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Improve Industrial Automation Through the Fusion of Cognitive Manufacturing and Echo State Wireless Sensor Network

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Abstract

Cognitive manufacturing faces major challenges due to the increasing industrial competition. Cognitive manufacturing has been directed toward agile strategies that harness artificial intelligence, machine learning, and computer vision approaches to overcome the obstacles of four-generation manufacturing. The integration of these strategies represents an important research direction in the engineering research society. This paper develops a new Automated Defect Detection System (ADDS) utilizing the Echo State Wireless Sensor Network (ES-WSN) as a random shallow technique to detect defects in products through image analysis and training. The system employs artificial intelligence and real-world factory datasets to predict defects. Benchmarks, for instance, Accuracy, precision, recall, and F1, were used to evaluate the performance of the suggested model. The results indicate good performance compared with state-of-the-art methods. The accuracy detected at peak iteration (3000 iterations) is not less than 99.78 percent with an Average Relative Error (ARE) equal to 2.7 percent and a processing time equal to 80 milliseconds. ES-WSN improved product quality assurance to 98 percent. The research focused on using shallow learning as a computer vision technique on real-time images of specific products to develop an ADDS and improve product quality in cognitive manufacturing.

Keywords: Automated Defect Detection System, Cognitive Manufacturing, Computer Vision, Echo State Wireless Sensor Network, Randomized Shallow Learning.

1 Introduction

Advanced industrial societies are witnessing a marvelous industrial revolution, especially after utilizing Artificial Intelligence (AI), Machine Learning (ML), and the Internet of Things (IoT). One of the most prominent pillars of this industrial revolution is cognitive manufacturing, which aims to integrate Computer Vision (CV) and AI computational knowledge to analyze and process data into complex manufacturing processes to increase and improve the quality of products. CV plays an interactive role

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in cognitive manufacturing (Kuric et al., 2022). Meanwhile, like any scientific field, knowledge manufacturing faced several problems, for instance, the detection of manufacturing defects and waste in production, which led to a lack of quality, the difficulty of controlling cognitive robots and automated systems, predicting equipment malfunctions, and poor preventive maintenance. In general, knowledge industries need to reduce the time spent on production to make more profits. Applying CV to monitor the product and prevent defects is still difficult due to the increasing complexity of the product and production systems. Manufacturing defects that are not recognized early in the production process can result in considerable loss of life and property later. Therefore, CV strategies should be applied in more efficient product control during the production line to avoid the spread of defects in the Product (Cruz et al., 2020). The community of scientists has contributed to addressing these cases using. From the product defect inspection aspect, computer vision was used to automatically inspect the product to detect manufacturing defects, reduce waste in production, and increase quality (Hütten et al., 2024). Modern technologies have played an important role in automating industrial processes and, at the same time, product inspection to detect manufacturing defects, reduce waste at the production stage, and improve the quality of industries. Studies have also shown the effectiveness of ML algorithms with Convolutional Neural Networks (CNN) in accurately identifying production defects on solid product surfaces (Yedukondalu et al., 2025; Giji Kiruba et al., 2023). In addition, using a model such as the One Class Classification (OCC) Model has been proven to be competent in detecting product defects in industrial data sets and improving quality control systems (Chaabi et al., 2023). Furthermore, the hybrid of Automated Optical Inspection (AOI) and ML has demonstrated high potential in detecting product distortions (Huang et al., 2021). The merger of CNN with standard deviation theories creates a new approach to quality control assurance of the industrial environment (Buitrago et al., 2025). Other studies focused on the intelligent control of cognitive robots and automated systems and how to manage them using data optimized by ML theories. Recent research has focused on the prospects for intelligent control of cognitive robots in fourth-generation (4G) factories, including ML to measure operator sentiment and quantum computing-based cognitive management. The goal is to establish hybrid intelligence between humans and cognitive robots to educate computers to make better predictions throughout the production life cycle (Kramarov et al., 2023). The hybrid usage of human-machine technology is more efficient in responding to production factors and the requirement for operators to manage the industrial system (Aygun et al., 2022). The development of hybrid cognitive manufacturing based on operator intervention at important points and the machine's preservation of operator actions for similar scenarios in the future achieves quick and efficient industrial system learning. These investigations have helped to strengthen the hybrid interaction between operators and cognitive robots in modern industry (Arshad et al., 2022). On the other hand, research utilizing shallow and random learning theories has played a prominent role in detecting early defects and ensuring high-quality products. Other studies have provided Deep Learning (DL) as another solution to detect defects in production systems to ensure product quality (Gao et al., 2022). These studies aimed to combine shallow and random with Recurrent Convolutional Neural Network (RCNN), to detect the defects in industrial products efficiently (Shastri & Trivedi, 2023). Shallow and random DL theories show a complex geometric model with a hierarchical prediction set that optimizes detecting defects in the product (Aquil & Ishak, 2020). Research focuses on creative random theories, such as Random Forest (RF) and K-Nearest Neighbor (KNN), by analyzing product features in predicted product defects. Some studies also reflect the critical role of advanced learning methods in the early detection of productive defects through integrating the Genetic Algorithms (GA) and DL (Alkaberi & Assiri, 2024). Besides, some research contributed to improving the series supply using CV strategies to track the product, which enhances the efficiency of the transportation and storage processes of the product (Caldeira et al., 2020). Integration of CV technologies into the management and organization of supply chains enhances product tracking, transportation, and storage efficiency

