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An Improved Intelligent Cloud-based Structure for Automated Product Quality Control

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Abstract: Regardless of the products, quality is the most crucial concern for all manufacturers in any manufacturing system. Quality management is a collection of procedures and instruments that can improve the overall system performance of a manufacturing facility. The dynamic nature of today's business climate and intense rivalry in the market have made quality tools and continuous improvement (CI) essential for long-term success and overcoming obstacles. The methodology of automating quality assurance with cloud computing is also explored in this study. Given how popular cloud computing has become lately. An increasing number of manufacturers are thinking about switching to a cloud-based quality system for their quality management. Because of this, the cloud's power, agility, and cost advantages are now essential for surviving in today's dynamic and uncertain manufacturing environment. Thus, utilizing machine learning methods and cloud computing, this work has provided a service-based proposal system for visual quality assurance. The model's accuracy in detecting defects in manufactured parts and response time are assessed. The model's average accuracy was estimated to be approximately 93%, while the average reaction delay was estimated to be approximately 8 seconds.

Keywords: Manufacturing, Quality Assurance, Customer Satisfaction, Visual Inspection, Cloud Computing

I. INTRODUCTION

In the context of manufacturing, quality assurance, or QA, refers to the methods that manufacturers use as part of a quality management system to maintain consistently, expected quality levels on the things they create. Quality assurance, which is frequently associated with quality control, or QC, is a component of the ecosystem that guarantees customers receive quality products free of unanticipated flaws. Quality assurance is crucial in any manufacturing environment, but it is especially important for types of manufacturers, such as those in the automobile sector and high-precision parts suppliers, because failure to maintain a high standard of quality might result in harm or death [1].

A combination of increasing customer expectations and technical improvements has increased the complexity of industrial systems. Businesses also encounter stochastic disruptions and cyclical demand, which results in an unequal utilization of industrial capacity. Effectively and efficiently planning and managing production has thus become a significant competitive advantage [2][3]. Production control deals with recurring tasks in the production process, such as order release or tool allocation, as well as short-term rescheduling because of unanticipated machine failures or departures from the schedule [4][5]. However when it relates to single-part and small-series production, the division of labor planning and production control is overly rigid and unsuccessful for the following reasons:

- Formulation of unworkable work plans without accounting for the current volume of income (e.g., machine utilization, tool condition)
- The decision-making space for production control is constrained due to the small number of process choices.
- The route possibilities were not systematically evaluated due to the manual rescheduling by the production planner.
- Put a focus on individual optimization criteria in production planning and control.

II. QUALITY ASSURANCE

Quality assurance, also known as QA, is the term used to describe the processes manufacturers use as part of a quality management system to maintain consistently, expected quality levels on the items they produce. A part of the ecosystem that ensures customers receive high-quality products free of unintended faults is quality assurance, which is commonly used in conjunction with quality control, or QC. Manufacturers control product quality through product testing (as opposed to quality verification). Quality assurance is necessary in all industrial environments, but some businesses, such as those in the automotive industry and suppliers of extremely precise parts, require it more than others because failing to maintain a high degree of quality could result in harm or even death [3].The idea of quality assurance was first introduced in the manufacturing industry as a systematic technique, and it has since spread to many different industries, including computer programming [4]. A company can utilize quality assurance to provide goods and services that meet the needs, requirements, and standards of its customers. It creates premium product offers that promote consumer loyalty and trust. The regulations and standards of a quality assurance program help to stop product faults before they happen.

