A Review on Quality Control in Production Line with Visual Inspection

Vishwanath K Anklagimath[1], Dr Manish Gangil[2]
[1]MTech Scholar, [2]Professor
[1]Department of Mechanical Engineering, SSSCE, RKDF University, Bhopal, India
[2]Department of Mechanical Engineering, SSSCE, RKDF University, Bhopal, India
vishwa.ankal@gmail.com[1] rkdfbhojpal@gmail.com[2]

Abstract- - ***The process of ensuring that manufactured goods or parts fulfil established quality standards and specifications is known as quality control in the manufacturing line. It entails a series of procedures and methods designed to prevent flaws, spot and fix any quality deviations, and continuously enhance the manufacturing process. In this work, review on quality control line based on machine learning and deep learning has been studied. In manufacturing, the monitoring of system and product health is examined. There includes discussion of the steps involved in the quality inspection and visual inspection processes, and an analysis of the major variables that influence the visual inspection process.***

Keywords: ***Quality Management, Quality Control, Visual inspections, Machine learning and Deep learning.***

I. INTRODUCTION

The process of ensuring that manufactured goods or parts fulfil established quality standards and specifications is known as quality control in the manufacturing line. It entails a series of procedures and methods designed to prevent flaws, spot and fix any quality deviations, and continuously enhance the manufacturing process. Delivering goods that meet or exceed customer expectations is the main objective of quality control, along with reducing waste, rework, and customer complaints. In order to retain customer satisfaction, build brand reputation, and achieve total corporate success, it is essential. Quality control procedures in a production line normally begin at the start of the manufacturing process and last until the finished product is prepared for distribution. It entails keeping an eye on and inspecting numerous production phases, such as the gathering of raw materials, the assembly, testing, packaging, and shipment.

The ability to gather vast amounts of data from factories and industrial facilities is a result of current manufacturing technology. Machine learning and deep learning techniques can be used to analyse data from all levels of an organisation. Real-time monitoring of operations in manufacturing facilities is made possible by interdisciplinary techniques like Industry 4.0 (I4.0), Cyber-Physical Systems (CPS), Cloud-Based Manufacturing (CBM), and Smart Manufacturing (SM). These methods significantly lower downtime and hence lower expenses for maintenance operations. According to Monte-Carlo estimates, the yearly maintenance expenses in the United States are estimated to be around USD 222 billion [1], and recalls due to defective products cost more than USD 7 billion annually [2]. Manufacturing companies are one factor in these comparatively high expenses. An interdisciplinary field of engineering known as prognostics and health management (PHM) focuses on the monitoring of system health, failure detection, failure diagnosis, and failure prognosis using metrics like remaining useful life (RUL). PHM technologies are being increasingly used in modern manufacturing techniques because they enable in-situ system evaluation. A Smart Manufacturing (SM) paradigm is made up of interconnected layers that can be integrated both vertically and horizontally [3]. The many layers according to the ISA-95 Automation Pyramid are depicted in Figure 1. Field devices made up of sensors and actuation gear make up the physical layer of SM. Data from every individual component must be combined into a single stream in order to monitor and analyse the devices on the physical layer. This stream then gives us a context for the entire process. In addition to providing context for the operation, properly organised data also enables the deployment of AI and ML algorithms more quickly. Early failure identification is made possible by the quicker application of ML- and DL-based condition monitoring systems. Data gathered from numerous sources with multiple parameters result in complex formats and occasionally redundant information. The availability of data, data preparation, and choosing relevant ML and DL methods for modelling are challenges in implementing PHM techniques for predictive maintenance effectively. To ensure that manufacturing data can be obtained and preprocessed for PHM, the proper measures must be done.

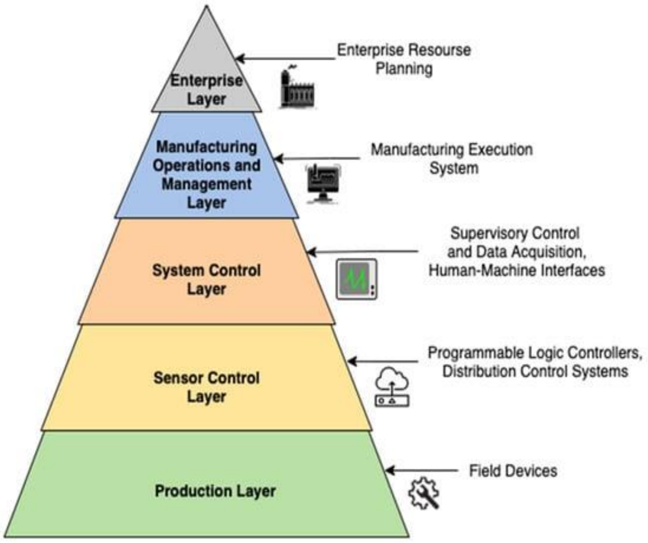

Figure 1. Top-down approach to manufacturing system according to ISA-95 Automation Pyramid

