IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received 27 November 2023, accepted 2 January 2024, date of publication 9 January 2024, date of current version 4 March 2024.

Digital Object Identifier 10.1109/ACCESS.2024.3351858

TOPICAL REVIEW

Application of Artificial Intelligence in Particle and Impurity Detection and Removal: A Survey

NUR AINI SYAKIMAH AHMAD SHUYUTI [1,2], (Graduate Student Member, IEEE), ERFAN SALAMI [1,2], (Member, IEEE), MAHIDZAL DAHARI [1], (Member, IEEE), HAMZAH AROF [1], AND HARIKRISHNAN RAMIAH [1,2], (Senior Member, IEEE)

[1]Department of Electrical Engineering, Faculty of Engineering, University of Malaya, Kuala Lumpur 50603, Malaysia
[2]Centre for Research in Industry 4.0, Faculty of Engineering, University of Malaya, Kuala Lumpur 50603, Malaysia

Corresponding author: Mahidzal Dahari (mahidzal@um.edu.my)

This work was supported in part by the Public Service Department of Malaysia.

ABSTRACT With the rapid development of artificial intelligence (AI), especially in machine learning and deep learning technologies, the particle and impurity detection and removal processes employed in many industries have been improved. Particles and impurities of any size, shape and in any condition can be detected using advanced technology in both areas. This paper presents a comprehensive overview of research papers that discuss the application of AI techniques for the detection and removal of particles and impurities. The publications featured in this review were mainly retrieved from the Web of Science (WoS) database, covering the timeframe from 2000 to 2023. This paper also covers the review on the impurity detection and removal specifically in edible bird's nest (EBN). The aim of this paper is to provide a valuable resource for the future development of AI applications in particle and impurity detection and removal technologies that have not been addressed in this study. Through the review and analysis of AI for particle and impurity detection and removal techniques in recent years, this paper includes the following parts: research trend in particle and impurity detection in general and AI methods in particle and impurity detection, applications of AI in particle and impurity detection in related industries including in EBN and AI applications in particle and impurity removal. This review study will offer advantages to researchers engaged in the field of AI with regards to the detection and removal of particles and impurities.

INDEX TERMS Artificial intelligence, machine learning, deep learning, impurity detection, particle detection, particle removal, edible bird's nest.

I. INTRODUCTION

Undesirable particle, contaminant or impurity detection is a critical aspect in various industries and scientific disciplines that consists of the analysis and identification of the materials. Particles and impurities have a significant effect on the quality of a product. They are among the elements that determine if the products are of high quality. Most industries, whether manufacturing processes, agriculture, food and beverages, environmental monitoring, or biomedical research, accentuate the detection and identification of particles or impurities in ensuring product safety, quality, and integrity. There are a variety of particles or impurities forms, such as dust, contaminants, foreign objects, or microscopic organisms. Sample particles and impurities images found in different types of products are shown in Figure 1.

Detecting, analyzing, and processing the impurities are vital especially in pharmaceutical, cosmetics as well as food and beverages sectors because the products are consumed by humans. Impurities in food can be in kinds of physical, chemical, and biological contaminants such as heavy metals, small metal chips, fine wires, or pesticides [5], [6], [7]. These impurities are extremely harmful to humans because of their health risk and hazard that can likely cause severe illness and

The associate editor coordinating the review of this manuscript and approving it for publication was Okyay Kaynak.

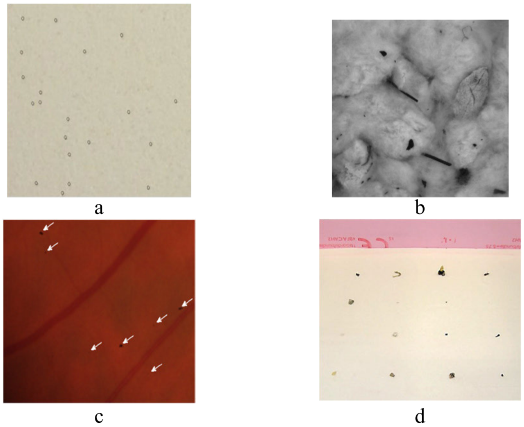


FIGURE 1. **(a) Impurities in flour after final image rendering process [1], (b) impurities in machine-harvested seed cotton [2], (c) dust particles in retinal images [3], and (d) impurities on the surface of a sugar heap [4].**

even death [8], [9], [10], [11]. The impurities will also affect the quality and the flavor of the food [12]. In manufacturing processes, impurities can affect the desired properties and the performance of the products. The metallic contaminants in semiconductor manufacturing will ruin the final products functionality [13]. The presence of contaminants inside metal during the manufacturing process has the potential to reduce the mechanical qualities of the products. This can lead to the formation of weak zones within the parts, ultimately resulting in their failure [14].

Particles or impurities of any size can have serious effects on the products. Contaminants at micro level can cause major problems to certain manufacturing processes, oil and gas industries, power transmission, and biomedical. The microparticle contaminants can ruin the high-power laser transmission in final optic assembly [15]. In electric and magnetic fields study, the particle detection facilitates a better catalyst nanoparticle by high-resolution holography statistical analysis [16]. The detection of impurities at micro level is highly important in biomedical fields. The identification of particles sizing 1 μm to 20 μm is essential as fungal, bacterial pathogens and human cells ranging around the size [17], [18], [19]. The detection of particulate matter (PM) in environment which is related to the respiratory tract is also essential in the field for constant and capillary air scrutinizing [20].

Conventionally, particle and impurity detection involved manual inspection and operation. Human-operated inspection and operation are inefficient because of high time consumption, subjective, low repeatability, low accuracy and prone to error [21], [22], [23]. However, with the developments in imaging technology and AI, automated particle detection systems have become increasingly established and reliable. Systems for particle and impurity detection often need image processing, AI techniques, and algorithms. It is crucial that the particle and impurity detection be automated in order to increase detection accuracy and lower the influence of human error. In some sectors, the particle and impurity removal and processing must be directly connected to the detecting system. This approach has the potential to save costs and assure the acceptance of the products.

The term "Artificial Intelligence (AI)" is applied to describe the mechanization of cognitive processes that are conventionally operated by humans, whereas machine learning (ML) relates to the AI method employed by systems to acquire the ability to perform these activities [24]. In addition, deep learning (DL) is a unique subdomain of ML that employs hierarchical structures or layered approaches in order to attempt learning high-level abstractions of data [25]. The link between AI, ML, and DL has been explained by Halbouni et al. [26] as illustrated in Figure 2.

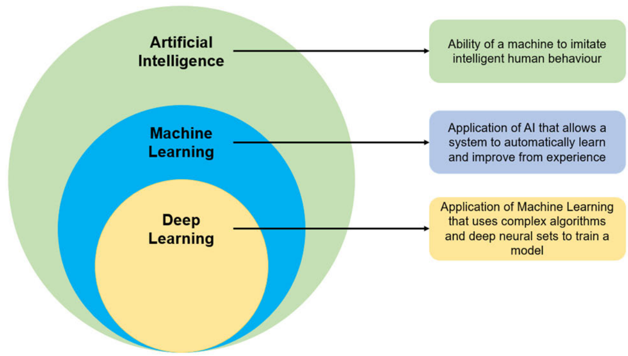


FIGURE 2. **Relationship between AI, ML and DL [26].**

Particle detection, like any other object detection method, is based on digital image processing and ML. The process can be divided into multiple phases, including image acquisition, image processing, feature extraction, image segmentation, and the application of ML algorithms for identification purposes [27], [28]. ML algorithms can effectively and precisely identify and categorize particles or impurities by being trained on extensive datasets that consist of labelled samples. This enables the algorithms to automatically detect and categorize these entities [29].

Over the last few decades, many journal articles have been published that focus on both particle and impurity detection in general and specifically in AI in particle and impurity detection. The objective of this study is to review the technologies of AI applications and methods in particle detection. This study provides an overview of various AI methods and their applications in particle and impurity detection in various industries as well as in particle and impurity removal. This paper is organized as follows: In Section II, we provide the research trend of particle detection in general and specifically using AI in particle and impurity detection and removal. In Section III, we explain the applications of AI in particle and impurity detection from the industries that mostly covered in the research in this field i.e., biomedical and medical, power, electrical and electronics, manufacturing, food and beverages, agriculture, and pharmaceutical. In Section IV, we describe the AI applications in particle and impurity removal. In Section V, we conclude the study. This paper is expected to foster collaboration between engineers and scientists to facilitate the rapid expansion of this research.

II. RESEARCH TREND

A bibliometric analysis was conducted to identify the scope and areas of interest that have been addressed in relation to the research trend study. The data were acquired from the Web of Science (WoS) database, widely regarded as the foremost comprehensive and extensively utilized bibliographic database, renowned for its reliability [30], [31]. Throughout the process of the research, a number of keywords and terms were used. Table 1 presents the searches together with the corresponding search phrases selected. The timeline of this analysis includes papers that have been published between the years 1970 and 2023.

TABLE 1. Search criteria.

Searching Criteria		
"particle* detection"	OR	"impurity* detection"
"artificial intelligence" OR "machine learning" OR "deep learning"	AND	"particle* detection"
"artificial intelligence" OR "machine learning" OR "deep learning"	AND	"impurity* detection"
"artificial intelligence" OR "machine learning" OR "deep learning"	AND	"impurity* removal"
"artificial intelligence" OR "machine learning" OR "deep learning"	AND	"particle* removal"

Note: * symbol has been used as a wildcard character for the searches.

The total number of yearly publications related to particle and impurity detection topics from 1970 to 2023 are shown in Figure 3. From the figure, it can be observed that even the number of publications by year is fluctuating but there has been a growth trend in the topics.

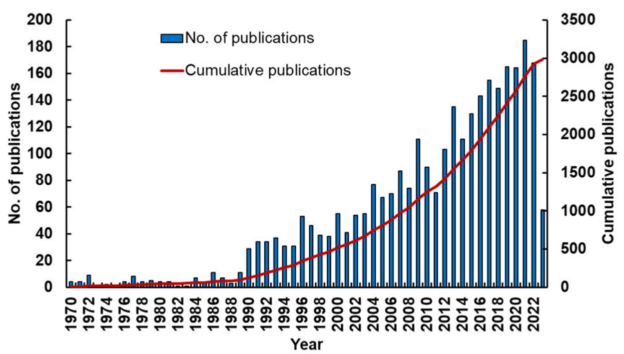


FIGURE 3. Number of publications by year and cumulative publications related to particle/impurity detection.

For papers publication specific to AI applications in particle and impurity detection, the total number of yearly publications and citations from 2007 to 2023 are shown in Figure 4. The graph shows that even though the research in

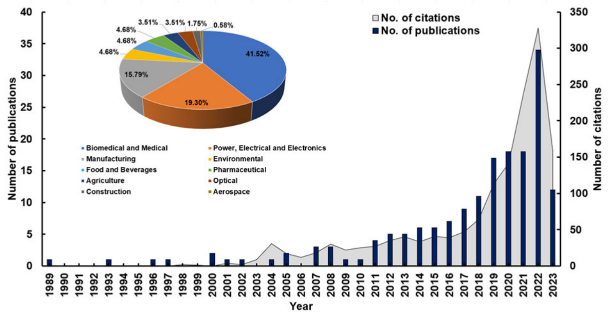


FIGURE 4. Number of publications and number of citations related to AI applications in particle/impurity detection by year from 1989 to 2023 with percentage of publications by industries.

this field began in 2007, the number of publications started to increase rapidly from 2017 onwards. In terms of citation, the figure shows the publications in this field had been cited yearly since 2007 except in 2011. There was a sharp increase in citation numbers after 2018. The most citations per publication were recorded in 2022. This trend is expected to continue in 2023 onwards. Additionally, Figure 4 depicts the percentage of publications by related industry. Biomedical and Medical industries contributed the most significant number of publications in this field. Other popular industries covered in the research in this field are Power, Electrical and Electronics, Manufacturing, Food and Beverages, Agriculture and Pharmaceutical.

