Quality Control in Production Line with Visual Inspection

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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, the topic of product health monitoring is discussed from the standpoint of the quality inspection procedure. 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. The casting process is evaluated, as well as the visual inspection procedure for casting goods. The proposed Smart Quality Inspection (SQI) AI-based approach is based on the difficulties associated with visual inspection. On casting product photos, a unique CNN model for SQI is created and used. The model inspects casting items with a high accuracy of 99.86%. Comparing all of the published papers on the dataset, the model's accuracy and F-1 score are the greatest. To simplify the inspection process, a shop floor application is also being created. The application's objective is to reduce as many aspects of the inspection procedure as possible. With AI-based inspection, the effects of several operator or individual factors, social factors, and organisational aspects are reduced. During the data collection, there were a number of environmental circumstances over which we had no control. For instance, we had no control over the camera setup or the lighting conditions utilised to shoot the pictures. This issue affects the vast majority of publicly available datasets. There aren't many factories with real-time access, though, where tests can be done.*

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

1. 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. [1], [2], [11], [3]–[10]
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 modeling [4]–[7] 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.

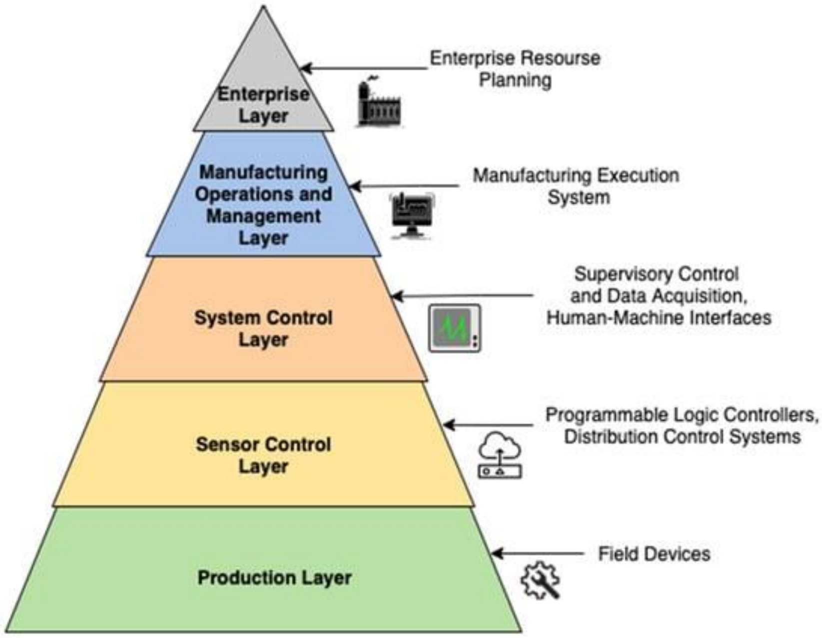

Figure 1. Top-down approach to manufacturing system according to ISA-95 Automation Pyramid

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 [8]–[11]. Manufacturers are implementing proactive maintenance strategies as both a cost-cutting tool and a competitive tactic [12].

2. Literature Review

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. [13]–[16]

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.[12] 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.[17] 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.[18] 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.[19] 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.[20] 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. 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.[21] 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.[22] propose and evaluate a novel loss function-based weakly-supervised semantic segmentation method with the intention of mitigating the negative impacts of weak annotations. 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.[23] 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.[24] 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.[25] 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.[26] 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.[27] 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.[28] 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.[29] 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.[30] 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. 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.[31] 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[24].

Li et al.[32] 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. [33] 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.[34] 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.

3. Proposed Methodology

3.1 Quality Inspection Process

The conventional quality improvement process is iterative and cyclical, involving the creation of inspection plans, their execution, and the evaluation of the outcomes [17]. Similar to this, the inspection procedure is made up of inspection plans that specify the many industrial processes that call for inspection. The examination of raw materials, sometimes referred to as incoming or receiving inspection, usually starts the process. [18]–[21] Then, inspections are carried out on a regular basis following various procedures. Most of the time, the type of these inspections is industry-specific. For instance, the inspection of microcontrollers would be very different from the examination of structural steel goods. A final inspection is undertaken at the end of the assembly line to evaluate whether the product is acceptable or has to be rejected. Similar to a departing inspection, this. In some circumstances, exit inspection. [22]–[25], [28]–[31]

The inspection process is an important decision process in the manufacturing/production system [26]. According to the Signal Detection Theory (SDT), probabilistic decisions are made at every step by the decision maker (operator) to determine whether the product is to be accepted or rejected [27]. Inspection is not an independent process in the manufacturing value chain but impacts many other operations [33]–[36]. The decision-making process for inspection involves multiple elements and should display the following characteristics as noted by [36]:

Precision: The decisions made should be well-informed, to ensure that there are no biases or errors.

