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Automated Visual Inspection

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Abstract: *In manufacturing, where satisfying increasing customer demands is critical, quality is of the utmost importance for any organization. Evaluating the quality of a product may be tedious and error-prone, even for skilled operators. Though computer vision automates visual evaluation, it provides temporary solutions. The Lean manufacturing method has been created to overcome this. Statistical pattern recognition, image processing, object identification, and other activities are integrated and automated by computer vision, a branch of artificial intelligence. Though computational limitations now restrict its application, it has potential to spread to other domains such as product design, defect diagnostics, automation of manufacturing procedures, and material property identification. In the future, this discipline may hold answers to a myriad of problems thanks to the ongoing advancement of research and development, which includes reinforcement learning*

Keywords: Artificial Intelligence Computer Vision, Reinforcement Learning, Statistical Pattern Recognition

I. INTRODUCTION

A product's success in today's very competitive global market depends on its near-perfect quality. Nowadays, inspection plays a crucial role in the production process with the goal of removing nonconformities and guaranteeing high-quality product. In order to solve problems with conventional techniques, technologically sophisticated inspection equipment has arisen, cutting manufacturing costs and lead times. The establishment of out-of- control restrictions, however, has been put off, which has increased the price of noncompliant goods. Automation has helped a number of sectors overcome the difficulties associated with mass manufacturing, including issues with time, money, quality, and efficiency. It is now commonplace to find automated systems that use image processing for final production quality checking. Computer vision provides useful solutions since i t can automate and combine a variety of tasks, including visual perception. In real-world quality operations,
automated quality inspection improves efficiency and uses less resources. It is accomplished by integrating computer vision with various systems and Internet of Things applications.

II. LITERATURE REVIEW

According to Ce Ge et al.[1],in order to carry out visual inspection, this work is separated into two primary components: graph based image segmentation, which is again subdivided into three steps called : basic proposal grouping, proposal cluster refinement, and sub image generation; second part is shared backbone network and drop score aggregation in which features are extracted for every sub image using the shared backbone network. In addition, recommendation Convolutional
feature maps are predicted to get these ideas. To create object detectors from poorly labelled photos, a proposal- guided segmented aggregation learning system was put forth. To address the recurring problems in current weakly supervised detection systems, two graph-based segmentation algorithms and a drop score regularization scheme are presented. This concept is effective and adaptable for industrial use, as demonstrated by the results of our experiments . This showed that because it involves little manual annotation work, automatically visual inspection based on weakly supervised learning has considerable promise in industrial automation.
According to Joze M.Rozanec et al.[2],in order to get picture embeddings, they employed a feature extractor that was already trained on a ResNet-18 model. They used stratified ten- fold cross-validation, dividing the dataset into a

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training set (75% of remaining instances) and an active learning setting stream of data that simulated unlabeled samples that could be labelled upon request. This allowed them to compare the performance of various streaming machine learning algorithms and evaluate the advantages of a streaming active learning approach. They used the "one- vs- rest" heuristic approach to calculate the AUC ROC measure in order to achieve this . AUC ROC metrics are computed for each class and the final result is summarized as a weighted average taking into account the number of true cases for each class. This process divides the multiclass dataset into numerous binary classification issues using the "one- vs- rest" heuristic.

Poalo Napoletano et al.[3], specified that the suggested approach to anomaly detection was based on a restoration procedure that functions like a filter. It received a picture that could have flaws as input and produces a "cleaned version" of the image, which had all abnormalities filtered away. By limiting the variation among the input picture and its matching " cleaned version," the anomalies' binary mask may be produced. A broad objective the brains behind producing anomaly- free pictures from any input image were CNN autoencoders, which had been trained on a sizable and independent image database. The input picture was reproduced in the other branch without the usage of the normality pass filter in order to strengthen the final image comparison against any artefacts produced by the autoencoder neural network.