A total of 23 countries were involved in the publications of AI applications in particle and impurity detection. Figure 5 shows the number of publications based on countries and continents. According to the data presented in the figure, China and the United States emerge as the leading contributors in terms of publication output, accounting for 34.00% and 16.00% respectively. Following closely behind are Germany with 10.00%, and Netherlands and Japan with 4.00% each. From Figure 5, Asia has the highest volume of publications pertaining to the subject matter, with Europe and North America following suit in terms of contribution.

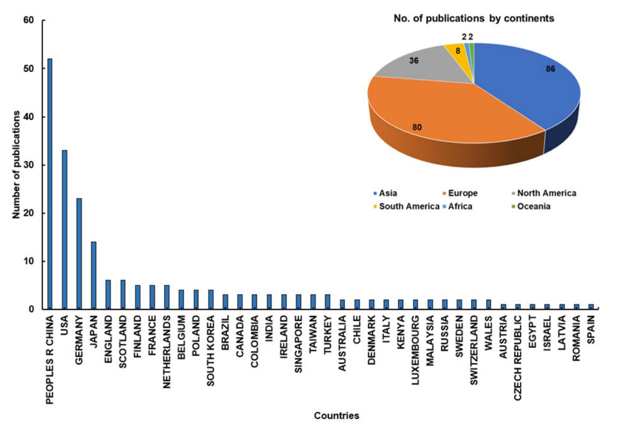


FIGURE 5. Publications in the field of AI applications in particle/impurity detection by counties and continents.

Based on the search result, bibliometric mapping was constructed using VOSviewer software. The map of keywords based on co-occurrence data can be constructed using the software using visualization of similarities (VOS) mapping technique [32]. Network visualization of publications based on keywords as analyzed using VOSviewer is shown in Figure 6. This visualization helps to identify the most frequent keywords in the research regarding particle detection. From Figure 6, the results show that ML and DL, the subsets of AI have been associated with particle detection.

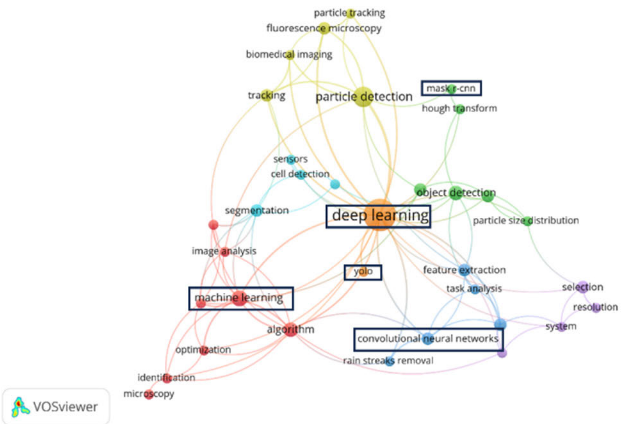


FIGURE 6. Network visualisation of keywords.

In this paper, a range of online AI techniques published since 2000 were reviewed for particle and impurity detection.

III. APPLICATION OF ARTIFICIAL INTELLIGENCE FOR PARTICLE/IMPURITY DETECTION IN RELATED INDUSTRIES

Particle detection is applied in various fields. In the medical domain, particle detection is employed for the analysis and statistical evaluation of cells. In the metallurgical sector, it is utilized for the analysis of particle sizes. In the chemical industry, particle detection is employed for the analysis of the composition of different reactant particles and the monitoring of changes occurring during the reaction process [33]. In this paper, we explore the application of AI techniques for particle and impurity detection in the popular industries, which are biomedical and medical, power, electrical and electronics, manufacturing, food and beverages, agriculture, and pharmaceutical. We delve into the fundamental principles, methodologies, and the performance of the detection models. We also discuss various types of particles or impurities that can be detected using AI, such as contaminants in manufacturing processes, pollutants in the food and beverages, and anomalies in medical images. In particle detection, most of the research covered digital image processing before classification process by AI algorithms.

A. BIOMEDICAL AND MEDICAL

As mentioned earlier, Figure 3 shows that the highest industry in particle and impurity research is in biomedical and medical industries. Particle and impurity detection in the biomedical and medical fields are important aspects of ensuring the safety and effectiveness of various healthcare products and procedures. In biomedical and medical applications, particles or impurities can encompass a wide range of substances, including contaminants, foreign bodies, microorganisms, chemicals, or undesired by-products. Detecting and removing these particles or impurities are vital to reduce the risk of adverse reactions, infections, or compromised treatment outcomes.

Zhu et al. [34] have performed research to detect particles for single particle analysis from image acquired by cryogenic electron microscopy using Hough Transforms algorithm. In the research, Leginon system was used to get KLH (protein) particles images for defocus pairs, first recorded near-to-focus (NTF) image and acquired farther-from-focus (FFF) image. Figure 7 below shows the flowchart of the detection method. The results indicate that total computational time for defocus images depends on the number of particles in the images in the order of 10 minutes. The average 89% of side-view KLH particles could be detected with false negative rate of 11% and false positive rates of 26% recorded.

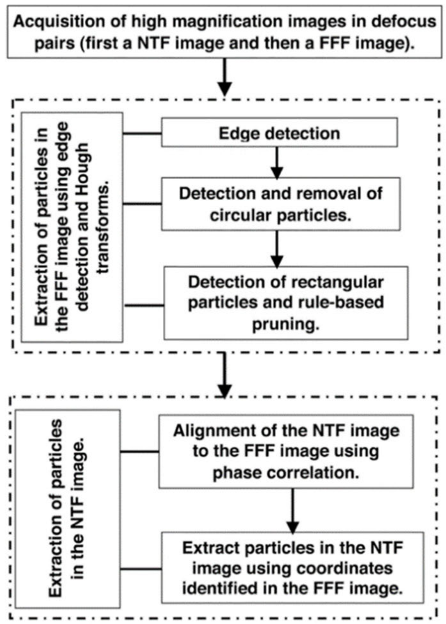


FIGURE 7. Overview of the proposed automated particle detection method [34].

Sierra et al. [3] applied the image segmentation method of image processing in their study to detect and remove dust particle artifact in retinal images on retinal fundus cameras. The image inputs were two or more color fundus images in the same position with artifacts acquired within the same session. For image localization, blob detection tasks were performed to detect candidate artifacts and to obtain the coordinate. The image segmentation was done via region growing. The segmentations in all images were compared using conjunction OR AND operation in MATLAB. The results show that the method can detect and remove all artifacts successfully and it is able to detect and remove artifacts in dark areas without introducing new artifacts. The researchers found that the method is robust and fast, however the artifacts with low contrast cannot be detected.

Research by Rossi and Barnkob [35] applies segmentation-free image processing technique to track the particles on microfluidic devices. This technique aims to identify particles and estimate their 3D positions using general defocusing particles tracking (GDPT). The result of the detection was then compared with the result using previous GDPTlab software that has segmentation step. The method without refinement step was also tested by adding more iterations. The researchers used ad hoc MATLAB routine to simulate the results and analyzed the evaluation time using different types of imaging which were fluorescent, brightfield, brightfield with disturbance. It is found that this method can detect overlapping particles although it does not require segmentation and the evaluation time takes place in 1s.

Ge et al. [36] have performed research on particle detection of complex images using Convolutional Neural Network (CNN). The researchers used series of residual networks (ResNet) for BasicBlock and Bottleneck. Figure 8 shows the series of ResNets applied in the study. The researchers have measured precision, recall and F-score to analyze the performance of the system where the four types of two-layers ResNets were trained, tested, and compared. The results of three non-learning-based approaches: Blob Detection, Canny Edge Detection and Connected Domain Detection were converted to Light-Spots Maps and their performances were

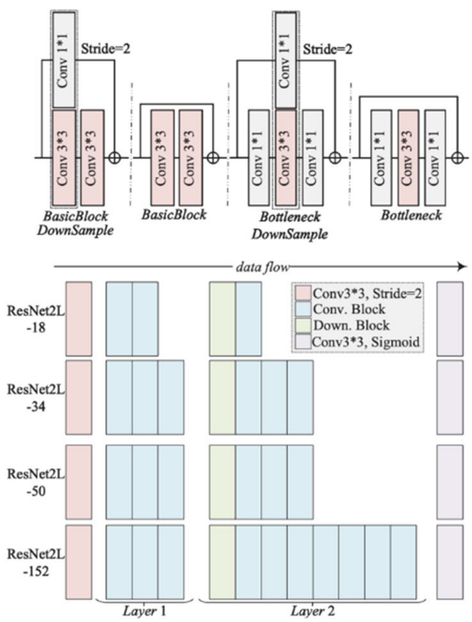


FIGURE 8. **Diagrams of ResNet2Ls. There are two different blocks of ResNets which are BasicBlock, for ResNet18 and ResNet34, and Bottleneck, for ResNet50 and ResNet152. The bottoms refer to four types of ResNet2Ls that have been derived by modifying the first two layers of ResNets. [36].**

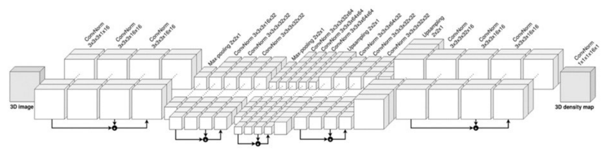


FIGURE 9. **Architecture of the proposed DM-DetNet3D network [39].**

evaluated. The findings of the study indicate that it is difficult to detect macroparticles sized over 50 pixels in diameter using this method, however it has better performance than three non-learning-based approaches: Blob Detection, Canny Edge Detection and Connected Domain Detection.

The study on Deconvolution Network, DetNet application on particle detection was conducted by Ritter et al. [37]. The authors used hybrid method whereby DetNet was used for particle detection in fluorescent microscopy images of live cells hybrid with bidirectional long short-term memory (LSTM)-based recurrent neural network (RNN) or deep particle hypotheses tracker (DPHT) for tracking [38]. The performance of this hybrid method, DetNet-DPHT was evaluated using image sequences of the Particle Tracking Challenge with different signal-to-noise (SNR) ratio and live cell fluorescence microscopy data of hepatitis C virus proteins. The results indicate that the performance provides state-of-the-art results or improves the results compared to classical methods, spot-enhancing filter using Gaussian filter (SEF-GF). For the same purpose, Spilger et al. [39] then established image-to-image mapping based on density map regression called Density Map DetNet 3D (DM-DetNet3D). This research provides detection of 3D particles in 3D fluorescence microscopy images for cellular processes analysis. The researchers applied the adaptive wing loss (AWing) technique to focus on particles in contrast to background image points network. This approach aims to enable the system to adapt to various values in the ground truth mask, thereby increasing sensitivity to errors specifically for particles as compared to background image points. To address the significant imbalance between particle and background image points in 3D images, a weighted loss map was employed. This approach involved assigning higher weights to particles and challenging background image points that were in close proximity to particles. The architecture of the DM-DetNet3D network is depicted in Figure 9. For performance evaluation of the method, 3D images of Particle Tracking Challenge (PTC) and 3D fluorescence microscopy images of chromatin structures and interneurons were used. The method was compared with 3D versions of SEF (SEF3D), which is based on Laplacian-of-Gaussian) and DetNet (DetNet3D) which is based on image-to-image mapping by voxel-wise binary classification. The findings show that the approach gives better performance than previous methods.

The study of detection of visible impurities in glucose or sodium chloride injection liquids was conducted by Ge et al. [40]. To segment the difference between images, the existence of foreign particles was determined according to the continuity and smoothness of their moving traces. Sequence image processing was used to remove obstructions to detection due to unevenness such as scratches, embossed symbols, and graduations on the bottle surface. In this study, CCD camera was used to acquire online injection's image sequence, Pulse-Coupled Neural Networks was applied to detect foreign particles and the system gave a rejection signal to main control system. The results indicate that the system can detect the visible impurities effectively with the detection speed of 0.05s and correct detection rate of 99.1%, which satisfies the needs of medicine preparation. The results also show that even when adjacent regions' intensity ranges significantly overlapped, the algorithm is still able to segment images.

