. Apply the trained model to classify each component
Step 5	Accessibility Check	1. Determine if all necessary parts/components are accessible based on the classification results. 2. If accessible, proceed to Step 6. 3. If not accessible, proceed to Step 9.
Step 6	Component Placement Verification	1. Verify the accuracy of component placements using image alignment techniques and reference templates. 2. If placements are accurate, proceed to Step 7. 3. If placements are inaccurate, proceed to Step 9.
Step 7	Production of Working Product	. If all components are classified as non-defective and accurately placed, produce a working product as the output.
Step 8	End Process (Non-Defective Product)	Conclude the process, indicating that the product is not defective and meets quality standards.
Step 9	: Missing Part Identification	Identify the description and location of any missing parts/components based on the segmentation and classification results.
Step 10	Defective Product Identification	If any component is classified as defective or if parts are missing, classify the product as defective.

4. Artificial Neural Network Model

Let us consider a function $f(z)$ which is a linear combination of $x_1,...,x_n$ such that

$$f(z) = Wx$$
$$f(x_1,...,x_n) = f(w_0 + w_1x_1 + ... + w_nx_n)$$
$$f(z) = \exp\left(\frac{i2\pi j}{k}\right)$$
$$if\ \frac{2\pi j}{k} \le \arg(z) < \frac{2\pi(j+1)}{k}$$
$$f(z) = \exp\big(i(\arg(z))\big) = e^{iArg(z)} = \frac{z}{|z|}$$
$$f(z) = \frac{1}{2}(1+\cos(\angle z))z$$
$$e \coloneqq d - o$$
$$\mathcal{L}(e) = \sum_{k=0}^{N-1} |e_k|^2$$
$$= \sum_{k=0}^{N-1} e_k\bar{e}_k.$$
$$(e_{log}) \coloneqq \sum_{k=0}^{N-1} (\log(o_k) - \log(d_k))\overline{(\log(o_k) - \log(d_k))}$$
$$\mathcal{L}(e_{log}) = \frac{1}{2}\left(log\left[\frac{\hat{r}_k}{r_k}\right]^2 + \left[\widehat{\emptyset}_k - \emptyset_k\right]^2\right)$$

Learning through complicated domain backpropagation is comparable to learning in the real world. Each neuron in the network receives the error determined after the forward pass, and the weights are changed during the backward pass. If the activation function of a neuron is $f(x) = u(x,y) + iv(x,y)$, where $z = x + iy, u$ and v are the real and imaginary parts of z. The partial derivatives $u_x = \frac{\partial u}{\partial x}$, $u_y = \frac{\partial u}{\partial y}$, $v_x = \frac{\partial v}{\partial y}$ are initially assumed to exist for all $z \in C$, so that the Cauchy-Riemann equations are satisfied. Given an input pattern, the error is given by

$$E = \frac{1}{2}\sum_k e_k\bar{e}_k\,,$$

$$e_k = d_k - o_k$$
$$o_j = f(z_j) = u^j + iv^j,$$
$$z_j = x_j + iy_j = \sum_{i=1} W_{jl}X_{jl}$$
$$\frac{\partial x_j}{\partial W_{jlR}} = X_{jlR}\,, \quad \frac{\partial_{yj}}{\partial W_{jlr}} = X_{jlI},$$

$$\frac{\partial x_j}{\partial W_{jlI}} = -X_{jlI}\,, \quad \frac{\partial_{yj}}{\partial W_{jlI}} = X_{jlR},$$
$$\frac{\partial E}{\partial W_{jlR}} = \frac{\partial E}{\partial u^j}\left(\frac{\partial u^j}{\partial x_j}\frac{\partial x_j}{\partial W_{jlR}} + \frac{\partial u^j}{\partial y_j}\frac{\partial y_j}{\partial W_{jlR}}\right)$$
$$+ \frac{\partial E}{\partial v^j}\left(\frac{\partial v^j}{\partial x_j}\frac{\partial x_j}{\partial W_{jlR}} + \frac{\partial v^j}{\partial y_j}\frac{\partial y_j}{\partial W_{jlR}}\right)$$
$$= -\delta_{JR}\left(u_x^j X_{jlR} + u_y^j X_{jlI}\right)$$
$$- \delta_{JI}\left(v_x^j X_{jlI} + v_y^j X_{jlI}\right)$$