(Deng et al., 2023). Scientific research has shown that the products can be tracked through colors or barcodes using CV strategies to reduce worker errors and improve product tracking. Moreover, it has become easy to recognize images in the supermarket and monitor products using DL. It is easy to detect empty or misplaced items in real-time, enhancing employee effectiveness and customer satisfaction. Overall, CV strategies have revolutionized traditional sourcing processes, improved warehouse operations, and ensured timely product availability by simplifying entire supply processes (Ahmadirad, 2025). In this paper, we discuss the technique of early detection of product defects ADDS using randomized shallow learning theories as a solution to improve cognitive manufacturing using CV. Where the ES-WSN was used while comparing it in terms of efficiency with developed theories using quality measures (Jiqing et al., 2024). This approach is implemented using a camera mounted on the robotic arm of the cognitive robot. Images are processed using ES-WSN to pre-estimate defects and rely on images where the system has learned to achieve proactive quality. The remainder of the study is organized as follows: the prior study section shows society's previous contribution to solving cognitive manufacturing obstacles. The next section is the methodology section, which illustrates the scheme procedure and related preliminary basic information about the suggested ES-WSN. Besides, the results section shows the results of execution observations. Results analysis, compared with other related methods, and discussion are shown in the discussion section. Finally, the conclusion section summarizes the paper's contribution (Fan et al., 2022). Descriptions of abbreviations are shown in Table 1.

Table 1: The Abbreviation Description

Term	**Description**
4G	fourth generation
ADDS	Automated Defect Detection System
AI	Artificial Intelligence
AOI	Automated Optical Inception
ARE	Average Relative Error
CNNs	Convolutional Neural Networks
CV	Computer Vision
DI	Defect inspection
DL	Deep Learning
ES-WSN	Echo State Wireless Sensor Network
GA	Genetic Algorithms
IoTs	Internet of Things
KNN	K-Nearest Neighbor
ML	Machine Learning
OCC	One Class Classification
PdM	Predictive Maintenance
RC	Reservoir Computing
RCNN	Recurrent Convolutional Neural Network
RF	Random Forest
RNN	Recurrent Neural Network
RPA	Robotic Process Automation
SLO	Sea Lion Optimization
SVM	Support Vector Machine

2 Prior Studies

There have been several studies looking into strategies to increase cognitive manufacturing efficiency, Table 2 describes these prior studies' barflies. In general, studies may be divided into four major categories that demonstrate the level of knowledge development that has contributed to the growth of industries.

- Intelligent control of production processes: Some studies have employed Robotic Process Automation (RPA) as a CV technique to replicate worker duties using a graphical interface to automate industrial operations. The objective was to construct robots designed to imitate tasks performed by workers via a visual interface. Some studies used a video monitoring system to track workers and analyze and manipulate their work patterns to improve productivity. Pathways are created to help the system in decision-making processes and distribute work tasks in the factory (Yevsieiev et al., 2024). Other research reflects the new collaboration between humans and cognitive robots by sophisticated tools to assemble and disassemble electronic devices using computer vision and deep learning. Other researchers have introduced a new technique for classifying products by color and size properties and applying CV on cognitive robots to improve the efficiency of production processes (Salman & Banu, 2023).
- Automated Inspection: Some studies have presented CV as an effective solution for detecting product defects by reviewing product features, for instance, finding the defects in the engine block, inspecting external weld defects utilizing the IRVISION system in welding robots, detecting small damages in Metal surfaces or using AI to identify defects in vehicles (Müller & Sharaf, 2024; Nakkina et al., 2022). Another study utilizes the CNN method to inspect the welding procedure for the pressure vessels. Some other papers addressed the vehicle accident and processing of these vehicles using Mask RCNN (Parhizkar & Amirfakhrian, 2022). In terms of Defect Inspection (DI) for electrical sockets in factories, some studies used DL in CV to reduce the defects in electrical sockets in real time (Trivedi et al., 2023; Patel, 2025).
- Maintenance Forecasting: There are many studies on activating the role of CV theories and cognitive manufacturing in the development of industrial automation in the aspect of early forecasting of maintenance, which reduces the consumption of production time. Cognitive companies continue to improve their laboratories' quality, safety, and productivity by reducing downtime and maintenance costs through predictive periodic maintenance. In some studies, computer forecasting has been used in automated inspections within a system to detect oil leakage in thermal power machines with a high accuracy of sometimes up to 99.13 percent. Also, in some studies that support sustainable manufacturing, Predictive Maintenance (PdM) is important. The PdM strategy was developed to manage and maintain data, feature selection, and forecasting using a combination of algorithms such as Jaya, Recurrent Neural Network (RNN), Sea Lion Optimization (SLO), and Support Vector Machine (SVM). Other studies have discussed a hybrid industrial approach to collaborative robots and artificial intelligence and how they interact with humans to enhance predictive maintenance (Sandini et al., 2024). Additional research suggests a predictive maintenance model to integrate automatic machine information and improve traditional maintenance strategies (Converso et al., 2023). Additional investigations discussed utilizing sustainable artificial intelligence in proactive maintenance strategies.
- Improving Supply Chains: Many researchers highlight the use of CV and AI to improve the efficiency ratio of the supply chain. Some researchers have used DETR as an AI tool to improve the efficiency of the commodity supply chain by reducing revenue loss by detecting defects in

