AI Intelligent learning for Manufacturing Automation

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Abstract: **The garment industry is experiencing a transformative shift by integrating intelligent learning technologies, including machine learning (ML) and deep learning. This applied research with case study examines the application of Convolutional Neural Networks (CNNs) for automating quality control in garment manufacturing, specifically focusing on the detection of sewing lines in captured images. Manufacturers can enhance efficiency, improve product quality, and reduce operational costs by utilizing advanced data analytics and image processing techniques. The CNN model is trained to identify unique features of sewing lines, allowing for real-time comparisons between machine outputs and standard benchmarks. This intelligent learning approach not only streamlines the inspection process but also enables predictive maintenance and data-driven decision-making, fostering adaptability to market demands. The findings highlight the potential of AI-driven solutions to replace manual inspections, ultimately driving innovation and sustainability in garment production. As the industry evolves, embracing intelligent learning technologies will be crucial for manufacturers seeking to maintain a competitive edge in an increasingly dynamic marketplace. This research underscores the importance of preparing high-quality training data to optimize CNN performance and ensure effective garment quality control.**

Keywords: **Artificial Intelligence, AI, Automation, Convolutional Neural Networks, Machine Learning, Garment Manufacturing, Quality Control.**

I. INTRODUCTION

The manufacturing industry is undergoing a profound transformation driven by the integration of intelligent learning technologies. As global competition intensifies and consumer demands evolve, manufacturers are increasingly turning to automation and artificial intelligence (AI) to enhance productivity, improve quality, and reduce operational costs. Intelligent learning, which encompasses machine learning (ML), deep learning, and advanced data analytics, is at the forefront of this revolution, enabling manufacturers to optimize processes, predict maintenance needs, and adapt to changing market conditions. Intelligent learning for manufacturing automation is poised to revolutionize the garment industry, offering solutions that enhance efficiency, quality, and responsiveness to market demands. Prof. Dr. Ray Wai Man Kong et al.'s [1] contributions to this field provide valuable insights into the practical applications of intelligent learning technologies in garment manufacturing. By embracing these advancements, manufacturers can not only improve their operational performance but also position themselves for success in an increasingly competitive and dynamic market. As the industry continues to evolve, the integration of intelligent learning will be crucial for driving innovation and sustainability in garment production.

The garment industry, like many sectors of manufacturing, is experiencing a significant transformation driven by the integration of intelligent learning technologies. As the demand for efficiency, quality, and responsiveness to market trends increases, manufacturers are turning to advanced automation solutions that leverage artificial intelligence (AI) and machine learning (ML). Prof. Dr Ray Wai Man Kong et al.[1], a prominent figure in the field of garment manufacturing has contributed valuable insights into how intelligent learning can enhance manufacturing processes, particularly in the context of the garment industry.

A. The Need for Intelligent Learning in Manufacturing

Manufacturing environments are characterized by complexity, variability, and the need for precision. Traditional manufacturing processes often rely on manual labour and fixed automation, which can lead to inefficiencies, high error rates, and limited scalability. As manufacturers strive to meet the challenges of Industry 4.0—characterized by smart factories, interconnected systems, and real-time data exchange—intelligent learning technologies offer a pathway to greater efficiency and innovation. Key Components of Intelligent Learning are shown the following:

i. Machine Learning (ML):

Machine learning algorithms analyze historical data to identify patterns and make predictions. In manufacturing, ML can be applied to various areas, including quality control, demand forecasting, and supply chain optimization. By learning from past performance, ML models can help manufacturers make data-driven decisions that enhance operational efficiency.

ii. Deep Learning:

A subset of machine learning, deep learning utilizes neural networks to process vast amounts of data. This technology is particularly effective in image and speech recognition, making it valuable for applications such as defect detection in visual inspections and predictive maintenance through audio analysis of machinery.

iii. Data Analytics:

Advanced data analytics tools enable manufacturers to extract actionable insights from large datasets generated by production processes. By leveraging real-time data, manufacturers can monitor performance, identify bottlenecks, and implement continuous improvement initiatives.

iv. Internet of Things (IoT):

The IoT connects machines, sensors, and devices within the manufacturing environment, facilitating the collection and exchange of data. Intelligent learning algorithms can analyze this data to optimize machine performance, predict failures, and enhance overall equipment effectiveness (OEE).

