Mechanical Engineering Advances 2024, 2(2), 1746.
https://doi.org/10.59400/mea.v2i2.1746

Review

The development of machine vision and its applications in different industries: A review

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CITATION

Zhang L, Jia X, Chang Q, et al. The development of machine vision and its applications in different industries: A review. Mechanical Engineering Advances. 2024; 2(2): 1746. https://doi.org/10.59400/mea.v2i2.1746

ARTICLE INFO

Received: 20 September 2024
Accepted: 12 November 2024
Available online: 22 November 2024

Abstract: In recent years, the development of machine vision research is rapid in several areas. In order to promote the better development of machine vision research, it is necessary to clarify its development and application direction. At present, there are few reviews on the application direction of machine vision. This paper sorts out the application of machine vision in various fields, and summarizes the current application status of machine vision from four main functions: recognition, measurement, classification and detection. This paper mainly introduces the improvement of different algorithms of machine vision and its application in medical, agriculture, manufacturing and other industries, providing guidance for the selection of machine vision research direction.

Keywords: machine vision; algorithm; applications; manufactruing

1. Introduction

Machine Vision (MV), also known as Computer Vision (CV), is an important section of Artificial Intelligence. As shown in **Figure 1**, it mainly helps people make decisions from four aspects: recognition, measurement, classification and detection to reduce workload. It helps human beings in measuring, deciding, and judging by using machines. **Figure 2** shows the evolution of machine vision. Since the concept of machine recognition was proposed in 1950, MV has experienced a long development process, with MV developing, it has plenty of applications in image processing, robotics, industry automation, optics, and so on. The versatility and flexibility of MV applications have been significantly improved. In this paper, the research group reviewed the MV applications released from 2018 to 2022 in these areas. **Figure 1** is a simple sketch of the mainly application areas of MV. And **Figure 2** shows a brief history of MV. The idea of MV was proposed in 1950s, but most applications were used in 2000s, because of the rapid development of computer science in 1990s.

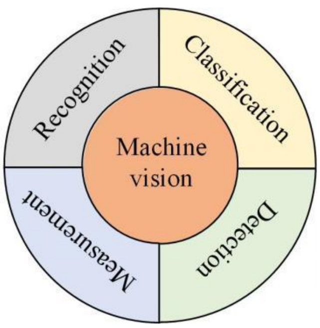


Figure 1. The main function of machine vision.

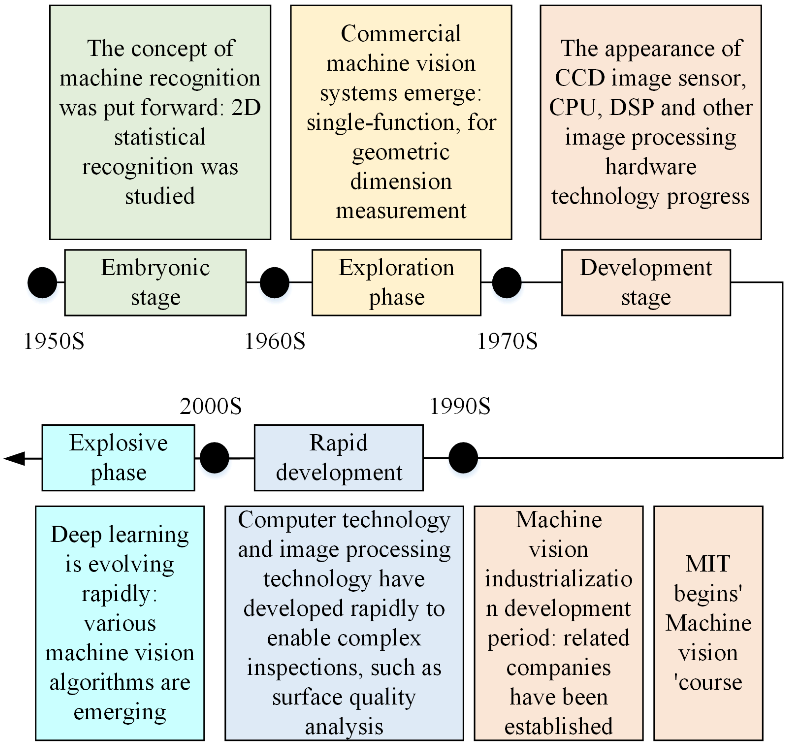


Figure 2. The main development process of machine vision.

2. Algorithm of machine vision

From the year of 2018, MV has been widely used in different areas because the development of algorithms and some research groups have summarized it. For example, In the paper of WU, Li, and Yao, the methods, applications, and challenges of Deep Learning in MV tasks have been reviewed. Also, they introduced some basic knowledge of algorithms in this area [1]. And Katti et al. studied the MV benefits from human contextual expectations [2]. This research group evaluate some MV algorithms with car/person classification. In Gorodokin's research, MV has been applied in traffic area [3]. By using MV algorithm, the congestion has been relieved, the drivers do not waste lots of time on waiting. Panagakis et al. summarized the application of tensor methods in Deep Learning, especially on visual data analysis and MV applications [4]. Besides, Zhang et al. reviewed adversarial network applications in MV [5]. They pointed out that applications have been more and more extensive, but they also came up with several challenges in this area. Also, Gustafsson et al. evaluate scalable Bayesian Deep Learning methods for robust MV [6]. The results show that ensembling consistently provides more reliable and practically useful uncertainty estimates. The research group of Whatmough et al. proposed a new CNN framework in MV area [7]. And the experimental results show that it can achieve very high energy efficiencies. Shu, Xiong, and Fan developed an interactive design of intelligent MV based on human-computer interaction mode [8]. They used several matrices to evaluate this mode. Wu et al. developed a MV algorithm to detect electrical connector defects. The accuracy of this work is 93.5% [9]. Wu et al. summarized the progress and challenges of applying 2D material photodetectors in sense-memory-computational integration and biomimetic image sensors for MV [10]. In underwater tasks, MV has a lot of applications to aid operators. And this area has been reviewed by Reggiannini [11].

These researches reviewed the development of MV algorithms before 2022. From the above works, it could be concluded that MV algorithm is an important topic and people would like to use MV as a tool in manufacturing, medicine, agriculture, and so on.

In the area of MV, Machine Learning is the most widely used tool. There are many researches to improve the accuracy and speed of MV by changing the Machine Learning algorithms. Akhtar et al. reviewed several works on it [12]. Deep Neural Networks behave well in many MV tasks. However, it requires a lot of parameters and operations. Goel et al. [13] surveyed the low-power MV methods to finish the same tasks with less memory requirement. O'Mahony et al. [14] compares the benefits and drawbacks of Deep Learning and traditional MV. The aim of this work is to improve the performance of MV algorithms and help operators get accurate results. Based on the analysis of Yang et al. [15], the research group proposed a GPU scheduler for MV applications. In real applications, the speed of operating MV is important. The operation cannot occupy a lot of time.

In the area of MV, recognizing images is important. Baygin et al. pointed out that MV is widely used in production lines because of it is low-cost and high-precision on image recolonization [16]. Talebi and Peyman's learned image resizer is jointly trained with a baseline vision model. In this paper, a method of resetting the image size is proposed and applied to the existing classification algorithm shown in **Figures 3** and **4**. It is found that the image quality is improved after resetting, and the **Figure 5** shows the effect of resetting the image size [17]. Several researchers focus on the integration of MV and national language processing. El-Komy et al. [18] generated a Faster Region Convolutional Neural Network based central server to detect the objects in the image to inform the blind person to avoid obstacles in their way. Li et al. [19] generated a new framework of machine learning algorithm for recognizing complex SEM image automatedly. Their framework detected the position of each molecule and labeled the chirality accurately. Besides, this framework does not require plenty of data, which is an important advantage. After summarizing the coding in both human and machine vision, Hu et al. [20] believed that the signal fidelity-driven coding pipeline design limits the capability of the existing image/video coding frameworks to fulfill the needs of both machine and human vision. Thus, they generated a new image coding framework to support both MV and human perception tasks together. In the work of Roggi et al. [21], an UAV-based automatic inspection method for photovoltaic plants analyzing has been proposed. Besides, testing a vision-based guidance method has been developed to finish this task. When autonomous vehicles driving into sun, the direct sunlight is a significant influence. Thus, Paul et al. [22] apply high dynamic range imaging algorithms to the MV system and measured the accuracy of performance in direct sunlight. In MV area, RGB images are usually used to train the algorithm. Datta et al. [23] developed a new algorithm to use raw images and the accuracy is acceptable. In the work of Rebecq et al. [24], they take a different view and propose to apply existing, mature MV techniques to video reconstructed from event data. They improve the quality of image by using their algorithm. Mennel et al. [25] show that an image sensor could constitute an ANN by itself. Besides, this framework can simultaneously sense and process optical images without latency. In real-time application, it is difficult for MV to implement at the edge. In order to solve this problem, Gamanayake et al. [26] developed a novel MV algorithm, which is named cluster pruning. The above mentioned works help people to detect objects with the assistant of MV.

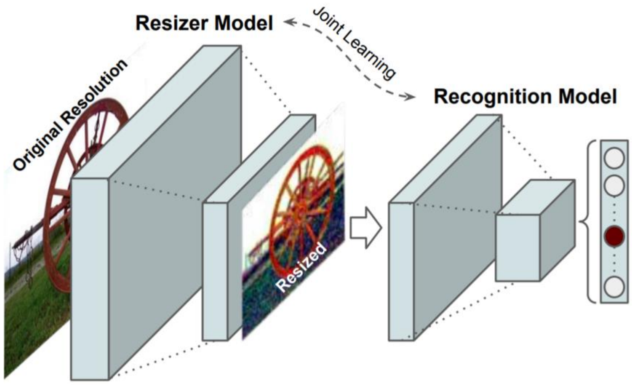


Figure 3. Proposed framework for joint learning of the image. Resizer and recognition models [17].