real-time with 96% accuracy (Ozek et al., 2025). Similarly, regarding logistics operations, some studies have confirmed the role of computer vision in improving warehouse management. Other studies have suggested machine learning approaches and their ability to integrate to improve decision-making and supply chain management. Some research has provided the Edge Gateway solution for intelligent manufacturing to accelerate horizontal and vertical communications of hierarchical network systems to detect defects in goods supply systems in real-time.

Additional research has also created sustainable industrial automation using AI and IoT sensor networks to analyze big data in decision-making for hyperphysical systems (Adeusi et al., 2024). Another research utilized the computer's vision of a highly efficient independent industry by enabling independent quality control and debugging in the supply chain (Yousif et al., 2025).

Table 2: The Analysis Of Prior Studies

Ref.	Method	Results	Gaps	Category
Kramarov et al., 2023	CV\ RPA	A robotic arm that uses computer vision to identify products by item features.	Not addressing the deformation.	Intelligent control of production processes
Nakkina et al., 2022	CV		Labor force shortages among working-age populations.	
Parhizkar & Amirfakhrian, 2022	CV-DL		Locations of screws for fastening and e-waste.	
Patel, 2025	CV		Calculation of load and motor power is excluded	
Kuric et al., 2022	CV\ SSIM	Detection of defects and cracks in product surfaces	Training requires a long time, as well as difficulty in determining the severity of defects	Automated Inspection
Bao et al., 2023; Converso et al., 2023	AI	Find defects in metal welds and vehicles	Small size detects limitations	
James et al., 2023	RCNN			
Cruz et al., 2020	CNN	Inspect the welding of pressure vessels	The study didn’t combine before and after welding in the same CV system. The capability of using IoT wasn’t discussed clearly.	
Ali et al., 2022; Tanaka et al., 2022	AI/ CV, PdM	Reduce equipment downtime by 34% Reduce maintenance costs by 10% Improve productivity by 25% Reduce labor costs for quality control by 5 to 20%	The data was reviewed according to a limited period that did not cover how industrial objects and cyber-physical systems are related.	
Yousif et al., 2025	CV/dual light	Detect oil leakage in thermal power machines	Difficulty and accuracy of examination using ultraviolet and blue dual light.	
Ahmadirad, 2025; Abdi et al., 2024; Syed et al., 2021	CV/ DETR, YOLO	Improving commodity supply chain management	Higher burden model	Improving Supply Chains
Dharma et al., 2022	CV/ IoT		Technical complexities	
Cong & Zhou, 2023	CV		Tested only in a simple laboratory environment	

3 Preliminary

In this part of the article, the approach used to identify product defects is illustrated using the proposed framework. As well as the method of data collection. ES-WSN, a recurring neural network model for detecting defects in a product, has been proposed. ES-WSN has low complexity and a good memory footprint.

Proposed Framework Architecture

The proposed framework considers the requirements of new cognitive manufacturing. The main idea of the proposed framework is to develop an intelligent system to discover defects in specific products through production time using one of the state-of-the-art methods. Under the umbrella of CV, the ES-WSN, as one of the RC approaches, is relatively faster than traditional neural networks because it uses shallow distribution rather than the backpropagation technique that consumes time. The framework is made up of four essential components.

1. Robot arm: The robot arm removes the defective product by responding to the intelligent control system.
2. Robot control system: The system sends a signal wirelessly to the robot arm depending on the RC\ ES-WSN detection.
3. CV model: The ES-WSN used to detect the defects in the product after learning the network, depends on the provided dataset.
4. Camera wireless sensor: Observe the product line.