B. Benefits of Intelligent Learning in Manufacturing Automation

Intelligent Learning in manufacturing automation is the trend of automation, manufacturing modernization to mix with digital modernization. The technology of intelligent learning is a soft technique which relates to computing engineering, system engineering and software. Technical automatic machinery is a hard technique which relates to mechanical engineering, electrical engineering and electronic engineering for the design of machines in mechanical parts for machinery, mechanisms, and electrical control and electricity circuits with the user interface.

The benefits of Intelligent learning can provide more benefits for controlling an automatic machine to perform more manufacturing excellence and output as shown following points.

(a) Enhanced Efficiency:

Intelligent learning systems can optimize production schedules, reduce downtime, and streamline workflows, leading to increased throughput and reduced operational costs. Based on the Mixed-Integer Linear Programming (MILP) for Garment Line Balancing from Prof. Dr. Ray Wai Man Kong et al. [2], it can optimize production planning and scheduling to enhance efficiency. The rule of intelligent learning can provide the decision-making algorithm for selecting the appropriate machinery and workstation to add the constraints in the algorithm of mixed-integer linear programming.

(b) Improved Quality:

By leveraging real-time data and predictive analytics, manufacturers can identify quality issues early in the production process, minimizing defects and ensuring consistent product quality. The visual streaming technology can use the camera to record the manufacturing products to determine the variation of output. Users can justify the output whether pass, marginal pass or fail to the system. The system can use the gradient boosting algorithm of machine learning in the gradient boosting regression to ensemble model that combines several weak learners to make a robust predictive model. It can be applied for the automation in quality control to improve quality.

(c) Predictive Maintenance:

Intelligent learning algorithms can analyze equipment performance data to predict when maintenance is needed, reducing unplanned downtime and extending the lifespan of machinery. The logistic regression algorithm deals with discrete values whereas the linear regression algorithm handles predictions with continuous values. So, logistic regression is suited for binary classification, wherein if an event occurs, it is classified as 1 and if not, it is classified as 0. Hence, the probability of a particular event occurrence is predicted based on the given predictor variables.

The equipment performance data can be stored in the database for the data model of the intelligent learning process. The logistic regression algorithm in intelligent learning can find a variation of data and then alert users for predictive maintenance before the machinery is down.

(d) Flexibility and Adaptability:

Intelligent learning enables manufacturers to quickly adapt to changing market demands and production requirements, allowing for more agile manufacturing processes. The linear regression algorithm in intelligent learning can find out the relationship between an independent and a dependent variable. It demonstrates the impact on the dependent variable when the independent variable is changed in any way. So, the independent variable is called the explanatory variable, and the dependent variable is called the factor of interest. The predicting forecast can refer to various factors. It can collect a dataset of order quantity, style, and product with known sale prices, including features such as size and colour as the appearance of outlook, selling quantity and season of the property.

Intelligent learning uses the data model to determine which features of products, colours and styles might influence the price of products.

Intelligent learning uses the dataset to train the model, finding the best-fitting line (linear equation) that minimizes the difference between predicted and actual prices.

It uses the trained model to predict prices for new product series and products, styles and models based on their features. It tests the model on a separate set of products with known prices to assess its accuracy.

Using the Linear Regression Algorithm of intelligent learning, the system can effectively estimate prices providing valuable insights for buyers and sellers.

Intelligent learning can help manufacturers quickly adapt to changing market trends and adjust production requirements increasing flexibility and adaptability.

(e) Data-Driven Decision Making:

By providing actionable insights from data analysis, intelligent learning empowers manufacturers to make informed decisions that drive continuous improvement and innovation. Decisions are very much informed by the human emotional state since this is what emotions are designed to do. Emotions quickly condense an experience, and evaluate it to inform our decision, so we can rapidly respond to the situation. While emotions serve to direct us, they are driven by our automatic survival nature. Human decisions not only rely on the data but also involve the preference experience. The data-driven decision tree is the intelligent algorithm as the supervised learning algorithm

for both classification and regression problems. Decision trees divide data sets into different subsets using a series of questions or conditions that determine which subset each data element belongs in. When mapped out, data appears to be divided into branches, hence the use of the word tree. It can make actionable insights from data analysis; intelligent learning can empower manufacturers in related manufacturing decisions.

