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Feature Correlated Auto Encoder Method for Industrial 4.0 Process Inspection Using Computer Vision and Machine Learning

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Abstract

From the perspective of the Industry 4.0 paradigm, the machine learning (ML) discipline has had a significant influence on the manufacturing sector. The industry 4.0 concept promotes intelligent sensors, gadgets, and equipment to create technology infrastructure sectors that collect information constantly. By analyzing the obtained data, machine learning approaches allow actionable insight to boost industrial productivity without dramatically altering the necessary resources. Furthermore, the capacity of machine learning applications to provide actionable analytics has facilitated the detection of complex manufacturing trends and paved the path for an integrated intelligent process in various activities in the supply chain, including smart and constant inspection, preventative maintenance, quality enhancement, process optimization, supply chain advancement, and workflow scheduling. This paper aims to present recent advances in the field of quality inspection in Industry 4.0 and develop a framework for quality inspection that can be fully utilized in the Industry 4.0 context using adaptive bilateral filtering and Feature Correlated Auto encoder (FCA) machine learning technique. The suggested approach makes full use of information from all sources along the manufacturing chain. Therefore, it complies with quality management standards within the context of Industry 4.0. The suggested model makes use of corrective measures based on data patterns discovered through predictive analysis. Result analysis was shown on some pre-trained deep learning models such as ResNet18, Vgg19, Alexnet, Squeezenet, auto encoder, and FCA and observed that the proposed FCA(Feature Correlated Auto encoder) achieved a better result.

Keywords: Manufacturing, Industry 4.0, Machine Learning, Computer Vision, Image Processing.

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1. Introduction

Industry 4.0 includes various technologies like the IoTs [1], cloud computing [2] [3], advanced robotics [4], big data analytics [5], and AI [6]. Prior to the beginning of the 4th Industrial Revolution, the vast majority of crucial technologies for Industry 4.0 have already been in existence for a substantial amount of time. However, the most novel aspect of Industry 4.0 is the ability of its components to interact with one another and work autonomously, without the need for human operators [7]. Incorporating a computer vision-based automation method into the production chain for the aim of detecting defective items, therefore, requires a nuanced combination of the technologies described below. This may serve to highlight the most important components and result in an enhanced product line.

Industry 4.0 has resulted in the emergence of a new subset of manufacturing known as Smart Manufacturing, which is primarily dependent on data analysis. It is a technologically driven method that employs the Internet of Things and other web-enabled devices to produce output and monitor processes. Its goal is to automate industrial processes by creating, optimizing, and utilizing vast volumes of data to boost efficiency, promote sustainable growth through supplier management, and identify potential system bottlenecks in advance [8]. By adding advanced analytics to analytics and utilizing AI and ML, manufacturers may gain a deeper understanding of how their assets and manufacturing process are operating. Figure 1 depicts the underlying technological components of the Fourth Industrial Revolution.

Industry 4.0 aims to create a cyber-physical ecosystem that makes use of existing technology and digital solutions. Combining information technology with operationally determined procedures will achieve this objective. The manufacturing industry is moving to a new mentality. Industry 4.0 will usher in the intelligent manufacturing era, ushering away the previous industrial period due to advances in machine learning and artificial intelligence [25]. Industry 4.0 will usher at the end of the previous manufacturing era. The paradigm shift shown by [26]-[30] has created new opportunities, which is a beneficial result. The Internet of Things and the spread of intelligent sensors enable the development of data-rich industrial environments that span all production sectors. Then, these conditions can be utilized to enhance production procedures. The Internet of Things is a subset of the Internet of Everything that enables wireless object-to-object communication and data transit. The Industrial Internet of Things may connect devices with embedded sensors, radio frequency identification (RFID) tags, control units, and electrical circuitry, among other components. Instead, the digital twin aids in simulating the problematic method, process, product line, or system so that it can be analyzed or optimized to enhance the performance of an online system. This is done to enhance the user experience overall. [9][31]-[33].

Cloud computing is a crucial facilitator of the data integration concept since it leverages connection speeds to save, retrieve, and analyze data. Furthermore, new technology, including advanced robots, VR, and 3-D printing [10] [11], enables current-generation production. Machine Learning methods, a subfield of Artificial Intelligence, can become the primary driving element in distinct applications, including predictive maintenance, process optimization, scheduling and resource, performance improvement, supply-chain management, sustainable development, and product quality, to name a few.