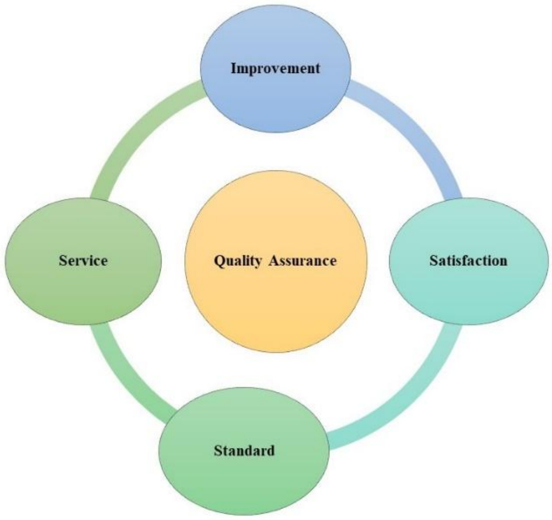

Figure 1: Quality Assurance [2]

Quality assurance is a systematic process for determining if a good or service complies with predetermined specifications (QA). Standards for developing or producing processes are established and maintained by QA. By improving work procedures and efficiency as well as client confidence and a firm's credibility, a quality assurance system enables a company to compete more effectively with competing businesses (Fig. 1).

A. Benefits of Quality Assurance

Quality assurance offers many benefits for manufacturers who emphasize it. The following three benefits of good quality assurance are highlighted in [5]-[9]:

Cost Savings: Since it is a proactive component of quality management, good QA helps to prevent quality issues. In other words, producers can save a lot of money since they do not have to account for as much waste, returns, and other byproducts of inferior goods.

Efficiency Boosts: In addition to producing more high-quality parts, companies may employ resources like time, money, and warehouse space for other profitable initiatives with fewer defective products. Producing high-quality goods requires fewer resources if mechanisms are in place to ensure their success.

Improvements in Customer Satisfaction: Customers benefit from better goods with higher levels of consistency, quicker turnaround times, and higher quality when manufacturers adopt effective quality assurance systems. Future customers will benefit from increased innovation and personalization with a lower risk of purchasing a substandard product due to the availability of more resources for these tasks.

B. Quality Assurance Methods

One of three techniques is used for quality assurance:

- Failure testing entails regularly putting a product through its paces to see if it breaks or malfunctions. For physical products that must survive stress, testing the product under extreme circumstances like heat, pressure, or movement may be essential. Software products may need to be put through rigorous load or heavy usage tests as part of the failure testing process.
- The statistical process control (SPC) methodology was developed by Walter Shewhart in the 1920s and 1930s at Bell Telephone Laboratories and Southern Electric Company. It is supported by factual data and analysis. This methodology uses statistical methods to oversee and control the production of the product.
- Total quality management (TQM), establishes the use of quantitative methods as the foundation for ongoing improvement. Data, analysis, and facts are used by TQM to support product planning and assessments.

The demand for quality management engineers will differ depending on the organization and industry. Using software as an example, a QA engineer's job description can include the following obligations:

- Usability testing
- Feature testing
- System testing
- Integration testing
- Developing test plans for the product based on automated scripts.

III. RELATED WORK

Quality inspection is a critical component of contemporary smart manufacturing systems (SMS). The manufacturing sector's objectives are to I) provide high-quality products; II) develop brand loyalty; III) comply with laws; and IV) limit the generation of waste (including staff and machine time, scrap materials, etc.) to maximize profit—are the reasons behind its popularity. There are several different quality inspection systems in use on the shop floor. These systems employ a range of technologies, including image-based systems, high-fidelity sensor systems, and human operators. Pomante et al. [5] focused his research on image-based quality inspection process and related technologies. Author presented the scope and benefits of vision-based quality inspection towards industry 4.0. To ensure visual quality inspection using camera, it is required to focus on different aspects such as scanner performance, reporting, data-driven optimization and monitoring. Babic et al. [6] extended this work by creating an effective MR quality program at various pediatric hospitals. The data that are input to machine learning software determines its functions; a tiny change in a training dataset has a big impact on the values of the learning parameters and, as a result, on the results of inference. Because of ML-based systems, quality assurance methodologies now have a new issue to deal with. This paper analyzes two widely held beliefs about the caliber of goods and services. It also offers a platform approach in which the co-creation of value is a crucial factor.

