International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 10 Issue: 03 | March - 2026 SJIF Rating: 8.659 ISSN: 2582-3930

AI Based Product Defect Detection Using Deep Learning a CNN, Yolo V8

Ch. Kodanda Ramu[1], K. Mounika[2], D. Praveen[3], Ch. Vinod[4], K.Bhavani Sankar[5]

[1]Associate Professor, Department of Computer Science & Engineering, Miracle Educational Society Group of Institutions, Bhogapuram, Vizianagaram, Andhra Pradesh, India - 535216

[2,3,4,5]B.Tech Student , Department of Computer Science & Engineering, Miracle Educational Society Group of Institutions, Bhogapuram, Vizianagaram, Andhra Pradesh, India - 535216

Email: kvr.chintu1978@gmail.com

---***---

Abstract - In current manufacturing sectors customer satisfaction is dependent on high product standards and minimizing financial impact from the release of defective products. The traditional methods of manually inspecting products are cumbersome, require a lot of resource (time and money) and prone to human error particularly when dealing with large scale production. This project proposes a system which will automatically detect product defects utilising artificial intelligence, computer vision, and machine learning techniques. The proposed solution will leverage Deep Learning methodologies, specifically Convolutional Neural Networks (CNN's), to analyse the images of finished goods taken throughout the manufacturing process. The model will be trained on a data set containing images of both defect and defect free products. Once trained the model will be able to identify surface defects including but not limited to cracks, scratched, dented or incorrectly assembled products in real time. The system will also apply several image pre-processing techniques such as resizing, normalising, and reducing noise in order to increase the accuracy of defect detection. The system will be developed using Python and associated libraries (e.g., Flask). By Utilizing AI & CV for QA Processes. Quality Control personnel will have the ability to upload product images and receive immediate feedback on defect detection results through the proposed solution incorporating artificial intelligence as part of quality inspection to provide a scalable, accurate, and cost-effective alternative to current defect detection practices. The results of this project demonstrate the real-world application of AI & Computer Vision in Smart Manufacturing and further illustrate the capabilities of intelligent systems to increase the quality control process of manufacturing.

Key Words: Product Defect Detection, Deep Learning, CNN, YOLOv8, Computer Vision, Smart Manufacturing, Industrial Automation

1.INTRODUCTION

To maintain the quality of their output, modern manufacturing industries rely heavily on the quality of their products. Therefore, the importance of maintaining product quality is essential for customer satisfaction, minimizing financial losses, and preserving a brand's reputation. Quality assurance in traditional manufacturing processes has primarily been achieved through manual visual inspections of a manufactured product. These methods tend to be labor intensive, produce inconsistent results, and have a high degree of variability. As a result, traditional inspection techniques often fall short of detecting subtle defects such as leakage; damaged containers; incorrect labelling; and contamination. Due to the increased rates of production and the complexity of packaging of consumer goods (i.e., containers with multiple components), traditional inspection techniques are limited in their ability to detect subtle defects. The emergence of advanced computer vision and artificial intelligence (AI) technologies offers opportunities for improved methods of qualitatively inspecting consumer packaged goods (CPG) in automated production environments.

Figure. 1 AI-based defect detection in production line

In automating the inspection process with advanced AI/Computer Vision capabilities, an automated inspection system can achieve much more consistent results than would be obtained through traditional inspection techniques and reduce the reliance on human labour in automated manufacturing environments. This paper proposes a product defect detection system based on AI and will describe the implementation and use of deep learning models, including convolutional neural networks (CNNs) and object detection models such as YOLOv8, for a CPG's automated inspection to detect and classify defects.