Figure 1 illustrates the prototype architecture for the proposed framework. The framework has been developed to integrate the CV with cognitive manufacturing. The proposed framework can identify defective products on time without consuming time in the quality assurance phase. The camera sensor is connected to the system to observe the product material. After the camera sensor finds that the product features are not the same as the ones the ES-WSN learned, the robot arm receives a signal from the robot control system to remove the product block from the production line. The proposed algorithm's significance comes from the capability of the ES-WSN to detect defective products on time, so it can reduce the manufacturing time-consuming.

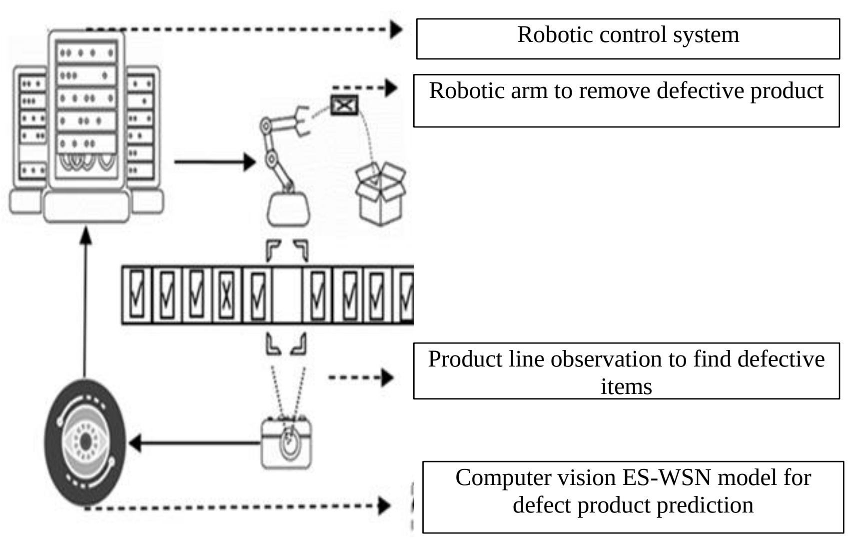

Figure 1: The Proposed Framework Architecture

The Proposed Echo State Wireless Sensor Network (ES-WSN)

ES-WSN is one of the Reservoir Computing (RC) strategies. ES-WSN is well adapted for shallow learning and chaotic time series (Bahmaid & Ghaleb, 2024). The design of an ES-WSN neural network is not similar to traditional neural network architecture, which usually becomes more computationally intensive, ES-WSN is so fast because there is no backpropagation phase on the reservoir, which is a random repeating environment. The traditional neural network can be disrupted by bifurcation. During training, ES-WSNs extract the features of the ideal product and compare them with those of the manufacturing line. Throughout the system's training phase, the weights in the input side are selected randomly, the reservoir-layer weights are fixed, and the output-layer weights are calculated (Tanaka et al., 2022). Figure 2 depicts the architecture of the ES-WSN neural network, with the black arrows representing non-trainable weights (fixed weights), the green arrows representing trainable weights, and the red arrows representing potential non-essential connections. The readout weights are determined depending on the product properties. In principle, the suggested ES-WSN network has three main layers: input, reservoir, and output(readout). Weights are normally changeable to obtain the required product qualities, except for set reservoir weights during training. After the ES-WSN is trained on a given product, the network can easily detect product defects throughout the manufacturing process, saving time spent re-sorting damaged components of the product during the product safety inspection procedure at the quality control stage (Sun et al., 2022).