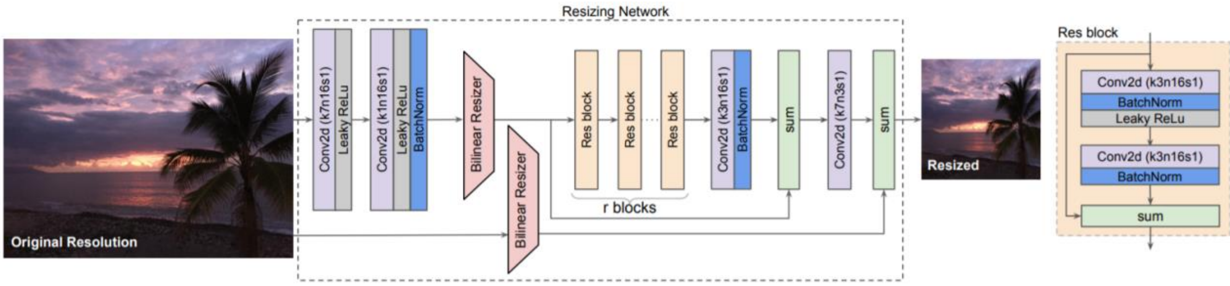


Figure 4. Proposed CNN model for resizing images [17].

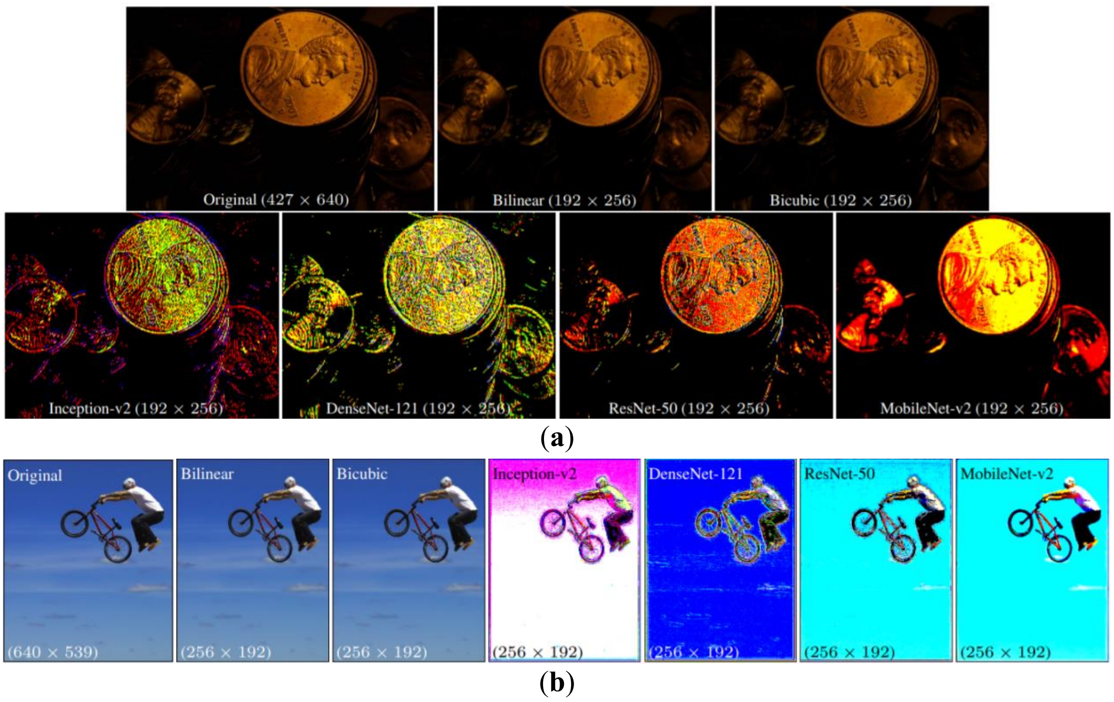


Figure 5. Examples of the proposed learned resizer trained with various classification models. **(a)** Improved recognition performance of coins; **(b)** improved recognition performance of bicycle rider.

Besides recognizing stationary objects, MV can also be used to detect moving 3D objects. MV is a good tool for object classification in production line. Cong et al. designed a MV system of two robot arms to do classification based on the shape and size of the objects [27]. In Gubbi's research, with the help of MV, the performance of predicting target tracking has improved significantly [28]. Wang et al. proposed a prototype neuromorphic vision system by networking retinomorphic sensor with a memristive crossbar [29]. This system is developed for fast letter recognition and object tracking. There was a paper published in the 2021 British Machine Vision Conference. In this work, multi-person activity recognition problem is tackled. They developed a new multi-branch CNN to increase the accuracy. This algorithm is trained end-to-end by using a multi-task learning framework [30]. In today's world, 3D object detection and tracking is an essential constituent in several applications. In the research of Shreyas et al., various 3D object detection and tracking methods are explained detailly for plenty of CV applications [31]. Ding et al. believed that moving object detection in image is a crucial point in CV research [32]. They developed a moving object detection algorithm based on robust image feature threshold segmentation with improved optical flow estimation. Two different optical flow methods has been presented in this paper. Autonomous driving in complex scenes is a challenge in auto industry. Fang's group improved the Mask R-CNN by replacing the backbone network ResNet with ResNeXt. In order to more intuitively evaluate the target detection and segmentation effects of the improved Mask R-CNN algorithm in different complex scenes, cityscape test dataset was selected for testing, and the experimental results were shown in **Figures 6** and **7**. The target detection and segmentation accuracy increased by 4.73% and 3.96% separately. In the manufacturing of gears, quality control has become a priority [33]. The aim of Moru and Borro's work is to deploy an improved MV application to determine the precise measurement of industrial gears [34]. Li et al. developed a Deep Learning algorithm to classify objects [35]. This MV framework can also be extended to other spectral-domain measurement systems. In the research of Yin's group, they proposed a novel method to count vehicles based on MV algorithm [36]. In bridge monitoring, it is important to identify moving loads accurately. Based on MV, Dan's group generated a novel method to tackle this problem [37].

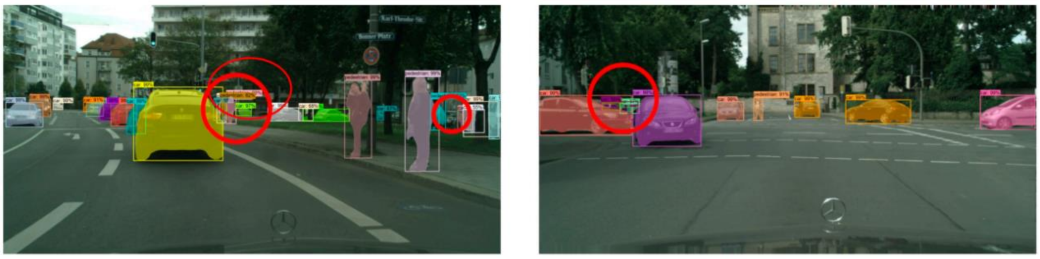


Figure 6. Test results of Mask R-CNN on cityscapes test dataset [33].

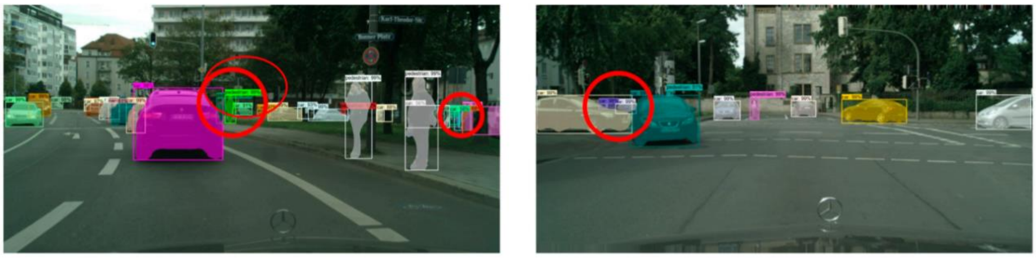


Figure 7. Test results of Improved Mask R-CNN on cityscapes test dataset [33].

Besides, some other MV algorithms are generated to help human beings to finish some work. In order to suppress impulse noise in MV, median filter is one of the predominant filters. Appiah et al. improve the output and running time of median filter. this research gives a discussion on pros and cons of several different median filters [38]. In the research of Kaushal's group, they found that if diversity-based subset selection done in the right way, the accuracy of the algorithm will increase by 5–10% [39]. And Zhang et al. present an effective method to improve the fine-level retrieval performance [40]. This method is based on a multi-level Gaussian loss function, and it takes the advantages of class-level similarity learning and full-level hierarchy labels in training. Semitsu et al. proposed a new method to measure the contributions of multiple datasets [41]. Contributions are calculated in a fair way that each trial are evaluated not by its improvements of accuracy, but by the number of data needed to make the improvements. Riba et al. introduced Kornia, which is an open-source MV library [42]. This library is used in MV to improve performance using hardware acceleration. In the area of big data, image and video coding techniques have developed rapidly in these years [43]. In order to fulfill the needs of both machine and human vision, Yang et al. developed a novel face image coding framework by considering both the compressive and generative models. Suma reviewed the applications of computer vision that is helpful in the interaction between the human and the machines [44]. The following **Table 1** and **Figure 8** are visual summary of this chapter.