Overall, putting in place efficient quality control procedures on the manufacturing line enables businesses to provide goods that are up to par, minimise waste, cut costs, and increase customer happiness. Instead of being solely related to production operations, maintenance engineering has recently become one of the most crucial topics in manufacturing organisational planning [4]. Manufacturers are implementing proactive maintenance strategies as both a cost-cutting tool and a competitive tactic [5].

II. LITERATURE REVIEW

A. Quality Inspection using Deep Learning algorithms

Utilising deep neural networks to undertake automated inspection and appraisal of items or processes is known as quality inspection using deep learning. Convolutional neural networks (CNNs) and recurrent neural networks (RNNs) are two deep learning techniques that are particularly useful for this task because they can automatically recognise and extract intricate patterns and characteristics from input data.

Convolutional Neural Networks (CNNs): Convolutional Neural Networks (CNNs) are a well-liked and efficient technique for quality inspection in several industries, including manufacturing, automotive, and electronics. Due to its capacity to automatically learn and extract pertinent features from visual input, CNNs are particularly well suited for image-based quality assessment jobs. In order to achieve quality inspection of laser welding spots during the production of batteries, Zhang et al. [1] suggested a method based on deep learning algorithm and conventional computer vision (TCV) algorithm. The template-based approach and TCV heuristic algorithms' findings shown high computing efficiency and guaranteed inspection accuracy. When using NVIDIA 1060 and Intel i7-6700, the entire method's inference time is less than 100 ms. Chu et al.'s [2] unique hybrid learning method-based edge-enabled IoT system for visual surface quality inspection uses a small number of labelled data and requires little in the way of iterative optimisation work. On a holdout data set gathered from actual factories, our technique outperforms the benchmark method by 7%–12% and achieves classification accuracies between 90% and 98%. Additionally, our hybrid learning system outperforms the benchmark method by 11%-34% and shows promise in identifying novel surface defects, with test recalls between 86% and 97%. A technique to increase the detection capacity was put out by Li et al. [3] The proposed method, which has been employed in the ferrite-bead inspection machine, achieves a classification average precision (AP) of 97.1% on the ferrite bead dataset using fewer than 200 fault samples and only image-level labels in the training procedure. Deutsche Arbeitsgemeinschaft fuer Mustererkennung (DAGM), KolektorSDD, and KolektorSDD2 achieve the best AP of defect classification of 100%, 100%, and 99.9%, respectively, when the proposed method is tested on various datasets for industrial quality inspection. Yu et al.[4] proposed a convolutional neural network model improvement. In order to optimise the hyperparameters of neural networks, the Particle Swarm Optimisation algorithm (PSO) with adaptive parameters is finally presented. The mean Average Precision (mAP) of the best model of EfficientNet-PSO on the validation set is 95.69%. FLOPs are 1.86B and F1 score is 0.94. This technique significantly enhances the flange plate and cylinder head defect detection accuracy and efficiency when compared to the other five deep learning neural network models, meeting the defect detection standards. Wu et al. [5] A classification activation map (CAM)-based weakly supervised defect segmentation technique is proposed. To close the gap between image-level and pixel-level supervision, we first employ a Siamese network. Then, three modules that are utilised to increase segmentation without increasing computation complexity—auto-focused subregion loss, max-pooling-based nonlocal attention, and log summation exponential global pooling—are modified to improve inspection performance. We conduct comparison experiments on the performance of the proposed strategy using the Deutsche Arbeitsgemeinschaft fuer Mustererkennung (DAGM) and KolektorSDD public datasets. Lema et al. [6] This work makes a novel contribution by framing the issue as one of object detection as opposed to semantic segmentation or categorization. Principal component thermography (PCT)-derived three-channel colour pictures are the images used as input for the deep learning algorithms. The signal-to-noise ratio (SNR) is enhanced through the utilisation of these photographs. Additionally, a system for automatically labelling ground truths is developed. You only look once (YOLO)v5 was chosen as the most popular deep learning detector algorithm after evaluation of the most extensively used deep learning detector algorithms, which was done due to its great average precision (AP) and quick inference time. When this approach is combined with active thermography, subsurface flaws can be found with accuracy and efficiency. Giap et al. [7] For the real-time quality assessment of smartphone physical buttons, we present a novel framework based on machine vision called highlight defect region by applying higher-order singular value decomposition of wavelet subband-based tensor (HHoWST). In the beginning, a cutting-edge image acquisition system is created to acquire a high-quality smartphone's physical button image dataset, which consists of 500 photos in total and 13,472 samples of six defect types. The third-order tensor of the physical button colour picture from the smartphone is then created using a wavelet subband. In order to estimate the components that include the global illumination information and emphasise the problematic areas of the image, higher-order singular value decomposition is presented. The tests on HHoWST photos show that our suggested approach considerably increases the defect detection effectiveness of deep learning models, such SSD, Faster. Rahman et al.