Validity: Decisions made must be valid and must not differ if the product were to be available for use.

Reliability: There must be consistency in the decisions made—repeatability and reproducibility. The decision process should not require recalibration.

Robustness: The decision-making must demonstrate versatility in detecting different types of defects.

Rapidness: The process must be quick and must be able to act before any more defective products are produced.

Note that the aforementioned qualities are required from all inspection processes, whether they are carried out by human operators or any other type of automation.

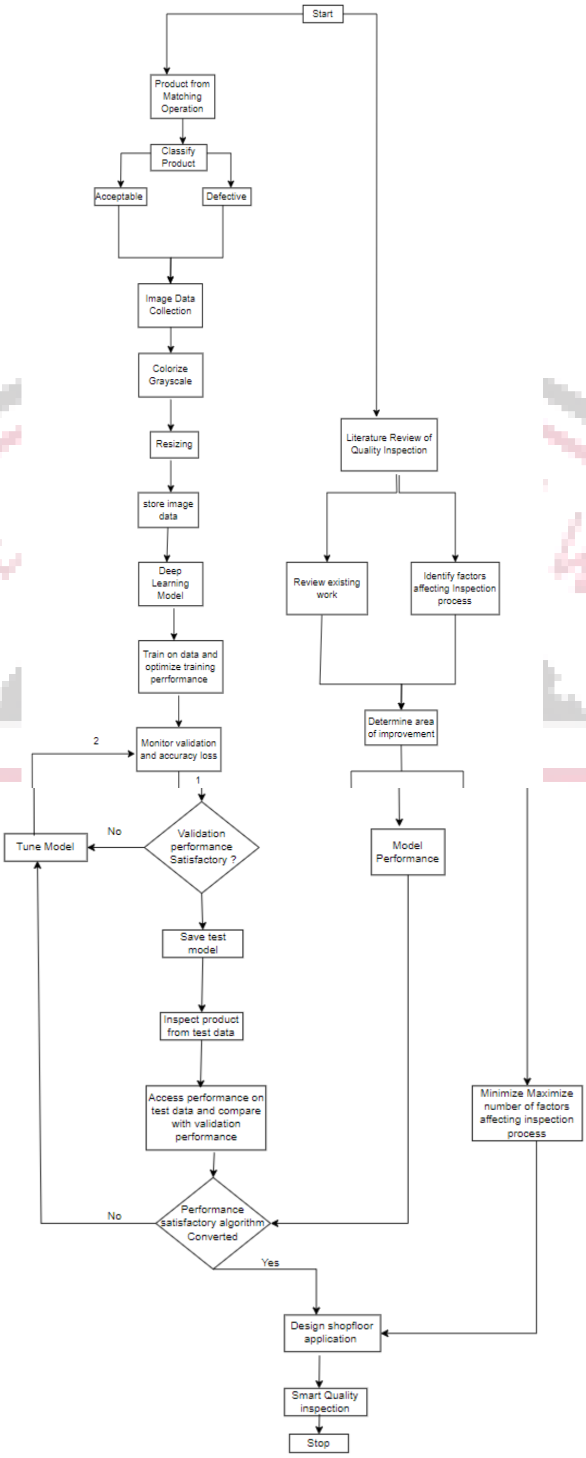

Figure 2: Flowchart depicting the process used to develop Smart Quality Inspection

4. Result and Discussion

Receiving the product, taking product photos, and image preprocessing are all steps in the SQI approach. Images taken with a Canon EOS 1300D camera and consistent lighting make up the casting data taken into account in our work. The image data had already undergone several augmentations, such as shearing, cropping, contrast adjusting, etc. The only pre-processing required before using the CNN model was rescaling the images.