Variable quality models are examined by Sreedher et al. [7] in both competitive and single-agent frameworks. To facilitate communication among the various communities with an interest in quality management, our objectives are to (1) give the reader a perspective on the state of the art in this field; (2) identify the distinctions between the various concepts of quality; and (3) develop a research agenda for the field. Along with the field's active researchers, the journal should be of interest to a larger community of academics and practitioners involved in process improvement, marketing, industrial engineering, and operations research who are interested in quality dynamics. The state-of-the-art approaches for additive manufacturing include in situ observations and in situ NDE. The focus is on methods that can be used to evaluate a component that is presently being producer’s quality and usefulness. This covers methods for determining temperature or density as well as other physical properties like electrical or thermal conductivity, the microstructure, chemical composition, the actual geometry, or methods for the quick identification of faults like cracks, voids, delamination, or inclusions. As a result, Nakajima [8] presented a way that is suitable for thermographic, acoustic, and electromagnetic data as well as techniques for investigating particle and fume emission.

Due to the scale and complexity of the systems and processes, Quality Assurance (QA) engineers are unable to provide timely manual feedback. A novel architecture for baseline process monitoring, automatic QA constraints verification based on process progress, and developer alerting of unfulfilled QA constraints are presented by Giovanni et al. [9]. Researchers use two different case studies to test their methodology: a community system that is open-sourced and a safety-critical air traffic control system. Following an event, trace connections frequently need to be filled in or adjusted, according to the analysis's conclusions. As a result, prompt and automatic restriction checking help has a significant potential to reduce rework.

Maierhofer et al. [10] explored these issues by increasing resolution of input image capturing sensors. This improvement in resolution resulted in improvement of accuracy. Author focused on hardware compatibility to improve the inspection quality. For testing an alloy of Ti-6Al-4V is manufactured and scanned on the proposed 3D scanner. This result in precise identification of melting pool. Mayr-Dorn et al. [11] created an ontology-based Bayesian network (BN) model that shows relation between quality parameters and quality control properties and proved that this data driven methodology will process robust monitoring and control for AM.

TABLE I. Recent Contribution of Researchers

Ref	Merits	Demerits
[6]	Ease an operator's work and make it more reliable falls under Industry 4.0 focus. This paper concludes that there is not one computer system that dominates the field. On the contrary, many researchers decided to develop their own image based control computer system.	Knowledge of Industry 4.0 needs to be more widespread. Partially automating their overall procedure Knowledge of Industry 4.0 needs to be more widespread. Many software and high resolution cameras are a possible cost issue Objects with reflective surfaces cause problems due to reflected background noise. There needs to be more emphasis on software comparison research which would help companies implement this type of quality inspection system and train employees
[7]	Work flow is well described considering different stages	Complicated setup Integration into workflows across different nodes of the health care system need to be explored Model fail to deal with large datasets of clinical management decisions correlated with clinical data inputs and patient outcomes.
[8]	Reviews two traditional views of service and product qualities. It introduces a platform view, in which co-creation of value is a major concern. Index Terms—dataset diver	Trustworthiness issues considering service and product quality. Discusses general disadvantages of ML and how it will improve, not in depth.
[9]	Literature on dynamic models of product quality is well explained Discusses the various definitions and measures of product quality. Give the reader a vantage point on the state of the art in this area	What are the quality trade-offs emerging when making goods more efficient? How can social media and network get further information about the product quality and consumption experiences? Which strategies and actions based on quality should firms undertake to increase the product desirability?
[10]	Two different case studies; one open source community system and a safety-critical system in the air-traffic control domain were studied in detailed Results from the analysis show that trace links are often corrected or completed after the fact and thus timely and automated constraint checking support has significant potential on reducing rework.	Measures need to be taken to quantify the actual effort reduction and gather qualitative feedback for further improvements. Need to study QA engineers and process engineers during the creation, evolution, and maintenance of process models (including constraints) with ProCon to understand how their task can be supported even better.