Table 1 briefly describes the work done on the functional application of different algorithms.

Table 1. Functions and applications of different algorithms.

Authors	Function	Application	Research outcome
Katti [2]	Detection	Traffic	Katti et al. studied the CV benefits from human contextual expectations.
Gorodokin [3]	Detection	Traffic	By using CV algorithm, the congestion has been relieved, the drivers do not waste lots of time on waiting.
Cong [27]	Detection	3D object detection	This work designed a MV system of two robot arms to do classification based on the shape and size of the objects
Shreyas [31]	Detection	3D object detection	In this research, various 3D object detection and tracking methods are explained detailly for plenty of CV applications.
Yin [36]	Detection	vehicle detection	This work proposed a novel method to count vehicles based on MV algorithm.
Wu [10]	Measurement	2D material photodetectors	This work summarized the progress and challenges of applying 2D material photodetectors in sense-memory-computational integration and biomimetic image sensors for MV

Table 1. (*Continued*).

Authors	Function	Application	Research outcome
Moru [35]	Measurement	measurement	This work deploys an improved CV application to determine the precise measurement of industrial gears.
Baygin [16]	Recognition	Image recognization	This work pointed out that MV is widely used in production lines because of it is low-cost and high-precision on image recolonization.
El-Komy [18]	Recognition	Image recognization	This work generated a Faster Region Convolutional Neural Network based central server to detect the objects in the image to inform the blind person to avoid obstacles in their way

The research group generated a topology diagram of this section and it is shown in **Figure 8**. This chapter introduces different algorithms of MV, such as Neural Network and Deep Learning. Also, MV could be used to detect both 3D and 2D objects or images.

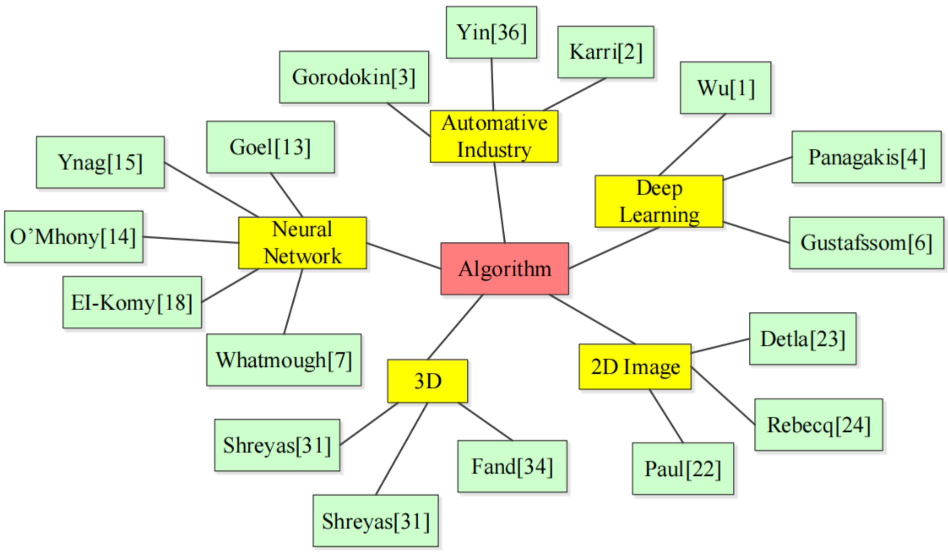


Figure 8. Topology Diagram of Algorithm of Machine Vision.

3. Agricultural applications of machine vision

In recent years, the application of MV technology in agriculture has become quite extensive and significantly promoted the development of intelligent agriculture. Many scholars did research on the application of MV technology in the agricultural field and this section summarized these results.

Nowadays, MV technology has been widely used in seed selection achieved a good classification effect yet. TU Ke-ling et al. [45] used MV technology to study the classification of high-quality and low-quality pepper seeds. They collected and processed the images and feature data, established a multi-layer perceptron neural network model with 15 features as variate. The experiment of pepper seed germination was also carried out. Nadia Ansari et al. [46] produced a total of 375 rice seed images from 3 varieties, extracted 20 important features, and then used relevant algorithms to establish a classification model to achieve the purity detection of rice seeds. Similarly, in the paper of Keling Tu and Peng Xu, the detection of corn seed purity was studied. Keling Tu et al. [47] scanned the images of both the germ and non-germ surfaces of the seeds and used them as data set. Then they used the fine-tuned transfer learning of VGG16 network to identify and classify the seed images. **Figure 9** shows that Peng Xu et al. [48] combined MV with deep learning algorithms and used the Convolutional Neural Networks (CNN) model to automatically classify five kinds of corn seeds.

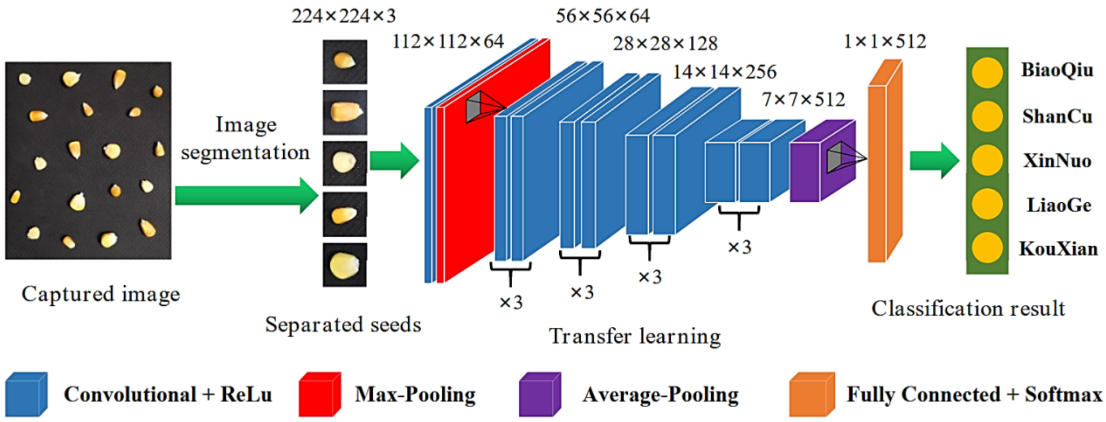


Figure 9. Process of transfer learning and classification of maize seeds [48].

There are plenty of MV applications on fruit classification. Mohammad Saber Iraji, S. Dhakshina Kumard and Li Liu all studied tomato grading with MV technology. Mohammad Saber Iraji's research proposed a deep stacked sparse auto-encoders (DSSAEs) method for tomato quality grading using image data directly based on MV and soft computing techniques [49]. The classification system of S. Dhakshina Kumar et al. performs classifications of tomatoes in three stages i.e. Tomato/Non-Tomato, Good/Defective and the type of defect, with digital images of samples captured in an experimental setup deployed using microcontroller [50]. Liu et al. [51] built a comprehensive tomato classifier based on the color, shape and size diameters. A grading platform was set up to verify the effect of the classifier [51]. MV application in beans is another important area and their classification has been getting attention. Belan et al. [52] proposed computational approaches for segmentation, classification, and detection of three of the main defects founded in beans (broken, bored, and moldy). In this way, grains can be located in the analyzed image, even if they are glued to each other. Then appropriate software together with the equipment were developed. Besides, Zhou et al [53]. developed a real-time computer-aided potato inspection system which can be used to sort out the good and bad potatoes. It can handle up to 50 potato images. Thinh et al [54]. created a system that can classify mangoes in terms of color, volume, size, shape and fruit density. This study also described the method and terminology of several tools that are used for image processing and analysis in sorting and classification of mangoes based on Artificial Intelligence. Ismail et al. [55] proposed and designed a low-cost MV system for grading the fruits based on their outer appearance and freshness. This system uses an end-to-end approach and can work both in offline and real time mode.

In addition, MV can also be used to estimate the volume of each crop fruit, so as to estimate global production Uluişik et al. [56] researched volume estimation of tomato. Five different images of a tomato are captured using high resolution digital cameras. Volume of the fruit is computed by estimating horizontal and vertical distance of captured images and the results are validated with experimental results. Innocent Nyalala et al. [57] developed a novel tomato weight and volume prediction method for tomatoes with no and partial occlusions. Polygon approximation for concave and convex point extraction algorithms were used to segment the occluded tomatoes. Furthermore, they developed seven models for regression using single-tomato image features and the seven models were compared. Besides, Concha-Meyer et al. [58] used MV technique to determine the volume of raw agricultural products with an irregular shape, such as tomato, white button mushroom and strawberry. In this study, the volume of each fruit was measured in less than five seconds.

Ripeness estimation of fruits and vegetables is a key factor for the optimization of field management and the harvesting of the desired product quality. Vrochidou et al. [59] investigated the most recent applications of MV techniques for ripeness estimation related to grapes, and provided an overview of the grape ripening estimation work. The paper also highlighted challenges and limitations of different estimation methods. In the paper of [60], a nondestructive approach was developed to estimate the physicochemical properties and ripeness levels of apples in orchard environments. They recorded videos of apples at four levels of ripeness and extracted color and texture features from these samples. Then five physicochemical properties were estimated and measured using neural network and corresponding algorithm. Anindita Septiarini et al. [61] proposed a classification method for the maturity level of oil palm fresh fruit bunch. The proposed method can distinguish three levels of maturity (raw, ripe, and half-ripe) according to color and texture features.