1.1 Background

In fast-moving consumer goods (FMCGs), the quality assurance for products such as shampoo bottles is essential to maintain consumer trust and remain competitive within the market. Any defect, including packaging, mislabeling, leakage, or foreign material contamination, will result in product recalls, customer dissatisfaction, and ultimately, significant economic losses. Historically, quality inspection has relied on the human operator; however, this approach limits productivity and results in variation due to fatigue, subjectivity and environmental conditions affecting individual performance. The rise of Industry 4.0 technologies such as Artificial Intelligence (AI), Deep Learning (DL), and automated vision systems provide industries with a pathway towards smart manufacturing. Convolutional Neural Network (CNN) models are utilised heavily for image classification, while architectures based on You Only Look Once (YOLO) can be used to detect objects with high speed and accuracy; therefore, both technologies are suitable for real-time inspection on production lines. Additionally, these new technologies provide industries with a scalable, efficient option compared to traditional methods because they can consistently and objectively evaluate the quality of a product.

1.2 Problem Statement

With manual inspection methods used in the FMCG industry being inefficient, unreliable and incapable of keeping pace with increasing production needs, it is likely that flaws in products such as shampoo will go undetected (e.g. incorrect labels/ leakage, damaged packaging etc.) which can lead to inferior quality of the product and unhappy customers. Additionally, as human inspectors become tired and provide subjective opinions, their reliability diminishes over time. Current solutions that use automated inspection systems are costly or their precision is not sufficient enough for the complex packaging found in consumer products. To address this issue, there is an urgent need for a cost-effective, intelligent defect detection system that will provide accurate defect identification, reduce the amount of people involved in inspection and ensure quality standards remain consistently high across very high-speed production lines.

2. LITERATURE REVIEW

The early investigations into automated defect detection and object recognition concentrated on locating agricultural pests through identification of their images, especially the fruit fly. The analysis carried out by Fang et al addressed the effects Bactrocera tau is having on crops and underscoring the necessity for an early warning system through detection and monitoring [1]. In addition, Huang et al studied the morphology and invasion risk posed by Bactrocera correcta, pointing out the potential hazards of invading this bug and how important identification technologies will be for preventing this infestation [2]. Zhang et al demonstrated the feasibility of the machine vision for tasks related to classification of biological organisms with the development of an automated fruit fly identification system using image processing techniques, thereby providing a means of detection through machine vision systems [3]. Wang et al presented a proposal to build an image recognition system for identifying Bactrocera species that improved the level of accuracy achieved by analyzing the digital images of those insect species [4]. Lou created a portable Android-based image recognition system for the detection of high risk fruit flies to demonstrate that recognition systems could be deployed on portable devices in practice [5]. Finally, Peng et al proposed a BP neural network model for an automatic classification system that offered a marked improvement over traditional methods of classification [6].

Research into the application of Artificial Intelligence (AI) and Machine Learning (ML) technologies in industrial production has expanded greatly over time. De Simone et al. examed the extent of adoption of AI/ML in manufacturing micro, small, and medium-sized enterprises (MSMEs), discussing various issues with implementation and solutions and limitations to machine learning. Presciuttini et al. have conducted a systematic review of applications of machine learning to Internet of Things (IoT) data within manufacturing environments; the purpose of this review being to highlight the need for explanation of the AI prediction to facilitate industrial decisions. In addition, Sadiku et al. examined the benefits and impact of AI on manufacturing, including increased automation, predictive maintenance, and increased quality control processes. In particular, recent studies are focussing on how to utilize computer vision systems for defect detection. Koubaa et al. developed a monitoring system for defect detection in addtive manufacturing and demonstrated that using visual inspection in real time can result in an increase in the reliability of finished products. Lakshmi et al. completed a comparative review of PCB defect detection procedures, concluding that the accuracy and reliability of machine learning-based methods significantly exceed those of the traditional rule-based systems. Helo and Hao, conducted a study that reviewed the application of AI in operation and supply chain management; they found significant improvement in efficiencies from intelligent automated processes. Fahle et al. published a systematic review of machine learning methods used in manufacturing; they provided an overview of the various machine learning methods that exist and the types of AI techniques that can be implemented in a number of manufacturing applications.

With the help of more than one author, Plathottam et al. combined a number of different articles to put together a list of how the artificial intelligence (AI) tools can be used in precise manufacturing, such as quality evaluation, distinguishing deviations, and improving how processes work; this is all summarised in [14]. Along those lines, Bertolini et al. gathered information from numerous sources, and provided an extensive summary of the different areas using machine learning and various machine learning tools for manufacturers. This summary included examples of how machine learning improves both productivity and reduces defects in manufacturing processes [15]. Finally, Arinez et al. discussed where AI is now, where it can end up, and how AI is helping advance manufacturing into smart factories and Industry 4.0 systems.