Oliveira et al. [41] have studied particle detection on electron microscopy (EM) micrographs using multi-classifier systems. The classifier in this method has been trained and performed on a single micrograph with patterns of particle and nonparticle so that it could identify if a new micrograph image contained a particle or not. Then, the researchers used a multi-classifier system to detect the particles on other micrographs. Five algorithms have been applied for generating individual classifiers which were Decision Trees (DTs), Multi-Layer Perceptron (MLP) neural networks, k-NN (k Nearest Neighbor), Naive Bayes (NB) classifier and Support Vector Machines (SVMs) and three other algorithms for multi-classifier, which were Bagging, AdaBoosting and StackingC. The results indicate that the multi-classifier method provided average accuracy of 89.64%, lower false positive (4.28) and negative rates (6.81), and better 3D structure reconstruction result.

Another research in hybrid method was performed by Dreisbach et al. [42] and Sax et al. [43] that tracks particle using neural networks and synthetic training data refinement in defocusing particle tracking velocimetry (DPTV). The method proposes two staged approaches, which are synthetic training data generation and refinement by unsupervised image-to-image translation. It performs object detection using deep learning on the recording gathered by the DPTV experiments. The network was trained with two kinds of synthetic and one semi-synthetic dataset to extract the particle position and size of real DPTV images. Figure 10 shows the two-stage approach in this method. For neural networks, the researchers used Faster R-CNN and RetinaNet. For performance, the method has been compared with particle detector trained on simple Gaussian particle image (PI), Hough transform. According to the study, the proposed method is capable of effectively addressing the issue of overlapping PIs, hence increasing reliability and accuracy. It also demonstrates higher measurement accuracy in determining diameters compared to the Hough transform. In addition to its robustness to inhomogeneous background illumination and image aberration, this approach exhibits strong performance.

Research on AI methods for particle detection in the biomedical and medical industries is advancing rapidly,

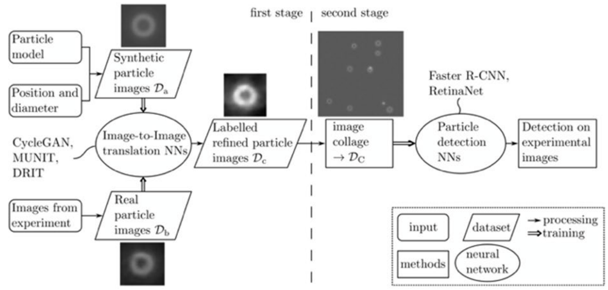


FIGURE 10. **Hybrid method proposed which applies two-stage approach, image-to-image translation neural networks and particle detection neural networks. [42].**

especially in the areas of medical imaging, microfluidic devices, and injectable liquids. The researchers have demonstrated that the methods exhibit superior performance in comparison to conventional methods.

B. POWER, ELECTRICAL AND ELECTRONICS

In the power, electrical, and electronics industry, particles or impurities can come from different sources, such as manufacturing processes, environmental contaminants, or the degradation of materials over time. These impurities can include dust, moisture, metal shavings, chemical residues, or other foreign substances that can interfere with the proper functioning of electrical components, affect electrical conductivity, or cause short circuits.

Oh and Christenson [44] have developed a particle detection system for Rutherford backscattering (RBS). RBS has commonly been applied in the electronics industry for material analysis, especially for inspection in semiconductors, superconductors, thin surface structures, metal and crystal orientations, metal and crystal damage, and polymers. The system aims to obtain the spectral data from an RBS analysis of the sample, which is Silicon (Si) wafer with silicon nitride (SixNy) coatings on the surface. The researchers conducted an analysis by comparing the results between LabVIEW and ADMCA, an analog and digital acquisition software by AMPTEK. The result shows that the automated system using LabVIEW gives comparable results with manual system which means that the developed system is reliable and accurate. Based on the study, it is found that the automated system is more time saving, minimizes the operators' workload and can reduce human error in sample positioning and beam localization time settings.

In alternative power generation methods, magnetic confinement fusion in deuterium-tritium plasmas must be clean, sustainable, and efficient. Thus, tokamak was built to achieve sustained nuclear fusion. The research by Cowley et al. [45] have introduced the automatic detection and tracking of impurity for tokamak camera. In the research, ML-based code called Robust Impurity Detector and Tracker (RIDAT) algorithm, using Python is applied. According to the study, the algorithm is robust and can be applied to various cameras and impurities. The code was separated into two modules which were image processing module and dust tracking module. In Image Processing Module the list of image frames from tokamak video footage were received as arguments and as outputs, a list of dust grains detected in each frame, along with the dust grain properties. In Dust Tracking Module the isolated detected grains were used as arguments and as outputs, a list of connected dust tracked spanning multiple frames. It was found that the classification accuracy was 65-100% and it could detect up to the order of 1000 dust particles from a single camera shot. The researchers suggested that the acquisition of additional training data should consider biases and involve a more thorough selection of parameters as the current training set only included the most prominent and readily identifiable grains.

C. MANUFACTURING

Particle and impurity detection plays a significant role in the manufacturing industry, where the presence of foreign particles or impurities can impact product quality, reliability, and safety. Detecting and controlling particles or impurities are essential to ensure the integrity of manufacturing processes and the final products produced. The impurities are usually found in mechanical parts because of the inclusions that exist in raw materials and fragments of different nature [14]. They can take the form of contaminants, dust, debris, metal shavings, or other foreign substances that can compromise the functionality or reliability of manufactured goods.

Galdon-Navarro et al. [46] have applied Near-Infrared (NIR) hyperspectral imaging and performed the comparison of latent variable using based and AI methods for impurity detection in PET recycling plant. The wavelength classes were classified as the materials in PET recycling, which were PET, PVC, transparent PVC and background. Multivariate image analysis (MIA) techniques were used to analyze hyperspectral images. From the study, it is found that the correspondence analysis gives higher average rates of true positive, false positive, false negative, and true negative.

In paper manufacturing, Bianconi et al. [47] conducted a study on impurity detection, which suggests employing a sequential approach to detect impurities. This approach involves initially classifying the paper as either defective or non-defective, followed by the application of thresholding techniques. The researchers have performed an analysis on the performance comparison between impurity detection using a sequential step approach and impurity detection using a thresholding method. The result shows that impurity detection exhibited a level of accuracy exceeding 96%. The method with classification step performed prior to thresholding, exhibits much greater accuracy compared to the impurity detection using direct thresholding.

D. FOOD AND BEVERAGES

Particle and impurity detection in the food and beverage industry is an important process that concentrates on ensuring the safety, quality, and integrity of food products consumed by humans. The current food and beverages industry requires advanced detection techniques and observing the regulatory standards, while avoiding product loss during the analysis process [48].

Huang et al. [49] have conducted the research to detect impurity in transparent liquid based on machine vision technology. This study used Realization Method Using Image Background Suppressing. The Fuzzy C-Means clustering algorithm was employed to effectively suppress impurities in the image backdrop. In the phase of impurity identification, the pre-recognition of impurities was accomplished by considering the grey and form features of the target, as well as prior knowledge and detection conditions. This allowed the detection and sorting of small targets in the detection process to achieve identification of too-large impurities and normal small particles. In this phase, fuzzy least squares support vector machines was used to achieve effective segregation of impurities and air bubbles. It is found that the method can reduce the recognition speed to 100ms for impurities' diameter less than 1mm with 99% recognition rate.

The study of melamine detection in milk powder has been performed by Fu et al. [9] using near-infrared (NIR) hyperspectral imaging technique to detect low level (less than 1.0%) melamine in milk powders. The setup of the experiment is shown in Figure 11. The image pre-processing for this method was by normalization and background removal. The spectrum of each pixel in the sample images was compared to the pure melamine spectrum using spectral similarity measures which were spectral angle measure (SAM), spectral correlation measure (SCM) and Euclidian distance measure (EDM). The result demonstrates that melamine contamination in milk powders can be detected using a combination of spectral similarity analysis and NIR hyperspectral imaging techniques.

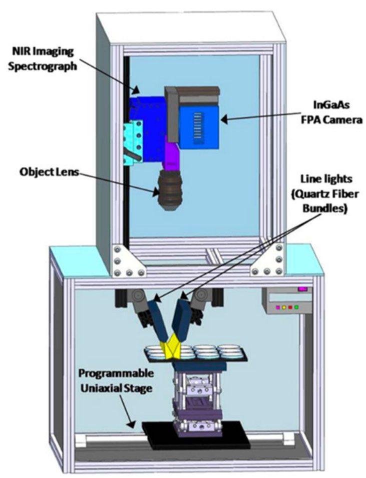


FIGURE 11. Semi-schematic of the NIR hyperspectral imaging system and its components [9].

Research of detection of impurities in granulated sugar were conducted by Albers et al. [4], [50] and Peichl et al. [51].

Albers et al. have investigated the possibility to detect the smallest impurities inside and on the surface of sugar heap using millimeter waves [50]. From this study, the researchers concluded that with the availability of sufficient signal strength from the wave interaction with the objects, it is feasible to detect small impurities in granulated sugar by using a more improved method. Peichl et al. and Albers et al. have studied the detection of small impurities during conventional material flow using millimeter-wave imaging technology (inverse synthetic aperture radar (ISAR) technology) [4], [51]. The difference in permittivity between granulated sugar and other substances induces a notable change in the behavior of radar reflectivity. The algorithm used was standard back-projection algorithm for ISAR processing. For analysis, the researcher used bumblebee on microwave absorber background and metal sphere on sugar heap. As for the result, the target can be clearly detected as a strong backscatter signal in ISAR images.

Research by Nunes et al. [52] aims to visually inspect the flour quality automatically based on number of particles detected. In this study, an acquisition board was used to allow the image captured using the commercial video cameras. The assessment of quality was determined by the number of identified particles within a predetermined time as specified by a technician. The software was developed with IMAQ Vision for LabVIEW. In this method there were two stages introduced to determine the number of detected particles, which were acquisition stage and processing stage. In acquisition stage, position of the flour samples was well-defined with optimum lighting condition. In processing stage, IMAQ Vision Builder was used for extraction of the image characteristics, then optical character recognition (OCR) was applied to allow the lot identification. Particle analysis was performed which the number of particles compared with maximum admissible number of particles defined by the user, if the number of particles exceeded the admissible number, it was considered as poor quality. The result shows that the system can detect the undesirable particles using digital image processing techniques.

He et al. [53] used CNN with gallery-guided graph architecture and region proposals for impurities detection in bottles used in wine industry. Figure 12 shows the overview of the impurity detection framework. As for analysis, comparisons have been conducted between the method and baselines methods which were Mask R-CNN, CornerNet and PANet to validate the effectiveness of region proposal generator. The result states that the performance of the proposed method was comparable with baselines with mAP of 80.84%, precision rate of 73.50%, recall rate of 86.49%, and F1 score of 75.52%. The method introduced also runs faster than the state-of-the-art methods.

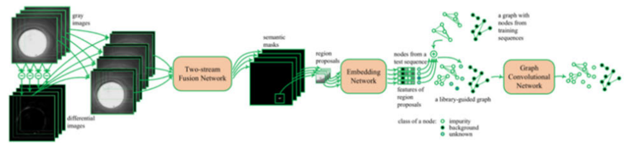


FIGURE 12. An outline of the framework for impurity detection: Three submodules make up the suggested methodology: a feature embedding network, a two-stream fusion network, and a graph convolutional network. Frame differencing is used to create differential images, which are then provided, concatenated with the original grey images at each time step, sent to a two-stream fusion network to create region proposals, and then each region proposal is treated as a node and added to a graph with similar nodes from training sequences, where their categories are determined using a graph convolutive. [53].