Technology and artificial intelligence (AI) can help organizations develop and thrive. The world's largest corporations use AI and machine learning in production and spend vast sums of money on their development. According to research, AI and machine learning approaches account for 40% of all potential value provided by analytics today. Data-driven methodologies automate data-driven learning, detecting underlying trends and making informed judgments. Operation, manufacturing, and post-production are the three primary components of this, all of which may be enhanced by inspections in Industry 4.0. Data analysis simulation or Product modeling may reduce mistakes and adjustments throughout product development while also improving product quality and packaging.

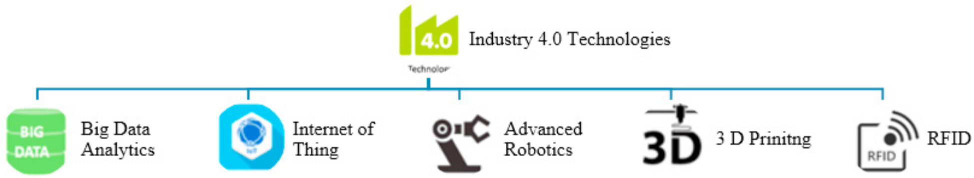

Figure 1 Industry 4.0 technological pillars.

Predictive maintenance extends the life of assets by improving asset availability and asset management and identifying flaws and weaknesses. Unplanned downtime is avoided. Also beneficial to increase supply chain visibility with location-based IoT services that provide actionable data [12]. AI systems for better decision-making have a lot of potential in the manufacturing environment. The IIoT, which enables extensive data harvesting, is a crucial enabler of Artificial Intelligence in industrial contexts. Big data analytics, in effect, necessitates AI in order to make real-time judgments. Machine learning, computer vision, and reinforcement learning are all key AI approaches that have previously been used in industrial applications. Computer vision was used to check structural health. Even with low-cost sensors, vision-based approaches provided great spatial resolution. Manufacturing systems' knowledge may be stored and organized using ontology. The brain-computer interaction of factory operators may be studied using AI. This may help with industry safety and ergonomics research. Manufacturing processes, such as additive manufacturing, provide data that may be analyzed for real-time surveillance, management, and fault minimization [13] [14]. Machine learning may be used to diagnose and forecast industrial equipment. Maintenance apps have made use of augmented reality devices. They provided more flexibility in terms of reconfiguring the maintenance method on the fly [15][34]. While various machine learning methods were used in a wide range of industrial uses in the previous study, there are numerous unanswered queries and challenges, ranging from Big-data curation, backup, and comprehension, to advanced topics like edge and fog computing and cybercrime phases of Intelligent manufacturing. As a result, this study provides a machine learning-based Industry 4.0 inspection framework that uses auto encoders for feature extraction and bilateral filtering for data pre-processing.

2. Related Works

In [16] outlines a system for evaluating the quality of items based on machine learning. According to the findings of this study, a Deep Learning predictive control technology and a high-quality optical quality assurance camera can be used in tandem to improve the accuracy of an automated visual inspection process in the Printing Industry 4.0 while simultaneously reducing its associated costs. It is technically impossible to produce a gravure cylinder without making some sort of fault, such as accidentally punching a hole in it. 100% of DNN sensor goods are manufactured with a classification accuracy of 98.4%. In the following investigation, we will apply these findings in three distinct ways. Make autonomous judgments on product quality without requiring human interaction by first forecasting the number of errors a cylinder will contain, and then helping human operation by transmitting the error probability to the operator. This will let you make decisions on the product's quality without human intervention.

The goal is to decentralize production processes and enable real-time monitoring, adaptation, and optimization based on the vast quantity of data collected on the shop floor and fed into machine learning algorithms. Because machines will function more effectively, and flexibly, and following demand variations, this technology revolution will result in substantial productivity improvements, resource savings, and lower maintenance costs. This study looks at how supervised Machine Learning methods, together with artificial vision, may be used to create an intelligent, collaborative inspection platform that performs quality control. The presented approach achieves impressive outcomes, with nearly 100% accuracy in correctly classifying consoles and abnormalities in pressure buttons and high values in detecting flaws in LCDs[17].