There is an overall indication, from past literature that there has been a shift from using traditional image processing to using deep learning to establish an automated/QC system. While there has been quite a bit of advancement made with respect to automatic defect detection in the agricultural and manufacturing industries, enough has not been developed to have robust, real-time defect-detecting tools/solutions for manufacturers of consumer goods.

2.1. Research Gaps

- Limited Focus on FMCG Products.
- High Implementation Cost of Industrial Solutions.
- Dataset Limitations and Generalization Issues.
- Insufficient Real-Time Deployment.
- Lack of Integrated Classification and Localization.

2.2. Objectives

- Develop Random Decision Forest and You Only Look Once (YOLO) methods that are able to visualize defects in an object.
- Choose a sample set of photos belonging to manufacturers, which have previously been visually identified by their manufacturer for the purpose of facilitating the model’s learning process.
- Examine the performance of the built models and algorithms (e.g. measure accurate metrics such as: accuracy, precision, recall and responsiveness, etc.).
- Demonstrate that the visual viewing systems and algorithms can be integrated into the facility so that real-time inspection capability exists on the production facilities.
- Create an affordable, reliable and accurate inspection system for manufacturers to provide quality assurance to their F.M.C. products in real time.

3. METHODOLOGY

The proposed system will utilize anAI based methodology and leverage deep learning methods to provide an automated detection of any product defects. The methodology follows a structured workflow process which consists of image acquisition, pre-processing, feature extraction, model building, training and deployment of the model to ensure accurate inspection and provide inspection in real time. High quality images of the products are being taken and developed by the automated inspection systems during the production process, then the images are input into the CNNs (Convolutional Neural Networks) to perform the product classification and use the YOLOv8 for defect localization. By following this methodical workflow, we will reduce human involvement and thus create an inspection system that is capable of achieving reliable product defect detection in real time of defects such as leaks, mis-labels, damaged packaging and foreign particles.

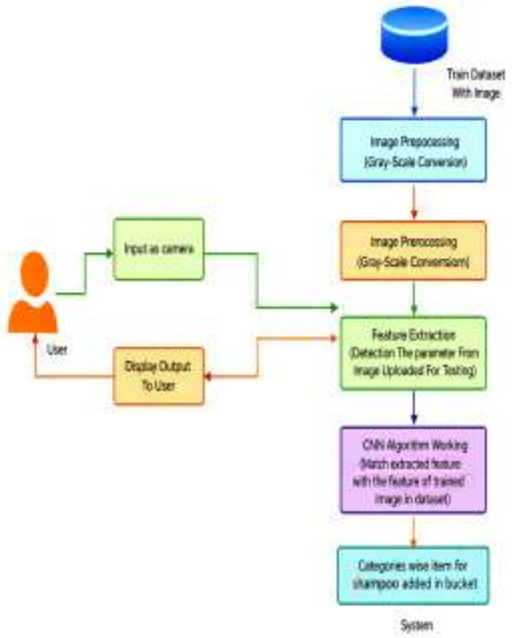

Figure. 2 Proposed AI-Based Product Defect Detection System Workflow Using CNN

3.1 Data Collection

The data collection phase begins with collecting a complete set of images of products using high quality cameras or sensors that can capture very detailed defect information. The image data set will consist of both defective and non-defective product images to allow for supervised learning to be performed. Annotation is also used, by drawing bounding boxes or by creating segmentation masks, to label locations of defects in the images; this would include drawing bounding boxes around scratches, dents, leaking areas, improperly labelled products etc... The annotated product images will serve as the training/validations data set for the deep learning algorithm.