IV. METHODOLOGY

Every step of the production or assembly process is where manufacturing operations try to achieve the best quality. More than half of these quality checks involve visual confirmation to make that the components are in the appropriate places, have the proper shape, color, and texture, and are free of any flaws like scratches, pinholes, foreign objects, etc. Due to the volume of inspections and the variety of products, as well as the fact that flaws may appear anywhere on the product and be of any size, automating these visual quality checks is particularly challenging [10]-[13]. There are various ways used in the business to find flaws in manufactured goods.

Manufacturing operations that are repetitive, risky, or need precision can benefit from autonomous systems. AI is used in conjunction with human operators to do tasks such as equipment calibration, robotics controls in assembly facilities, predictive maintenance, and more. To attain autonomous production, cloud computing services are combined with artificial intelligence and machine learning [14], or cyber-physical systems. With the use of wireless, time-sensitive connectivity and sensors, machines in factories using this new manufacturing ecosystem can monitor and observe the entire production process as well as make autonomous decisions that may be decentralized. Faster response times because of such improvements enable systems to communicate almost instantly. In the case of cloud computing, they can also be sent to a central place for analysis and decision-making. A private edge cloud on-site at production locations is another option that is more practical because it lacks both the drawbacks of on-device solutions and the latency challenges of the cloud.

C. Visual Inspection for Quality Assessment

On the one hand, quality control helps manufacturing businesses succeed financially by spotting errors at the very beginning of the production process [6]. The visual inspection can, however, be automated for more accuracy, reproducibility, and ultimately, better quality control. Today, comprehensive automation of quality control systems is advancing quickly because of developments in computer vision and artificial intelligence. The ability of the AI and vision algorithms to evaluate photos makes these automated control systems swiftly and precisely invaluable on the production line. The videos from the production site are recorded by the cameras that were positioned above the conveyor belt. They are sent to the edge cloud's video analytics component. The object inspection system then carries out two tasks: first, it determines whether an object is traveling along the conveyor belt; second, it analyzes the objects by pre-established standards and determines whether the created object has any anomalies.

We discuss the demands that such use cases place on the communication infrastructure as we show a cloud-based visual inspection use case for quality assurance in production sites. One of the main advantages of this strategy is that, as shown in Fig. 2, rather than needing individual dedicated compute units for each of the numerous visual inspection stations at a single production site or set of production sites, these computation-intensive processes can be outsourced to the cloud.

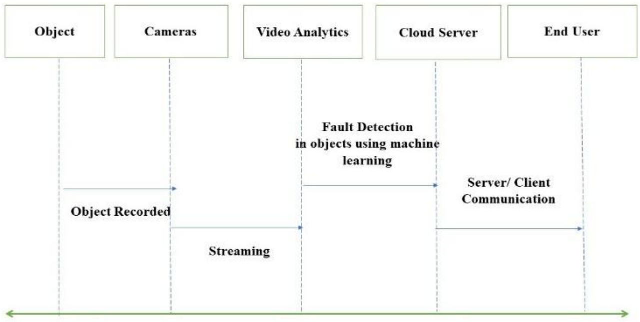

Figure 2: Cloud-based Visual Inspection System [6]

In fig 2, the integration of cloud services are included with AI based quality inspection. With increasing real-time inspection demand, on-premise edge clouds are becoming important for delivering robust, and low-latency computing. As the quality inspection sensors are limited with resources. Therefore, cloud comes as boon for them. The entire captured images or videos captures during inspection are transferred to cloud server for their real-time processing. At cloud server end, the AI integrated detection model will process these high-latency data and send result back to inspection unit. Therefore, cloud serves as backbone for such real-time latency-constraint tasks.