[8] gives a thorough analysis of the various AOI systems utilised in the opto-, micro-, and electronic sectors. The common flaws of electronic components that are inspected, such as semiconductor wafers, flat-panel displays, printed circuit boards, and light-emitting diodes, are first described in this review [9], [10]. The choice and configuration of the camera and illumination sources is then covered in terms of the hardware setups utilised to acquire photographs. The preprocessing, feature extraction, and classification techniques used for this purpose are explained in relation to the inspection algorithms used for identifying flaws in electronic components. We also analyse recent studies that employed deep learning methods. The article's conclusion describes present patterns and potential future study directions. Guan et al.[11] Using feature visualisation and quality assessment, a unique recognition approach for steel surface flaws is proposed. This algorithm is based on improved deep learning network models. Results of the experiments indicate that the suggested approach may significantly raise the average classification accuracy, and the model can converge quickly, which is advantageous for identifying steel surface defects using the VSD network model of feature visualisation and quality assessment. Yao et al.[12] propose and evaluate a novel loss function-based weakly-supervised semantic segmentation method with the intention of mitigating the negative impacts of weak annotations. In order to conclude energy and storage different methods are used [13]–[16]. Despite their variations and unique challenges, the detection results for both examples demonstrate that using weak annotations does not prevent either from obtaining a competitive performance level. Guiot et al.[17] introducing RobustSleepNet, a deep learning network capable of handling arbitrary PSG montages and automatically classifying sleep stages. RobustSleepNet achieves 97% of the F1 of a model explicitly trained on this dataset when tested on an unknown dataset. With any clinical setup, RobustSleepNet thus opens the door to performing high-quality out-of-the-box automatic sleep staging. We also demonstrate that, when compared to a model trained solely for this dataset, fine-tuning RobustSleepNet using a portion of the unknown information enhances the F1 by 2%. As a result, finetuning may be employed to achieve cutting-edge performance on a particular population. Yang et al.[18] By using the industrial prior knowledge encoder to encode the prior knowledge into the instructor mask and the mask-to-defect construction network to produce the defect details in accordance with the mask. The produced samples from the fake domain are then transformed into the real defect domain using the fake-to-real domain transformation GAN. Studies show that our method's synthesised image quality beats cutting-edge generative techniques, and by fine-tuning the inspection model with the generated samples, the model's performance in defect recognition and localisation has also improved.

Tan et al.[19] outlines a multi-algorithm fusion image processing technique and develops a model for failure-defect detection and dropper recognition on its foundation. The results of the test are confirmed by catenary photos obtained from a real high speed train. The algorithm's stability, real-time performance, and detection accuracy are sufficient for high-speed railway inspection and maintenance.

Pal et al.[20] Using a deep metric learning-based (DML) framework, provide a unique method for detecting cervical precancers that makes no attempt to mark the cervix. The DML is a cutting-edge learning approach that can more effectively deal with data scarcity and bias training brought on by class imbalance data. Three popular state-of-the-art DML approaches are compared: batch-hard loss minimization, contrastive loss minimization, and N-pair embedding loss minimization. ResNet-50, MobileNet, and NasNet, three well-known Deep Convolutional Neural Networks, are set up for training with DML to create class-separated (i.e., linearly separable) picture feature descriptors. Finally, the collected deep features are used to train a K-Nearest Neighbour (KNN) classifier.

Zhu et al.[21] To achieve the goals of effective and high-quality rotor manufacture, an instrumentation system for the quick inspection of rotor faults was designed. According to the executed experimental experiments, this implementation is capable of achieving an inference time of under 200 ms and an accuracy of above 99%. It is demonstrated that when compared to traditional approaches, the developed system performs better. With improved deep learning algorithms, the created, portable, and adaptable system has exceptional potential for usage in real-time rotor flaw detection.