Intelligent learning for manufacturing automation represents a paradigm shift in how manufacturers operate and compete in the global marketplace. By harnessing the power of machine learning, deep learning, and advanced data analytics, manufacturers can optimize their processes, enhance product quality, and respond swiftly to market changes. As the industry continues to evolve, the adoption of intelligent learning technologies will be crucial for manufacturers seeking to achieve operational excellence and maintain a competitive edge in an increasingly complex and dynamic environment. Embracing these advancements not only paves the way for greater efficiency but also fosters a culture of innovation that is essential for long-term success in the manufacturing sector.

II. LITERATURE REVIEWS

Intelligent learning, particularly through machine learning (ML), has emerged as a transformative force in various industries, including manufacturing. This literature review explores the key concepts, applications, and advancements in intelligent learning and machine learning, focusing on their implications for manufacturing processes, particularly in sectors like garment manufacturing.

1. Conceptual Framework of Intelligent Learning and Machine Learning

Intelligent learning refers to systems that can learn from data, adapt to new inputs, and perform tasks that typically require human intelligence. Machine learning, a subset of artificial intelligence (AI), involves algorithms that enable computers to learn from and make predictions based on data.

(a) Supervised Learning:

Involves training a model on labelled data, where the desired output is known. Common applications include classification and regression tasks from Olawoye et al [3].

(b) Unsupervised Learning:

Involves training a model on unlabelled data to identify patterns or groupings. Applications include clustering and anomaly detection from İbrahim Yazici et al [4].

(c) Reinforcement Learning:

Involves training an agent to make decisions by rewarding desired actions and penalizing undesired ones, often used in robotics and automation by Rachna Vaish et al [5].

2. Applications in Manufacturing

The application of intelligent learning and machine learning in manufacturing has been extensively documented in the literature. Machine learning algorithms are used to analyze production data and detect defects in real time. Studies have shown that computer vision systems powered by deep learning can significantly improve defect detection rates (Zhang et al., 2020) [6]. Research indicates that machine learning models can predict equipment failures by analyzing historical maintenance data and sensor readings. This proactive approach reduces downtime and maintenance costs (Lee et al., 2014) [7]. Intelligent learning techniques are employed to enhance demand forecasting and inventory management. Machine learning models can analyze historical sales data and external factors to improve accuracy in demand predictions (Choi et al., 2021) [8].

Machine learning algorithms can optimize manufacturing processes by analyzing data from production lines to identify inefficiencies and suggest improvements (Kumar et al., 2019) [9]. Despite the promising applications of intelligent learning and machine learning in manufacturing. The concern of data quality and availability is how the effectiveness of machine learning models is heavily dependent on the quality and quantity of data. Inconsistent or incomplete data can lead to inaccurate predictions (Wang et al., 2018)[10].

Integration with Legacy Systems is that many manufacturing facilities still rely on legacy systems that may not be compatible with modern machine learning technologies. Integrating new solutions with existing infrastructure can be complex and costly (Bai et al., 2020)[11].

Skill Gap is often a lack of skilled personnel who can effectively implement and manage machine learning systems in manufacturing settings. This skills gap can hinder the adoption of intelligent learning technologies (Kamble et al., 2020)[12].

The literature suggests several future directions for research and application of intelligent learning and machine learning in manufacturing about explainable AI, Real-Time analytics and sustainability. As machine learning models become more complex, there is a growing need for transparency and interpretability in AI decision-making processes. Research into explainable AI can help stakeholders understand and trust machine learning outcomes (Doshi-Velez & Kim, 2017) [13].

The real-time analytics integration of real-time data analytics with machine learning can enhance decision-making processes in manufacturing. Future research may focus on developing systems that can analyze data in real time and provide actionable insights (Zhao et al., 2021) [14]. There is an increasing emphasis on using intelligent learning technologies to promote sustainable manufacturing practices as sustainability. The research from Khan et al., in 2021 can explore how machine learning can optimize resource use, reduce waste, and improve energy efficiency.