3.2 Data Preprocessing

The preprocessing phase ensures the input data is consistent and appropriate for training a model (i.e., all images are resized to the same dimensions as well as normalized by scaling the pixel values to lie within a specific range, usually [0,1]). Dataset augmentation is performed to generate more diversity in the dataset and therefore help the model generalize by applying transformations to images (e.g., rotation, flipping, zooming). Noise reduction techniques (i.e. filters) are applied to help remove distracting background noise and thus improve the visibility of defects. Additionally, the images are often converted to grayscale to simplify the features of the images and thus reduce the processing time for future image analysis.

3.3 Feature Extraction

Feature extraction identifies the features that differentiate defective products from non-defective products. Typically, these features can be manually extracted through traditional means (e.g., edges, textures, and color histograms). However, deep learning models can learn the relevant features through automated hierarchically learned feature sets based on raw images. Through convolutional neural networks, the model can identify complex relationships between objects as well as between objects and their location in space, allowing it to find subtle product defects without requiring the expert to tell it which features are important in identifying defects.

3.4 Model Selection

The model(s) that are chosen will depend on the complexity of the defect detection task that needs to be completed. Conventional machine learning algorithms (e.g., support vector machines, random forests, K-nearest neighbours, etc.) are capable of processing simple patterns (or, in other words, can be used when the process of detecting defects is becoming simpler). However, when more complex and real-time defect detection is required, deep learning models (e.g., convolutional neural networks) are preferred. An example of this is the use of a convolutional neural network to classify defective and non-defective products. An example of another type of model that is utilized is YOLOv8, which allows for real-time detection and localisation of defects by locating the exact position of defects in an image.

3.5 Model Training and Validation

The dataset is split into a training set, validation set, and testing set to facilitate an objective measure of the performance of the model(s). Hyperparameters such as learning rate, batch size, and number of epochs are optimised to achieve the best possible results. Suitable loss functions (also known as objective functions) for the model are determined for each task; for example, cross entropy is often used for the classification task, while intersection over union (IoU) is typically used for the detection task. The models are assessed against a variety of metrics, including accuracy, precision, recall, F1 score, and ROC-AUC, to provide assurance of reliable and robust performance across all defect detection tasks.

3.6 Real-Time Deployment and Detection

At the end of training, the final models were used in a prototype for inspection systems. These prototype systems can be integrated into the manufacturing production line as they are designed to be real-time and will work to process images of products as they are received, marking any defects detected as they are detected by drawing a bounding box around the defect. The systems will be used to send an alert or report to the quality control engineer, allowing them to immediately pull any defective item from the production line. The use of automated deployment will allow for the inspection of products to be faster and more uniform, thus improving the overall quality of manufacturing.

4. RESULTS AND DISCUSSIONS

A system based on artificial intelligence (AI) to identify product defects using images collected from the production line was evaluated for its ability to detect defect presence and location within shampoo products produced under simulated manufacturing environments. The model used Convolutional Neural Network (CNN) techniques to classify and detect defects using a method based on the YOLO architecture. The results obtained show that the automated approach improves accuracy and consistency significantly compared to manual inspection methods. The ability of the CNN-based model to detect several different defect types (packaging damage, leaking products, improper labels and foreign materials) was effective. Image preprocessing techniques used (e.g., normalization, augmentation, noise reduction) increased the visibility of features used for classification and enhanced the performance of the model.

The proposed system represents a highly reliable and efficient inspection process since it is able to differentiate between defective and non-defective product with a high degree of reliability and very low probability of false inspection outcomes. The proposed AI-based video inspection (CCTV) model provides fast and accurate identification of product defects in shampoo products manufactured at high rates, making it useful for deployment in production lines. The real-time processing capabilities of the proposed system due to the use of YOLO architecture allow for immediate detection of defective products so they can be removed from the production stream, thus minimizing waste and preventing defective products from being sold to end consumers. Automated inspection of postal vehicles will benefit from the elimination of human fatigue and emotion, thus allowing for the application of consistent, predefined quality standards for the inspection process.