Ran et al.[22] based on YOLOv5s, suggests an enhanced attention and feature balanced YOLO (AFB-YOLO) algorithm. The experimental findings on the imaging of wind turbine blade flaws reveal that our technology performs significantly better. AFB-YOLO's detection accuracy has increased by 4.0% and has a mean average precision (mAP50) of 83.7% when compared to the original YOLOv5s model. The trials presented here show that AFB-YOLO is more reliable and efficient than cutting-edge detectors.

Xie et al.[23] the critical step in gold wire bonding quality inspection, we provide a unique framework for completely automated gold wire bonding size-related measurement.For the first time, high-accuracy quantitative assessment of gold wire bonding structures on the scale of 0.02 mm is accomplished using the suggested automated framework. The experiments show that the suggested measurement framework is successful. Yi et al.[24] offers a complete deep learning (DL) approach that locates and categorises foreign particles using adaptive convolution and multiscale attention. In order to extract fine-grained features and lessen the intraclass differences between particles, we first introduce the pixel-adaptive feature extraction (PAFE) method. We validate the suggested technique on a liquid pharmaceutical dataset, reaching a missed detection rate of 3.6%, to support the aforementioned activities [25]–[29]. With a potential 15 frames per second (FPS) pace, our technology is an order of magnitude faster than other methods. On a wine dataset, we also assess the model's applicability.

Tavanapong et al.[S19] Focusing on two categories of artificial intelligence (AI) tools used in clinical trials, this presentation will outline the current state of colonoscopy video analysis techniques. These are (2) the detection of anomalies and (1) analysis and feedback for enhancing colonoscopy quality. Both new deep-learning techniques and methods that leverage conventional machine learning algorithms on meticulously created hand-crafted features are covered in our survey. Finally, we outline the discrepancy between the state-of-the-art technology available today and desirable clinical qualities, and we draw conclusions about future developments in endoscopic AI technology that will close the existing gap.

Li et al.[30] recommends the two-parameter CFAR approach based on initial detection, as well as detection methods based on the Logistic Distribution model and the Adjoin Covariance Correction Model (ACCM). The experimental findings demonstrate that the ACCM model put forward in the study fits the ocean background's long tail characteristic under complicated ocean conditions quite well. When compared to the Loglogistic Distribution model, it has a goodness of fit that is over 50% better, and its ocean target detection false alarm rate is 77.78% lower.

Vuoluterä et al. [31] To reduce image backdrop and align the products in the photographs, an image processing technique was developed. The networks were originally trained on the same data from five variants, and then retrained with additional data from a sixth variety in order to compare the flexibility of the two approaches. Overall, it was discovered that the modular networks performed their classification less accurately and more slowly than the traditional single networks did. The retraining times were about equal in both methods, but the modular networks were more than six times smaller and took less time to train initially. The predicted accuracy did change once the single network was retrained, however the modular network did not experience this change.

Das et al.[32] focused on the improvement of the defect identification process using Optical Character Recognition and Image Smoothing. Additionally, a Residual Neural Network model for the Surface Detection Problem is described.

QUALITY MANAGEMENT

Using quality management systems, a company may make sure that all of the goods and services it offers adhere to predetermined standards (European Committee for Standardisation, 2015a). When evaluating a product's quality, manufacturing companies may take into account a variety of factors, such as adherence to tolerances or surface quality. This raises the risk of delivering unreliable, subpar goods or services because it undermines customer confidence, creates a negative reputation, and reduces the competitiveness of the company. Furthermore, low quality could have additional effects. Compliance with rules, like as those governing food safety or assuring brake performance in automobiles, is necessary not only to safeguard the end user but also to avoid expensive recalls, negative news, and legal repercussions such. Lean manufacturing, Six Sigma, and other methods like Total Quality Management have all emerged to support the objectives of achieving quality. These strategies frequently cross over or can be employed in tandem with one another, but they all aim to meet or exceed customers' expectations for quality, dependability, price, and delivery. These factors are not solely internal because suppliers may have a big impact on whether they can be met and customers' needs may change over time.