From Nurpeisova A.[15], Convolutional Neural Networks (CNNs) are the most used type of deep learning method for face recognition. The main advantage of the deep learning method is that you can use a large amount of data for training to get a reliable idea of the changes in the training data. This method does not require the development of specific characteristics that are robust to various types of class differences (such as lighting, posture, facial expression, age, etc.) but can be extracted from the training data. The main disadvantage of deep learning methods is that they need to use very large datasets to train, and these datasets must contain enough changes to be able to generalize to patterns that have never been seen before. Some large-scale face datasets containing images of natural faces have been made public and can be used to train CNN models. In addition to learning recognition features, neural networks can also reduce dimensionality and can be trained with classifiers or use metric learning methods.

Intelligent learning and machine learning are reshaping the landscape of manufacturing, offering innovative solutions to enhance efficiency, quality, and adaptability. While significant progress has been made in applying these technologies, challenges related to data quality, integration, and skill gaps remain. Future research should focus on addressing these challenges and exploring new applications, particularly in the context of sustainability and real-time analytics. As the manufacturing sector continues to evolve, the integration of intelligent learning will be crucial for driving innovation and maintaining competitiveness.

III. IMAGE RECOGNITION FOR INTELLIGENT LEARNING

Image recognition is a crucial technique to improve the speed of tedious tasks and process images more accurately than manual image inspection. Image recognition is the main driver in deep learning applications as follows:

(1) Visual Inspection for manufacturing:

Identifying garments, products and work-in-progress as defective or non-defective in manufacturing can quickly inspect thousands of parts on an assembly line or workshop.

(2) Image Classification:

The camera can capture the image for categorizing images and verifying the content of the image. It is especially useful in automation such as image retrieval and systems for manufacturing automation.

(3) Automated Driving:

The ability to recognize an image is crucial to autonomous driving applications for machinery in automation.

(4) Robotics:

Image recognition can be used by robots and automated machines to identify objects and enhance autonomous navigation by identifying locations, garments, products, works in progress or objects.

Referring to the Image Recognition Using Machine Learning from MathWorks (MathWorks, Inc.), the image can be captured by the high precision and speed camera. The image can be captured for image recognition as shown below Fig.1.

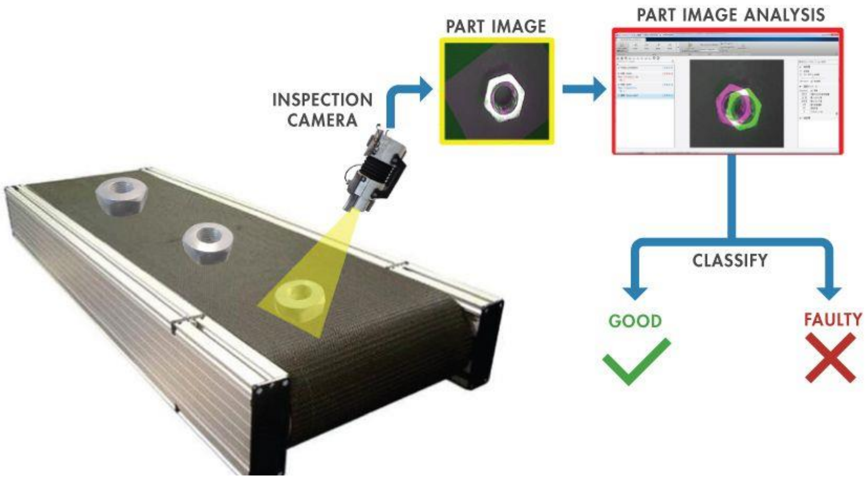

Figure 1: Image recognition in a visual inspection application for part defects

The screen can be captured for image recognition and the core technology is at the centre of these applications. It identifies objects or scenes in images and uses that information to make decisions as part of a larger system. Image recognition is helping these systems become more aware, essentially enabling better decisions by providing insight into the system. Referring to the deep learning approach can apply to image recognition; it involves the use of a convolutional neural network to automatically learn relevant features from sample images and automatically identify those features in new images.