In the process of agricultural production, machine vision technology can be used to find the disease situation of crops in time, so as to facilitate the treatment of diseases and avoid production reduction. Different rice diseases and insect pests have similar symptoms shown in **Figure 10**. It takes experienced workers and huge time to distinguish them artificially, and machine vision can capture small differences between different diseases, at the same time can reduce the use of separate time. Mahadi Hasan Kamrul et al. developed a model which can recognize six main rice disease that is commonly seen in the paddy fields of Bangladesh [62]. This research builds on authentic data set and the accuracy rate of the model is high. Mahmud et al. [63] established an artificial cloud lighting condition system for detecting strawberry powdery mildew leaf disease. Texture analysis based on color co-occurrence matrix was used to extract image features and discriminant analysis (quadratic) for classification. Kim et al. [64] developed an onion downy mildew detection system for large-scale automatic monitoring. Symptom identification is realized based on the images periodically captured through automatic detection, and the crop disease region can be positioned. Palei et al. [65] overviewed the papers related to citrus diseases and fruit grading between 2010 and 2021. Symptomatic information about citrus diseases is provided, and the related techniques (image processing, machine learning and deep learning) are analyzed. In the paper of [66], a simple and inexpensive detection system of ochre spot disease was studied, and the images used in the system were captured from a low-cost RGB camera which is placed on board a drone. And the algorithm which could process limited-quality images from a low-cost camera has been developed else. Jiang et al. [67] proposed a method for detecting the infected apples using convolution neural network and it can timely prevent further infections caused by environmental factors.

Figure 10. A little portion of dataset [62].

Pest identification and classification based on MV is a prerequisite for accurate and real-time pesticide spraying of precision agriculture. Lins et al. [68] presented a method to automate the counting and classification of aphids using image processing, MV, and deep learning. A software named Aphid CV was developed for implementing the proposed method. The disadvantage of this method is that the overlapping insects are classified as one. Liu et al. [69] developed a multispectral MV system to detect common invertebrate pests on green leaves in natural environment.

For intelligent agriculture, identifying weeds based on MV is a prerequisite for accurate weed removal. In the research of [70], an efficient automated weed detection system was developed. Besides, two kinds of feature extraction techniques, two classification algorithms and two data sets were touched on, and their influence on recognition accuracy was analyzed. Abouzahir et al. [71] proposed a new method of weed detection. **Figure 11** shows that a histogram based on color indices is used to discriminate between three classes: soil, soybean and weeds. However, a major drawback of this method is that color indices can be sometimes sensitive to outdoor illumination changes, which will affect the performance of the system. In the paper of [72], two main challenges (dealing with changing light and crop/weed discrimination) are firstly listed, followed by the detailed review of methods for dealing with those challenges. Wu et al. [73] analyzed the advantages and disadvantages of several existing methods, and introduced several related plant leaves, weed data sets, and weeding machinery. Lastly, the problems and difficulties of the existing weed detection methods are analyzed, and the development trend of future research is prospected.

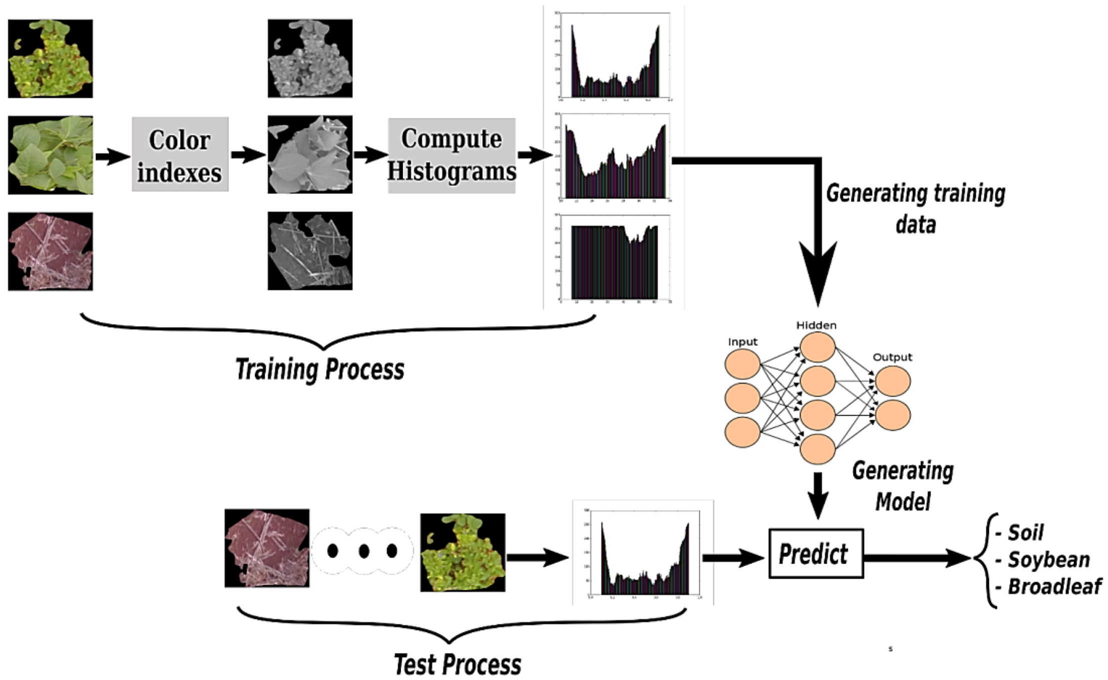


Figure 11. Classification system based on the color indices to predict plants types as well as soil and residues [72].

In recent years, MV-based methods have been applied to monitor animal behaviors worldwide. In the study of [74], a new deep learning method (i.e., an integration of background-subtraction and inter-frame difference) was developed for automatically recognizing dairy calf scene-interactive behaviors based on MV-based technology. Besides, Guo et al. [75] also developed and tested a method to identify the floor distributions of broiler chicken, including the total number of chickens on the house floor and their distribution in drinking and feeding zones. Zhang et al. [76] proposed an automated fish population counting method based on a hybrid neural network model to estimate the number of farmed Atlantic salmon. In this method, convolution kernels of different sizes are used to adapt to the changes in angle, shape, and size caused by the motion of fish, so the counting is real-time, accurate, objective and lossless.

MV technology is also widely integrated into various agricultural equipment, acting as their eyes, and plays a key role. In the article of [77], an automatic sorting device for agricultural products was designed. The sorting test platform based on a visual servo was built, and the target classification, positioning and sorting tests were carried out using tomatoes and oranges as the test objects. Kanagasingham et al. [78] attempted to integrate GNSS, compass and MV into a rice field weeding robot to achieve fully autonomous navigation for the weeding operation. Terra et al. [79] proposed a low-cost modular robotic system to automate agricultural sprayers using MV and individual nozzle control. In the early process of plug seedlings culture, sweet corn seed misses are inevitable. Bai et al. [80] developed an automatic supplemental seeding device using MV technique for corrections of seeding errors of plug seeder, and replacement of the manual reseeding. The paper of Henry Williams et al. [81] presents a kiwifruit harvesting robot. The robot consists of four harvesting arms, end effectors designed specifically for kiwifruit detachment, and a MV system employing convolution neural networks. By using MV, the harvest of different crops could be increased because MV could help farmers to irrigate and spread manure more scientific.

Table 2 briefly describes the work done on the functional application in agriculture.

Table 2. Functions and applications in agriculture.

Authors	Method	Function	Material	Research outcome
TU [45]	MLP	Detection	Pepper Seeds	This method was effective in predicting the germination of pepper seeds based on their seed color and size.
Mohammad [49]	Deep Stacked Sparse Auto-Encoders (DSSAEs)	Classification	Tomatoes	The system can directly classify tomato image data without using image processing technology to extract features, and the accuracy rate can reach 95.5%.
Selman [56]	Thresholding	Classification Detection	Tomatoes	Five different images of each fruit were used and the estimation error is under 20%.
S. Sabzi [60]	Hybrid Multilayer Perceptron	Recognization Detection	Apples	1356 apples in natural orchard environments were examined and the correct classification rate is 97.86%.
Mahadi [62]	Convolutional Neural Network, Inception-v3, MobileNet-v1, Resnet50	Detection	Rice	The validation accuracy rate of disease detection is about 98%.
Elison [68]	Inception-v3	Classification Recognization	Aphids	A software named AphidCV was developed for identifying aphids and the AphidCV can saves time during the processes of counting and sorting.
Saad [71]	BPNN, SVM	Recognization	Soil, Soybean and Weeds	An overall accuracy of 96.601% for BPNN, and 95.078% SVM.
Guo [74]	Integrated Background Model	Measurement	Dairy Calf	The scene-interactive behaviors of entering or leaving the resting area, turning around, and stationary were identified automatically and the success rate is between 93% and 97%.

Figure 12 is a topology diagram generated by this research group. In the area of agriculture, MV could apply in several fields, such as seed selection, fruit classification, pest identification, and so on.