$$\begin{aligned}\frac{\partial E}{\partial W_{jlI}} &= \frac{\partial E}{\partial u^j}\left(\frac{\partial u^j}{\partial x_j}\frac{\partial x_j}{\partial W_{jlI}} + \frac{\partial u^j}{\partial y_j}\,\frac{\partial y_j}{\partial W_{jlI}}\right)\\ &\quad + \frac{\partial E}{\partial v^j}\left(\frac{\partial v^j}{\partial x_j}\frac{\partial x_j}{\partial W_{jlI}} + \frac{\partial v^j}{\partial y_j}\,\frac{\partial y_j}{\partial W_{jlI}}\right)\\ &= -\delta_{JR}\left(u_x^j(-X_{jlI}) + u_y^j X_{jlR}\right)\\ &\quad - \delta_{JI}\left(v_x^j(-X_{jlI}) + v_y^j X_{jlR}\right)\end{aligned}$$

where $\delta_j = -\partial E/(\partial u^j) - i\partial E/\partial v^j$, $\delta_{jR} = -\partial E/\partial u^j$ and $\delta_{jI} = -\partial E/\partial v^j$. By combining equations , the gradient of the error function with respect to W_{jl} is given by

$$\begin{aligned}\nabla_{wjl}E &= \frac{\partial E}{\partial W_{jlR}} + \frac{i\partial E}{\partial W_{jlI}}\\ &= -\bar{X}_{jl}\left(\left(u_x^j + iu_y^j\right)\delta_{jR} + \left(v_x^j + iv_y^j\right)\delta_{jI}\right)\end{aligned}$$

Hence, given a positive constant learning rate α, the complex weight W_{jl} must be changed by a value ΔW_{jI} proportional to the negative gradient:

$$\Delta W_{jl} = \alpha\bar{X}_{jl}\left(\left(u_x^j + iu_y^j\right)\delta_{jR} + \left(v_x^j + iv_y^j\right)\delta_{jI}\right)$$

For an output neuron, δ_{jR} and δ_{jI} are given by

$$\delta_{jR} = \frac{\delta E}{\delta u^j} = \epsilon_{jR} = d_{jR} - u^j$$

$$\delta_{jI} = \frac{\delta E}{\delta v^j} = \epsilon_{jI} = d_{jI} - v^j$$

And in compact form, it will be

$$\delta_j = \epsilon_j = d_j - o_j$$

The chain rule is used to compute δ_{jR} and δ_{jI} for the hidden neuron. Note that k is an index for a neuron receiving input from neuron j. The net input z_k to neuron k is

$$z_k = x_k + i_{yk} = \sum_l (u^l + iv^l)(W_{klR} + iW_{klI})$$

where l is the index for the neurons that feed into neuron k. Computing δ_{jR} using the chain rule yields

$$\begin{aligned}\delta_{jR} &= -\frac{\delta E}{\delta u^j} = -\sum_k \frac{\delta E}{\delta u^k}\left(\frac{\delta u^k}{\delta x_k}\frac{\delta x_k}{\delta u^j} + \frac{\delta u^k}{\delta y_k}\frac{\delta y_k}{\delta u^j}\right)\\ &\quad - \sum_k \frac{\delta E}{\delta v^k}\left(\frac{\delta v^k}{\delta x_k}\frac{\delta x_k}{\delta u^j} + \frac{\delta v^k}{\delta y_k}\frac{\delta y_k}{\delta u^j}\right)\\ &= \sum_k \delta_{kR}\left(u_x^k W_{kjR} + u_y^k W_{kjI}\right)\\ &\quad + \sum_k \delta_{kI}\left(v_x^k W_{kjR} + v_y^k W_{kjI}\right)\end{aligned}$$

Similarly, δ_{jI} is computed as:

$$\begin{aligned}\delta_{jI} &= -\frac{\delta E}{\delta v^j} = -\sum_k \frac{\delta E}{\delta u^k}\left(\frac{\delta u^k}{\delta x_k}\frac{\delta x_k}{\delta v^j} + \frac{\delta u^k}{\delta y_k}\frac{\delta y_k}{\delta v^j}\right)\\ &\quad - \sum_k \frac{\delta E}{\delta v^k}\left(\frac{\delta v^k}{\delta x_k}\frac{\delta x_k}{\delta v^j} + \frac{\delta v^k}{\delta y_k}\frac{\delta y_k}{\delta v^j}\right)\\ &= \sum_k \delta_{kR}\left(u_x^k(-W_{kjI}) + u_y^k W_{kjR}\right)\\ &\quad + \sum_k \delta_{kI}\left(v_x^k W_{kjR} + v_y^k W_{kjI}\right)\end{aligned}$$