The case study of visual recognition has applied image recognition to intelligent learning. It shows the image captured from the camera to the visual recognition system. It creates a Deep Learning Model for intelligent learning. While the development engineer can build a deep learning model from scratch, it may be best to start with a pre-trained model that applies the application.

From Nurpeisova A. et al., the mathematical program is applied to the CNN a block for constructing an object recognition model (search for the coordinates of a person's surface in a figure, determining the information zonal location, preprocessing and normalization; the object recognition authentication block (authentication algorithms for an object to be identified by controlling access to the photo recognition system of a user registered in the database); a block for calculating information identification marks (convolutional neural networks, correlation indicators, Minkowski distance, etc.).

The mathematical model of face recognition is presented below. Let us define a set of sewing line images in the database $X_1, X_2, X_3 \dots\ X_n$. The sets are divided into n classes, where each class corresponds to a sewing line in Fig. 2. For each image, we define a vector of k values:

$$\mu = \left(\mu_{1,}\mu_{2,}\mu_3 \dots\dots \mu_k\right)^{\tau} \tag{1}$$

where τ is the transpose operator. For the formula (1), the distance function is defined as $d(\mu_1, \mu_n)$ for the feature vector at the greatest distance μ in the input object belongs to the class X_n.

$$d(\mu_l, \mu_n) > d(\mu_j, \mu_n), l \neq j, j = 0,1,2, \dots\dots n-1 \tag{2}$$

For the formula (2), the class X_n must exceed a pre-computed threshold value $d(\mu_l, \mu_n) > \tau c$. The input to the image of the sewing line recognition algorithm is an image, and the output is a sequence of image frame coordinates (0 sewing line frames,1 sewing line frame or multiple face frames). The conventional sewing line in garment piece detection algorithm is a "scanning" and "distinguishing" process, that is, the algorithm scans a range of images and then determines in turn whether an image area is a sewing line. The input to the sewing line registration algorithm is a standard image, and the output is a sequence of coordinates of the key points of sewing line features. The determination of scanning and distinguishing methods are the same as image recognition from Nurpeisova A. et al.