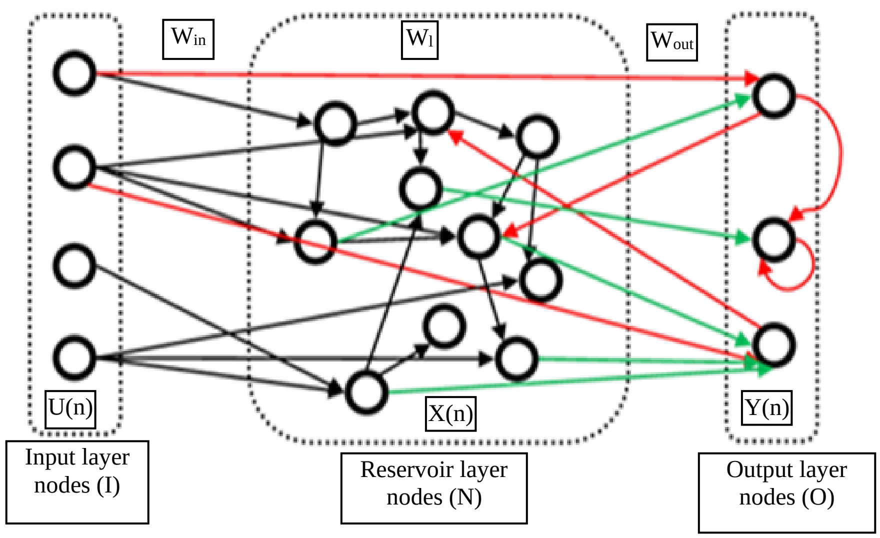

Figure 2: The Stratum of ES-WSN As One of the RC Optimizations

Data Collection

Some studies released a dataset on product surface defects (Song et al., 2024). These studies contain nine kinds of defects that can be found in specific products. The dataset has 7000 grayscale images suitable for training. Our study focused on defects including cracking, scratches, surface pitting, gouges, and grooves. The dataset was subjected to ES-WSN learning, which involves applying a time-camera sensor to existing training images to identify product defects. That scenario can achieve better prediction for new defective product images.

Defect Collection

In general, ES-WSN depends on the quality and quantity of the streaming dataset and is compared with camera sensor images. ES-WSN is based on the RC approach that follows the CV approach used in usual shallow learning for optimization. The dataset images consist of 7000 images of PC architecture. The test has been done on the PC architecture to find the defects in the whole structure. The ES-WSN algorithm was learned using 6000 images for training and 1000 images for testing. The frame size of the image in the dataset is equal to 150×150. The procedure to find the defects in the PC architecture is shown in Figure 3. The scenario in the figure illustrates the capability of the ES-WSN to find five detectors in the structure. From the scenario shown in the figure, the framework can recognize the defects in the PC architecture, utilize the ES-WSN, and remove them from the production line immediately using the robot arm. That can reduce the time consumed through quality assurance proceedings. The scenario starts with initialization, gathering the dataset images, then moving to the learning and testing part of the ES-WSN algorithm to be ready for defect comparison and detection with the camera sensor images through the production line. Concerning the feature extraction, two Input layers with 30 nodes for each layer have been configured. The activation function at the end of each node has been chosen as Sigmoid. Regarding the reservoir layer, the network is configured to have four ES-WSN layers, and each layer has 8 nodes with a (Tanh) active function. The spectral radius has been set to 0.8 and the connectivity to 0.2 to meet design requirements. The training rate for weights is 0.002 to achieve 3000 iterations. Equation (1-3) shows the input, output, and stationary dynamic nodes. The h can be combined from input/ output weights. The d(n) in Equation (4) represents the leaner computation of x. The results are updated internally as shown in Equations (5-6). The weights (win and wr) are initialized randomly, while wr is not a trainable value. The weights start with a random generating matrix as shown in Equation (7) and are then scaled to meet conditions as shown in Equation (8) (Bruneo & De Vita, 2022). Table 3 shows the nomenclature discretion.

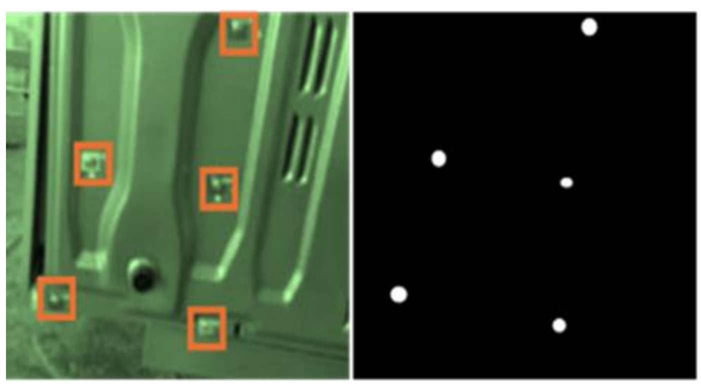

Figure 3: Defect Detection Using The Proposed Framework

Table 3: The Nomenclature Description

Acronyms	Description
x(n)	Function of input
u(n)	The function of computing the reservoir state
y(n)	Function of output
w_{in}, w_r, w_b	Matrix of I×R, R×R, R×O
F(.), g(.), σ	Sigmoid function to wrapping equation
d(n)	Stationary deterministic dynamic node
h	Input/ output echo function

$$x(n+1)=f\big(w_{in}\cdot u(n+1)+w_r\cdot x(n)+w_b\cdot y(n)\big) \quad (1)$$

$$y(n+1)=g(w_{out}\cdot[u(n+1), x(n+1), y(n)]) \quad (2)$$

$$d(n)=h(u(n),u(n-1), \ldots,d(n-1),d(n-2), \ldots) \quad (3)$$

$$d(n)\approx y(n)=\sum_i w_i x_i(n) = \sum_i w_i h_i(u(n), \ldots,y(n-1),\ldots) \quad (4)$$