The expression for δ_j is obtained by combining equations (_) and (_):

$$\delta_j = \delta_{jR} + i\delta_{jI} = \sum_k \bar{W}_{kj}((u_x^k + i\,u_y^k)\delta_{kR} + (v_x^k + iv_y^k)\delta_{kI})$$

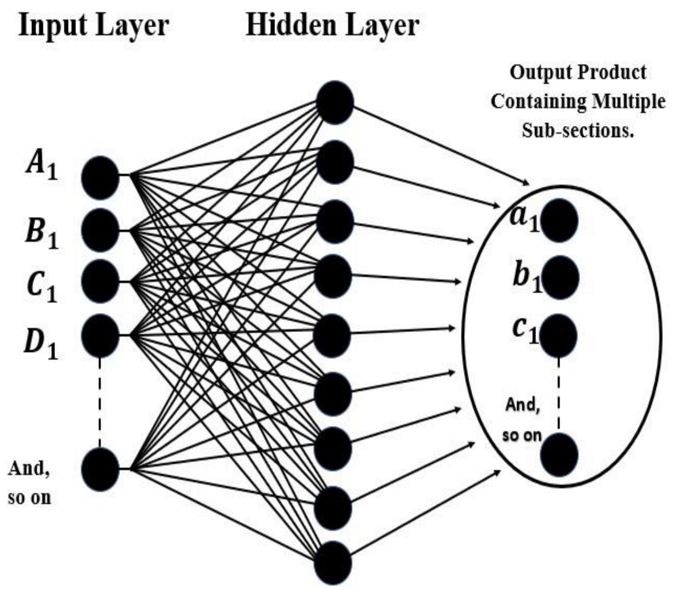

Figure 7. N-N architecture for general optimum model

where δ_j is computed for neuron j starting in the output layer using above equations for the neurons in the hidden layers. After computing δ_j for neuron j, is used to update its weights

Learning through complicated domain backpropagation is comparable to learning in the real world. Each neuron in the network receives the error determined after the forward pass, and the weights are changed during the backward pass (figure7). Where are the actual and fictitious components of if a neuron's activation function is and if The Cauchy-Riemann equations are fulfilled since it is first believed that the partial derivatives exist for all. The mistake is represented by given an input pattern by

$$\Delta W_{jl} = \alpha\bar{X}_{jl}\left(\left(u_x^j + iu_y^j\right)\delta_{jR} + \left(v_x^j + iv_y^j\right)\delta_{jI}\right)$$

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$$z_k = x_k + i_{yk} = \sum_l (u^l + iv^l)(W_{klR} + iW_{klI})$$

where l is the index for the neurons that feed into neuron k. Computing δ_{jR} using the chain rule yields

$$\delta_{jR} = -\frac{\delta E}{\delta u^j} = -\sum_k \frac{\delta E}{\delta u^k}\left(\frac{\delta u^k}{\delta x_k}\frac{\delta x_k}{\delta u^j} + \frac{\delta u^k}{\delta y_k}\frac{\delta y_k}{\delta u^j}\right) - \sum_k \frac{\delta E}{\delta v^k}\left(\frac{\delta v^k}{\delta x_k}\frac{\delta x_k}{\delta u^j} + \frac{\delta v^k}{\delta y_k}\frac{\delta y_k}{\delta u^j}\right) = \sum_k \delta_{kR}\left(u_x^k W_{kjR} + u_y^k W_{kjI}\right) + \sum_k \delta_{kI}\left(v_x^k W_{kjR} + v_y^k W_{kjI}\right)$$

Similarly, δ_{jI} is computed as:

$$\delta_{jI} = -\frac{\delta E}{\delta v^j} = -\sum_k \frac{\delta E}{\delta u^k}\left(\frac{\delta u^k}{\delta x_k}\frac{\delta x_k}{\delta v^j} + \frac{\delta u^k}{\delta y_k}\frac{\delta y_k}{\delta v^j}\right) - \sum_k \frac{\delta E}{\delta v^k}\left(\frac{\delta v^k}{\delta x_k}\frac{\delta x_k}{\delta v^j} + \frac{\delta v^k}{\delta y_k}\frac{\delta y_k}{\delta v^j}\right) = \sum_k \delta_{kR}\left(u_x^k(-W_{kjI}) + u_y^k W_{kjR}\right) + \sum_k \delta_{kI}\left(v_x^k W_{kjR} + v_y^k W_{kjI}\right)$$