1) EDIBLE BIRD'S NEST (EBN) THE "CAVIAR OF THE EAST"

Nowadays, the use of edible bird's nests (EBNs) has been prevalent, primarily in the Asian region, owing to their recognized health and beauty benefits. EBN, also referred to as the "Caviar of the East," has garnered a reputation for being an expensive and lavish traditional beverage that has been enjoyed for centuries, dating back to the Tang Dynasty (618-907 AD) and the Sung Dynasty (960-1279 AD) [54], [55]. The swiftlet species of *Aerodramus* and *Collocalia (Apodidae)* in Southeast Asia and the Pacific Islands areas secrete EBNs during breeding, using their salivary glands with minimum presence of feathers or grass [56], [57]. Bird's nests appear to be the only nests that are safe for human consumption [58]. Figure 13 illustrates the images of unprocessed and processed raw EBNs obtained from Malaysia. Today, EBN products have expanded beyond beverages and have gained recognition as an ingredient in beauty products and cosmetics. Therefore, the demands for EBN are growing, posing challenges for ensuring quality assurance in EBN processing and its products [59].

FIGURE 13. The samples of EBNs collected in Malaysia: (a) Unprocessed raw and (b) processed raw.

A research trend study has been conducted in response to the growing demand for EBN products. This trend analysis attained a total of 80 publications from the Web of Science (WoS) Core Collection database. Figure 14 displays the annual count of publications and citations pertaining to EBN topics spanning the years 1977 to 2023. As shown in the figure, there has been a growing level of interest in EBN throughout the last four decades. Researchers have increasingly focused their attention on EBN. Particularly, a significant increase in publications occurred in 2012, with 87.5% of all articles coming from the present decade. Figure 14 also demonstrates that the articles in these topics have gained a substantial quantity of citations. The analysis

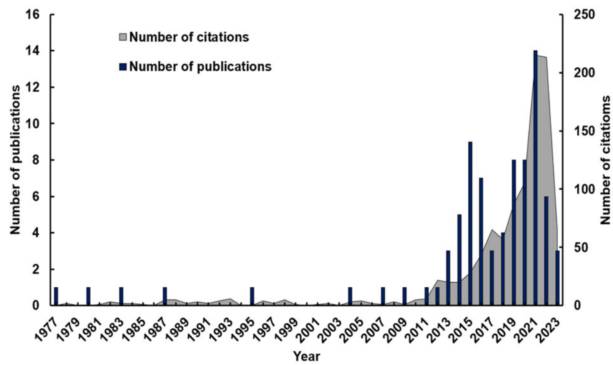


FIGURE 14. Number of publications and citations related to EBN.

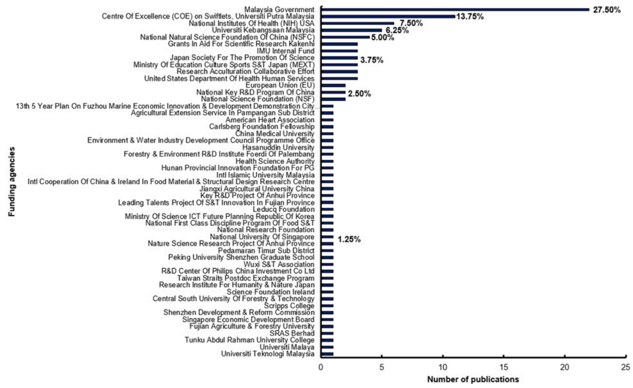


FIGURE 16. Funding agencies for research in EBN.

reveals that over 90% of citations were obtained within the most recent decade, indicating a projected rise in research interest in EBN beyond the year 2023.

Figure 15 illustrates the distribution of publications related to EBN by countries. According to the figure, Malaysia emerges as the leader in EBN research, as it accounts for 60.0% of the overall publications in this field. China and the United States accounted for 12.5% of the total papers each, while Japan contributed 10.0% of the overall publications. Figure 15 also illustrates that Asia exerts a greater influence globally in comparison to other continents, suggesting that the continent exhibits a more significant research interest in EBN.

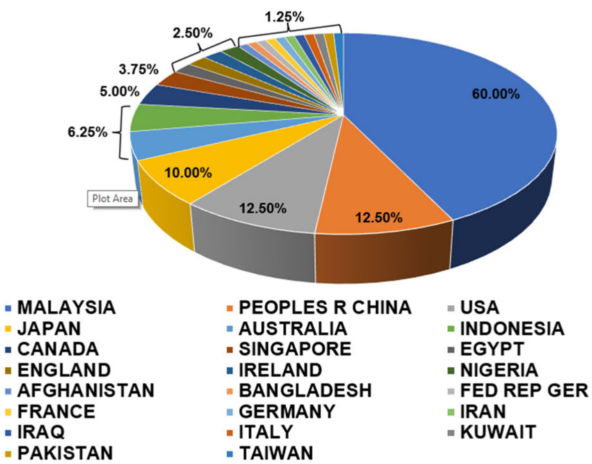


FIGURE 15. Publications in EBN by countries.

The funding sources for the research conducted in EBN are depicted in Figure 16. Based on the data presented in the figure, it can be observed that the Malaysian Government provided financial support amounting to 27.50% of the research conducted in this particular field. Some of the prominent funding bodies for research on EBN include the Centre of Excellence (COE) on Swiftlets at Universiti Putra Malaysia, the National Institutes of Health (NIH) in the United States, Universiti Kebangsaan Malaysia, and the National Natural Science Foundation of China (NSFC). According to the data presented in Figure 16, most of the research projects (57.5%) were financially supported by sponsors originating from Malaysia. This finding also indicates that Malaysia is at the lead of EBN research.

According to Figure 17, a total of 58 sources have published articles on EBN. The top six journals include a minimum of three articles in EBN research. According to the data presented in Figure 17, the publication with the highest frequency was found in the journal Frontiers in Pharmacology, followed by the Universiti Kebangsaan Malaysia (UKM) Faculty of Science and Technology (FST) Colloquium. These two sources accounted for approximately 6.25% of the total publications in the EBN dataset. The subsequent four prominent publishers in EBN research comprise Food Research International, Foods, Forktail, and International Food Research Journal. Collectively, these publishers account for 3.75% of the total publications in EBN.

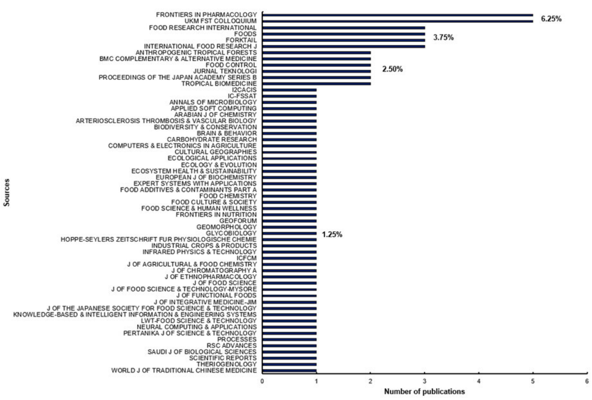


FIGURE 17. Sources of EBN research.

EBNs are secreted during the breeding by swiftlets species of Aerodramus and Collocalia (Apodidae) in Southeast Asia and Pacific Islands regions using salivary gland with minimum feathers or grass [56], [57]. They are mainly collected in Malaysia, Indonesia, Thailand, Vietnam, and China. Swiftlets typically build their nests in caves along the coast and in the mountains, but due to the high demand for EBNs, they are bred in abandoned stores and house farms. The EBN's quality assurance regarding dimensions, composition, and form is critical for ensuring that this alternative harvesting technique yields safe and high-quality goods in line with its high price and economic value. Prior to sale, the EBN must be free from impurities and contaminants that are hazardous to human consumption. Particles, feces, dirt, sand, grass, sticks, feathers, spots (such as rust and wood), fibers, and egg fragments are common types of impurities found in EBN [60]. Figure 18 shows impurities normally found in EBN.

FIGURE 18. Various impurities commonly found in EBN.

Most of EBN's inspections have been performed manually. The assessment of EBN's quality and value was predominately dependent on subjective individual experiences, lack of scientific verification or quantification [61]. Presently, an EBN visual inspection is performed by a human operator employing a magnifying glass, as depicted in Figure 19. Visual inspection relies on human judgement to examine the product, primarily to ensure that the EBN product is clean with minimal impurities following the cleaning procedure. This will lead to inconsistency and increase the possibility of errors occurring in the practice [62]. Automating the inspection of EBN is necessary in order to establish a standardized approach for quality assessment, reduce human errors associated with grading, and enhance the examination process of product quality [63].

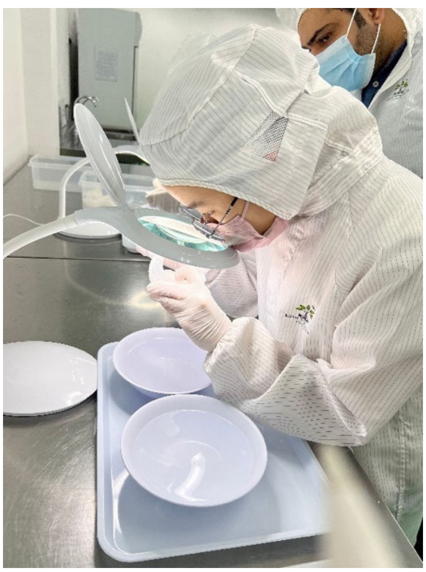


FIGURE 19. Manual inspection for EBN.

Several research have been performed regarding the application of AI in EBN impurities detection. The study conducted by Goh et al. [64] focuses on the detection and characterization of impurities present in EBN. This investigation employed a small chamber, a red LED light source, and a camera as the primary tools for analysis. The researchers employed thresholding, noise reduction techniques, and flood fill technique in order to enhance the quality of the image. The K-Means clustering algorithm was employed to conduct a comprehensive analysis, separating intensity values into background and EBN categories. The Fuzzy C-Mean algorithm was used to detect impurities. The proposed system demonstrates the efficacy of the K-Means algorithm in identifying impurities of varying sizes. However, it encounters difficulties in accurately detecting tiny impurities and exhibits a tendency to misclassify holes. In general, the K-Means method exhibits its capacity to effectively detect impurity locations in the context of 2D image segmentation.

In their study, Yee et al. [65] employed an image fusion-based segmentation algorithm for detecting impurities in EBN. The researchers enhanced optical clarity and achieved consistency by implementing a low-angle blue diffused and red-diffused backlight. The method employs two images for each EBN, captured under different lighting settings. Before combining the two images to get the final image, two pre-processing procedures were performed simultaneously, which involved segmenting impurities and EBN area from the background. The detection of impurities became visible as dark regions on the final image after applying the threshold value. The findings indicate a true positive/recall rate of 93.39%, a precision rate of 71.17%, and a false-negative detection rate of 4.8%. However, the study has a significant misclassification rate of 32.25%. The result can be attributed to detection errors arising from the presence of non-uniform EBN intensities. Moreover, several impurities that are misclassified as impurities by the system are in fact dark topographies, holes, shadows, and EBN salivary strands.

The research conducted by Yeo and Yen [66] aims to enhance the detection of impurities in the inhomogeneous intensity of EBN. This was achieved by applying the U-Net deep learning model and a hybrid auto-encoder model. The study suggests that the complexities arising from inconsistencies in the shape, density, and thickness of the EBN contribute to increased complexity in image processing and analysis of this structure. The U-Net model demonstrates its capability to analyze inhomogeneous EBN pictures. The U-Net model underwent reinitialization and training with enhanced hyperparameters. The observed misclassification false-positive rate was improved at 10.08% compared to 32.25% in previous study.

The anomaly detection technique developed by Yeo and Yen [60] employed a hybrid autoencoder and a single convolutional layer classifier to identify EBN contaminants. This study examines the presence of foreign substances, such as non-white dirt and other contaminants that have comparable color or intensity with the edible bird's nest (EBN). The training process involved utilizing a hybrid autoencoder model to replicate the non-impurity areas inside the EBN images, specifically for impurities segmentation. Additionally, a single convolutional layer classifier was used and trained to detect impurities. The model demonstrated a detection rate of over 92% for impurities and an undetected rate of 5.63%. Notably, the model successfully recognized impurities with a size smaller than 0.20mm.