A total of 6633 photos make up the training dataset, of which 5307 were used solely for training the model and the remaining 1326 were utilised in the validation set to fine-tune it. We use the 'Autotune' option from the Tensorflow library to optimise the model's performance and utilisation of computing resources. As previously mentioned, the Conv2D and Dense layers utilised ReLU activation functions, and a sparse-categorical cross-entropy loss was taken into consideration. The model was built using the Adam optimizer, however it's important to note that various alternative optimisation techniques were also investigated. The Adam optimizer very barely outperformed the Root Mean Squared

Propagation (RMSProp) and Nesterov-accelerated Adaptive Moment Estimation (Nadam) . Although it was intended for the training phase to last up to 20 epochs, it was finished in 13. This is because early halting conditions were included as a protection against overfitting [37]. When the validation loss does not decrease, we use it as the benchmark for early stopping, and the model's execution is halted. At the conclusion of each epoch, the training and validation accuracy as well as the training and validation losses have been tracked. The training and validation set's accuracies and losses are plotted by epoch in Figure 3.

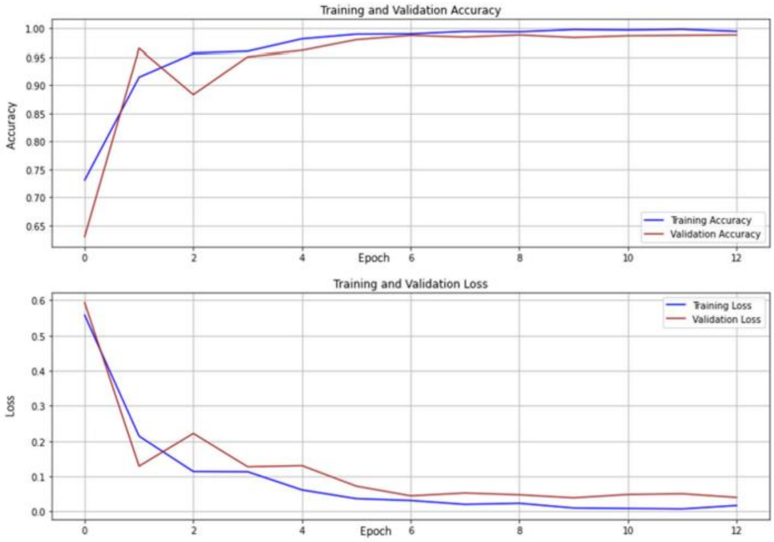

Figure 3: Monitoring the accuracy and loss of the training and validation set.

715 test photos are used to evaluate the model's performance. Overall, the model surpasses all other models that are currently available from published research and reaches an accuracy of 99.86%. Figure 4.2-4.5 contrasts the suggested model using SQI's performance measures with those of other models. The fig 4.2 presents different techniques used for quality inspection, along with their corresponding accuracy values. Accuracy is a metric that measures the overall correctness of a model's predictions.
An accelerated CNN approach achieved an accuracy of 99.72%. Proposed SQI: The proposed SQI model achieved the highest accuracy of 99.86% for quality inspection. These accuracy values indicate the overall correctness of the models' predictions for quality inspection. Higher accuracy values indicate better performance and more reliable identification and classification of instances during the quality inspection process.