The goal of this work is to use machine learning and machine vision technologies to create a general method for automatically identifying materials [18]. This will help make robots used in Industry 4.0 and other machine tools and material handling systems smarter. This method will be used to automatically tell what things are. The red, green, and blue parts of the RGB color model are found by making and analyzing a set of surfaces made from four different materials. These surfaces need to be identified and put into groups in order to get the red, green, and blue parts. Four tests that looked at the capabilities of the classifier showed that the procedure given was correct. Also, its durability has been tested in a wide range of camera settings, lighting levels, and lens focal lengths to make sure it can handle different situations. Conclusions Based on the results, it looks like the proposed method could be used without making a lot of changes to the way things are done in the industry right now. A brand-new, generalized method based on SVM was made so that flat materials that are processed in a typical production setting can be easily recognized and put into groups. They used ML strategies and software for machine vision to reach this goal. The information in the collection comes from 3559 different samples. To be more specific, an SVM, which is a machine learning classifier, was trained with 2491 examples. Then, 1068 examples were used to test this classifier and make sure it could correctly identify the examples. When we used a method called "tenfold cross-validation" on 10 different examples, we found that the results we had already gotten about how accurate our model was still held true. This backed up the results we had found at the start.

In this study [19], we make a model for controlling the quality of a product using machine vision. This model uses two kinds of computer vision: a classifier for the inspection process and a linear regression for predicting what will happen next. The proposed method makes it easier to find problems early on in the production process. This helps make sure the quality of the product before moving on to the next step. The technology also helps collect production and historical data on defective and non-defective items, which can then be used to improve manufacturing processes. This information can be used to improve quality and cut costs. CNNs can be used in the recommended method, but only in certain ways and under certain conditions. For these models to reach their full potential, they need a lot of computing power and a lot of training data. Based on the results, experts in the field can then choose the machine learning models that work best for a system to make it as efficient as possible. Since it has a high R squared score (0.90%), the strategy called "decision trees" is the one that fits the process prediction the best.

This study combines production process data [20] and ML regression models, such as machine operating parameters from warped, resizing processes, with inspection results from the quality control department from the standpoint of data science. The regression algorithms are then used to forecast the parameters of the textile process. This study also uses categorization methods to predict textile quality. Experiments reveal that our model can predict quality levels with 90.8 percent accuracy using ten-fold cross-validation testing. The best predictive model for predicting has a mean square error (MSE) of less than 0.01 percent. The suggested method can give a complete analysis data of process parameters by integrating the two models above. When compared to earlier stochastic algorithms, it performs well. Because the suggested OPRS may assist technicians in accurately determining operating settings, even for a novel kind of yarn, it can aid in closing the technical skill shortage in the textile production process.

This study challenges conventional practices by offering new architectures for monitoring induction motor difficulties [21]. Real-world ML approaches are integrated into the proposed IoT infrastructure in order to detect various motor failure types. In addition, cyberattacks are considered, with the recommended IoT architecture capable of detecting and preventing the attack. The effectiveness of the suggested IoT framework based on machine learning has been demonstrated through a series of tests. The research findings reveal that the proposed IoT architecture is preferable for diagnosing motor issues and ensuring computer security. The results reveal that the algorithm is capable of achieving a classification accuracy of approximately 96.43 percent.

The article talks about a method that comes from GA. In version 4.0 of Industry [22], there are three different types of assets: human, virtual, and physical. The spread of computers everywhere has increased the need for high-tech tools that can be used to identify and keep track of assets. RFID tags, QR codes, and LoRa tags, to name a few, are among these devices. The center of the fourth industrial revolution, also called Industry 4.0, is the information that is made as a byproduct of manufacturing. The data that the Industrial Internet of Things collects is thought of as a digital asset. Huge amounts of industrial data can be used in many ways, such as to predict when a piece of manufacturing equipment might break down. By using predictive maintenance, the owner of a business can figures out if a broken part needs to be replaced before it causes a chain reaction of other problems further down the production line. So, in the age of Industry 4.0, it's important to have good asset management to make the most of resources and keep up with predictive maintenance practises. This study shows how management activities that are driven by a Genetic Algorithm (GA) can be combined with Machine Learning (ML) to do predictive maintenance in fog computing. The findings show that the suggested approach excels in execution time, cost, and energy consumption. In comparison to the second-best results, the execution time is 0.480 percent quicker, the cost is 5.430 percent cheaper, and the energy consumption is 28.10 percent lower. The prediction models trained, and testing accuracy is 95.10 percent and 94.50 percent, respectively.