Based on the specifications outlined in the Malaysian Standard Edible-Bird Nest (EBN) – Specification MS 2334:2011, the classification of EBN into Grades I, II, and III is based on many properties, including shape, size, level of cleanliness, and presence of impurities [67]. EBN with less amount of impurities will exhibit a greater value in comparison to EBN with more impurities due to the potential deformation of the EBN's structure caused by the impurity removal process, resulting in significant waste [68], [69]. Hence, impurity detection element is important in the grading process of EBN. The research conducted on automated grading systems for EBN includes the detection of impurities as a crucial stage within the feature extraction process. The HSV (hue, saturation, value) color model was used in the research to detect impurities present on EBN. The saturation layer is considered the most effective layer for distinguishing the difference between shadow and impurities due to their almost identical color. The number of white pixels increases with the presence of impurities in the EBN. Koay et al. [68] developed a classification method utilizing the hybrid system Adaptive Neuro Fuzzy Inference System (ANFIS), which incorporates the advantages of fuzzy inference systems (FIS) and artificial neural networks (ANNs). ANFIS is a type of fuzzy logic system that involves the training of its parameters applying Artificial Neural Network (ANN)-based approaches in its fundamental form [70]. This study evaluates the performance and accuracy of the ANFIS classification method with the K-Nearest Neighbors (KNN) classifier. The study analyses the accuracy of the system by employing several data pre-processing techniques, including min-max normalization, z-score normalization, decimal scaling, linearization, and sigmoid function. Additionally, the researchers compared the system's accuracy across varying proportions of training and testing data. The study findings indicate that the ANFIS classification technique, in combination with Fuzzy C-Means clustering approaches, demonstrated a higher accuracy rate of 88.24% in classifying the grades of EBN. In comparison, the KNN classifier, when using linearized data, achieved a slightly lower accuracy rate of 83.27%.

Gan and Weng [71] proposed K-means based bat algorithm clustering, a hybrid method that combines the bat algorithm with K-means clustering to improve the accuracy and efficiency of classification. This study assesses the accuracy of the model in comparison to the standard bat algorithm (BA). By using decimal scaled data, the standard BA classifier demonstrated the accuracy rate of 80.29%, whereas the KMBA classifier surpassed this performance by achieving a higher accuracy rate of 85.60%. The researchers proposed the use of a larger data set with better quality images to enhance the accuracy.

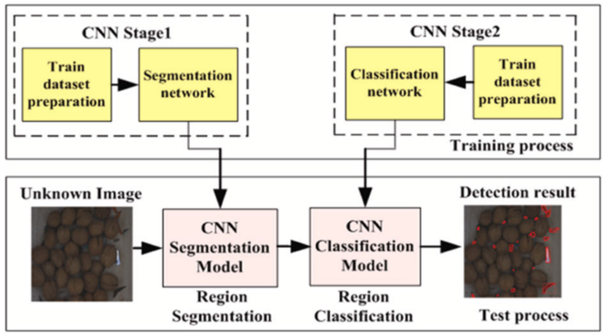


FIGURE 20. Two-stage convolutional networks detection flowchart [72].

E. AGRICULTURE

Particle and impurity detection in agriculture is fundamental for ensuring food safety, environmental sustainability, and the overall productivity of the agricultural sector. By implementing advanced detection techniques and adhering to regulatory standards, farmers, agricultural scientists, and regulatory agencies can enhance agricultural practices, protect consumer health, and support the production of high-quality and safe food products.

The research by Rong et al. [72] used two-stage different CNNs to detect various-sized impurities such as leaf debris, paper scraps, plastic scraps, and metal pieces in walnuts as shown in Figure 21 below. The first stage of CNN completed the image segmentation while the second CNN stage detected the impurities in walnuts images in real-time. In the processes, detailed aspects of walnut images were extracted from low-level layers to high-level layers using multiscale residual fully convolutional networks and classification approach based on convolutional networks. Segmentation was completed by a single convolutional network layer, while detection was completed by fully connected

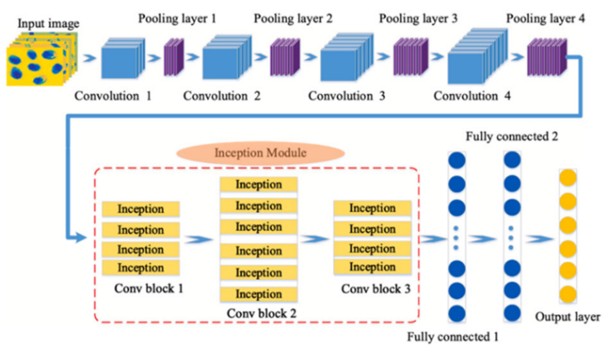


FIGURE 21. Structure of Wheat-V2 CNN [76].

layers in the classification network. The algorithm was performed using Visual Studio 2015 C/C++ and open source TensorFlow calculation software library. The method has achieved 99.4% accuracy to segment the object regions in the test images, 96.5% accuracy to classify the foreign objects in the validation images and 100.0% accuracy on the detection in test images. The processing times for segmentation and detection of each image were less than 60ms. This method however is limited to a single channel with one camera in the visible light imaging environment, thus additional image views of the samples and different waveband images should be obtained for more accurate results.

Sharma and Sawant [73], Vithu et al. [74] and Shen et al. [75], [76] have studied about the impurity and quality detections in wheat and rice grains. Sharma and Sawant used image processing algorithm on rice and grain samples using MATLAB and applied Neural Network (NN) classifier to categorize the samples into good, bad and medium quality [73]. The findings show that the system is fully automated, cost effective, reliable and less time-consuming. Vithu et al. have applied color machine vision system and multi-class support vector machine (SVM) classifier to identify dockage in paddy [74]. The algorithm measured five morphological and nine color features from the image acquired by the system and managed to achieve up to 90.5% accuracy. This system is found to be rapid, nondestructive and can be used at commercial level. In detecting impurities in wheat, Shen et al. have applied an improved neural network called WheNet [75]. In image pre-processing phase, Wiener filtering algorithm and the multi-scale Retinex re-enhancement algorithm were applied to reduce influence of motion, shading and differences in light, for classifying and labelling the images. To identify the impurities, the researchers applied CNN by improving and optimizing the network research, Inception_v3 using Adam optimization algorithm before developing WheNet. The findings show that WheNet achieved the most efficient result where it gave shorter training time of 11h, with 99.29% average accuracy, higher mean values for AUC (0.975) and higher recall rate of 98.0%. Shen et al. have then improved the previous study by applying hybrid method to detect impurities in wheat [76]. The detection of impurities in the study applied terahertz spectral imaging and CNN. The spectral characteristics of wheat, wheat husk, wheat straw, wheat grain, weed and ladybugs within the range of 0.2-1.6 THz were studied using THz spectral imaging and the corresponding frequency-domain spectra were obtained using Fourier transformation. This method performs the detection by analyzing the time-domain waveform, frequency-domain curve, absorption coefficient, refractive index, and imaging characteristics of samples at different frequencies in the band of 0.2–1.6 THz. Novel Wheat-V2 CNN was designed to extract the data and information regarding spectral imaging features. Figure 21 shows the structure of Wheat-V2 CNN. The results show that the designed Wheat-V2 model can recognize the impurities in wheat images effectively with a high recognition average accuracy of 98.07%.

The research by Chen et al. [77] uses hybrid method of Genetic Algorithm and Support Vector Machine (SVM) to detect kernel-like impurities (KLIs) for wheat quality evaluation. Three methods, genetic algorithm (GA)/support vector machine (SVM), principal components analysis (PCA)/SVM and linear discriminant analysis (LDA) were applied for feature selection and classification. The performance of pairings was compared, and it is found that GA/SVM achieved outstanding accuracy of 99.34%. This method is found to be feasible to extract a small quantity of useful features without any extra image or data processing for online KLI classification and only two useful features are enough for online wheat classification.

F. PHARMACEUTICAL

Particle and impurity detection is a vital aspect of the pharmaceutical industry that focuses on ensuring the safety, quality, and efficacy of the products. In the pharmaceutical manufacturing process, it is essential to identify and monitor the presence of any foreign particles or impurities that may affect the purity or integrity of the final product. Particle and impurity detection plays a crucial role in pharmaceutical regulatory compliance as well. Compliance with the regulations ensures that medications meet the required standards of safety, efficacy, and quality, providing assurance to healthcare professionals and patients alike.

The study conducted by Kragh et al. [78] aims to detect impurities for cylindrical transparent containers by employing camera as well as MATLAB image acquisition and processing to acquire the images. The radius of each particle was measured using angular frequency to approximate its position within the container. In this study, a simple algorithm in MATLAB has been used that enabled the system to determine whether the particle is inside or outside by comparing the radius of the particles location. The result indicates that the particle detection was 85% accurate.

In the study conducted by Ge et al. [79] an advanced method of Extreme Learning Machine called Online Sequential Extreme Learning Machine (OS-ELM) has been used to detect impurities automatically for ampoule injection. To realize the detection process, the ampoules were passed through the high-speed rotating station (HSRS) and moved into the abruptly stopping station (ASS) of the inspection system. The image acquisition was done with CCD camera. As a foreign particle judging criterion, the moving trajectory of the target was constructed using spatial information, such as the centroid's coordinates. Area, mean grey value, geometric invariant moments, and wavelet packet energy spectrum were employed in supervised learning to predict and classify the type of foreign particles. The results of this study show that the method obtained excellent accuracy of 95.5% and repeatability in foreign particle detection and classification, and it was extremely

TABLE 2. AI methods in particle and impurity detection for different applications.

Reference	Industry	Application	Method	Results
Zhu et al. [34]	Biomedical	To detect particle for single particle analysis.	Hough Transforms	Average accuracy=89% False negative rate=11% False positive rate=26%
Sierra et al. [3]	Medical	To remove dust particles on retinal fundus cameras.	Conjunction OR AND operation using MATLAB code	The method was robust and fast but artifacts with low contrast were not detected.
Rossi et al. [35]	Biomedical	To track the particles on microfluidic devices.	General defocusing particles tracking (GDPT)	Evaluation time of about one second.
Ge et al. [36]	Medical	To detect particle of complex images for industrial workpiece or medical image.	Convolutional Neural Network (CNN)	ResNet2Ls outperform three non-learning-based methods and it was difficult to detect macroparticles sized over 50 pixels in diameter.
Ritter et al. [37]	Biomedical	To detect particle in fluorescent microscopy images of live cells.	Deconvolution Network, DetNet	Performance gives state-of-the-art results or improves the results compared to classical methods, SEF-GF
Spilger et al. [39]	Biomedical	To detect 3D particle in 3D fluorescence microscopy images.	Density Map DetNet 3D	The approach gives better performance than previous methods.
Ge et al. [40]	Medical	To detect visible foreign particles in glucose or sodium chloride injection liquids.	Pulse-Coupled Neural Networks	Correct detection rate of 99.1%
Oliveira et al. [41]	Biomedical	To detect particle on electron microscopy (EM) micrographs.	Multi-classifiers	Average accuracy=89.64% False positive=4.28 False negative=6.81
Dreisbach et al. [42] and Sax [43]	Biomedical	To track particle in defocusing particle tracking velocimetry (DPTV).	Neural networks and synthetic training data refinement	Detection rate for this method increases and false positive rate is reduced.
Oh and Christenson [44]	Electronics	To detect particle for Rutherford backscattering (RBS).	LabVIEW	Comparable result with manual system.
Cowley et al. [45]	Power	To detect and track impurity for tokamak camera.	Robust Impurity Detector and Tracker (RIDAT) algorithm	Classification accuracy=65-100%
Huang et al. [49]	Food and Beverages	To detect impurity in transparent liquid.	Fuzzy C-Means clustering	Recognition rate=99%
Fu et al. [9]	Food and Beverages	To detect melamine in milk powder.	Spectral similarity analysis and NIR hyperspectral imaging techniques	Melamine contamination can be detected using the combination methods.
Albers et al. [4, 50] and Peichl et al. [51]	Food and Beverages	To detect the smallest impurities inside and on the surface of sugar heap.	Inverse synthetic aperture radar (ISAR) technology	Target can be clearly detected as a strong backscatter signal in ISAR images.
Nunes et al. [52]	Food and Beverages	To visually inspect the flour quality automatically based on number of particles detected.	IMAQ Vision for LabVIEW	System capable to detect the undesirable particles using digital image processing techniques.
He et al. [53]	Food and Beverages	To detect impurity in bottles used in wine industry	CNN with gallery-guided graph architecture and region proposals.	F1 score =75.52%
Goh et. al [64]	EBN	To characterize EBN impurity size.	K-Means clustering algorithm	Accuracy of Fuzzy C-Means is as same as K-Means, but false detection rate is higher.
Yee et. al [65]	EBN	To detect EBN impurities.	Optical segmentation and image fusion algorithm.	True positive/recall rate=93.39%
Yeo and Yen [60, 66]	EBN	To detect EBN impurities.	a) U-Net deep learning model and hybrid autoencoder model b) Hybrid autoencoder and single convolutional layer classifier	Accuracy=96.69% Detection rate=92%
Koay et al. [68]	EBN	Automated grading system for EBN.	Adaptive Neuro Fuzzy Inference System (ANFIS)	Accuracy=88.24%
Gan and Lai [71]	EBN	Automated grading system for EBN.	Bat algorithm clustering based on K-means (KMBA)	Accuracy=85.60%
Rong et al. [72]	Agriculture	To detect various-sized impurities in walnuts.	Two-stage different convolutional neural networks (CNN)	Accuracy=100%.0
Sharma and Sawant [73]	Agriculture	Quality classification.	Neural Network (NN) classifier	The system is fully automated, cost effective, reliable and less time consuming.
Vithu et al. [74]	Agriculture	To identify dockage in paddy.	Multi-class support vector machine (SVM)	Accuracy=90.5%

accurate in differentiating air bubbles from glass chips with a 99.83% accuracy.