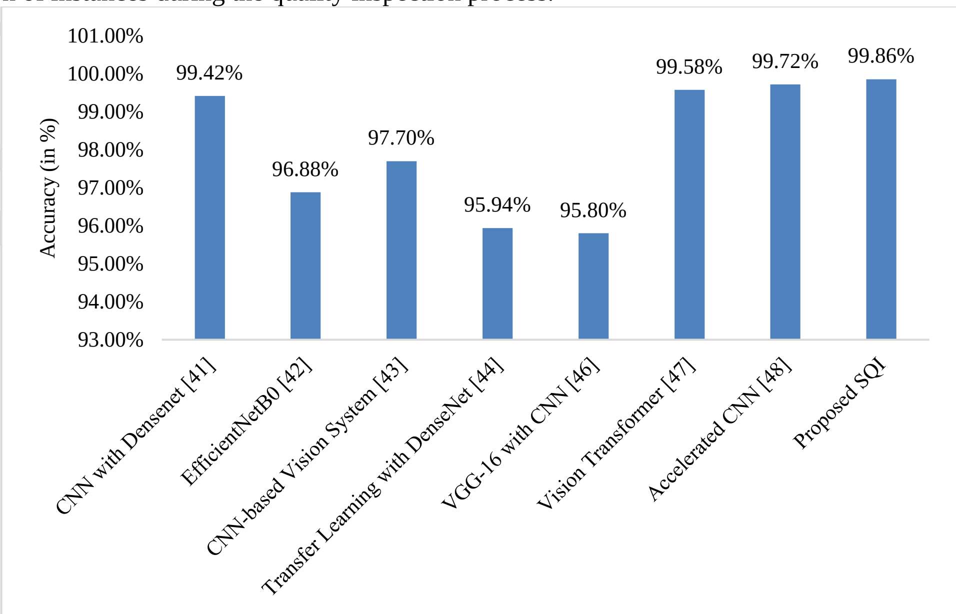

Figure 4: Accuracy Performance Evaluation

The fig 4 summarizes the precision rates achieved by different techniques in a certain task. CNN with Densenet [38]: Achieved a precision rate of 99.08%. EfficientNetB0 [39]: Achieved a precision rate of 97.11%. Transfer Learning with DenseNet [40]: Achieved a precision rate of 97.96%. VGG-16 with CNN [41]: Achieved a precision rate of 98.70%. Proposed SQI: Achieved the highest precision rate of 99.62%. These precision rates indicate the accuracy of each technique in correctly identifying or classifying certain data or objects. The proposed SQI technique demonstrated the highest precision rate among the listed methods.

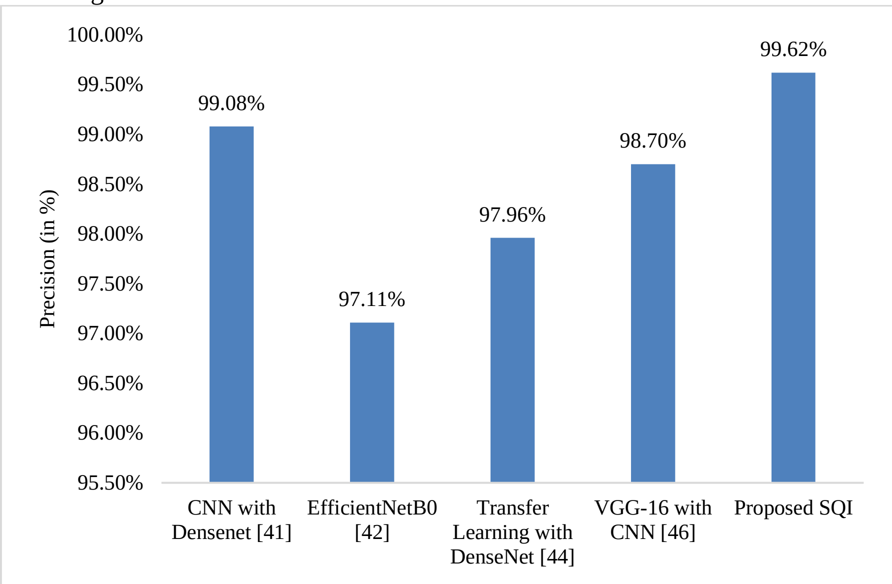

Figure 5: Precision Performance Evaluation

The fig 5 presents a comparison of two different techniques and their precision rates. The techniques are as follows: CNN with Densenet [42]: This technique achieved a precision rate of 99.54%. It utilizes a convolutional neural network (CNN) architecture combined with Densenet. Proposed Smart Quality Inspection (SQI) Model: This technique achieved a higher precision rate of 99.81%. It is a newly proposed model specifically designed for smart quality inspection. The precision rate measures the accuracy of the techniques in correctly identifying or classifying certain data or objects. In this comparison, the proposed SQI model demonstrated a slightly higher precision rate compared to the CNN with Densenet technique.