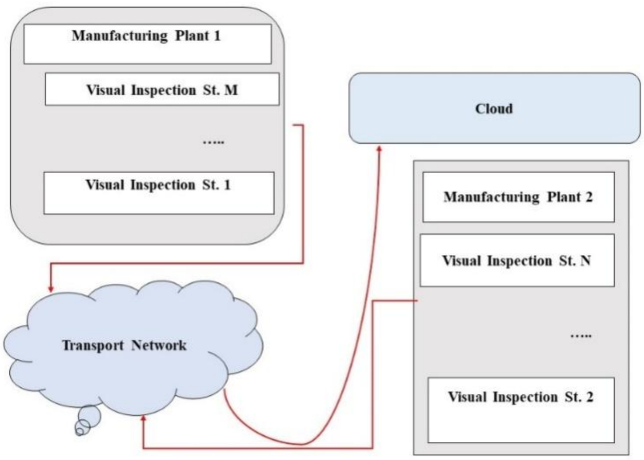

Figure 3: Off-Premises Cloud Concept for Visual Inspection Stations [11]

One of the main advantages of this strategy is that, as shown in Fig. 3, rather than needing individual dedicated compute units for each of the numerous visual inspection stations at a single production site or set of production sites, these computation-intensive processes can be outsourced to the edge cloud.

D. Conceptual Study of Autonomous Quality Control for Core Inspection

The sequential tasks that the autonomous system for core inspection must complete when applied to the inspection are modified by the definitions provided for core perception, fault identification, and decision-making.

- **Core perception:** Using an optical sensor system and an acquisition method, one can perceive the current core. This is accomplished by systematically gathering the products—images, point clouds, or both—from various angles that are pertinent to the inspection task.
- **Defect detection:** Extraction and decision-making preparation of the acquired perception results. This relates to the recognition of recurring quality variations that may affect reusability as well as the identification of the component on which they emerge in the context of remanufacturing. The challenge here is that the quantity and kind of the quality flaws are unknown in advance.

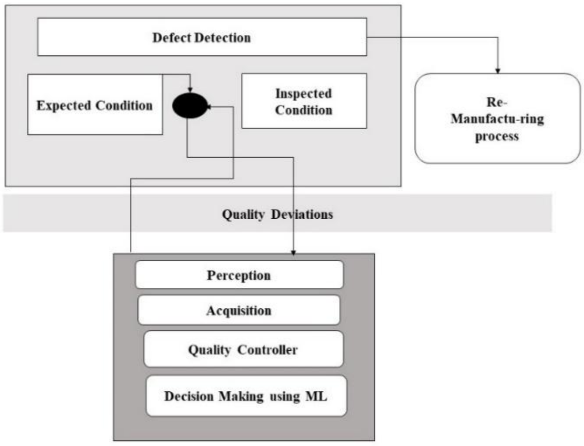

Figure 4: Schematic Visualization of Autonomous Quality Control [15]

Then, as shown in fig 4, these sequential duties can be presented as a quality control issue. An acquisition process detects the returning core. The processed version of the examined core condition may take the form of pictures, point clouds, or even colored point clouds. By examining the collected core data, quality deviations in pictures (such as corrosion) or point clouds (such as missing sections) are found. The quality controller can decide on the core's reusability and quality grade by comparing these quality deviations to an anticipated core condition. The processed version of the examined core condition may take the form of pictures, point clouds, or even colored point clouds. By examining the collected core data, quality deviations in pictures (such as corrosion) or point clouds (such as missing sections) are found. The quality controller can decide on the core's recyclability and quality grade by comparing these quality deviations to an anticipated core condition.

V. RESULT ANALYSIS

This section discusses the implementation details, result analysis, and comparative state-of-art. The designed model is implemented on the Tesla P100-PCIE GPU provided by Google Colab. Keras and TensorFlow are used as a backend for the implementation of the proposed model. This section presents the description of performance evaluation metrics. The result analysis is also presented further which elaborates on the performance of the designed model. This section also presents the comparative state-of-art of the proposed model with existing state-of-art models for quality assurance. In this paper, we have used the data samples of the defective and non-defective casting product images for quality inspection. The dataset is taken from the Kaggle source [16]. The image of the submersible pump impeller among the casting products was utilized as the data set. The inspection model is implemented using pre-trained transfer learning model such as ResNet50. The phrase "Residual Network" can be abbreviated as "ResNet" having 7x7 convolution layer with 64 filters and a stride of 2 is utilized in ResNet50. After that, a softmax layer is added to classify the abnormalities in manufacturing parts. By using transfer learning model, detection accuracy was improved with reduced computational complexity.