The summary for AI methods used in particle and impurity detection for different types of applications and industries is shown in Table 2.

IV. ARTIFICIAL INTELLIGENCE APPLICATION IN PARTICLE AND IMPURITY REMOVAL

Removal of particles and impurities is important in most products and industries. As for electronics industry, the advancements in current technology have made impurities removal crucial to ensure the high yield of electronic components manufacturing [80]. The presence of unwanted particles or impurities during the manufacturing process of any product will contribute to product damage, lower product quality and even health risk if it is related to humans. Traditional methods for particle and impurity removal often rely on human operators, rule-based systems, or predefined algorithms. These approaches have limitations in adaptability, and robustness, as they struggle to handle complex and dynamic environments. AI techniques offer a promising solution to overcome these challenges and enhance the efficiency and effectiveness of these processes.

The work conducted by Subramaniam et al. [81] examines the processing of EBN impurities using machine vision and a robotic arm. An image processing algorithm was applied to identify dirt in the image acquired using machine vision techniques. The implementation of image extraction techniques of the RGB color plane was employed to capture and assess the dirt location. The LabVIEW vision blocks technique was utilized to analyze particles falling between the size range of 0.04mm^2 to 0.60mm^2 to ascertain their respective coordinates. The mechanical element of the device used an industrial six-axis-robotic arm. The end effector was designed specifically to employ suction operation through a 1mm-diameter sharp nozzle to remove particles with dimensions of up to 0.04mm^2. The precision of the end effector was determined to be 0.01mm. The system configuration for the EBN processing prototype described in the study is shown in Figure 22. The findings of this study indicate that, on average, 80% of dirt was successfully removed. The researchers acknowledged the constraints of the study, specifically regarding the image processing component's ability to handle only two-dimensional images and the requirement for the EBN samples to have a minimal thickness, not exceeding 2mm.

Qing et al. [82] proposed case-based reasoning and case retrieval algorithm for rice and wheat combined harvester aimed to improve the cleaning loss rate and impurity rate. The system used air flow to remove both light and heavy impurities in rice and wheat. The sensor system was used to collect control quality values and the input was sent to the controller. By applying the case-based reasoning, cleaning condition parameters were used as control parameters to provide desired cleaning impurity rate and cleaning loss rate. This web-based system enables the users to search

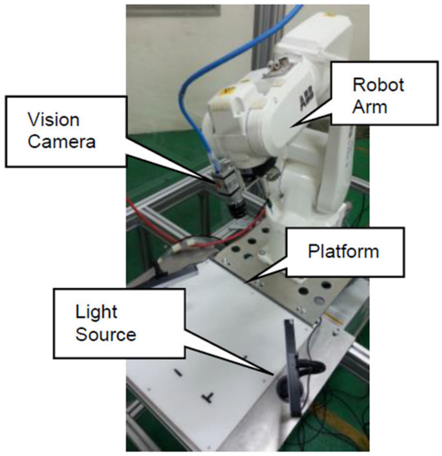


FIGURE 22. The configuration of the system for the EBN processing.

current cleaning conditions in the problem description part, and case-based reasoning system recalls the cleaning control cases that fit the current problem using similarity calculations. The overall system learns from the previous case to execute the cleaning control scheme. The study has verified that the case-based reasoning system's effectiveness could optimize the cleaning control parameters compared to human operator process.

Most of the previous research has been limited to the detection of particles and impurities using AI methods. There is a lack of studies on the application of AI for particle and impurity removal, which creates a potential for additional research in this field.

V. CONCLUSION

Particle and impurity detection plays an important part in various industries and scientific fields. By employing the AI techniques, its subsets and other analytical methods, automated systems can efficiently detect, analyze, classify, and process the particles or impurities, providing valuable insights for quality control and ensuring the integrity of materials and products. The continuous progress in imaging technologies and AI algorithms is consistently improving the accuracy and efficiency of particle detection systems. This progress is essential in facilitating the development of products and materials that are safer, more environmentally friendly, and of superior quality across many industries. A concise overview was provided in this paper about the background context of particle and impurity detection, processing, and AI methods. This study also examines the research trend in order to offer insights into the present state of research regarding this topic. A thorough review has been done on machine-learning techniques applied for the detection of particles and impurities across several industrial sectors. This work is believed to be a useful supplement to the existing literature on object detection, as it particularly examines the application of AI methods in the context of particle and impurity detection. This review will provide a basis for researchers who are interested in this topic, encouraging them to explore new research avenues.

ACKNOWLEDGMENT

The authors acknowledge the utilization of ChatGPT-3.5 (Open AI, https://chat.openai.com), to summarize their initial remarks in the introduction parts.

REFERENCES

[1] J. M. Zhao and C. C. Xue, "A flour impurity detection system based on image processing," *J. Phys. Conf. Ser.*, vol. 634, Jul. 2020, Art. no. 012129, doi: 10.1088/1742-6596/1634/1/012129.

[2] C. Zhang, T. Li, and W. Zhang, "The detection of impurity content in machine-picked seed cotton based on image processing and improved YOLO v4," *Agronomy*, vol. 12, no. 1, p. 66, Dec. 2021, doi: 10.3390/agronomy12010066.

[3] E. Sierra, A. G. Marrugo, and M. S. Millán, "Dust particle artifact detection and removal in retinal images," *Optica Pura Aplicada*, vol. 50, no. 4, pp. 379–387, Dec. 2017, doi: 10.7149/opa.50.4.49075.

[4] T. Albers, M. Peichl, S. Dill, and T. Kempf, "MMW ISAR concept for detection of impurities in sugar production," in *Proc. 11th Eur. Conf. Synth. Aperture Radar (EUSAR)*, Jun. 2016, pp. 1–4.

[5] M. Meenu, C. Kurade, B. C. Neelapu, S. Kalra, H. S. Ramaswamy, and Y. Yu, "A concise review on food quality assessment using digital image processing," *Trends Food Sci. Technol.*, vol. 118, pp. 106–124, Dec. 2021, doi: 10.1016/j.tifs.2021.09.014.

[6] S. Tanaka, T. Ohtani, Y. Narita, Y. Hatsukade, and S. Suzuki, "Development of metallic contaminant detection system using RF high-Tc SQUIDs for food inspection," *IEEE Trans. Appl. Supercond.*, vol. 25, no. 3, pp. 1–4, Jun. 2015, doi: 10.1109/TASC.2014.2361893.

[7] Y.-Z. Feng and D.-W. Sun, "Application of hyperspectral imaging in food safety inspection and control: A review," *Crit. Rev. Food Sci. Nutrition*, vol. 52, no. 11, pp. 1039–1058, Nov. 2012, doi: 10.1080/10408398.2011.651542.

[8] L. W. Moharkar and S. Patnaik, "Detection and quantification of milk adulteration by laser induced instumentation," in *Proc. IEEE 5th Int. Conf. Converg. Technol. (I2CT)*, Mar. 2019, pp. 1–5, doi: 10.1109/I2CT45611.2019.9033883.

[9] X. Fu, M. S. Kim, K. Chao, J. Qin, J. Lim, H. Lee, A. Garrido-Varo, D. Pérez-Marín, and Y. Ying, "Detection of melamine in milk powders based on NIR hyperspectral imaging and spectral similarity analyses," *J. Food Eng.*, vol. 124, pp. 97–104, Mar. 2014, doi: 10.1016/j.jfoodeng.2013.09.023.

[10] W. Sriratana, N. Narknam, R. Apichitanon, and N. Tammarugwattana, "Application of webcam for inspection of Rice grain quality by using image processing technique," in *Proc. 20th Int. Conf. Control, Autom. Syst. (ICCAS)*, Oct. 2020, pp. 1134–1139, doi: 10.23919/ICCAS50221.2020.9268316.

[11] D. Wu and D.-W. Sun, "Advanced applications of hyperspectral imaging technology for food quality and safety analysis and assessment: A review—Part I: Fundamentals," *Innov. Food Sci. Emerg. Technol.*, vol. 19, pp. 1–14, Jul. 2013, doi: 10.1016/j.ifset.2013.04.014.

[12] N.-F. Huang, D.-L. Chou, and C.-A. Lee, "Real-time classification of green coffee beans by using a convolutional neural network," in *Proc. 3rd Int. Conf. Imag., Signal Process. Commun. (ICISPC)*, Jul. 2019, pp. 107–111, doi: 10.1109/ICISPC.2019.8935644.

[13] K. Dobashi, M. Saito, and T. Hayashi, "Advanced quality control of quartz parts for semiconductor equipment based on the food industry's well-established QC methodology (HACCP)," in *Proc. Int. Symp. Semiconductor Manuf. (ISSM)*, Oct. 2008, pp. 29–32.

[14] X. Liu, P. Xing, B. Gupta, B. Wu, J. Yang, J. Zhang, B. Ducharne, N. Yang, and C. He, "An improved sensor for the magnetic susceptibility imaging technique for detecting impurities in non-ferromagnetic materials," *Sens. Actuators A, Phys.*, vol. 279, pp. 240–247, Aug. 2018, doi: 10.1016/j.sna.2018.05.035.

[15] Z. Wei, Z. Song, X. Zhang, and Z. Meng, "Microparticle detection with optical microfibers," *IEEE Photon. Technol. Lett.*, vol. 25, no. 6, pp. 568–571, Mar. 2013, doi: 10.1109/LPT.2013.2241422.

[16] F. Ichihashi, A. Koyama, T. Akashi, S. Miyauchi, K. Morooka, H. Hojo, H. Einaga, Y. Takahashi, T. Tanigaki, H. Shinada, and Y. Murakami, "Automatic electron hologram acquisition of catalyst nanoparticles using particle detection with image processing and machine learning," *Appl. Phys. Lett.*, vol. 120, no. 6, Feb. 2022, Art. no. 064103, doi: 10.1063/5.0074231.

[17] E. H. Bernhardi, K. O. van der Werf, A. J. F. Hollink, K. Wörhoff, R. M. de Ridder, V. Subramaniam, and M. Pollnau, "On-chip microparticle detection and sizing using a dual-wavelength waveguide laser," presented at the Conf. Lasers Electro-Opt. Eur. Int. Quantum Electron. Conf. CLEO EUROPE/IQEC, Munich, Germany, May 2013, p. 1.