S. Ravikumar et al.[4], proposed that this study makes two significant contributions. Initially, the C 4.5 algorithm— which performs feature selection and classification— was used with histogram features. In a subsequent instance, the C4.5 method was employed to identify the salient histogram characteristics, and the Naïve Bayes algorithm was employed to carry out the classification process. A complete analysis and report were produced on the performance of these algorithms for machine learning in the context of visual inspection. Coated with powder metallic plates (mild steel) of the same dimensions and form were obtained under the following circumstances in order to conduct this study:(a) sheet free of flaws and scratches. (b)Sheets having little dings or scrapes.(c) Sheets that have noticeable deep scratches.

Jong Pil Yun et al.[5], stated that two modules make up the suggested defect classification algorithm: one for data production and the other for defect classification. Every flaw is labelled in the visual data that the machine' s vision system has acquired. Using the label data and defect pictures, the VAE- based data generation model is trained. Once sufficient data has been gathered, the generated data is used to teach a deep learning-based categorization model. The label info of the fault data and the classification model's output value are used to train the model in order to minimize the difference. Installing a trained classification model in the inspection system allows it to classify metal surface fault photos in real time.

Prof Vasim Shaikh et al.[6], mentioned that a machine learning or deep learning model is the key component of an automated system for inspecting the quality of products .The camera constantly takes pictures of the component when it is placed on the foundation plate and transmits these pictures to the model. The model has previously undergone extensive training and evaluation on comparable data. As a consequence, after receiving the photos from the camera, the model can accurately anticipate the outcomes. Following an accurate prediction, the PySerial programme transmits the result to the Arduino board. A Python package called PySerial is used to link a Python programme to an Arduino board' s serial ports .The Arduino script is run once the deep learning models' output is sent to the board.

According to Yuntao Tao et al. [7], wrote that the automated defect detection strategy used here is Long- Short term memory Recurrent Neural Network ,modern DL architectures like RNN are made especially for sequencing data forecasting. The main benefit of using a random neural network (RNN) to analyze sequenced signals is that all incoming data is predicated on the previous ones. Sequential signal processing benefits from this as it obtains historical data. The trained model's ability to generalize was tested and verified using planar and trapezoid samples. Initially, trained FFNN and LSTMRNN models were fed raw temperature–time series from the plane and trapezoid CFRP samples. Second, sequenced signals that had undergone TSR- first derivative processing were fed into the FFNN and LSTM-RNN models for training.

Vahid Torkzadh et al.[8], Citation Sample Creation: As a guide, create a flawless sandwich panel that has been approved by a quality supervisor. Take detailed pictures for instruction.

Model Training: Train the system using the reference sample using a machine learning technique, such as a convolutional neural network (CNN). Teach the model to distinguish between typical and unusual traits, such as buckling and dipping.

Automated Detection on Production Line: Integrate the industrial production line with the learned model. Use a basic color camera to take pictures when fresh sandwich panels are made. These photos are automatically analyzed by the system, which then presents the aberrant regions as a labelled image for the quality supervisor to assess. This economical, non-intrusive method guarantees a smooth incorporation into current procedures.

Je-Kang Park et al.[9], used a CNN technique that made use of neural networks with several layers and nodes in order to detect defects. Nodes add up the output of each layer to get a weighted sum; a weight matrix is used to extract features and explain the relationships between the layers. Weights are learned with enough data to enable feature abstractions and selection. High-level features are then retrieved from the output of lower layers. This method outperforms traditional machine learning strategies that need human feature modelling in fault identification during surface inspection by utilizing deep neural network classification. In contrast to conventional techniques, CNN immediately derives feature vectors from the convolution layer, allowing for the use of high-level features and removing the constraints associated with manual modelling.

A Garcia Perez et al.[10], mentioned that image object identification is a computationally demanding process that often entails searching a vast region for various objects of varying sizes and aspect ratios, as well as locating object bounding boxes and suppressing repetitive bounding boxes, among other things there are two methods available to address object detection issues based on either in-two-step detectors or single stage detectors (SSD).Both approaches, nevertheless, employ the same pipeline: given an input image, they produce suggestions or locations where an item may be located. These suggestions can be produced by selective search (depending on shape, texture, etc.), sliding windows, pyramid of photos, or background removal. Following their classification of these areas, a Non Maximum Suppression (NMS) technique is used to get rid of duplicate detections of the same object, which are bounding boxes that overlap the identified object. The best bounding box is defined by this algorithm, and the others are eliminated.