The designed model is evaluated on the following matrices:

$$\text{Response Delay (RD)} = |T_{stop} - T_{start}| \quad (1)$$

Where, T_{stop} = stop execution time and T_{start} start execution time.

$$\text{Accuracy} = (\text{TrP} + \text{TrN})/(\text{TrP} + \text{TrN} + \text{FlP} + \text{FlN}) \quad (2)$$

Where, TrP = True Positive (condition when both actual and predicted values are of defective quality).
TrN = True Negative (Condition when both actual and predicted values are of good quality).
FlP= False Positive (Condition, when actual is of bad quality and predicted, is of good quality).
FlN= False Negative (Condition, when actual is of good quality and predicted, is of bad quality).

The result analysis in terms of response time is presented below in table II. In table II, we have evaluated the response delay of the designed model for object detection to its processing over the cloud. The response delay is evaluated in three steps. In the first step, the object is detected from the image and its average response time is approx. 4sec. Then data is uploaded to the cloud server, then its average upload time is approx. 2 sec. And finally, in average defect detection time is evaluated which is approx. 2sec. Therefore, the overall processing time is evaluated as to be approx. 8sec.

TABLE II. Response Delay Evaluation

Tasks Performed	Average Response Delay (in sec)
Object Detection	~4s
Data Uploading	~2s
Detection	~2s
Total Delay	~8s

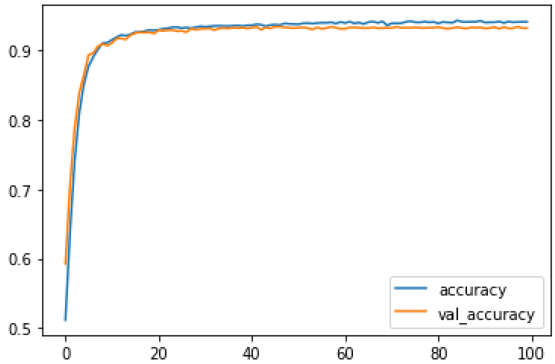

Figure 5: Training and Validation Performance of the Detection Model

Fig 5 shows the training and validation performance of the detection module in terms of the accuracy curve. The model is trained for 100 epochs. The entire dataset is divided into a 70:30 ratio of training and testing samples. The accuracy gets increased and reaches up to 90% after epoch 20 and then gets constant accuracy approx. 93% for training and validation samples. The average accuracy of the detection model is approx. 93%.
Fig 6 shows the comparative analysis of automated quality assurance with existing state-of-art techniques. In [15] author used the CNN model and achieved an accuracy of 86%, and our proposed model has maximum accuracy of 93%. Therefore, it can be inferred that the quality assurance model has achieved more robust results.

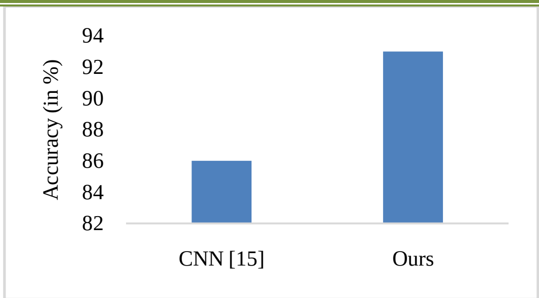

Figure 6: Comparative State-of-Art

VI. CONCLUSION

The complexity of industrial systems has risen because of rising customer expectations and technological advancements. It is necessary to invest in stronger quality control systems, particularly when a tiny manufacturing error could cause the organization to suffer a significant loss. An extensive human team is required for a non-automated quality control system, which raises costs and reduces reliability. This paper provides a methodology of quality control using machine learning and cloud computing for products that display automated behavior as a result. The result analysis is presented in terms of response delay and detection accuracy of the model. From the result, it was observed that the average response delay is approx. 8 sec and average detection accuracy are approx. 93%. In the future, the work will be extended to reduce the response time and can handle noise that may occur during data communication.