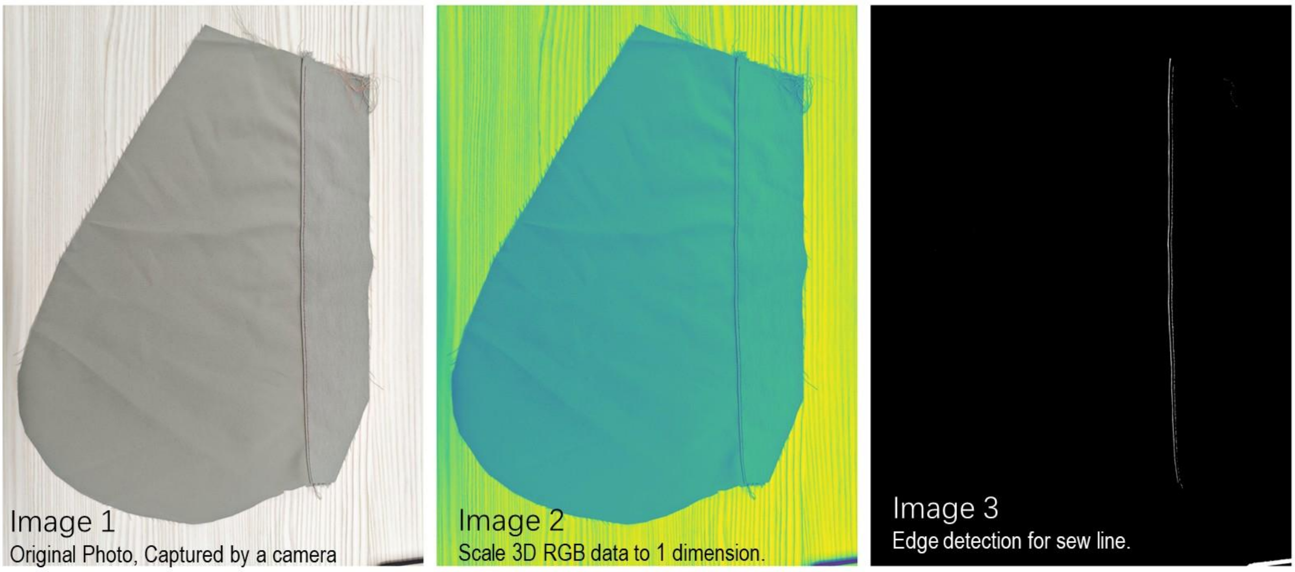

Figure 2: Image recognition photo and proceeding image

The image is being processed for image recognition in the calculation for scanning and distinguishing the vector and related location. The first image is captured by the camera. The second image applies Python Numpy's asarray function to calculate the array of the colour figures to sum the array with the axis 2 parameters. The numpy.asarray() function in Python is an integral part of the Numpy library, used extensively for converting various input data types like lists, tuples, and other array-like objects into a Numpy ndarray. This function is crucial for ensuring compatibility and efficient handling of mathematical operations in data analysis and scientific computing.

In this program of case study, it utilizes the numpy.asarray() function to convert different data types into Numpy arrays. Additionally, the program understands the subtleties of its behaviour when dealing with inputs that are already Numpy arrays and how it differs from similar functions like numpy.array() in Fig. 3.

Part of the Python program is shown below followings:

C: > Users > RayKong > Documents > Image Process.py

```
from PIL import Image
from numpy import *
from matplotlib.pyplot import *
img = asarray(Image.open('fabric.jpg'))
img_bw = sum(img, axis=2)

figure(figsize=[15, 7])
subplot(131)
imshow(img)
axis('off')
subplot(132)
imshow(img_bw)
axis('off')
subplot(133)
imshow(img_bw > 220, cmap='Greys')
axis('off')
tight_layout()
savefig('temp.pdf')
show()
pause(1e-5)
```

Figure 3: Image recognition photo and proceeding image

The array of captured images has been summed with axis 2 in the Numpy function. The imshow function in the matplotlib.pyplot.imshow(img, cmap='gray) displays a white image as a black colour. The sewing line in the garment part can be shown the sewing line.

The image of the sewing line in an array can be compared between the output of the garment from machinery and the standard part. The image data are presented to the network and passed through the network layers. The first step in a Convolutional Neural Network (CNN) is to detect and investigate the unique features and structures of the objects to be differentiated. Filter matrices are used for this. Once a neural network such as Fig. 3 has been modelled by a programmer, these filter matrices are initially still undetermined and the network at this stage is still unable to detect patterns and objects in Fig. 2.

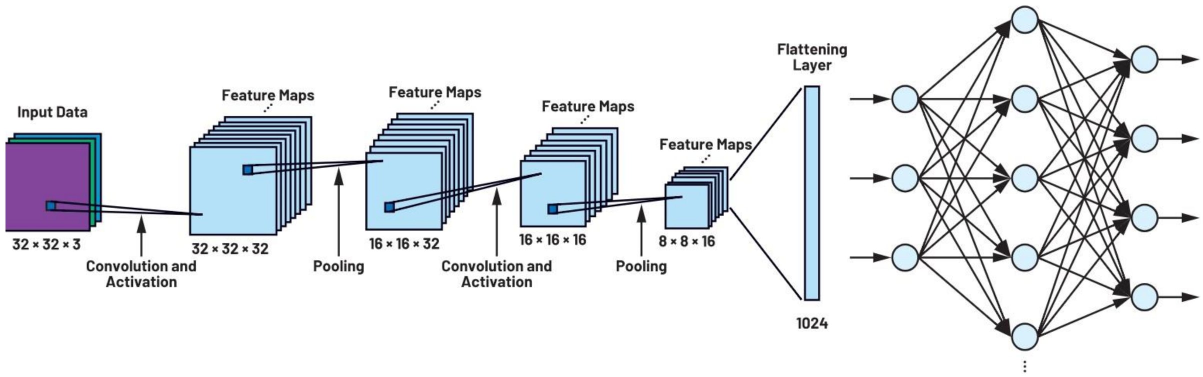

Figure 4: Convolutional Neural Network schematic diagram

The captured image has been determined by all parameters and elements of the matrices to maximize the accuracy with which objects are detected or to minimize the loss feature. This CNN process is known as neural network training for intelligent learning as shown in the schematic diagram in Fig. 4 the Training of Convolutional Neural Networks from Ole Dreessen [16]. For the application of image recognition in the garment industry, the networks are trained once during development and testing. After that, the model has been trained for use and the parameters no longer need to be adjusted. If the system is classifying familiar objects, no additional training is necessary. Training is only necessary when the system is required to classify completely new objects.