B. Quality Inspections

Visual quality inspections, which are used to confirm the quality of a part or product, are one of the key methods of quality control. Inspections can be carried out at any point during the manufacturing process, whether they are on raw materials, products, or components used during the manufacturing process, or on final goods. Inspection subjects are rejected if they don't fulfil quality standards, while those who do move on to the next stage of manufacturing or are given to the customer [3]. At the conclusion of the production process, human operators perform the traditional form of inspection, checking all or a sample of the final goods. However, in addition to finished goods inspection, in-process or in situ examination of parts and products is also a widespread practise. Visual inspection procedures are normally only capable of detecting surface flaws like scratches and deformations, whereas other approaches are typically needed to identify internal quality problems [3].

There are a number of drawbacks to manual inspections, including operator boredom, weariness, inability to keep up with production speeds, and inconsistent judgements [3]. Even if 100% of all items are inspected, these factors reduce the reliability of inspections, increasing the likelihood that either non-defective or defective products will be rejected. Additionally, human inspection is costly, time-consuming, and even impractical or impossible to complete. [4].

Machine vision technology-based automatic inspection systems are an alternative to using human operators. When compared to manual inspections, machine vision inspection has a few important advantages, according to [5]. First off, machine vision systems are more accurate and precise than people are. Another consideration is speed, as inspections can be completed more quickly than traditional quality evaluations. Due to the system's lack of fatigue or boredom, measurements are reproducible and can be performed continually with the same level of accuracy. Thus, it is more feasible and cost-effective to use machine vision systems to verify all products, 100% of the time. [5] further highlight the noncontact inspections carried out by machine vision, which lowers inspection risk. Increased use of solid state switching devices, non-linear and power electronically switched loads, unbalanced power systems, lighting controls, computer and data processing equipment, as well as industrial plant rectifiers and inverters, has led to issues with power supply quality and the problems that follow. These electronic-type loads produce excessive harmonics, high current distortion, inrush, and pulse-type current phenomena. A power quality (PQ) issue typically comprises changes in the electric service voltage or current, such as voltage dips, fluctuations, brief interruptions, harmonics, and oscillatory transients that cause expensive electronic equipment to malfunction or fail. Therefore, before suitable mitigating action can be taken to improve power quality, the origins and causes of such disruptions must be understood [33]–[37]. The efficient automatic detection and classification of disturbance waveforms is one of the key difficulties in power quality issues. Many utilities carry out PQ monitoring for their industrial and important clients in order to identify, address, and minimise the PQ issue. PQ monitoring would be vital in a deregulated electricity system for improving customer services and fostering utility competition.

Without putting the overall state of the industrial environment into context, it would be negligent to talk about quality inspection, a key step in the QC process. In manufacturing, there are two main components to health monitoring. The system's health is checked first, along with the effectiveness of the machinery and equipment. Monitoring the product's health over the course of its life is the second area. PHM deals with component-level and system-level health monitoring for the system. On the product side, QC methods are used to ensure the product's safety and quality. Brief summaries of these subjects are provided in the next section. A discipline known as prognostics and health management (PHM) keeps track of the health of a system, finds problems, treats problems, and forecasts future problems. Critical tools and components can have their working status tracked in real-time using sensors and field devices enabled by the Internet of Things (IoT). SMEs may now use PHM on the shop floor thanks to the accessibility of low-cost embedded devices and microcontrollers like the Raspberry Pi, STM32, Arduino, etc. Once enough information has been gathered, the health indices and metrics created can be included into models to forecast component failures and provide estimates of Remaining Useful Life (RUL). Data-driven strategies for PHM have hitherto relied on ML models. To successfully extract useful characteristics or features from the data, however, specialist expertise is frequently required for ML models for prognostics or failure detection [12]. The automatic extraction of high-level characteristics from inputs like audio signals, vibration signals, image data, etc. is a capability of DL approaches. Therefore, adopting DL for prognostics and diagnostics applications has a benefit. The various PHM approaches—data-driven, physics-based, hybrid, and use-case on health monitoring of a milling machine tool—are reviewed in depth by a methodology described in [11]. Quality management has become crucial to organisational planning and strategies as a result of the creation of extremely complex products and the growth of contemporary manufacturing processes [13]. Setting quality standards, making sure the product complies with them, and enhancing the overall product quality are all parts of the quality control (QC) process. Operators inspect the product during the various phases of manufacturing as part of the quality control (QC) process. Figure 1 illustrates the quality control procedure as seen through the lens of health monitoring, which includes product inspection. The total quality control process is constantly evolving because of how dynamic the production environment is. Methodologies for product inspection are prescribed by techniques like Design of Experiments (DoE), Failure Mode and Effects Analysis (FMEA), Quality Function Deployment (QFD), and Acceptance Sampling. Although these methods have been very effective in quality control, there is a chance to evaluate all of the items. The state of the product is evaluated by examination, measurement, testing, gauging, or comparison to ascertain whether it complies with intended requirements [3]. Quality inspection is a planned and organised process. The majority of the time, a human operator inspects the product to determine its conformity during a quality inspection. However, the inspection's accuracy and dependability are frequently subpar. According to Harris [4], operators' inspections become less accurate as product complexity rises. The accuracy of appropriately rejecting precision made parts by human operators was found to be 85% in a research by the Sandia National Labs [5], compared to the industry average of 80%. Another recent study found that operator errors were responsible for 23% of the quality control faults in the oil and gas sector [6]. Computer vision-based systems have been used to examine a variety of items throughout the years, including disc heads, steel strips [7], syringes [8], and semiconductors [9]. Vision-based systems typically consist of an algorithm that is trained to spot differences between the desired attributes and the product under examination. Although these systems contribute to some automation of the inspection process, their application on the shop floor still faces significant difficulties [10]. ML and DL-based models have been used in several works to improve the quality assessment process [38]–[41]. However, a lot of researchers concentrate on enhancing the performance of models and do not take into account an all-encompassing strategy for examination. While one of the primary objectives of the inspection process is to achieve that, there are a number of neglected issues that have an impact on the inspection process. A technique or approach that outlines how a data-driven method can be implemented on the shop floor in a user-friendly and trouble-free way is also required. In order to do that, this study suggests a two-pronged strategy for the quality inspection process[21].