References

[1] Narkevich M, Logunova O, Kornienko V, et al. An empirical approach to quality assurance of materials, products and structures in industrial safety. Transp Res Procedia 2022; 63: 119–128.

[2] Zhang M, Tao F, Huang B, et al. A network-based model robustness improvement method for product quality assurance. CIRP Ann 2022; 71: 381–384.

[3] Kornas T, Knak E, Daub R, et al. A Multivariate KPI-Based Method for Quality Assurance in Lithium-Ion-Battery Production. Procedia CIRP 2019; 81: 75–80.

[4] Khanjani A, Sulaiman R. The process of quality assurance under open source software development. Isc 2011 - 2011 IEEE Symp Comput Informatics 2011; 548–552.

[5] Pomante L, Muttillo V, Křena B, et al. The AQUAS ECSEL Project Aggregated Quality Assurance for Systems: Co-Engineering Inside and Across the Product Life Cycle. Microprocess Microsyst 2019; 69: 54–67.

[6] Babic M, Farahani MA, Wuest T. Image Based Quality Inspection in Smart Manufacturing Systems: A Literature Review. Procedia CIRP 2021; 103: 262–267.

[7] Sreedher G, Ho ML, Smith M, et al. Magnetic resonance imaging quality control, quality assurance and quality improvement. Pediatr Radiol 2021; 51: 698–708.

[8] Nakajima S. Quality Assurance of Machine Learning Software. 2018 IEEE 7th Glob Conf Consum Electron GCCE 2018 2018; 143–144.

[9] De Giovanni P, Zaccour G. A survey of dynamic models of product quality. Eur J Oper Res. Epub ahead of print 13 June 2022. DOI: 10.1016/J.EJOR.2022.06.010.

[10] Maierhofer C, Altenburg SJ, Scheuschner N. In Situ Real-Time Monitoring Versus Post NDE for Quality Assurance of Additively Manufactured Metal Parts. Handb Nondestruct Eval 40 2022; 697–733.

[11] Mayr-Dorn C, Vierhauser M, Bichler S, et al. Supporting quality assurance with automated process-centric quality constraints checking. Proc - Int Conf Softw Eng 2021; 1298–1310.

[12] Wang R, Law A, Garcia D, et al. Development of Structured Light 3D-Scanner with High Spatial Resolution and its Applications for Additive Manufacturing Quality Assurance. Int J Adv Manuf Technol. Epub ahead of print 15 April 2021. DOI: 10.21203/RS.3.RS-409368/V1.

[13] Chen R, Lu Y, Witherell P, et al. Ontology-Driven Learning of Bayesian Network for Causal Inference and Quality Assurance in Additive Manufacturing. IEEE Robot Autom Lett 2021; 6: 6032–6038.

[14] Aashish Arora and Rajeev Gupta. A Comparative Study on Application of Artificial Intelligence for Quality Assurance in Manufacturing. 4th International Conference on Inventive Research in Computing Applications (ICIRCA). 2022. DOI: 10.1109/ICIRCA54612.2022. 9985522.

[15] Hasibur Rahman, Md. Omar Faruq, Talha Bin Abdul Hai, Wahidur Rahman, Muhammad Minoar Hossain, Mahbubul Hasan, Shafiqul Islam, Md. Moinuddin, Md. Tarequl Islam, Mir Mohammad Azad,

"IoT enabled mushroom farm automation with Machine Learning to classify toxic mushrooms in Bangladesh", Journal of Agriculture and Food Research, Volume 7, 2022, 100267, ISSN 2666-1543, https://doi.org/10.1016/j.jafr.2021.100267.

[16] S. Oh, J. Cha, D. Kim and J. Jeong, "Quality Inspection of Casting Product Using CAE and CNN," 2020 4th International Conference on Imaging, Signal Processing and Communications (ICISPC), 2020, pp. 34-38, doi: 10.1109/ICISPC51671.2020.00014.