[18] M. Roy, D. Seo, J. Kim, S. Seo, and S. Oh, "Smartphone based automated microparticle analysis system," presented at the 3rd Int. Conf. Comput., Commun., Control Inf. Technol. (C3IT), Hooghly, India, Feb. 2015, pp. 1–3.

[19] C. Vonesch, F. Stauber, and M. Unser, "Design of steerable filters for the detection of micro-particles," in *Proc. IEEE 10th Int. Symp. Biomed. Imag.*, Macro, CA, USA, Apr. 2013, pp. 934–937.

[20] F. Foncellino, L. Barretta, E. Massera, and A. Corigliano, "Piezoelectric MEMS for microparticles detection," in *Proc. IEEE Sensors*, Oct. 2021, pp. 1–4.

[21] T.-C. Chen and S.-Y. Yu, "The review of food safety inspection system based on artificial intelligence, image processing, and robotic," *Food Sci. Technol.*, vol. 42, May 2022, Art. no. e35421, doi: 10.1590/fst.35421.

[22] M. Mabaso, D. Withey, and B. Twala, "Spot detection methods in fluorescence microscopy imaging: A review," *Image Anal. Stereol.*, vol. 37, no. 3, pp. 173–190, 2018, doi: 10.5566/ias.1690.

[23] C. Li, Y. You, D. Chen, Z. Gu, Y. Zhang, T. P. Holler, X. Ban, Y. Hong, L. Cheng, and Z. Li, "A systematic review of rice noodles: Raw material, processing method and quality improvement," *Trends Food Sci. Technol.*, vol. 107, pp. 389–400, Jan. 2021, doi: 10.1016/j.tifs.2020.11.009.

[24] K. A. Stephanie, *The Era of Artificial Intelligence, Machine Learning, and Data Science in the Pharmaceutical Industry*. London, U.K.: Academic, 2021.

[25] Y. Guo, Y. Liu, A. Oerlemans, S. Lao, S. Wu, and M. S. Lew, "Deep learning for visual understanding: A review," *Neurocomputing*, vol. 187, pp. 27–48, Apr. 2016, doi: 10.1016/j.neucom.2015.09.116.

[26] A. Halbouni, T. S. Gunawan, M. H. Habaebi, M. Halbouni, M. Kartiwi, and R. Ahmad, "Machine learning and deep learning approaches for CyberSecurity: A review," *IEEE Access*, vol. 10, pp. 19572–19585, 2022, doi: 10.1109/ACCESS.2022.3151248.

[27] J. Panigrahi, P. Pattnaik, B. B. Dash, and S. R. Dash, "Rice quality prediction using computer vision," in *Proc. Int. Conf. Comput. Sci., Eng. Appl. (ICCSEA)*, Mar. 2020, pp. 1–5, doi: 10.1109/ICCSEA49143.2020.9132967.

[28] F. Xiao, H. Wang, Y. Li, Y. Cao, X. Lv, and G. Xu, "Object detection and recognition techniques based on digital image processing and traditional machine learning for fruit and vegetable harvesting robots: An overview and review," *Agronomy*, vol. 13, no. 3, Feb. 2023, Art. no. 639, doi: 10.3390/agronomy13030639.

[29] U. S. Shanthamallu, A. Spanias, C. Tepedelenlioglu, and M. Stanley, "A brief survey of machine learning methods and their sensor and IoT applications," in *Proc. 8th Int. Conf. Inf., Intell., Syst. Appl. (IISA)*, Larnaca, Cyprus, Aug. 2017, pp. 1–8.

[30] I. Rodríguez-Rodríguez, J.-V. Rodríguez, N. Shirvanizadeh, A. Ortiz, and D.-J. Pardo-Quiles, "Applications of artificial intelligence, machine learning, big data and the Internet of Things to the COVID-19 pandemic: A scientometric review using text mining," *Int. J. Environ. Res. Public Health*, vol. 18, no. 16, Aug. 2021, Art. no. 8578, doi: 10.3390/ijerph18168578.

[31] J. Zheng, R. Liu, X. Zhong, and R. Zhang, "web of science-based virtual brand communities: A bibliometric review between 2000 and 2020," *Internet Res.*, vol. 33, no. 2, pp. 606–637, Apr. 2023, doi: 10.1108/intr-11-2021-0800.

[32] N. J. van Eck and L. Waltman, "Software survey: VOSviewer, a computer program for bibliometric mapping," *Scientometrics*, vol. 84, no. 2, pp. 523–538, Aug. 2010, doi: 10.1007/s11192-009-0146-3.

[33] Z. Ye, X. Jiang, Z. Wang, and W. Xiao, "Prospect of particle detection technology based on digital image processing," in *Proc. Int. Conf. Electr. Inf. Mechatronics (ICEIM)*, Jiaozuo, China, Dec. 2011, pp. 591–594, doi: 10.4028/www.scientific.net/AMM.143-144.591.

[34] Y. Zhu, B. Carragher, F. Mouche, and C. S. Potter, "Automatic particle detection through efficient Hough transforms," *IEEE Trans. Med. Imag.*, vol. 22, no. 9, pp. 1053–1062, Sep. 2003, doi: 10.1109/TMI.2003.816947.

[35] M. Rossi and R. Barnkob, "A fast and robust algorithm for general defocusing particle tracking," *Meas. Sci. Technol.*, vol. 32, no. 1, Jan. 2020, Art. no. 014001, doi: 10.1088/1361-6501/abad71.

[36] Y. Ge, Y. Liu, and C. Xu, "Particle detection of complex images based on convolutional neural network," in *Proc. 41st Chin. Control Conf. (CCC)*, Jul. 2022, pp. 7228–7233, doi: 10.23919/CCC55666.2022.9902474.

[37] C. Ritter, R. Spilger, J.-Y. Lee, R. Bartenschlager, and K. Rohr, "Deep learning for particle detection and tracking in fluorescence microscopy images," in *Proc. IEEE 18th Int. Symp. Biomed. Imag. (ISBI)*, Nice, France, Apr. 2021, pp. 873–876, doi: 10.1109/isbi48211.2021.9433759.

[38] R. Spilger, A. Imle, J.-Y. Lee, B. Müller, O. T. Fackler, R. Bartenschlager, and K. Rohr, "A recurrent neural network for particle tracking in microscopy images using future information, track hypotheses, and multiple detections," *IEEE Trans. Image Process.*, vol. 29, pp. 3681–3694, 2020, doi: 10.1109/TIP.2020.2964515.

[39] R. Spilger, V. O. Chagin, C. S. Bold, L. Schermelleh, U. C. Müller, M. C. Cardoso, and K. Rohr, "Deep neural network for 3D particle detection in 3D fluorescence microscopy images via density map regression," in *Proc. IEEE 19th Int. Symp. Biomed. Imag. (ISBI)*, Kolkata, India, Mar. 2022, pp. 1–4, doi: 10.1109/isbi52829.2022.9761509.

[40] J. Ge, Y. Wang, B. Zhou, and H. Zhang, "Intelligent foreign particle inspection machine for injection liquid examination based on modified pulse-coupled neural networks," *Sensors*, vol. 9, no. 5, pp. 3386–3404, May 2009, doi: 10.3390/s90503386.

[41] L. M. Oliveira, R. B. Paradeda, B. M. Carvalho, A. M. P. Canuto, and M. C. P. de Souto, "Particle detection on election microscopy micrographs using multi-classifier systems," in *Proc. 7th Int. Conf. Hybrid Intell. Syst. (HIS)*, Sep. 2007, pp. 216–221, doi: 10.1109/HIS.2007.51.

[42] M. Dreisbach, R. Leister, M. Probst, P. Friederich, A. Stroh, and J. Kriegseis, "Particle detection by means of neural networks and synthetic training data refinement in defocusing particle tracking velocimetry," *Meas. Sci. Technol.*, vol. 33, no. 12, Dec. 2022, Art. no. 124001, doi: 10.1088/1361-6501/ac8a09.

[43] C. Sax, M. Dreisbach, R. Leister, and J. Kriegseis, "Deep learning and hybrid approach for particle detection in defocusing particle tracking velocimetry," *Meas. Sci. Technol.*, vol. 34, no. 9, Sep. 2023, Art. no. 095909, doi: 10.1088/1361-6501/acd4b4.

[44] K. Oh and M. P. Christenson, "Design of an automated particle detection system for Rutherford backscattering (RBS) using LabVIEW," *Instrum. Sci. Technol.*, vol. 47, no. 3, pp. 312–324, May 2019, doi: 10.1080/10739149.2018.1540430.

[45] C. Cowley, P. Fuller, Y. Andrew, L. James, L. Simons, M. Sertoli, S. Silburn, A. Widdowson, I. Bykov, D. Rudakov, T. Morgan, S. Brons, J. Scholten, J. Vernimmen, P. Bryant, and B. Harris, "Robust impurity detection and tracking for tokamaks," *Phys. Rev. E, Stat. Phys. Plasmas Fluids Relat. Interdiscip. Top.*, vol. 102, no. 4, Oct. 2020, Art. no. 043311, doi: 10.1103/PhysRevE.102.043311.

[46] B. Galdón-Navarro, J. M. Prats-Montalbán, S. Cubero, J. Blasco, and A. Ferrer, "Comparison of latent variable-based and artificial intelligence methods for impurity detection in PET recycling from NIR hyperspectral images," *J. Chemometrics*, vol. 32, no. 1, Jan. 2018, Art. no. e2980, doi: 10.1002/cem.2980.

[47] F. Bianconi, L. Ceccarelli, A. Fernández, and S. A. Saetta, "A sequential machine vision procedure for assessing paper impurities," *Comput. Ind.*, vol. 65, no. 2, pp. 325–332, Feb. 2014, doi: 10.1016/j.compind.2013.12.001.

[48] R. Siche, R. Vejarano, V. Aredo, L. Velasquez, E. Saldaña, and R. Quevedo, "Evaluation of food quality and safety with hyperspectral imaging (HSI)," *Food Eng. Rev.*, vol. 8, no. 3, pp. 306–322, Sep. 2016, doi: 10.1007/s12393-015-9137-8.

[49] B. Huang, J. F. Li, J. C. Wang, Y. Z. He, and W. Shang, "Impurity detection using machine vision," *Adv. Mater. Res.*, vols. 468–471, pp. 2057–2060, Feb. 2012, doi: 10.4028/www.scientific.net/AMR.468-471.2057.

[50] T. Albers, M. Peichl, and S. Dill, "Detection of very small impurity particles in high-quality granulated sugar," in *Proc. German Microw. Conf.*, Mar. 2015, pp. 315–318, doi: 10.1109/GEMIC.2015.7107817.

[51] M. Peichl, T. Albers, and S. Dill, "Detection of small impurities in bulk material by MMW radar," in *Proc. 16th Int. Radar Symp. (IRS)*, Jun. 2015, pp. 294–299, doi: 10.1109/IRS.2015.7226383.

[52] E. Nunes, E. Abreu, J. C. Metrolho, N. Cardoso, M. Costa, and E. Lopes, "Flour quality control using image processing," in *Proc. IEEE Int. Symp. Ind. Electron.*, vol. 1, Jun. 2003, pp. 594–597, doi: 10.1109/ISIE.2003.1267318.

[53] W. He, H. Song, Y. Guo, X. Yin, X. Wang, G. Bian, and W. Qian, "A gallery-guided graph architecture for sequential impurity detection," *IEEE Access*, vol. 7, pp. 149105–149116, 2019, doi: 10.1109/ACCESS.2019.2946861.

[54] M. F. Marcone, "Characterization of the edible bird's nest the 'Caviar of the East,'" *Food Res. Int.*, vol. 38, no. 10, pp. 1125–1134, Dec. 2005, doi: 10.1016/j.foodres.2005.02.008.

[55] N. H. Jamalluddin, N. A. Tukiran, N. A. Fadzillah, and S. Fathi, "Overview of edible bird's nests and their contemporary issues," *Food Control*, vol. 104, pp. 247–255, Oct. 2019, doi: 10.1016/j.foodcont.2019.04.042.