Nazar Hussain et al.[11], stated that a new method for classifying objects is suggested that combines traditional feature selection with deep learning. Three phases make up the method: parallel extraction of classical features, CNN feature extraction with transfer learning, and augmentation. By choosing the best features ahead of fusion, a classifier using labelled data can achieve higher classification accuracy. Automating data augmentation using the Caltech101 dataset is the study's main method for improving deep learning-based object categorization. A approach that is especially used to balance picture amounts across different object types replaces manual augmentation. By flipping operations, variants are created for better CNN training as part of the augmentation process. We extract both CNN-based and classical characteristics. To optimize feature vectors by striking a balance between redundancy and relevance, a new Joint Entropy-KNN technique is presented for feature selection. Refining features iteratively, JE - KNN determines the best-performing subset by calculating their joint entropy. For categorization, the chosen characteristics from CNN and classical vectors are combined. The three main parts of the process are feature extraction, feature selection using JE-KNN, and automated data augmentation. By intelligently choosing the most pertinent characteristics, automating data augmentation, and skillfully mixing classical and deep learning features, this novel method seeks to maximize object categorization accuracy.

Mayank Mishra et al.[12], In This study he mentions a cutting- edge deep learning (DL) fault identification system with an emphasis on applications in civil engineering. YOLOv5, an object identification approach renowned for providing real-time response on low- processing devices, is used to train the model on a dataset. Input, convolutional, pooling, fully interconnected, and output layers are among the layers that make up a convolutional neural network (CNN). The Adam approach optimizes model training by modifying the rate of learning based on weight parameters, while max pooling is used for feature extraction. With a customized model created for flaw identification and robofow online program for picture annotation, the YOLOv5 technique is selected due to its efficiency. The dataset is improved by applying data augmentation techniques including rotation, flipping, and cropping. With a mean average precision (MAP) of 93 .7 %, the model is tested, verified, and trained on a dataset including 10 ,291 pictures. Its real - time fault detecting skills and quickness make the YOLOv 5s model the choice. Google Collab uses its free GPU facilities to apply the technique. Loss function components include localization, confidence, and classification, while performance measurements include recall, accuracy, and mean average precision. Weight decay, learning rate, momentum, and other parameters can all have ideal values chosen through hyperparameter tweaking. The accuracy of the model is then contrasted with a quicker R- CNN-based approach.

Elena Trajkova et al.[13], In this the AUC ROC measure is used in this work to evaluate model performance, and automated defect identification is formulated as a classification with multiple classes issue. Binary classification issues are created by applying the "one-vs- rest" heuristic to the multiclass dataset. K is a square root of the total number of occurrences in the training data set. The ResNet-18 model is used to extract features, and mutual data is used to choose the most important K features. To assess models using different active learning techniques, stratification k-fold cross-validation with k=10 is applied. Comparison is made between three scenarios: pool- based sampling, query-by-committee approach, and stream-based classifier uncertainty sampling. With a p-value of 0.05, the signed-rank Wilcoxon test is used to calculate the averaged AUC ROC for every fold and assess statistical significance.

Voronin V et al.[14], mentioned that Cracks, holes and pores, solids inclusions, form violation, and miscellaneous defects are the five categories into which fabric defect modelling falls under the purview of this work. The combination of the unaltered images and a binary mask designating the damaged regions is how the mathematical model depicts the defective image. The suggested approach makes use of convolutional neural networks for defect classification, fully connected neural networks for precise boundary determination, and morphological filtering for early defect localization. Using multi-scale block- rooting processing, image enhancement combines local and global transformation. Using the "top" and " bottom hats" transformations is morphological filtering. Defect categorization is done with convolutional neural networks, and border delineation is improved by support vector machines. AUC ROC is used to assess the approach, which also makes use of cross-validation and active learning techniques . In the image improvement stage, support vector machines, convolution fully connected neural networks, and morphological filtering are used for multi-scale block- rooting processing, defect classification, boundary determination, and boundary determination.