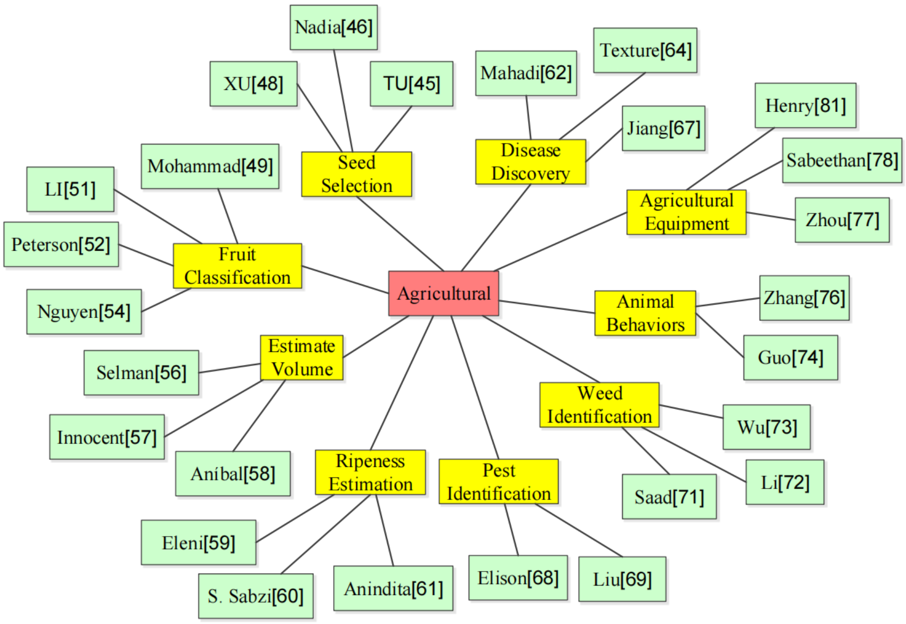


Figure 12. Topology diagram of agricultural applications of machine vision.

4. Medical applications of machine vision

MV also has plenty of applications in medical area, such as processing medical images; realizing automatic detection of tumors; analyzing case characteristics to help doctors diagnose diseases, and so on. MV has improved the efficiency and accuracy of medical detection and treatment.

Wood et al. [82] built a deep learning model, which analyzed the neuroradiology report, obtained the report features and give corresponding checks. This model breaks through the bottleneck of CV model development. In the paper of [83], a CV system was built for detection of missing tablet in the pharmaceutical industry. Assembly line camera captures images of packages. The RGB format images are converted to HSI color format for images. Then, by comparing the position and quantity of the circles, the pills are identified, and informations such as whether the pills are lost or where they are lost are obtained. The CV system increases productivity and safeguards consumer safety. Sethy et al. [84] developed an application of image processing, Machine Learning (ML) and Deep Learning (DL) techniques in breast cancer diagnosis. The authors also proposed a computer vision-based method on diagnosis of breast cancer, it can find the exact location of breast abnormalities, which can help in breast-conserving surgery or partial mastectomy. Compared with the existing methods, the proposed method is highly accurate. Alkadi's [85] group trained a deep convolutional encoder-decoder architecture to address prostate lesions in magnetic resonance (MR) images. They proposed a 3D sliding window approach, an experiment conducted on 19 patient data, which outperforms traditional pattern recognition and machine learning methods. Gu et al. [86] built a user-friendly CV interactive system based on Exercise Check. The research of [87]. enhanced a Convolutional Neural Network (CNN) model and proposed an integrated acceleration method, which detects COVID-19 symptoms from CT (Computed Tomography) chest scan images. In order to increase the computing speed, they implemented a hardware-based acceleration method on a re-configurable platform (FPGA). It involves reducing the number of vectors that need to be processed in classification tasks, the method is a unique advantage for particular application.

The paper of Kollias [88] introduced a baseline method consisting of DL methods based on CNN-RNN networks applied to the second Covid-19 competition. They splited the database to training, verifying and testing. The first two datasets are used for training and validation of machine learning models, while the latter will be used to evaluate the developed models. Ismael et al. [89] proposed a method which uses Residual Networks in the field of artificial intelligence to improve the accuracy of recognizing brain cancer. They adopted a computer-aided diagnosis (CAD) system assisting doctors and radiologists in diagnosing and classifying brain tumors. The method achieves the highest accuracy rate of 99% by training brain tumor model containing 3064 MRI images of 3 types. Therefore, the method enables doctors to make correct treatment choices and helping save lives. Gu and Yang [90] established an automated method for diagnosing breast cancer by using CV, artificial intelligence technology and DL to observe cancer from B-ultrasound images. This method can quickly enhance the correct diagnosis rate and reduce the difference in the operation level of urban and rural doctors. Khemasuwan's [91] group provided information of artificial intelligence in pulmonary medicine for pulmonary experts, described the concept of artificial intelligence and some necessary needs of ML and DL, and reviewed some literature of CV too. The main content of the literature is the application of CV in medical imaging. They finally concluded with a discussion of the limitations and challenges in incorporating artificial intelligence into clinical pulmonary practice. The paper of [92]. presented a novel strategy combining bounding box annotations from multiple clinicians, and took advantage of deep neural networks for building an automated system in which complex patterns are derived to address this difficult task. Two deep learning-based CV methods were evaluated by the initial data collected in this study, automatic detection and classification of oral lesions detect oral cancer early.

In the work of [93], self-supervised learning is used to improve the effectiveness of medical image classification. There are two main classifications: classification of dermatological conditions from digital camera images and classification of multi-label chest X-rays, while a novel Multiple Instance Contrastive Learning (MICLe) method is introduced. Top-1 accuracy increases by 6.7% on dermatology and chest X-ray classification, which outperforms strongly supervised baselines pretrained on ImageNet. The paper of [94]. discussed CV and artificial intelligence. From the perspective of application, it describes the application of artificial intelligence and machine vision in patient care in details, and how to achieve satisfactory results of artificial intelligence through different model to help driving cars. To predict cancer, pathologists evaluated the microscopic appearance of biopsy tissue samples based on morphological characteristics that correlate with patient outcome. Aksac et al.'s [95] article used 162 kinds of breast cancer histopathological tissue images to form a database, and the task is to automatically divide them into 6 types that are required in medicine. Zhou et al. [96] introduced Adaptive GraphSage which is a graph convolution technology that combines multi-level features in a data-driven manner. A deep neural network model is trained in the paper of Chao's research, it simplified the classification of genome-wide cancer types and can accurately classify 17 cancer types across the genome. Treating each cancer type as an associated task using a meta-learning approach outperforms traditional neural network classifiers [97].

Image segmentation is important in medical image processing. It has been extensively researched and developed in order to refine clinical analysis and application. In the paper of Chen et al. [98], a new DL model was proposed to solve this limitation. The new model considers the internal area as a deep learning-based model, and inside and outside the area of interest and the size of the boundary were considered during the learning process. Convolutional Neural Network (CNN) methods were used in many biomedical segmentation tasks. Shah et al. [99] proposed another CNN-based method that uses dilated convolutions and residual connections for training and inference based on traditional filters. They increased the use of dilated convolutions and residual connections, training and inference are performed using an efficient patch-based method, reducing unnecessary calculations. CV has been successful used in solving various complex healthcare problems. Ulhaq et al. [100] aimed to conduct a preliminary review of the existing literature on CV to combat COVID-19, collected information about available research and pointed out future research directions, and provided them to CV researchers to save their precious time. In the work of Rehman et al. [101], a computer vision-based FC-DSCNN CAD system was proposed to detect micro-calcification clusters in mammograms and classified them as malignant and benign. This research results showed that the performance of this method was higher than traditional methods. Abdelrahman et al. [102] discussed structured convolutional neural network (CNN) databases for mammography. It began with an introduction to computer-aided detection (CAD) and CNN-based CV models for mammography. Then, the literature of mammography training dataset was discussed. Rakhlin et al. [103] reviewed deep convolutional neural network computational methods for breast cancer histology image classification. For the 4-class classification task, the classification accuracy is 87.2%, and for the 2-class classification task, the classification accuracy is 97.3%. This method outperforms other common methods in automatic pathology classification, and the source code has been released.

Since the birth of deep learning, medical imaging community has developed deep learning-based methods for many applications including image recognition. The research of Haskins provided an overview of DL for medical images, introduced the evolution and research challenges of DL for medicine in the past few years, and also highlighted future research directions and possible new levels in this field [104]. Esteva et al. [105] investigated recent advances in the application of modern CV techniques in medicine. Especially in medical imaging and clinical diagnostic applications. In the work of Zheng et al. [106], an efficient Adaboost algorithm (DLA-EABA) was established using DL to detect breast cancer. A tumor classification method was developed by using a deep convolutional neural network (CNN) to traditional CV methods. In the paper of Amiri et al. [107], keratoconus disease was first introduced and then 33 images were used. In the research of Wu et al. [108], two-dimensional (2D) fractional convolutions were used on ARFI-VTI images to accurately predict lesions in ROIs. A multilayer MV classifier was used to screen tumors. The paper of Gupta and Bhavsar [109] mentioned that DL methods were applied in CV and had also been applied to medical image analysis. However, existing methods are unsatisfactory for multi-layer feature classification. Specifically, this work focused on building a framework that considered both layers and inter-layer dependencies. Therefore, they selected the best subset of layers according to the information theory measurement (ITS), conducted experiments on the BreaKHis dataset, and verified that the multi-layer feature fusion performance is better.