TABLE I. MANUFACTURING CONTROL IN INDUSTRY 4.0

Ref	Method	Inspection/ Quality Control/ Fault Detection Type
[16]	DNN	Printing Industry 4.0
[17]	Machine Learning	Robotic Inspection Station
[18]	SVM	Identification and classification of materials
[19]	CNN	Defective Product Inspection
[20]	Machine Learning	Improve Quality and Efficiency of Textile Process
[21]	Machine Learning	Online Fault Diagnosis of Induction Machines
[22]	Genetic Algorithm	Fog Computing based Predictive Maintenance

3. Proposed Methodology

As a machine is manufactured by industry, the first manufactured design is not entirely efficient with any product and can have several mishaps and faults. These might happen for a variety of causes, including unfavorable weather conditions or excessive exposure of the equipment to moisture. Motor faults may occur as a result of these factors. These errors and blunders may result in a slew of unneeded costs and financial losses for the industry. This study proposes Predictive Maintenance in Industry 4.0 model based on machine learning and computer vision techniques to prevent these things from occurring.

Fig 2 depicts the methods used for problem identification in the manufacturing process utilizing image processing tools. The photos were first obtained from datasets, as stated below. As a pre-processing step, an adaptive bilateral filter is used. To break down the images and extract the features, an autoencoder was used. The recovered features were encoded to minimize dimensionality, and the acquired relevant characteristics were rated using feature correlation criteria. The classifier was given this ideal feature vector matrix for error identification and performance assessment. Each stage is outlined below:

3.1. Pre-processing: Gaussian Adaptive Bilateral Filtering

With a bilateral filter, you can smooth out a picture while keeping its edges, which is a big improvement. With a bilateral filter, images are made smoother and less noisy, but the edges are not changed in any way. Even though different solutions using bilateral filters tried to get rid of the artefacts.

In the captured image, *I*, some artefacts that needed to be removed are present. In this step, a Gaussian bilateral filter [23] is used. In this, the Gaussian blur method, which corresponds to low pass filter (LPF), will be first performed to *I* to create an LP guidance image. Mathematically, the weighted sum of pixels presents nearby the central pixel of I is represented as:

$$fun(n) = \sum_{j} Wt^{g}_{m,n}\ I_n \tag{I}$$

$$Wt^{g}_{m,n} = \frac{1}{ker_m} \exp\left(-\frac{|n-m|^2}{\sigma_s^2}\right) \tag{ii}$$

As the value of σ_s^2 increases, it is seen that there is a loss of some edge features. In filtered input I, if over smooth is observed then it is observed that g and I are equal. For non-identical or unequal values of g and I the Gaussian spatial kernel is used that can be explained from the Gaussian blur process. As a result, the bilateral Gaussian-adaptive kernel is mathematically represented as:

$$Wt_{i,j}^{GABF} = \frac{1}{ker_i} \exp\left(-\frac{|n-m|^2}{\sigma_s^2}\right) exp\left(-\frac{|I^m - \bar{g}_n|^2}{\sigma_r^2}\right) \quad \text{(iii)}$$

Where, $\bar{g}_n$ = low-pass guidance filter

As a result, the Gaussian Adaptive Bilateral Filtering (GABF) output $fun(n)$ maybe evaluated as:

$$fun(n) = \sum_j Wt_{m,n}^{GABF} I_n \quad \text{(iv)}$$

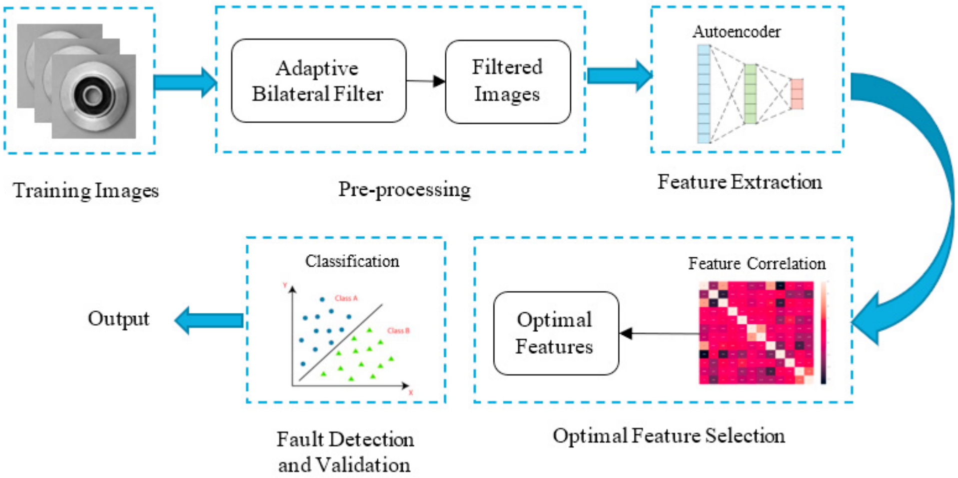

Fig. 2. Flowchart of Proposed Methodology

3.2. Feature Extraction: Stacked Auto encoder

The goal of an auto encoder (AE), which uses neural networks, is to learn features without being told what to do. The idea is to give the computer some information, and have it come up with results that are almost exactly the same as the information it was given. This technique is often used for feature extraction and reducing the number of dimensions. A basic AE will have an input layer, an output layer, and a visible layer. It will also have a hidden layer. Figure 3 shows an example of how AE can be used in the real world. At first, an encoder is used to change data from hidden layers with more dimensions into hidden layers with fewer dimensions. This is called dimensionality reduction. The decoder subsequently recreates the hidden layer's lower dimensional data. The reconstruction error is calculated using the reconstructed data and the input. Then, backpropagation is used to update the network. Due to the dimensionality reduction, AE will acquire as many features as possible that can more precisely describe the data distribution during the encoding stage so that the decoder may more accurately utilize these learned new features to reconstitute the data distribution.

The encoding network may be represented by a conventional neural network function that has been activated, where Z represents the latent dimension. The latent dimension Z is given by:

$$Z = \sigma(Wx + b) \quad \text{(v)}$$

In the same way, the decoding network may be described in the same way, but with various weights, biases, and perhaps activation functions.

$$X' = \sigma'(W'z + b') \quad \text{(vi)}$$

We can then write the loss function of such network functions, and we'll utilize that loss function to training the NN network using the conventional backpropagation process.

$$L(x,x') = \|x - x'\|^2 = \|x - \sigma'(W(Wx + b)) + b'\|^2 \quad \text{(vii)}$$

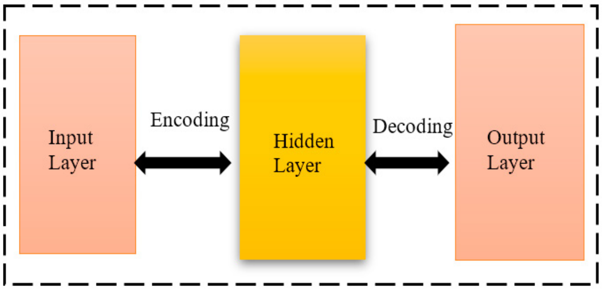

Fig 3. Basic Principle of the Autoencoder

3.3. Optimal Feature selection and fault detection

Using feature correlation criteria, the gathered relevant features were assessed. This ideal feature vector matrix was given to the classifier for fault detection and performance evaluation.

4. Results and Discussions

4.1 Dataset Description

Bearing casting image dataset taken from Mechanical and AI Lab (MAIL) at Carnegie Mellon University [24]. In this dataset, faulty cast bearing and correctly casted bearing images are provided individually.

4.2 Parameter used

Manufacturing defect image classification is evaluated on the following parameters: Accuracy = the proper classification of testing data is referred to as accuracy. It is mathematically formulated as:

$$\frac{TP + TN}{TP + TN + FP + FN} \quad \text{(viii)}$$

Precision = Precision relates to the accuracy of the data under consideration. It's a statistic for evaluating whether or not a positive event is true. It is expressed mathematically as:

$$\frac{TP}{TP + FP} \quad \text{(ix)}$$

Recall =**:** Recall is used to determine the frequency of positive events. It is mathematically formulated as:

$$\frac{TP}{TP + FN} \quad \text{(x)}$$

F1 score = the harmonic mean of accuracy and recall is what it's termed. It is expressed mathematically as:

$$\frac{2}{1/precision + 1/Recall} \quad \text{(xi)}$$

Instances that are false positives (FP) or false negatives (FN) are the opposite of true positives (TP) or true negatives (TN).