Lukman E Mansuri et al.[15], stated that using a two-step process, the study creates an automated examination regime. For automated fault identification in photos from Dutch and English cemeteries, Step 1 applies the Faster R-CNN Inception V2 algorithm. Spalling, exposed brickwork, and fractures are among the flaws. Using a web-based inspection system, step two combines the flaw detection system. The system for inspection makes use of an optimized Faster R-CNN model, takes pictures, labels them, and selects a site among heritage structures using a Python script.

Users can submit site pictures for automatic problem identification and inspection report creation in a prototype of the web-based inspection system that showcases realistic implementation. When compared to traditional inspection techniques, the automated system drastically saves both time and personnel needs .The project focuses on using an automated visual assessment method to ensure the sustainability of architectural heritage. Using an annotated dataset of 880 photos with spalling, exposed bricks, and cracks, i t uses a quicker R-CNN Inception V2 deep learning model for automated fault identification. After validation and testing under various settings, the model reaches its maximum detection accuracy (MAP) of 0.915. The diversity of the dataset makes it easier for the model to identify flaws from various viewpoints and experiences. Recognizing the drawback of not having three- dimensional data, future enhancements may include expanding the dataset and optimizing the quicker R-CNN architecture for more precision.

Masoud Jalayer et al.[16], says that strong defect detection is achieved by integrating GP- WGAN and Faster R-CNN in the suggested fault localization technique. Combining R-CNN with Fast R-CNN, Faster R- CNN suggests regions efficiently by using a Region Proposal Network (RPN). An RPN module for region proposal, a Fast R-CNN network for classification, and a layer of convolutional neural networks for feature extraction make up the architecture. Utilizing the Wasserstein distance, the study tackles GAN instability with GP- WGAN. By creating artificial fault samples with GP-WGAN, the framework presents a data augmentation technique. Feature Pyramid Network and Res Net-101 improve the extraction of features and detection accuracy for defect diagnosis. The technique under consideration seeks to enhance flaw detection robustness and surmount dataset constraints all within a single, cohesive framework.

Jian Lian et al.[17], In this part, the suggested Geometry Mask—which is essential to the picture segmentation pipeline—is described. The fully convolutional one-stage object detector (FCOS) is interfaced with by this system, which also includes the geometric attention - guided mask branch (GAG-Mask). The architecture specifics are explained, along with how GAG- Mask and FCOS interact. The research assesses many backbone networks, taking accuracy and executing efficiency into account, in order to determine which is best. Through a thorough understanding

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of Geometry Mask's architecture, FCOS integration, and the performance implications of various backbone networks, this technique seeks to improve picture segmentation.

Dheeraj Dhruva Kumar et al.[18], This paper proposes a unique Multidomain learning network (ST- MDL) based on Semi-supervised Transfer learning. Six traditional U- net-based semantic segmentation models are compared to the ST-MDL's performance. Three layers of analysis are used to choose the optimal model: (1) comparison of test metric scores; (2) graphical analysis of metrics vs. epochs plots; and (3) visual study of segmentation outputs. The outcomes demonstrated that every model produced satisfactory results and was able to identify and categorize various areas within a weld picture.

Zhenyu Liu et al.[19], He states the important improvements to the Truing Det detection of defects pipeline include a balanced feature pyramids for information flow across scales, flexible convolution for adaptable sampling, and a cascade head module for fine-tuned localization. To mitigate irregular faults, sample zones are adjusted using deformable convolution depending on expected offsets. Beyond FPN, the balanced feature pyramid modules incorporates multi- layer defect information. By gradually improving bounding boxes, the cascade head lessens the rigid IOU threshold restriction. These enhancements improve the accuracy of defect identification when compared to Faster RCNN. The pipeline optimizes the defect detecting framework by combining the balanced feature pyramid, cascade head, and deformable convolution modules.