In recent years, DL has been widely used in histopathology image analysis. Gupta and Bhavsar [110] believed that multi-layer features were important because different regions of the image contain different levels of information. They proposed a DenseNet sequence framework to extract multi-layer deep features. Experiments on the BreaKHis dataset show that the proposed framework achieves good performance in most cases. Working with histopathology images is time-consuming when analyzing images of different levels. CV and ML methods automate the diagnosis of pathology, reducing analysis time. In the paper of Sheikh et al. [111], a multi-feature network (MSI-MFNet) model was proposed, which can learn the overall structure and texture features. Their proposed model outperforms existing models in terms of accuracy, sensitivity and specificity. Liu et al. [112] used DNN segmentation to design a 3D image compression framework for MV. This method was to extract and retain important image features. Harned et al. [113] summarized the capabilities of artificial intelligence and MV, and the advances in MV that have changed technical regulations for manufacturers. In the work of Mok and Chung [114], an algorithm was presented for 3D affine medical image registration. The method used a convolutional visual transformer to learn global affine registration, which outperforms CNN-based affine registration methods in terms of registration accuracy and generalization, while retaining the operational advantages of learning-based methods. In Wu's [115] research, a multi-layer MV classifier was proposed to automatically identify lung disease categories from chest X-ray images. For digital image texture analysis, convolution operations were used to enhance symptom features and remove noise. Yoo et al. [116] developed an automated CNN-based pipeline for the detection of prostate cancer (PCa) in patients. To test the automated pipeline, DWI images of 427 patients were used as a dataset, which received good test results. The paper of Hassan et al. [117] provided a brief overview of AI, CV, and CT medical images for the diagnosis of COVID-19. The authors analyzed previous reviews, and after an in-depth analysis, 114 studies were collected. According to the analysis, AI and MV have potential in the rapid diagnosis of COVID-19, and further research is needed to bring accurate and effective models to clinics.

The utilization of image processing and MV in medicine has increased in recent years. In the paper of Zhang et al. [118], a new method of image processing was proposed for early detection of skin cancer. Deniz et al. [119] introduced transfer learning and deep feature extraction methods, and pre-train CNN models. AlexNet and Vgg16 models are adopted in feature extraction, and then the obtained features were classified by support vector machine (SVM) [119]. Experiments were carried out on the breast cancer dataset and the accuracy was evaluated. Evaluation results show that transfer learning produces better results than deep feature extraction and SVM classification. Zhao et al. [120] mentioned the development of a DL model that can diagnose the severity of acne based on images, and its diagnosis results were as accurate as dermatologists.

Table 3. briefly describes the work done on the functional application in medical field.

Table 3. Application of machine vision in medical field.

Authors	Method	Function	Material	Research outcome
Zhao [83]	vision	Detection	Tablets	The obtained RGB format images are transformed into HSI color format. The tablets could be identified and determined by carrying out of the image segmentation.
Dimitrios [88]	CNN-RNN	Recognition Classification	CT images	Detection of COVID-19 from COV19-CT-DB database. The basic of model diagnoses COVID-19
Sarah [89]	CNN Networks	Detection Classification	Brain MRI images	The accuracy of outperforming is 99% higher than others on the same dataset.
Shekoofeh [93]	MICLe	Detection Classification	Chest X-ray Dermatology	The accuracy improvement is 6.7% and 1.1% in mean AUC.
Zhou [96]	GCN CNC-Net	Detection Classification	Colorectal cancer histology images	Outperforming current methods on a large scale colorectal cancer grading
Khalil [101]	CNN	Detection Classification	Mammograms	The method obtains a score of 0.97 with a 2.35 and 0.99 true positive ratio with 2.45 false positive per image.
Alexander [103]	CNN CAD	Detection Classification	Breast cancer histology image	The 4-class accuracy is 87.2% and the 2-class accuracy is 93.8%.
Wu [109]	2D convolution	Detection Classification	ARFI-VTI images	Dimensions of feature patterns from 32 × 32 to 16 × 16 size.
Taimoor [114]	BN-ReLU convolution CNN	Classification	Breast cancer images	The accuracy reaches 90% and 98% without data argumentation and with data augmentation scenarios.
Wu [119]	2D convolution vision	Detection Classification	Digital chest X-ray images	The mean recall is 98.68%, the mean precision is 82.42%, the mean accuracy is 83.57%.
Zhao [120]	CNN	Detection Recognition	Magnetic resonance imaging	The receiver operating characteristic curve of 0.87 and 0.84 at slice level and patient level.

Based on different model, the applications of MV are classified and showed in the following topology diagram **Figure 13**.

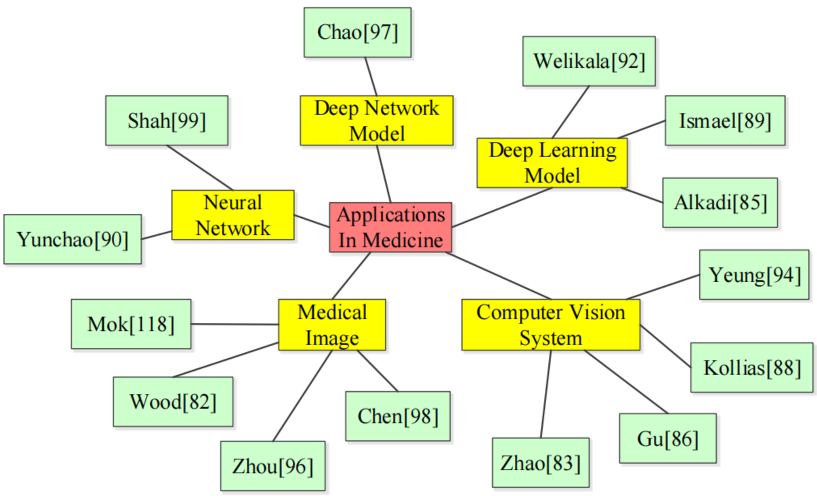


Figure 13. Topology diagram of medical applications of machine vision.

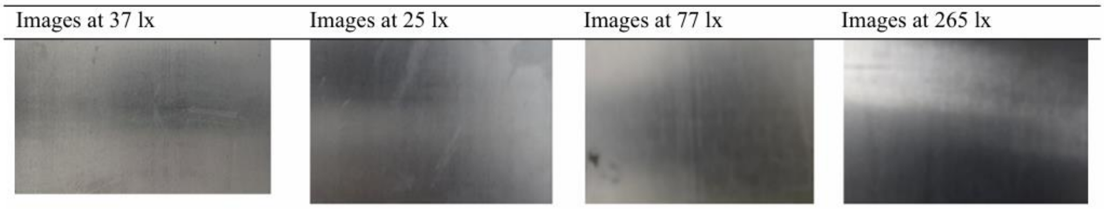
5. Manufacturing applications of machine vision

With the development of technology, MV technology has been widely used in manufacturing, most of which are used in work-piece classification, defect detection, and work-piece processing degree prediction. MV tools would help to improve the quality of the fabricated parts.

The obvious features of simple classification used for scenes, common MV algorithms can achieve the function of simple classification. Yu et al. [121] investigated a fusion of near infrared spectroscopy (NIR) and MV for improving the accuracy of recognizing surface defects in wood. It was found that the combination of NIR and Back Propagation Neural Network (BPNN) showed better discrimination accuracy with 92.7% for the training set and 92.0% for the test set. Chen et al. proposed a missing-pin chip detection system based on the YOLOv4-tiny algorithm and a small-size AXU2CGB platform, which has a two-layer ping-pong optimization as well as an FPGA gas pedal structure with multiple parallel convolutional kernels, and achieves a detection speed of 0.468 seconds per image, 89.33% mean average precision (mAP), and 100% missing-pin recognition rate [122]. The detection efficiency is greatly improved and the power consumption is reduced. Lin et al. [123] proposed an intelligent hybrid strategy for edge-inconsistent feature detection using machine vision, and a feature classification model based on deep CNN was established using K-Means clustering strategy. In order to reduce the error between the regression output of the network and the labeled values, a hidden layer of -1 neuron was introduced. The results showed that the combined model was able to classify different types of geometric contour edge features with 100% correctness, and the average dice similarity index between the model results and the actual edges was 0.84, and the maximum error of HO shape was less than 0.06 mm for a work-piece with a size of 142 × 119 mm. Liong et al. [124] developed an automatic mechanism to classify leather defects in order to control leather quality in combination with machine vision. Manual feature extractors (edge detectors and statistical methods) and data-driven (artificial neural network) methods were utilized to represent leather patches. A variety of classifiers (decision trees, support vector machines, nearest neighbor classifiers, and ensemble classifiers) were then utilized to determine whether a test sample patch contains a defective segment. The classification accuracy was found to be 84%, which can be further improved by subsequently substituting the CNN for the artificial neural network and tuning the classifier parameters.