$$x(n+1)=\sigma(w_b x(n)+w_{in}u(n+1) \quad (5)$$

$$y(n+1)=w_{out}x(n+1) \quad (6)$$

$$w_{random}=[-w_{in},w_{in}]<1 \quad (7)$$

$$w_{random}=\frac{\rho_{desired}}{\rho(w_{random})} \quad (8)$$

Benchmarks

There are several benchmarks to estimate the performance of the proposed model. First, the accuracy represents the ratio between correctly predicted images and total images in the dataset, as shown in Equation (9). Whereas, the precision represents the correct positive prediction divided by the total positive prediction, as shown in Equation (10). Recall is the number of correct guesses divided by the total correct production, as shown in Equation (11). The F1-score is a harmonic value between Recall and Precision that is illustrated in Equation (12). Finally, ARE is the average of the prediction error outgains compared to the total prediction, as shown in Equation (13) (Abdi et al., 2024).

$$Accuracy = \frac{True\ posative + True\ negative}{True\ positive\ +\ False\ positive + False\ negative} \quad (9)$$

$$\text{Precision}= \frac{\text{True positive}}{\text{True posative+False positive}} \quad (10)$$

$$\text{Recall}= \frac{\text{True positive}}{\text{True posative+False negative}} \quad (11)$$

$$F1=2\times\frac{\text{Precision Recall}}{\text{Precision Recall}} \tag{12}$$

$$ARE\ \frac{\left|\begin{array}{c}\text{measured prediction err.}\\ \text{- total prediction err.}\end{array}\right|}{\text{total prediction error}}\% \tag{13}$$

4 Results

Figure 4-6 represents the results that come from testing the suggested ES-WSN model, which compares the results of the selected dataset with the readings of the camera sensor in the factory to reach an accurate prediction to find defective products through the production line, saving production time. The accuracy parameters were read after each specified number of iterations, and the readings started from 100 to 3500 iterations. The details in Figure 4 declare that the peak accuracy value can be shown at the 3000 iterations with a value of 99.78% where the accuracy begins to decline after this value because the model accuracy reaches a level to focus on small details that cannot be considered as a defect in the product. Figure 5 also shows the improvement of quality assurance in the production line by 98% at the peak point (3000 iterations). Figure 6 illustrates the ARE value for each iteration. The error rate of 3000 iterations is 2.7%. The output layer samples are classified into the defective product (1) or undefective product (0), where the train-test-split function is utilized in the scikit-learn software library, which is one of the Python software libraries utilized in learning the proposed model. The ES-WSN model starts with the learning procedure using 90% (6000 samples) of the dataset, and for the testing procedure, the model uses 10% (1000 samples) of the dataset. The process of learning the system was repeated several times, from 100 to 3500 iterations, to achieve the best results so that the model improved the ability to predict product defects with high accuracy. The increased redundancy allowed the system to identify product defects faster and more accurately.

Figure 4: The Accuracy Percentage Values After Utilizing The ES-WSN Model to Detect Product Defects