The automated system will also visually depict the defective areas on the vehicle using bounding boxes to assist the quality assurance experts in validation of the inspection results provided by the automated inspection process. The proposed automated postal vehicle inspection system will also provide a higher level of transparency and confidence in the use of an automated inspection process. The trained model can also be scaled to inspect other categories of fast-moving consumer goods (FMCG), such as bottles, with very few changes to the system. One limitation of the proposed approach to automated inspection is that the performance of the trained model is dependent on the quality and variety of the training set. If a defect occurs infrequently (rarely occurs in the training set), it may be difficult for the automated system to accurately identify the target defect through bounding boxes. Furthermore, poor lighting or visual obstructions may also affect the performance of the model to correctly identify a defective condition. Future enhancements to the model should include enhancing the training set with a broader range of defect categories, utilizing the latest training set augmentation techniques and adding more sensors as a part of the automated inspection process.

The experiments conducted show that the proposed AI-based system for detecting defects has been proven successful in delivering a dependable and efficient source of automated quality inspections in manufacturing environments; therefore meeting an important goal of the Fourth Industrial Revolution that is related to intelligent manufacturing and production systems having their own smart capabilities.

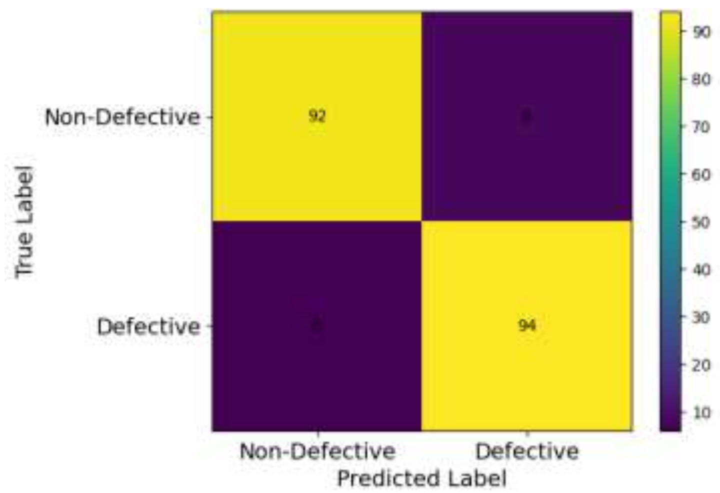