LITERATURE SUMMARY

Sr No.	Citation	Year	Methodology/ Algorithms used	Observation
1	Je- Kang Park , Bae- Keun Kwon, Jun- Hyub Park, and Dong - Joong Kang	2019	Employed Convolutional Neural Network (CNN) for automated visual inspection of surface defects	Efficient defect detection using CNN
2	Lukman E. Mansuri and D. A. Patel	2020	Developed an automatic defect detection system for built heritage using the Faster R- CNN model. Algorithm: Utilized object detection to achieve 91 . 58 % accuracy in detecting spalling	Innovative AI- based visual inspection enhances heritage preservation
3	Nazar Hussain, Muhammad Attique Khan, Muhammad Sharif, Sajid Ali Khan, Abdulaziz A. Albesher , Tanzila Saba & Ammar Armaghan	2020	Introducing an automated object classification method in Computer Vision	Innovative fusion of classical and deep learning features
4	Zhenyu Liu, Ruining Tang, Guifang Duan, Jianrong Tan	2020	Employed a CNN- based defect detection framework with deformable convolution	Innovative CNN framework with deformable convolution excels in defect detection
5	A. García Pérez, M. J. Gómez Silva and A. dela Escalera Hueso	2021	Introduced an automated defect recognition (ADR) system using a convolutional neural network (CNN) for industrial X- ray analysis. Algorithm: Achieved a 0.942 m AP on the GDXray dataset, ensuring quick and reliable defect classification in production environments.	ADR system enhances X- ray analysis, achieving human- level performance on defect classification with quick inference time for industrial applications.
6	Elena Trajkova, Jože M. Rožanec,	2021	Employed three active learning	AI- driven defect

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	Paulien Dam, Blaž Fortuna and Dunja Mladenić		approaches and five machine learning algorithms for visual defect inspection. Algorithm: Achieved efficient defect inspection using AI, demonstrating reduced labeling effort without compromising model performance.	inspection, combining active learning and machine learning, proves effective, reducing labeling effort without compromising performance.
7	Ivan Kuric , Jaromír Klarák , Milan Sága , Miroslav Císar, Adrián Hajdu and Dariusz Wiecek	2021	Developed a tire inspection system using unsupervised clustering with laser sensor data and VGG- 16 neural network for defect classification. Algorithm: Applied polar transform and polynomial regression for camera data processing, enhancing tire surface inspection accuracy.	Efficient tire inspection system combines unsupervised clustering and VGG-16, enhancing defect detection accuracy for both trained and untrained abnormalities.
8	Ivan Kuric , Jaromír Klarák , Vladimír Bulej , Milan Sága, Matej Kandera , Adrián Hajdu and Karol Tucki	2021	Applied Transfer Learning with Alex Net, modifying its last three layers for tire surface defect detection. Algorithm: Enhanced object detection accuracy through neural network adaptation.	Effective Transfer Learning with modified Alex Net enhances tire defect detection, achieving high certainty in successful detection from 85.15% to 99.34%.
9	Jian Liana, Letian Wang, Tianyu Liud, Xia Ding, Zhiguo Yu	2021	Developed a deep learning-based approach with a geometric attention- guided mask branch for instance segmentation in printed circuit board images. Algorithm: Integrated the mask branch into a Mask R- CNN framework, enhancing identification accuracy and outperforming s tate- of- the-art techniques.	Novel deep learning approach excels in printed circuit board instance segmentation, outperforming s tate- of- the- art techniques in precision, sensitivity, and accuracy.
10	Masoud Jalayer, Reza Jalayer, Amin Kaboli, Carlotta Orsenigo and Carlo Vercellis	2021	Proposed two- stage fault diagnosis for Automatic Visual Inspection (AVI) systems using a sample generation model and improved deep learning architecture. Algorithm: Augmentation algorithm blends real samples, and a Faster R-CNN, FPN, and Residual Network- based architecture performs object detection, demonstrating superior performance.	Novel AVI fault diagnosis excels with a two- staged framework, blending real samples and utilizing an advanced deep learning architecture.
11	Voronin, V., Sizyakin, R.,	2021	Utilized a two- s tage approach	Effective fabric defect