III. Deep Learning

A smaller area of the larger field of AI and ML research is deep learning. Any deep learning application relies on Artificial Neural Networks (ANNs), which are condensed mathematical models of how brain neurons communicate with one another [6]. As seen in Figure 2, ANNs are built up of layers of neurons, with every neuron coupled to every other neuron in both the previous and following layers. Every connection carries a weight, often a value between 0 and 1, which is multiplied by the value received from the preceding neuron. In order to simulate the way that actual neurons process information, each neuron sums up all the incoming values and uses the result as input for an activation function. Values are transmitted from the input layer through the network. [7].

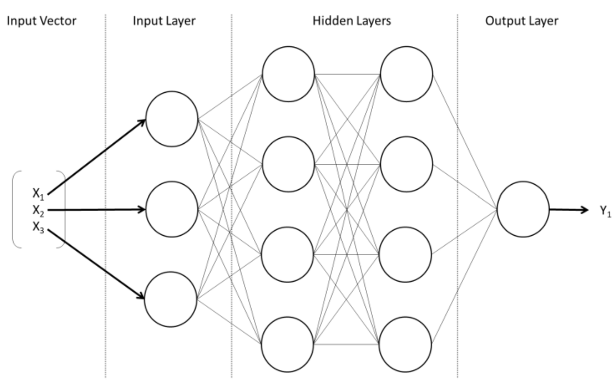

Figure 2: Structure of a simple neural network.

The first mathematical model for building ANNs was proposed in 1943, therefore the concept is by no means new. The field's funding and interest have fluctuated throughout the years, with the worst times known as "AI winters" for their extreme conditions. Despite these obstacles, research continued, and deep neural networks began to take shape in the 1980s. These new ANNs made use of extra layers, earning them the moniker "deep" in order to solve more challenging problems [8].With the invention of CNN AlexNet ten years ago, there has been a recent increase in interest in deep learning. AlexNet participated in the 2012 ImageNet Large Scale Visual Recognition Challenge, which challenges image recognition software to categorise images into 1000 distinct groups. No other entry was able to match the accuracy of AlexNet, which recorded a mistake rate of just 15,3% in the top five positions compared to a second-place finisher's error rate of 26,2% [H8]. A rush to iterate and enhance the design resulted from AlexNet's ability to surpass aMll current visual recognition techniques. In the years that followed, a number of different CNN architectures succeeded to attain error rates that were lower than those of a person.

IV. CONCLUSION

A major problem is that individuals are not necessarily encouraged to take responsibility for the quality of their own work. Rejected product is expensive for a firm as it has incurred the full costs of production but cannot be sold as the manufacturer does not want its name associated with substandard product. Some rejected product can be re-worked, but in many industries it has to be scrapped – either way rejects incur more costs, A quality control approach can be highly effective at preventing defective products from reaching the customer. However, if defect levels are very high, the company's profitability will suffer unless steps are taken to tackle the root causes of the failures.

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