The expression for δ_j is

$$\delta_j = \delta_{jR} + i\delta_{jI} = \sum_k \overline{W}_{kj}\left((u_x^k + i\,u_y^k)\delta_{kR} + (v_x^k + iv_y^k)\delta_{kI}\right)$$

where δ_j is computed for neuron j starting in the output layer, neurons in the hidden layers. After computing δ_j for neuron j is used to update its weights.

4.1 non-Gradient based Approach

The learning process of a neural network based on the multi-valued neuron (MVN) is derivative-free and relies on the error-correction learning rule, in contrast to the gradient-based method. Learning is simplified to a straightforward movement around the unit circle for a single neuron, with weight correction in the MVN controlled by the cell's mistake. There are no gradients because the relevant activation functions are not differentiable.

Considering MLMVN with one hidden-layer and a single output as shown in Figure 3. If T is the target, Y_{12} is the output, and the following definitions are assumed:

- $\epsilon^* = T - Y_{12}$: global error of network
- $w_0^{12}, w_1^{12}, \ldots, w_n^{12}$: initial weighting vector of neuronY_{12}
- Y_{il}: initial output of neuron Y_{12}
- Z_{12}: weighed sum of neuron Y_{12} before weight correction
- ϵ_{12}: error of neuron Y_{12}

The weight correction for the second to the mth (output) layer, and then for the input layer are given by

$$\widetilde{w}_i^{kj} = w_i^{kj} + \frac{C_{kj}}{(N_{j-1}+1)}\epsilon_{kj}\bar{\tilde{Y}}_{i,j-1}, \qquad i = 1,\ldots,n$$

$$\widetilde{w}_0^{kj} = w_0^{kj} + \frac{C_{kj}}{(N_{j-1}+1)}\epsilon_{kj}$$

$$\widetilde{w}_i^{k1} = w_i^{k1} + \frac{C_{k1}}{(n+1)}\epsilon_{k1}\bar{x}_i, \qquad i = 1,\ldots,n$$

$$\widetilde{w}_0^{k1} = w_0^{k1} + \frac{C_{k1}}{(n+1)}\epsilon_{kj}$$

$$\widetilde{w}_i^{km} = w_i^{km} + \frac{C_{km}}{(N_{m-1}+1)}\epsilon_{km}\bar{\tilde{Y}}_{i,m-1}, \qquad i = 1,\ldots,n$$

$$\widetilde{w}_0^{km} = w_0^{km} + \frac{C_{km}}{(N_{m-1}+1)}\epsilon_{km}$$

For the second till the $(m-1)$th layer (kth neuron of the jth layer ($j = 2,\ldots,m-1$)), the correction rule is

$$\widetilde{w}_i^{kj} = w_i^{kj} + \frac{C_{kj}}{(N_{j-1}+1)}\epsilon_{kj}\bar{\tilde{Y}}_{i,j-1}, \qquad i = 1,\ldots,n$$

$\widetilde{w}_0^{kj} = w_0^{kj} + \frac{C_{kj}}{(N_{j-1}+1)|z_{kj}|}\epsilon_{kj}$Given a pre-specified learning precision ω, the condition for termination of the learning process i4

5. Supply Chain Optimization

Figure 8. Optimization

Image processing AI improves quality control and inspection processes in manufacturing and production by detecting defects, verifying product labels, performing visual inspections, and accurately measuring dimensions, reducing manual errors and ensuring adherence to quality standards(figure 8).

6. Ethical Considerations

Organisations must address ethical issues while using image processing AI to guarantee ethical and responsible usage of the technology. The prevention of discriminatory results should be a primary concern, and AI systems must be created and taught to minimise biases based on gender, ethnicity, or other protected characteristics. The importance of informed consent and transparency calls for open and honest communication with the people whose photographs are processed, as well as explicit explanation of the system's goal, scope, and effects. Organisations should be held accountable for the decisions and actions made by AI systems, provide human oversight, and remedy any possible harm brought on by mistakes or prejudices. Accountability and accountability should be created.