Figure. 3 Confusion Matrix Defective vs non-defective

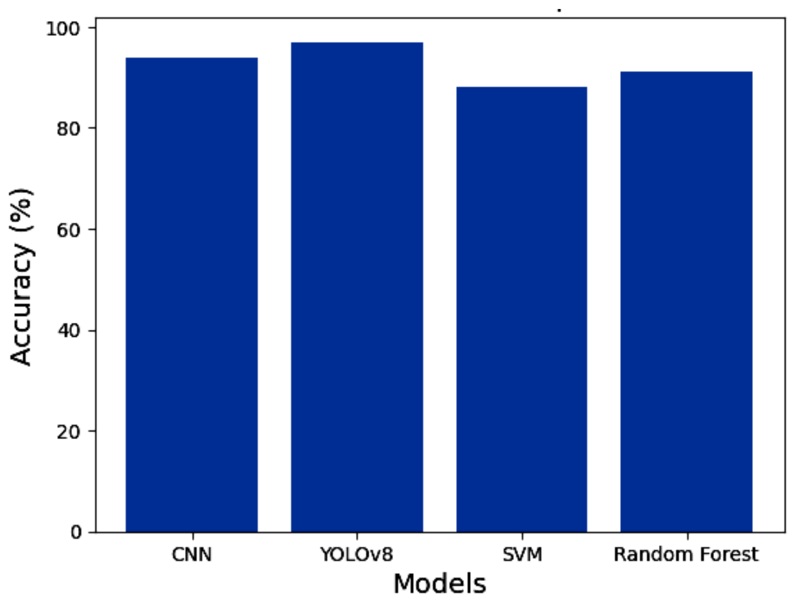

Figure. 4 Model Performance Comparison

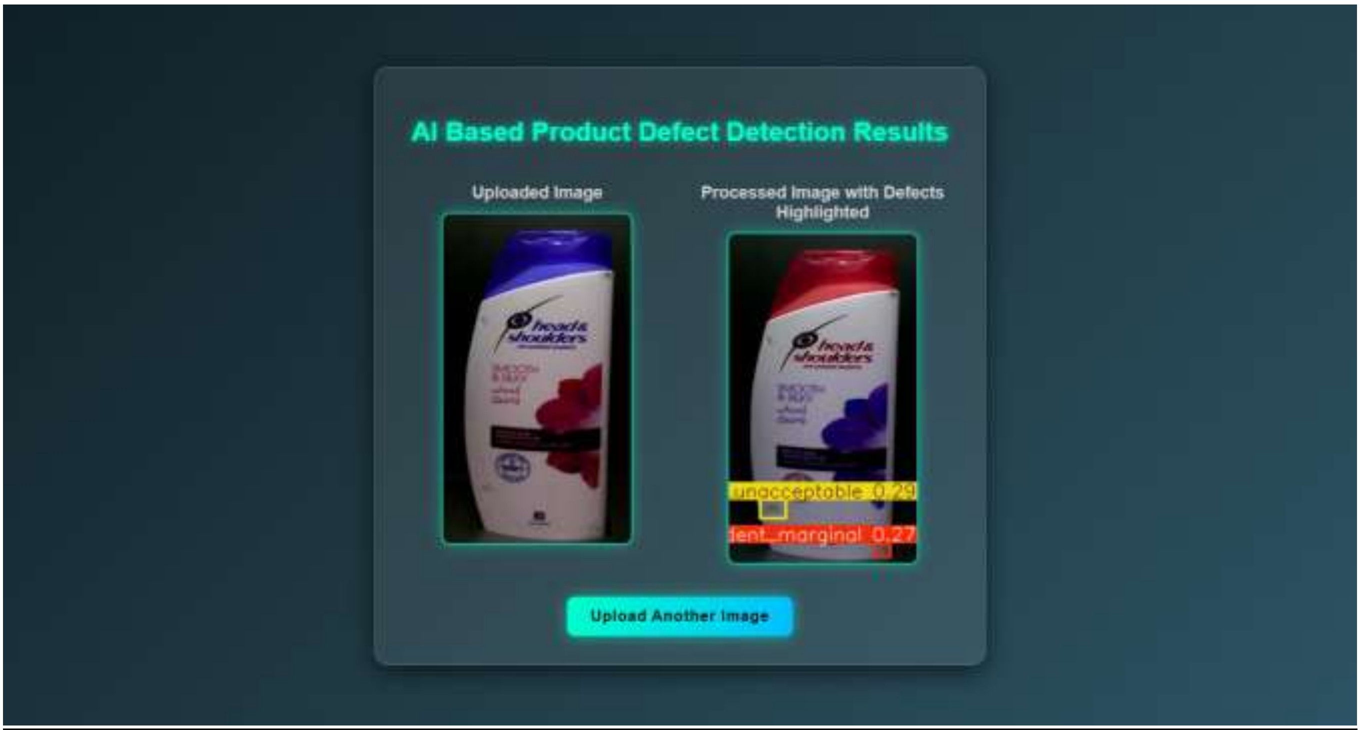

Figure. 5 Application User Interface

5.CONCLUSIONS

Many fast moving consumer goods (FMCG) companies use the use of artificial intelligence (AI) for detecting defects in their products, which has improved the quality control methods that most companies use to maintain the quality of their products. AI has the ability to analyse 1,000s of samples of products at the same time and in real time, whereas traditional manual inspections typically only analyse one sample at a time. AI can identify even the smallest imperfections in products with a high degree of accuracy. By using AI for defect detection, FMCG companies see fewer errors from their employees during the inspection process and can produce products at their target production rate while maintaining product quality. AI-based detection also results in decreased costs associated with producing flawed products and increases the number of products that need to be returned or repaired. When AI incorporates predictive analytics, this potential to improve the predictive ability of detecting and preventing future problems, and allowing the manufacturer to implement innovative predictive maintenance procedures to prevent disruptions in production, is greatly enhanced. Regarding compliance, AI also helps the manufacturer ensure that they meet regulatory requirements, as well as meet consumer expectations, which results in a better brand image and increased consumer confidence in the products produced by a manufacturer, both of which are essential in the highly competitive FMCG market.