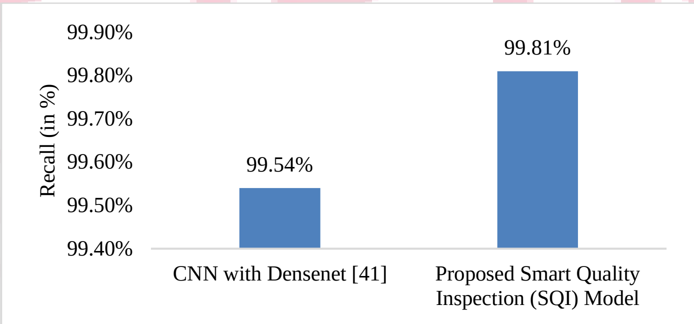

Figure 6: Recall Performance Evaluation

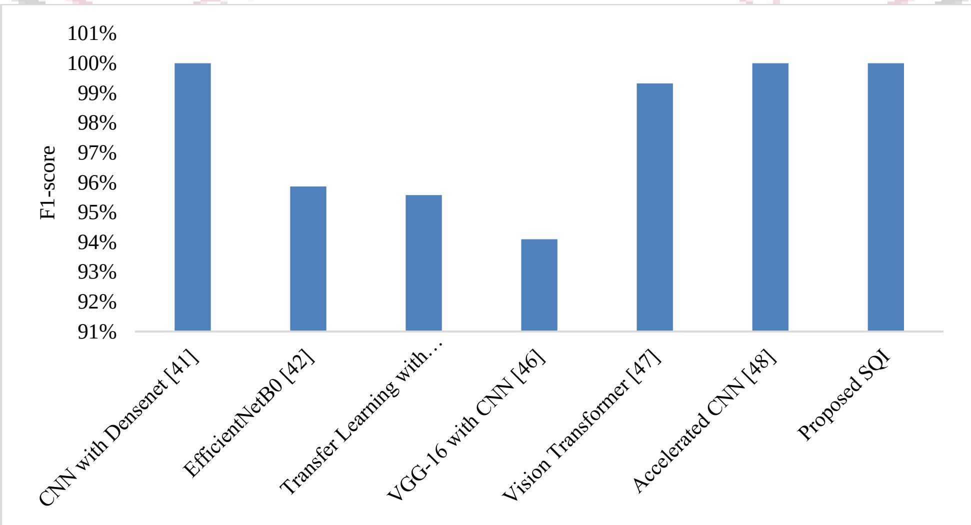

Figure 7: F1-score Performance Evaluation

The fig 7 provides information about different techniques and their corresponding F1-scores, which measure the overall performance of a classification model. Here are the techniques and their respective F1-scores:

We can examine the casting goods by using the SQI shop floor application. We examine a subpar and an acceptable product to show the features of the programme. The outcomes of the inspection of a defective product and an acceptable product are shown in Figure 6 (a,b), respectively. A literal click of a button inspects the merchandise. The operator can then enter identifying information about the product, equipment, etc. to record the inspection procedure. The data entered is kept in a spreadsheet that serves as an inspection log (see Figure 6 c).

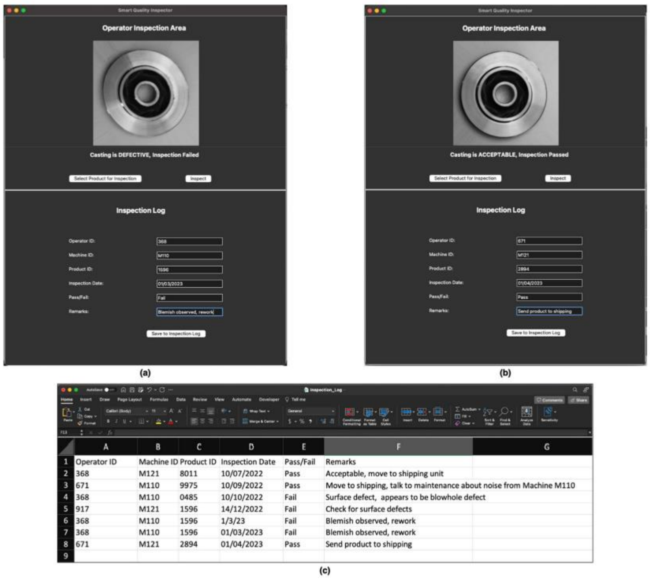

Figure 6: Shop floor application for Smart Quality Inspection. (a) shows the inspection of a defective product, (b) shows the inspection of an acceptable product, and (c) shows the results of the inspection documented in the inspection log (spreadsheet opened in Microsoft Excel).

5. Conclusion and Future Work

In this work, the topic of product health monitoring is discussed from the standpoint of the quality inspection procedure. The proposed Smart Quality Inspection (SQI) AI-based approach is based on the difficulties associated with visual inspection. On casting product photos, a unique CNN model for SQI is created and used. The model inspects casting items with a high accuracy of 99.86%. Comparing all of the published papers on the dataset, the model's accuracy and F-1 score are the greatest. To simplify the inspection process, a shop floor application is also being created. The application's objective is to reduce as many aspects of the inspection procedure as possible. With AI-based inspection, the effects of several operator or individual factors, social factors, and organisational aspects are reduced. Even a few task and environmental elements are under control. For instance, in an automated inspection system, external variables like the time of day and shift length would not affect the performance of the AI model. Additionally, the programme enables the quality inspector to record their observations from the inspection process and store in log. This issue affects the vast majority of publicly available datasets. There aren't many factories with real-time access, though, where tests can be done.

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