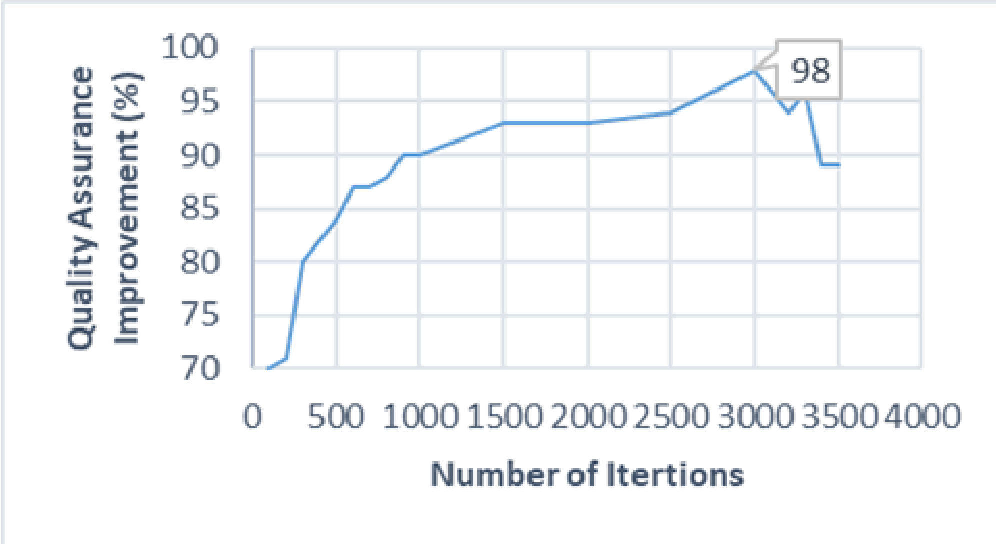

Figure 5: Quality Assurance Improvements After Utilizing The ES-WSN Model

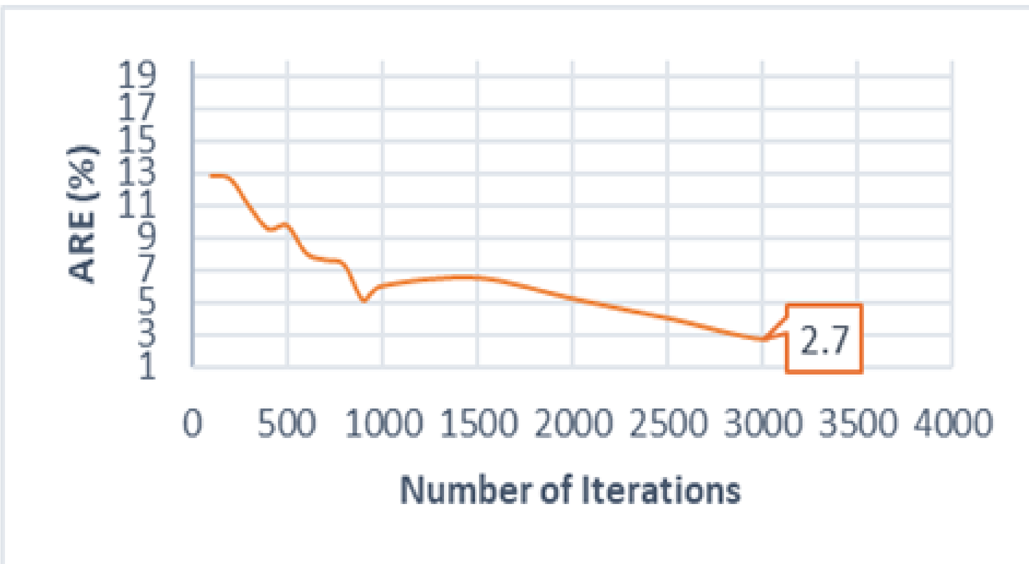

Figure 6: ARE Percentage for Each Iteration Band After Utilizing the ES-WSN Model

5 Discussion

The ES-WSN was used to calculate the similarity between the pre-processed dataset and the images taken from the camera sensor. The most accurate percentage of achieving the goal of whether the product is good or not is 99.78% when the iterations are 3000. The neural network model in the ES-WSN was trained using Django (Python) and the principle of TensorFlow by taking advantage of the reservoir properties of the ES-WSN, which follows RC algorithms, which achieves a faster execution time because it uses graphical units, which is the approach used in the CV. The main target of utilizing the proposed approach is to activate the role of cognitive robots in modern factories and boost them using the CV approach from multiple aspects. This strategy achieves high quality and rapid production in the production process. Moreover, there is no need to inspect the product after production in length and accurately because the inspection and sorting process has been carried out during the production period.

It is also worth noticing the limitations of the suggested algorithm in case of increased iterations. Increasing the iterations beyond the appropriate limit may change the benefit result of the proposed theory. The result of the training procedure in the proposed case study, according to the configuration that has been configured, is that the optimal number of repetitions in this study is 3000 iterations, which achieves an ARE error rate equal to 2.7 %.

Performance Analysis and Comparison

A series of comparisons and analyses was conducted to show the advantages of using shallow learning with state-of-the-art models of common relevance. Five different models have been analyzed and compared to their benchmarks: the RNN model, the SVM model, the LSTM model, the DNN model, and the CNN model. For a comprehensive view, Table 4 shows the results of each model's benchmarks in terms of accuracy, recall, precision, and F1-score according to model complexity. As shown in the table, the proposed ES-WSN model was distinguished in terms of accuracy, with a value of 99.78%, while the RNN model showed a decline of 86.52% due to a high backpropagation. The Recall was close except for the RNN and SVM models, with values of 29.45% and 75.3% respectively. The results in Table 4 also showed the effect of the F1-score, where its value in our proposed model was 99.6% and the Precision value was 99.8%. The time required to identify defects in the product, or the so-called speed of learning or discovery time, is an important factor in inferring the success of the proposed model. Figure 7 shows a comparison to see how much time model learning takes. The figure shows the average processing time for artificial neural network models. The proposed model spends less processing time, 80 milliseconds, while the highest processing time in the LSTM model is due to the large number of network backpropagations. The factor of feature extraction in the ES-WSN model was a decisive factor, as there are no backpropagations like the rest of the models; rather, it depends on the method of extracting features and reservoirs that are in line with the shallow learning approach.