REFERENCES

[1] Y. Fang, Z. H. Li, M. Qin, *et al.*, "The potential economic impact of the pumpkin industry caused by *Bactrocera tau* (Walker)," *Plant Quarantine*, vol. 29, no. 3, pp. 28–33, 2015.

[2] Z. Huang, Q. X. Guo, Q. M. Wu, and K. H. Huang, "Morphology, hazards and China invading risk of *Bactrocera correcta*," *Acta Agriculturae Jiangxi*, vol. 26, no. 4, pp. 61–63, 2014.

[3] L. Zhang, X. L. Chen, X. W. Hou, C. L. Liu, L. M. Fan, and X. J. Wang, "Construction and testing of automated fruit fly identification system—*Bactrocera* Macquart (Diptera: Tephritidae)," *Acta Entomologica Sinica*, vol. 54, no. 2, pp. 184–196, 2011.

[4] L. Wang, L. L. Huang, H. Y. Yang, and L. W. Gao, "Developing and testing of image identification system for *Bactrocera* spp.," *Plant Quarantine*, no. 5, pp. 29–35, 2013.

[5] L. Z. Lou, "Research and implementation of Android-based image recognition system for high-risk fruit flies," M.S. thesis, Jiangxi Agricultural Univ., Jiangxi, China, 2015.

[6] Y. Q. Peng, M. X. Liao, Y. H. Zhang, *et al.*, "Study on automatic classification system for fruit flies based on BP neural network model," *Acta Agriculturae Universitatis Jiangxiensis*, vol. 38, no. 6, pp. 1205–1210, 2016.

[7] V. De Simone, V. D. Pasquale, and S. Miranda, "An overview on the use of AI/ML in manufacturing MSMEs: Solved issues, limits, and challenges," *Procedia Computer Science*.

[8] Presciuttini, A. Cantini, F. Costa, and A. Portioli-Staudacher, "Machine learning applications on IoT data in manufacturing operations and their interpretability implications: A systematic literature review," *Journal of Manufacturing Systems*.

[9] M. N. O. Sadiku, A. J. Ajayi-Majebi, and P. O. Adebo, "Artificial intelligence in manufacturing," in *Emerging Technologies in Manufacturing*, Cham, Switzerland: Springer International Publishing.

[10] S. Koubaa, M. Baklouti, H. Mrad, A. Frikha, B. Zouari, and Z. Bouaziz, "Defect detection in additive manufacturing using computer vision monitoring," in *Design and Modeling of Mechanical Systems V*, Cham, Switzerland, 2023.

[11] G. Lakshmi, V. U. Sankar, and Y. S. Sankar, "A survey of PCB defect detection algorithms," *Journal of Electronic Testing*, vol. 39, no. 5, pp. 541–554, Dec. 2023.

[12] P. Helo and Y. Hao, "Artificial intelligence in operations management and supply chain management: An exploratory case study," *Production Planning & Control*, vol. 33, pp. 1–18, Apr. 2021.

[13] S. Fahle, C. Prinz, and B. Kuhlenkötter, "Systematic review on machine learning (ML) methods for manufacturing processes—Identifying artificial intelligence (AI) methods for field application," *Procedia CIRP*, vol. 93, pp. 413–418, 2020.

[14] S. J. Plathottam, A. Rzonca, R. Lakhnori, and C. Iloeje, "A review of artificial intelligence applications in manufacturing operations," *Journal of Advanced Manufacturing and Processing*, vol. 5, 2023.

[15] M. Bertolini, D. Mezzogori, M. Neroni, and F. Zammori, "Machine learning for industrial applications: A comprehensive literature review," *Expert Systems with Applications*, vol. 175, p. 114820, Aug. 2021.

[16] J. F. Arinez, Q. Chang, R. X. Gao, C. Xu, and J. Zhang, "Artificial intelligence in advanced manufacturing: Current status and future outlook," *Journal of Manufacturing Science and Engineering*, vol. 142, no. 11, 2020.