Training data is required to train a network, and later, a similar set of data is used to test the accuracy of the network. In the Fig. 2 dataset, for the case study, the data are the set of images within the object classes to determine the edge of sewing line and then compare the standard image to which acceptable sewing line. The most complicated part of the overall development of an AI application is learnt the marginal pass image of these images of sewing garments before training a CNN. It means that our garment quality controller should prepare the pass sample of the sewing line in the garment to capture the images.

The application of Garment Recognition with intelligent learning is following the CNN to develop the checking system to replace the manual checking of workmanship.

IV. CONCLUSION

Prof. Dr. Ray Wai Man Kong et al. has published extensively on various aspects of the garment industry, focusing on the intersection of technology, efficiency, and sustainability. His research often explores how intelligent learning and automation can address the unique challenges faced by garment manufacturers. Key contributions include:

Innovative Solutions: Prof. Dr. Ray Wai Man Kong [17] [18] [19] [20] [21] [22] [23] has advocated for the adoption of innovative technologies, automation and automatic machinery design for the garment industry which can apply the above intelligent learning technology and its image recognition system with AI, to enhance productivity and quality in garment manufacturing. His work highlights case studies and practical applications that demonstrate the effectiveness of these technologies.

Sustainability Initiatives: Recognizing the environmental impact of the garment industry, Prof. Ray Wai Man emphasizes the role of intelligent learning in promoting sustainable practices. By optimizing resource use and reducing waste, manufacturers can achieve both economic and environmental benefits.

Educational Outreach: Through his publications and academic initiatives, Prof. Dr. Ray Wai Man aims to educate industry stakeholders about the potential of intelligent learning technologies. His efforts contribute to a broader understanding of how these advancements can reshape the future of garment manufacturing.

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REFERENCES

[1] Kong, R. W. M., Ning, D., & Kong, T. H. T. (2025). Line Balancing in the Modern Garment Industry. International Journal of Mechanical and Industrial Technology, 12(2), 60-72. https://doi.org/10.5281/zenodo.14800724

[2] Kong, R. W. M., Ning, D., & Kong, T. H. T. (2025). Mixed-Integer Linear Programming (MILP) for Garment Line Balancing. International Journal of Scientific Research and Modern Technology (IJSRMT), 4(2), 64-77. https://doi.org/10.5281/zenodo.14942910

[3] Olawoye, Babatunde & Fagbohun, Oladapo & Popoola-Akinola, Oyekemi & Akinsola, J E T & Akanbi, Charles. (2024). A supervised machine learning approach for the prediction of antioxidant activities of Amaranthus viridis seed. Heliyon. 10. https://doi.org/10.1016/j.heliyon.2024.e24506

[4] İbrahim Yazici, Ibraheem Shayea, Jafri Din (2023), A survey of applications of artificial intelligence and machine learning in future mobile networks-enabled systems, Engineering Science and Technology, an International Journal, Volume 44, 2023, ISSN 2215-0986, https://doi.org/10.1016/j.jestch.2023.101455

[5] Rachna Vaish, U.D. Dwivedi, Saurabh Tewari, S.M. Tripathi (2021), Machine learning applications in power system fault diagnosis: Research advancements and perspectives, Engineering Applications of Artificial Intelligence, Volume 106, 2021, 104504, ISSN 0952-1976, https://doi.org/10.1016/j.engappai.2021.104504

[6] Zhang, Y., Wang, Y., & Liu, Y. (2020). A deep learning approach for defect detection in garment manufacturing. Journal of Manufacturing Processes, 57, 1-10.

[7] Lee, J., Kao, H. A., & Yang, S. (2014). Service innovation and smart analytics for Industry 4.0 and big data. Procedia CIRP, 16, 3-8.