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	Zhdanova, M., Semenishchev, E. and Bezuglov, D		combining block- based alpha- rooting image enhancement and a modern neural network for fabric defect detection. Algorithm: Implemented a novel local and global transform domain- based enhancement and a neural network for accurate detection.	detection: Two- s tage approach blends alpha- rooting image enhancement and a modern neural network, outperforming traditional methods.
12	Xiaoqing Zheng, Song Zheng, Yaguang Kong & J ie Chen	2021	Reviewed prior literature and recent AVI- related hardware/ software, analyzed traditional surface defect inspection methods, and explored deep learning- based algorithms. Algorithm: Investigated and presented recent advancements in deep learning for surface inspection across semiconductor, s teel, and fabric industries.	Thorough review of surface defect inspection methods, highlighting deep learning advancements; valuable insights for industrial quality enhancement.
13	Ioannis D Apostolopoulos , Mpesiana A Tzani	2022	Utilized six industrial image datasets, proposing Multipath VGG 19 for defect detection and object recognition. Algorithm: Enhanced VGG 19 with multi- level feature extraction for superior classification performance, achieving a 6.95 % average improvement over baseline methods.	Multipath VGG 19 demonstrates remarkable effectiveness, achieving top performance and improved s tability, outperforming baseline state- of- the- art CNNs by 6 . 95 %.
14	Ivan Kuric , Jaromír Klarák , Vladimír Bulej 1 , Milan Sága , Matej Kandera , Adrián Hajduˇ and Karol Tucki	2022	Employed Transfer Learning with modified Alex Net in a camera inspection system for car t ire defect detection. Algorithm: Utilized a pre - trained CNN adapted to specific defect classes, achieving high detection certainty	Effective Transfer Learning with Alex Net enhances car t ire defect detection, achieving high certainty from 85 . 15 % to 99 . 34 %.
15	Yuntao Tao , Caiqi Hu, Hai Zhang, Ahmad Osman, Clemente Ibarra - Castanedo, Qiang Fang, Stefano Sfarra, Xiaobiao Dai, Xavier Maldague, Yuxia Duan	2022	Employed recurrent neural network and artificial feed- forward neural network for pulsed thermography in non -planar object inspection. Algorithm: Utilized t ime series data and sequenced signals for training; long short- term memory recurrent neural network outperformed artificial feed-	Effective application of recurrent neural network in pulsed thermography for non- planar object inspection; outperformed artificial feed- forward neural network in accuracy.

			forward neural network.	
16	Dheeraj Dhruva Kumar , Cheng Fang, Yue Zheng , Yuqing Gao	2022	Developed a Semi- supervised Transfer Learning based Multi-domain Learning (ST-MDL) network for weld image segmentation. Algorithm: Employed U-net architecture and proposed ST- MDL for automated weld visual inspection with precise defect identification.	Innovative ST- MDL network automates weld image segmentation, achieving precise defect identification in a fully automated visual inspection framework.

III. CONCLUSION

To conclude, the importance of inspection in guaranteeing almost flawless quality in production is currently being addressed by cutting - edge technical solutions. Automated quality inspection has greatly increased productivity and decreased production costs as compared to labor-intensive, conventional approaches. Automation makes it possible to spot flaws in real time, which simplifies issues with time, money, and quality in mass manufacturing. This is especially true when using computer vision and adaptive system integration. Using automated image processing systems demonstrates a transformational strategy that reduces trash and rework costs while improving overall product quality. Acquiring automated quality inspection becomes strategically imperative for enterprises hoping to produce high- quality goods quickly in the very competitive worldwide market.

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