Compared with the simple classification, the image features corresponding to the complex classification are similar, and the different characteristics are difficult to find, so more accurate algorithm parameters and the application of new algorithms are needed. Lin et al. [125] used MV technology to detect defects in products processed using selective laser melting. Multi-layer Perceptron (MLP) is mainly used to classify stripe defects generated during processing. The number of neurons in the input layer was set to 4, and the number of neurons in the output layer was 2. The defect recognition accuracy of MLP reaches 98.33%, and the time consumption was faster than that of SVM. Ryu et al. [126] generated a new method for segmentation using the ability of a line scan camera in order to identify fine scratchings on the edge of a steel plate. Focusing on using Gabor filter had a scratch on the boundary of the error, to identify a particular area has a defect, then according to the extracted features using SVM classifier to classify. Through the experimental verification of 2061 frames of images collected from real samples, the true detection rate of the method is 97.26%, and the false detection rate is 1.66%. Masinaei et al. [127] used MV technology for coal detection to recover fine coal particles and found that SVM classifier with linear kernel had the highest accuracy and generalization ability. Wang et al. [128] proposed a CNN-based MV method to improve the quality of image data and assist in improving the accuracy of defect recognition. This method was mainly used for single-camera CNN based MV grayscale images, and can greatly improve the accuracy of image classification and target detection when training the data of industrial image enhancement. The research of Jain et al. [129] significantly improved the performance of CNN for classifying surface defects with a GAN-based enhancement scheme. The results showed that the sensitivity and specificity of the classical enhanced CNN are 90.28% and 98.06%, respectively. In contrast, the comprehensive enhanced CNN obtained better results, with a sensitivity and specificity of 95.33% and 99.16%, respectively. Hao's [130] group developed a method for real-time classification and location of steel defects. An industrial inspection robot scanned the steel surface to generate an image, and the surface defect detection algorithm recognized the image. The deformable convolution enhanced backbone network is used to extract complex features of multi-shape steel surface defects. Then, the feature fusion network of the balanced feature pyramid is used to generate high-quality multi-resolution feature maps for detecting multi-size defects. The results show that the model achieves 0.805 mAP and shows high efficiency. Zhang et al. [131] proposed a CP-YOLOv3-dense neural network for fast and effective detection of rigid band defects. The model used YOLOv3 as the basic network to prioritize the image, and then replaced the two residual network modules with two dense network modules. The results showed that the CP-YOLOv3 dense network had a detection accuracy of 85.7%, a recall rate of 82.3%, an average detection accuracy of 82.73%, and a detection time of 9.68 ms per image. Boikov et al. [132] changed the method of using a single data to train the model and proposed a method of training neural networks for vision tasks based on comprehensive data. The generated symmetric distributed billet defect data set was used as the comprehensive data training set to train two neural networks, Unet and Xception. Under the training of the comprehensive training set, the two neural networks have achieved good results in the classification and segmentation of steel work-piece surface defects in images. The Dice score and accuracy on synthetic data are 0.62 and 0.81, respectively.

Real-time quality detection in the process of work-piece processing can reduce the defect rate of the work-piece, and can adjust the work-piece processing according to the real-time status, which is also the development trend of machine vision application in the manufacturing industry, but it also puts forward higher requirements for the improvement of the algorithm. Dynamic testing the quality of the work-piece is the purpose of most of the MV applications. Penumuru et al. [133] developed a based on SVM method of classification for typical machining environment accurate identification and classification was the plane of the material. Quadratic programming was used to minimize the plane boundary. Through the mapping function, the linearly non-separable data can be projected into the high-dimensional space to become linearly separable. Kernel-Svm was used for linearly non-separable data. The number of samples in the training set was 2491, and the number of samples in the test set was 1068. **Figure 14** shows that the surface images of different materials under different lighting conditions. The training results showed that the SVM did not overfit and the accuracy was 100%, which was verified by ten-fold cross validation. But this 100% accuracy was limited by the same lighting conditions. Benbarrad et al. [134] proposed a product quality control inspection model based on MV for classification and process prediction of product inspection. Inception v3 was found to be the most suitable model for classification and recognition, which can reach 95% accuracy in a faster time. Decision tree was more suitable for process prediction and achieve a very high R2 score (0.99), achieving high accuracy predictions. Machining tool wear condition has a direct relationship between the work-piece machining quality, so the real-time processing tool condition is also very important. Peng et al. [135] set up a tool wear monitoring platform based on MV. The structural similarity algorithm and Harris Angle detection algorithm were used to solve the problem of automatic shooting of the tool and realize the automation of the monitoring. At the same time, the binary morphology method was used to improve the image quality, and the gray co-occurrence matrix method was used to detect the tool wear value. It was found that the error rate between the calculated wear value of the monitoring system and the actual wear value was less than 5.73%, which met the requirements of industrial precision. With the development of manufacturing industry, many of the artifacts is developing toward miniaturization, it also calls for machine vision can carry on the detection of small objects. Dai et al. [136] proposed a small object detection network model to detect the position and quality of spot welding of automobile body. They proposed a recognition method based on yolov3, the network architecture is shown in the **Figure 15**, and compared the proposed method with other existing methods, the effect is shown in the **Figure 16**. In **Figure 17**, the green bounding box represents the good spot welds detected from the image, while red box denotes the bad spot welds. The number represents the confidence that there are spot welds in the bounding box. Zhang et al. [137] used ML method to collect coal photos in real time and detect multi-parameter information of coal online. Finite Erosion and Precise Expansion (FEED) algorithm and particle edge region segmentation algorithm were used to segment the overlapping particles, and 29 features were extracted and optimized. The total ash content error was found to be 2.54%. The method will likely be widely used in the coal processing industry.



(**a**)

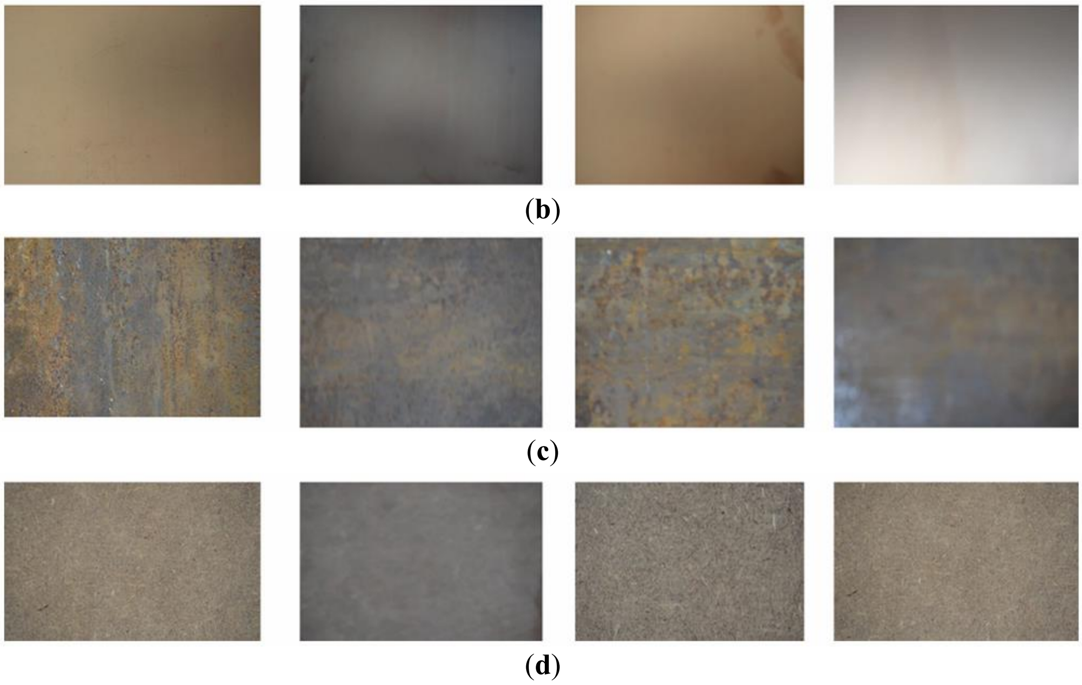


Figure 14. Surface images under different lighting conditions: (**a**) aluminium; (**b**) copper; (**c**) mild steel-rusted; (**d**) MDF [133].

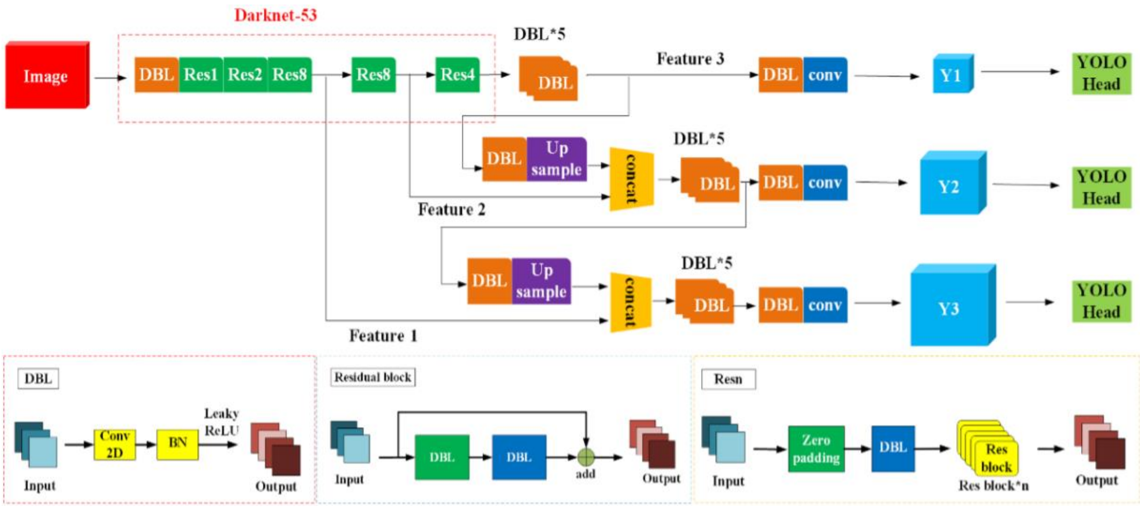


Figure 15. YOLOv3 architecture for object detection [136].