4.3 Result Analysis

This section describes the simulation result of the proposed FCA. For simulation, the MATLAB platform is used for

training and testing purposes. For training and testing different samples of faulty and correct casting bearing rings. For training, the model is trained for 1000 epochs with 600 samples of training data and 200 samples of testing data.
Four performance parameters that are accuracy precision-recall and f-measure are compared evaluated. The proposed model FCA is compared with Resnet18, Squeeze net, Alex net, Vgg19, Auto encoders without feature correlation, and the proposed method with featured correlated auto encoders (FCA). The result shows that the proposed feature correlated auto encoders outperform all the techniques mentioned above regarding accuracy, precision, and recall and f measure.
Fig 4 shows the accuracy comparison of all the techniques. Accuracy of Resnet18 is 67.60 percentage, Sqeeuzenet has accuracy of 64 %, Alex net has accuracy of 63.40%, Vgg19 has accuracy of 63.60% and auto encoder without pre-processing and correlation achieved 73% of classification accuracy. Proposed FCA the accuracy of 80% i.e. maximum all mention techniques.
Fig 5 shows the precision comparison of all the techniques. Proposed FCA the precision of 87.5% i.e. maximum all mention techniques. Auto encoders obtain the 80% precision without pre-processing and feature-correlated approach. Precision of Resnet18 is 70.18%, Sqeeuzenet has precision of 71.92%, Alex net has precision of 67.50%, and Vgg19 has precision of 81.76%.
Fig 6 shows the Recall comparison of all the techniques. Proposed FCA the recall of 82.35% i.e. maximum all mention techniques. Auto encoders obtain the 81.15% recall without pre-processing and feature-correlated approach. Recall of Resnet18 is 57.12%, Sqeeuzenet has Recall of 50.94 %, Alex net has Recall of 50%, and Vgg19 has Recall of 50.27%.
Fig 7 shows the F-Measure comparison of all the techniques. Proposed FCA the F-Measure of 84.84% i.e. maximum all mention techniques. The minimum F-Measure is obtained by the Alex net process i.e., 57.45%. F-Measure of Resnet18 is 62.98 percentage, Sqeeuzenet has F-Measure of 59.64 %, AE without pre-processing and FC has F-Measure of 80.57%, and VGG19 has F-Measure of 62.26%.