Table 4: The Model Benchmarks Comparison

Models	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-score (%)**	**Ref.**
Recurrent Neural Network (RNN)	86.52	84.3	29.4	43.5	(Sayin et al., 2025)
Support Vector Machine (SVM)	97.71	75.3	75.3	75.3	(Syed et al., 2021)
Long Short-Term Memory (LSTM)	96.50	98.8	99.3	99.6	(Dharma et al., 2022)
Deep Neural Network (DNN)	97.89	99.2	97.3	98.2	(Cong & Zhou, 2023)
Convolutional Neural Network (CNN)	87.11	99.7	99.4	99.6	(Razzaq & Shah, 2025)
Echo State Wireless Sensor Network (ES-WSN)	99.78	99.8	99.3	99.6	*

* Proposed algorithm

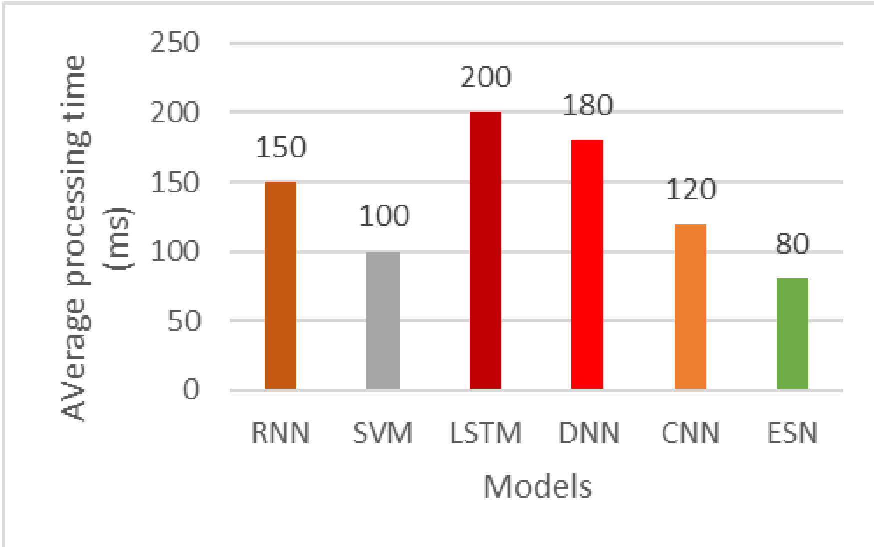

Figure 7: Processing Time for ES-WSN Suggested Model Compared with State-of-the-Art Models (RNN, SVM, LSTM, DNN, and CNN)

Limitations

Although the proposed algorithm has shown promising results in detecting defects in the production line, some obstacles appeared in this proposed study. Increasing the dataset images is one of the important issues to be discussed. This dataset is used to learn the ES-WSN through the learning phase, which is an important aspect to increase detection accuracy, reducing the time consumed by detection on the production line. Besides, the variation in surface texture, angles, and lighting could affect the detection accuracy. Moreover, it is difficult to detect small defects that cannot be easily discovered because of the noise, background, or overlapping complex defects, which can all affect the image quality and resolution. The maintenance of the manufacturing tools is also an aspect to consider.

6 Conclusions

This paper presents a significant study about activating artificial intelligence in the management of cognitive factories and activating the role of cognitive robots instead of inaccurate human diagnosis in identifying defective products during manufacturing, utilizing the ES-WSN based on the shallow learning principle. The ES-WSN model is one of the CV algorithms that uses RC insight in processing images to detect product defects during the production process using artificial intelligence. The study is accompanied by a comprehensive description of modern CV algorithms and a comparison with the proposed method. The results illustrate the significance of the proposed ES-WSN model. The accuracy is equal to 99.78%, and the processing time is equal to 80 milliseconds through 3000 iterations. Besides, the increase in iterations may come with unexpected results exceeding 3000 iterations. In general, the results illustrate the framework's effectiveness based on the ES-WSN with the RC approach in detecting and classifying product defects during the production period in real-time and with a better performance according to the performance benchmarks. The results are important to improve the mechanism to detect defects in product pieces during the manufacturing procedure in real-time and reduce production time. Future work will focus on enhancing the performance of the existing model by increasing the number of photos in the dataset and extracting more features from the reservoir layer.

Author Contributions

Conceptualization, Ali Saifaldeen Alkhafaji, and Ibtihaal M. Hameed. Software, Marwan Kadhim Mohammed AL-shammari. Validation Ibtihaal M. Hameed, and Ali Saifaldeen Alkhafaji. Investigation Marwan Kadhim Mohammed AL-shammari. Writing the first draft, Ibtihaal M. Hameed. Reviewing and editing by Marwan Kadhim Mohammed AL-shammari, and Ali Saifaldeen Alkhafaji. All authors have read and agreed to the published version of the manuscript.

Conflicts of Interest

The authors declare no conflict of interest.

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