[56] Y. Dai, J. Cao, Y. Wang, Y. Chen, and L. Jiang, "A comprehensive review of edible bird's nest," *Food Res. Int.*, vol. 140, Feb. 2021, Art. no. 109875, doi: 10.1016/j.foodres.2020.109875.

[57] Y. Yu-Qin, X. Liang, W. Hua, Z. Hui-Xing, Z. Xin-Fang, and L. Bu-Sen, "Determination of edible bird's nest and its products by gas chromatography," *J. Chromatograph. Sci.*, vol. 38, no. 1, pp. 27–32, Jan. 2000, doi: 10.1093/chromsci/38.1.27.

[58] J. Chen, P. Lim, S. Wong, and J. Mak, "Determination of the presence and levels of heavy metals and other elements in raw and commercial edible bird nests," *Malaysian J. Nutrition*, vol. 20, no. 3, pp. 377–391, 2014.

[59] K. M. Tay, C. H. Jong, and C. P. Lim, "A clustering-based failure mode and effect analysis model and its application to the edible bird nest industry," *Neural Comput. Appl.*, vol. 26, no. 3, pp. 551–560, Apr. 2015, doi: 10.1007/s00521-014-1647-4.

[60] Y. H. Yeo and K. S. Yen, "Development of a hybrid autoencoder model for automated edible bird's nest impurities inspection," *J. Electron. Imag.*, vol. 31, no. 5, Jun. 2022, Art. no. 051603, doi: 10.1117/1.Jei.31.5.051603.

[61] M. Yang, S.-H. Cheung, S. C. Li, and H.-Y. Cheung, "Establishment of a holistic and scientific protocol for the authentication and quality assurance of edible bird's nest," *Food Chem.*, vol. 151, pp. 271–278, May 2014, doi: 10.1016/j.foodchem.2013.11.007.

[62] F. S. A. Saad, A. Y. M. Shakaff, A. Zakaria, M. Z. Abdullah, A. H. Adom, and A. A. M. Ezanuddin, "Edible bird nest shape quality assessment using machine vision system," in *Proc. 3rd Int. Conf. Intell. Syst. Model. Simul.*, Feb. 2012, pp. 325–329.

[63] F. S. A. Sa'ad, M. F. Ibrahim, A. Y. M. Shakaff, and A. Zakaria, "Edible bird nest shape inspection using Fourier descriptor (FD) and farthest Fourier point signature (FFPS) method," *Jurnal Teknologi*, vol. 76, no. 12, pp. 17–24, Oct. 2015.

[64] K. M. Goh, L. W. Kin, P. H. Ting, D. Koe, and R. J. K. R. Wong, "Size characterisation of edible bird nest impurities: A preliminary study," presented at the 21st Int. Conf. Knowl. Based Intell. Inf. Eng. Syst., Marseille, France, 2017.

[65] C. K. Yee, Y. H. Yeo, L. H. Cheng, and K. S. Yen, "Impurities detection in edible bird's nest using optical segmentation and image fusion," *Mach. Vis. Appl.*, vol. 31, nos. 7–8, p. 68, Sep. 2020, doi: 10.1007/s00138-020-01124-y.

[66] Y.-H. Yeo and K.-S. Yen, "Impurities detection in intensity inhomogeneous edible bird's nest (EBN) using a U-Net deep learning model," *Int. J. Eng. Technol. Innov.*, vol. 11, no. 2, pp. 135–145, Apr. 2021.

[67] *Edible-BirdNest (EBN)-Specification*, Dept. Statist. Malaysia, Kuala Lumpur, Malaysia, 2011.

[68] M. Y. Koay, S. X. C. Loh, K. M. Goh, and W. K. Lai, "Feature selection for automated grading of edible birds nest with ANFIS," presented at the 10th Int. Conf. Bioinf. Biomed. Technol., May 2018.

[69] K. H. Tan, F. C. Chia, and H. Alan, "Impact of swiftlet's moult season on the value of edible bird nests," in *Proc. Int. Chem., Biol. Environ. Eng.*, vol. 63, 2014, p. 17.

[70] M. Al-Mahasneh, M. Aljarrah, T. Rababah, and M. Alu'datt, "Application of hybrid neural fuzzy system (ANFIS) in food processing and technology," *Food Eng. Rev.*, vol. 8, no. 3, pp. 351–366, Sep. 2016, doi: 10.1007/s12393-016-9141-7.

[71] J. E. Gan and W. K. Lai, "Automated grading of edible birds nest using hybrid bat algorithm clustering based on K-means," in *Proc. IEEE Int. Conf. Autom. Control Intell. Syst. (I2CACIS)*, Jun. 2019, pp. 73–78.

[72] D. Rong, H. Wang, L. Xie, Y. Ying, and Y. Zhang, "Impurity detection of juglans using deep learning and machine vision," *Comput. Electron. Agricult.*, vol. 178, Nov. 2020, Art. no. 105764, doi: 10.1016/j.compag.2020.105764.

[73] D. Sharma and S. D. Sawant, "Grain quality detection by using image processing for public distribution," in *Proc. Int. Conf. Intell. Comput. Control Syst. (ICICCS)*, Jun. 2017, pp. 1118–1122, doi: 10.1109/ICCONS.2017.8250640.

[74] P. Vithu, J. Anitha, K. Raimond, and J. A. Moses, "Identification of dockage in paddy using multiclass SVM," in *Proc. Int. Conf. Signal Process. Commun. (ICSPC)*, Jul. 2017, pp. 389–393, doi: 10.1109/CSPC.2017.8305876.

[75] Y. Shen, Y. Yin, C. Zhao, B. Li, J. Wang, G. Li, and Z. Zhang, "Image recognition method based on an improved convolutional neural network to detect impurities in wheat," *IEEE Access*, vol. 7, pp. 162206–162218, 2019, doi: 10.1109/ACCESS.2019.2946589.

[76] Y. Shen, Y. Yin, B. Li, C. Zhao, and G. Li, "Detection of impurities in wheat using terahertz spectral imaging and convolutional neural networks," *Comput. Electron. Agricult.*, vol. 181, Feb. 2021, Art. no. 105931, doi: 10.1016/j.compag.2020.105931.

[77] F. Chen, P. Chen, D. Li, and F. Cheng, "Kernel-like impurity detection according to colour band spectral image using GA/SVM," *Imag. Sci. J.*, vol. 63, no. 8, pp. 469–475, Nov. 2015, doi: 10.1179/1743131x15y.0000000022.

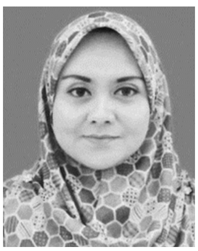
[78] M. Kragh, K. Bjerge, and P. Ahrendt, "3D impurity inspection of cylindrical transparent containers," *Meas. Sci. Technol.*, vol. 28, no. 1, Jan. 2017, Art. no. 017002, doi: 10.1088/1361-6501/28/1/017002.

[79] J. Ge, S. Xie, Y. Wang, J. Liu, H. Zhang, B. Zhou, F. Weng, C. Ru, C. Zhou, M. Tan, and Y. Sun, "A system for automated detection of ampoule injection impurities," *IEEE Trans. Autom. Sci. Eng.*, vol. 14, no. 2, pp. 1119–1128, Apr. 2017, doi: 10.1109/TASE.2015.2490061.

[80] N. Jai-Ngam, S. Pattanapairoj, and K. Tangchaichit, "Computational fluid dynamics to develop a micro particle cleaning process using turbulent air flows in the hard disk drive industry," in *Proc. 15th Int. Conf. Electr. Eng./Electron., Comput., Telecommun. Inf. Technol. (ECTI-CON)*, Chiang Rai, Thailand, Jul. 2018, pp. 588–591.

[81] Y. Subramaniam, Y. Che Fai, and E. S. L. Ming, "Edible bird nest processing using machine vision and robotic arm," *Jurnal Teknologi*, vol. 72, no. 2, Jan. 2015.

[82] J. Qing, X. Zhengxing, Z. Jinglei, Z. Yude, H. He, Z. Zhengyong, and W. Rujin, "Study of a cleaning intelligent control system for rice and wheat combine harvester," in *Proc. IEEE Int. Conf. Artif. Intell. Inf. Syst. (ICAIIS)*, Mar. 2020, pp. 400–406, doi: 10.1109/ICAIIS49377.2020.9194934.



NUR AINI SYAKIMAH AHMAD SHUYUTI (Graduate Student Member, IEEE) received the B.E. degree in mechatronics engineering from International Islamic University Malaysia, Selangor, Malaysia, in 2006, and the M.E. degree in mechatronics engineering from the University of Malaya, Kuala Lumpur, Malaysia, in 2017, where she is currently pursuing the Ph.D. degree with the Department of Electrical Engineering. Her research interests include image processing, machine learning, and robotics. She was a recipient of the Federal Training Award issued by the Public Services Department Malaysia. She is also a Graduate Technologist registered under the Malaysia Board of Technologists (MBOT).

ERFAN SALAMI (Member, IEEE) received the B.Eng. degree (Hons.) in mechatronics engineering from UCSI University, Malaysia, in 2012, the M.Sc. degree in aerospace engineering from Universiti Putra Malaysia, Malaysia, in 2015, and the Ph.D. degree in aerospace engineering from the University of Malaya, Malaysia, in 2021. He is currently a Postdoctoral Research Fellow with the Department of Electrical Engineering, University of Malaya. His research interests include image processing, the IoT applications, smart manufacturing, asset monitoring, object detection, deep learning applications, bio-mimetic micro aerial vehicles (BMAV), unmanned aerial systems (UAS), and urban air mobility (UAM).

MAHIDZAL DAHARI (Member, IEEE) received the B.Eng. (Hons.), M.Sc., and Ph.D. degrees in computer systems, instrumentation and control from Universiti Teknologi Petronas, Malaysia, in 2002, 2006, and 2009, respectively. He is currently an Established Academician and a Practicing Engineer. He has published (to date) more than 100 papers in journals and conference proceedings both locally and internationally. He has supervised more than 50 Ph.D. and master's students. He is actively involved in many consultancy projects, especially in the fields of fluid flow, natural gas, and hydrogen technology. His research interests include instrumentation, automation, robotics, and control strategy, especially related to manufacturing technology, industrial robots, and oil and gas applications. He is a Chartered Engineer of the Institute of Electrical Technology, U.K., and a Professional Engineer registered under the Board of Engineers Malaysia.

HAMZAH AROF received the B.Sc. degree from Michigan State University, USA, and the Ph.D. degree from the University of Wales, U.K. He is currently a Professor with the Electrical Engineering Department, University of Malaya, Malaysia. He is also an Established Academician. He has published more than 100 articles. His research interests include image and signal processing, robotics, and photonics. He is a Professional Engineer registered under the Board of Engineers Malaysia.

HARIKRISHNAN RAMIAH (Senior Member, IEEE) received the B.Eng. (Hons.), M.Sc., and Ph.D. degrees in electrical and electronic engineering (analog and digital IC design) from Universiti Sains Malaysia, Malaysia, in 2000, 2003, and 2008, respectively. In 2002, he was with Intel Technology Sdn. Bhd., performing high-frequency signal integrity analysis. In 2003, he was with SiresLabs Sdn. Bhd., Cyberjaya, Malaysia, working on a 10-Gb/s SONET/SDH transceiver solution. He is currently an Associate Professor with the Department of Electrical Engineering, University of Malaya, Kuala Lumpur, Malaysia, working on RF integrated circuit (RFIC) and RF energy harvesting circuit design. He has authored or coauthored several articles in technical publications. His current research interests include analog-integrated circuit design, RFIC design, VLSI system design, and radio frequency energy harvesting power management module design. He is a member of the Institute of Electronics, Information and Communication Engineers. He was a recipient of the Intel Fellowship Grant Award, from 2000 to 2008. From 2014 to 2018, he received continuous international research funding in recognition of his work, such as the Motorola Foundation Grant. He is a Chartered Engineer of the Institute of Electrical Technology and a Professional Engineer registered under the Board of Engineers Malaysia.