[8] Choi, T. M., Cheng, T. C. E., & Zhao, X. (2021). Machine learning in supply chain management: A review and future directions. International Journal of Production Research, 59(1), 1-20.

[9] Kumar, A., Singh, R. K., & Singh, S. (2019). Machine learning in manufacturing: A review. Journal of Manufacturing Systems, 51, 1-12.

[10] Wang, Y., Gunasekaran, A., & Ngai, E. W. T. (2018). Big data in logistics and supply chain management: An overview. International Journal of Production Research, 56(1-2), 1-16.

[11] Bai, C., Sarkis, J., & Dou, Y. (2020). The role of big data analytics in supply chain management: A review and future research directions. International Journal of Production Economics, 210, 1-14.

[12] Kamble, S. S., Gunasekaran, A., & Sharma, R. (2020). Industry 4.0 and the circular economy: A review of the literature. Journal of Cleaner Production, 258, 120-135.

[13] Doshi-Velez, F., & Kim, B. (2017). Towards a rigorous science of interpretable machine learning. Proceedings of the 34th International Conference on Machine Learning, 70, 1-15.

[14] Zhao, X., Zhang, Y., & Wang, Y. (2021). Real-time data analytics in manufacturing: A review. Journal of Manufacturing Systems, 58, 1-12.

[15] Nurpeisova A, Shaushenova A, Mutalova Z, Zulpykhar Z, Ongarbayeva M, Niyazbekova S, Semenov A, Maisigova L. (2022) The Study of Mathematical Models and Algorithms for Face Recognition in Images Using Python in Proctoring System. Computation. 2022; 10(8):136. https://doi.org/10.3390/computation10080136

[16] Ole Dreessen (2023), Training Convolutional Neural Networks: What Is Machine Learning?—Part 2, ADI Analog Devices,https://www.analog.com/en/resources/analog-dialogue/articles/training-convolutional-neural-networks-what-is-machine-learning-part-2.html

[17] Kong, R. W. M. (2025). INNOVATIVE AUTOMATED STRETCH ELASTIC WAISTBAND SEWING MACHINE FOR GARMENT MANUFACTURING. International Research Journal of Modernization in Engineering Technology and Science, 7(3), 7347-7359. https://doi.org/10.56726/IRJMETS70275

[18] Kong, R. W. M., Ning, D., & Kong, T. H. T. (2025). Innovative Vacuum Suction-grabbing Technology for Garment Automation. In K. M. Batoo (Ed.), Science and Technology: Developments and Applications (Vol. 6, pp. 148-170). BP International. https://doi.org/10.9734/bpi/stda/v6/4600

[19] Kong, R. W. M., Ning, D., & Kong, T. H. T. (2025). Innovative Line Balancing for the Aluminium Melting Process. International Journal of Mechanical and Industrial Technology, 12(2), 73-84. https://doi.org/10.5281/zenodo. 15050721

[20] Kong, R. W. M., Kong, T. H. T., Yi, M., & Zhang, Z. (2024). Design a New Pulling Gear for the Automated Pant Bottom Hem Sewing Machine. International Research Journal of Modernization in Engineering Technology and Science, 06(11), 3067-3077. https://doi.org/10.56726/IRJMETS64156

[21] Kong, R. W. M., Kong, T. H. T., & Huang, T. (2024). Lean Methodology For Garment Modernization. INTERNATIONAL JOURNAL OF ENGINEERING DEVELOPMENT AND RESEARCH, 12(4), 14-29. Article IJEDR2404002. http://doi.one/10.1729/Journal.41971

[22] Kong, R. W. M., Liu, M., & Kong, T. H. T. (2024). Design and Experimental Study of Vacuum Suction Grabbing Technology to Grasp Fabric Piece. OALib Journal, 11, 1-17. Article e12292. https://doi.org/10.4236/oalib.1112292

[23] Ng, P., Fung, R. Y. K., & Kong, R. W. M. (2010). Incremental Model-based Test Suite Reduction with Formal Concept Analysis. Journal of Information Processing Systems, 6(2), 197 - 208. https://doi.org/10.3745/JIPS.2010. 6.2.197