7. Result & Discussion

The Internet of Things (IoT), big data analytics, artificial intelligence (AI), and automation were among the Industry 4.0 technologies that the study found to have made substantial development. These technologies have kept developing quickly, allowing for better data gathering, analysis, decision-making, and process optimisation across sectors.

- The healthcare industry has shifted towards AI image processing for rapid and accurate diagnosis of illnesses, including COVID-19, enhancing patient outcomes.
- The pandemic exposed supply chain weaknesses, prompting AI for image processing to forecast demand and improve quality control, enhancing product quality and enhancing logistical efficiency.
- The pandemic has accelerated the adoption of remote monitoring and maintenance solutions, utilizing AI for image processing to detect equipment abnormalities and anticipate maintenance needs, thereby reducing downtime and improving operational efficiency.
- Post-pandemic changes have led to merchants using AI for retail layout customization, face recognition, and security enhancement. AI is also being used in smart cities to monitor traffic flow, population density, and environmental variables, ensuring efficient urban management and public safety.
- Continuous Improvement: ANNs can learn from new data and feedback, leading to improved accuracy overtime and contributing to a culture of continuous improvement.
- Complex Inspections: ANNs can handle multi-dimensional data and complex inspection tasks that involve multiple criteria for quality assessment.
- To implement ANNs for quality control and inspection in Industry 4.0:Data Collection: Gather labelled training data, including images or sensor data of both defective and non-defective products.
- Network Architecture: Choose an appropriate neural network architecture, such as CNNs for image analysis or Recurrent Neural Networks (RNNs) for time-series data. Train the neural network using the prepared data and appropriate training algorithms. This involves adjusting the network's parameters to minimize the error between predicted and actual outcomes. Ensure its accuracy and generalization.

The research highlights the remarkable progress of Industry 4.0 technologies, particularly image processing AI, in the post-COVID-19 era. The applications discussed signify their role in reshaping industries and enabling resilience in the face of unprecedented challenges. As technology continues to evolve, careful consideration of ethical, regulatory, and skill development aspects will be vital to fully harness the potential of these innovations.

8. Conclusion

In this research paper, we explored the progress of Industry 4.0 technologies, with a specific focus on image processing AI, and their applications in the post-COVID-19 era. The key findings of this study can be summarized as follows:-
Industry 4.0 technologies, including image processing AI, have played a crucial role in addressing the challenges posed by the COVID-19 pandemic.

- Image processing AI has been applied in various domains, such as contactless operations, quality control, supply chain optimization, remote monitoring, and enhanced safety measures. Technological advancements in image processing AI, including improved accuracy, real-time processing, explain ability, and multimodal integration, are shaping its future potential.

- Integration of image processing AI with other Industry 4.0 technologies, such as IoT, robotics, and big data analytics, offers synergistic benefits and enhanced capabilities. Ethical considerations, data privacy, security, and workforce training are important implementation challenges that need to be addressed when deploying image processing AI systems.
Continuously monitor the network's performance, retraining or fine-tuning it as needed to maintain accuracy and adapt to changing conditions.

The use of ANNs in quality control and inspection brings automation, accuracy, and efficiency to the process, ultimately leading to improved product quality, reduced defects, and enhanced customer satisfaction.

AI can significantly enhance quality control and inspection processes in Industry 4.0 by providing accurate, automated, and efficient methods for detecting defects, anomalies, and ensuring product quality.

- The successful implementation of image processing AI can lead to improved efficiency, productivity, safety, and customer experiences, with potential implications for business models.

Key Takeaways

From this study, several key takeaways emerge:
- Image processing AI has emerged as a powerful tool in Industry 4.0, enabling automated visual perception, analysis, and decision-making.

- The COVID-19 pandemic has accelerated the adoption of image processing AI and other Industry 4.0 technologies, as businesses seek to enhance resilience, efficiency, and adaptability.

- Image processing AI applications span across industries, from manufacturing and healthcare to retail and transportation, providing tangible benefits such as improved quality control, enhanced safety, and optimized processes.
- Implementation challenges related to data privacy, security, ethics, and workforce training need to be carefully addressed to ensure responsible and effective deployment of image processing AI systems.

- The future holds great potential for technological advancements, integration with other Industry 4.0 technologies, and implications for business models, offering exciting opportunities for organizations to leverage the capabilities of image processing AI.

Author's Contribution

The author Mr. Makund Arora confirms sole responsibility for the following: study conception and design, data collection, analysis and interpretation of results, and manuscript preparation.

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