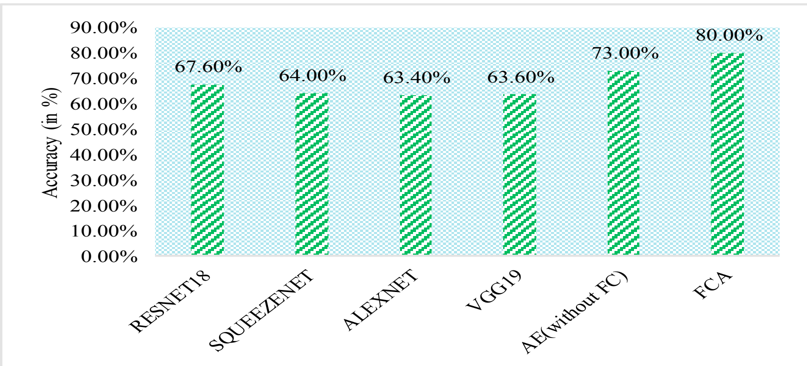

Fig. 4. Accuracy Comparision

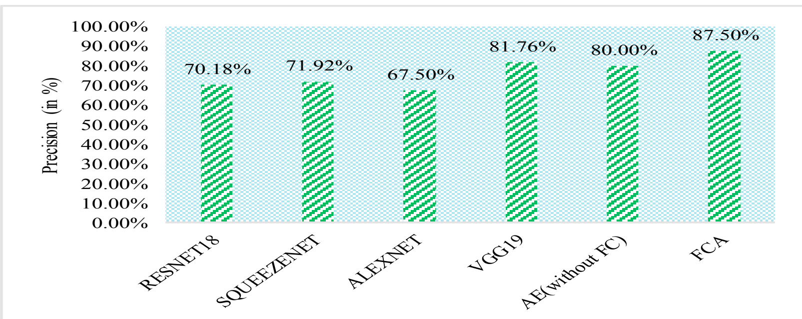

Fig. 5. Precision Comparison

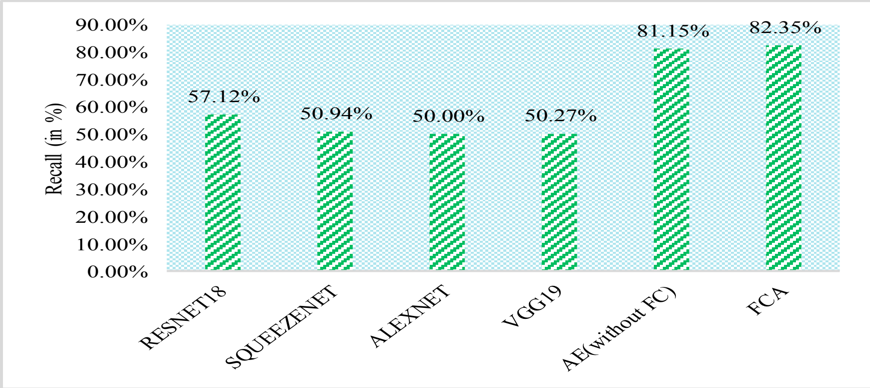

Fig 6. Recall Comparison

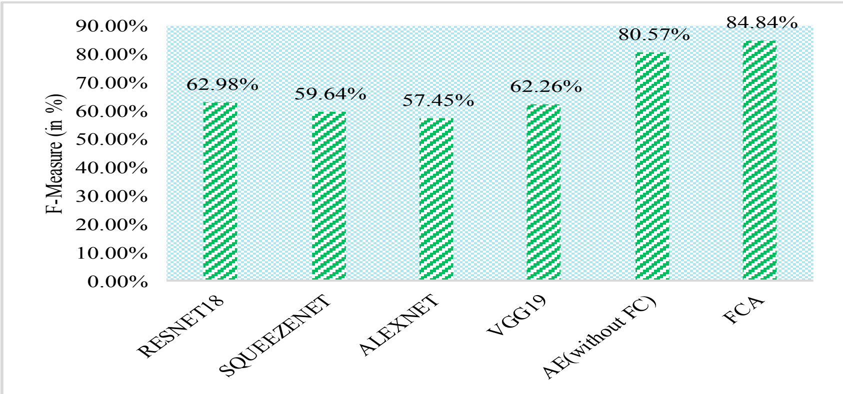

Fig 7. F-measure Comparison

5. Conclusion

As Industry has a lot of different jobs, but inspection control is the one that stands to gain the most from technological advances. Combining computer vision with techniques for machine learning is seen as a cutting-edge innovation in industry 4.0 because it allows for continuous, quick inspections to be done on a regular basis (around the clock) and helps producers get the most work done in the least amount of time. This is because it makes it possible for computer vision and machine learning to work together. Using the information that vision equipment gives us, we will be able to find and report bad goods, figure out what went wrong and why, and act quickly and correctly in the field of industrial automation. In this study, a computer vision model was combined with a machine learning model using Feature Correlated Auto Encoders and Bilateral Filtering. This model bridges the gap between the detection of broken items and the ongoing optimization of manufacturing processes by estimating the best settings for making products that aren't broken. Feature Correlated Auto Encoders and Bilateral Filtering are used to make this happen. To meet the quality management requirements of Industry 4.0, the proposed model uses all of the data from the integrated technologies along the production chain. This model was made using predictive research to find patterns in the data and offer ways to fix them to keep the quality of the product high. Several different machine learning algorithms are compared in order to figure out how the suggested system works. The performance of these algorithms is then judged by things like accuracy, F-measure, recall, and precision. Accuracy, Precision, Recall, and F-Measure were all at least 80% for the proposed Feature Correlated Auto encoder (FCA), and F-Measure was at

84.84%. Based on the results of this research, it seems that the model that has been proposed can meet most of the requirements for putting these methods into practice effectively. Industry 4.0 is an idea that encourages the use of sensors, devices, and machines that are always connected to the internet and collect data. Using algorithms made for machine learning, we can look at the data we collect and come up with ideas that could make industries run more efficiently. This could be done without making a big change to the number of resources needed. The fact that machine learning applications can provide analytics that can be used has made it possible to integrate intelligence into a wide range of supply chain tasks. These activities include smart and continuous inspection, preventive maintenance, quality improvement, process optimization, supply chain advancement, and workflow scheduling. Machine learning applications have made it easier to spot complex manufacturing trends and also made it easier to spot complex manufacturing trends. In this piece of research, we use adaptive bilateral filtering and the Feature Correlated Autoencoder (FCA) machine learning technique to create a quality inspection system that can be used in the context of Industry 4.0. In the context of Industry 4.0, this article talks about some of the more recent changes that have been made to the way quality is checked.

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