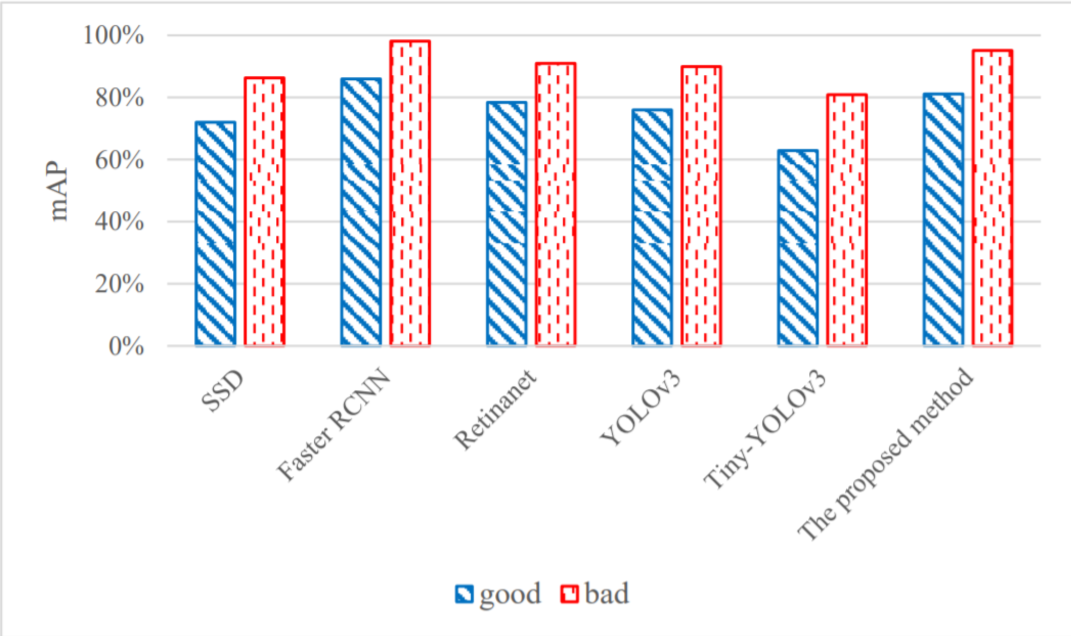


Figure 16. Comparisons between the proposed model and typical object detection algorithm on the spot welds dataset [136].

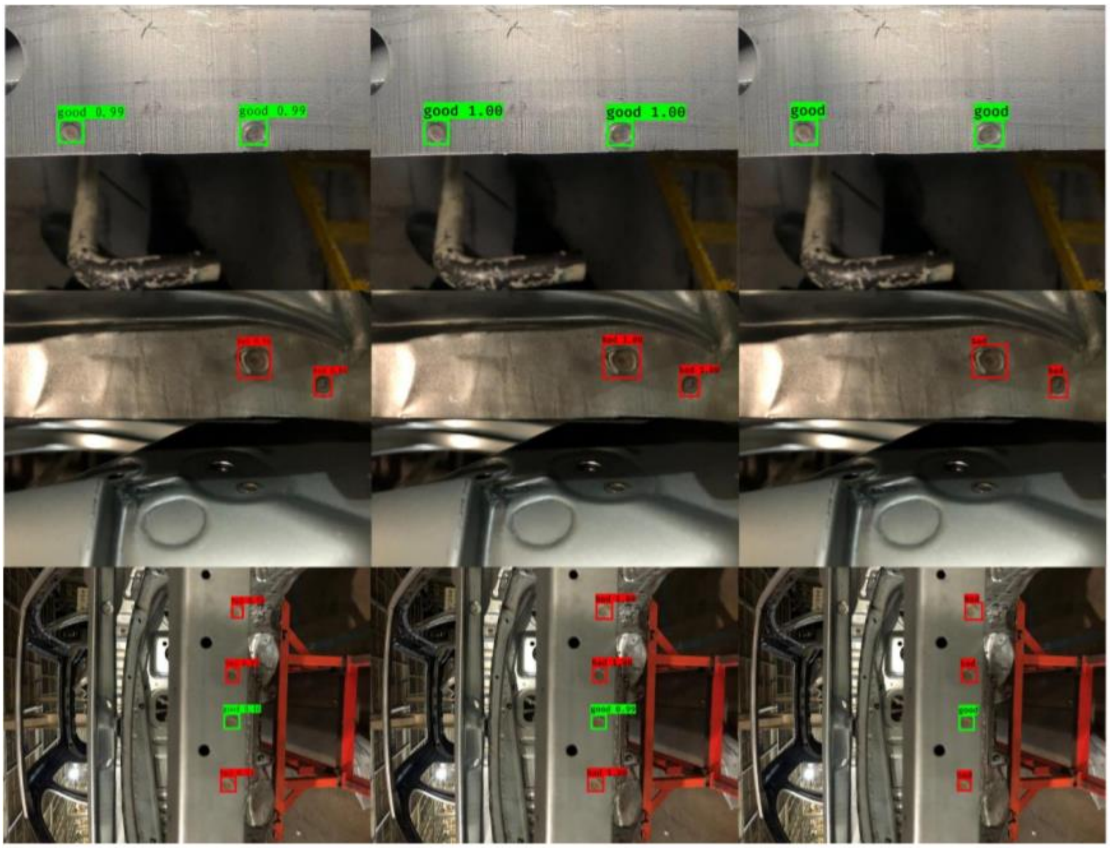


Figure 17. Some examples of spot welds detection results. YOLOv3(left), the proposed model (middle) and the ground truth (right) [136].

The research group generated a topology diagram of MV applications in the area of manufacturing and it is shown in **Figure 18**:

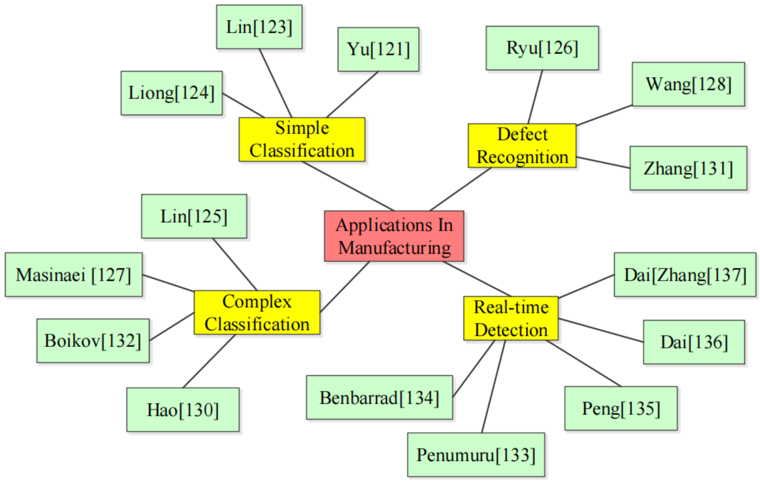


Figure 18. Topology diagram of manufacturing applications of machine vision.

Table 4 briefly describes the work done on the functional application in manufacturing.

Table 4. Application of machine vision in manufacturing.

Authors	Method	Function	Material	Research outcome
Massinaei [127]	SVM	Measurement Detection	Coal powder	The quality of the powder in the collection pipe can effectively predict the appropriate parameters of metallurgy.
Penumuru [133]	SVM	Classification Recognition	Metal Fiberboard	Training set 2491, verification set 1068, through the ten-fold cross-verification method, the accuracy of 100%.
Liong [124]	ANN CNN	Detection Classification	Leather	The classification accuracy rate was 84% in approximately 2,500 samples of 400 × 400 leather patches.
Wang [128]	CNN YoloV4	Classification Detection	Metal	Image enhancement using CNN can effectively improve the accuracy of surface defect recognition and detection by YoloV4.
Dai [136]	YoloV3 + MobileNetV3	Detection	Welded part	When the detection time is within 0.506s, the accuracy rate is 89.32%, which effectively balances the detection time and accuracy.
Lin [125]	MLP	Detection Classification	Metal of SLM	The recognition accuracy is 98.33%, but it will increase the print molding time.
Benbarrad [134]	Inception v3	Detection	Metal Ore	Can achieve 95% accuracy in the allowed time
Yu [121]	NIR + BPNN	Recognition	wood	The backpropagation neural network model showed better discrimination accuracy of 92.7% for the training set and 92.0% for the test set.
Peng [135]	GLCM	Detection	Metal cutter	The binary morphology method improves the image quality, and the error rate between the predicted and actual tool wear values is less than 5.73%.
Lin [123]	K-Means	Classification Detection	Metal	The accuracy rate is 100%, and the proposed method can recognize geometric shapes less than 0.06 mm well.
Zhang [137]	Finite-Erosion-and-Exact-Dilation	Detection	Coal	Various parameters of coal were predicted, and it was found that the comprehensive error remained within 2.54%.

6. Other applications of machine vision

In the previous sections, the applications of MV in agriculture, medicine, and manufacturing have been reviewed. Besides, MV also has other applications in human recognition, traffic, research assistance, and so on. In this chapter, these applications are introduced.

Compared with traffic accidents caused by violating traffic rules, fatigue driving can lead to accidents with higher mortality and public hazards. Sikander and Anwar [138] studied a new method based on machine vision to predict driver fatigue based on driver's facial movements. The **Figure 19** shows the framework details of the proposed 3D machine vision-based fatigue detection method for facial motion unit recognition. The technology reconstructs the driver's facial movements based on photo-metric stereo and identifies fatigue-related facial movements. Compared with other methods, this method improved the accuracy of driver fatigue identification by 95%. Zhao et al. [139] studied a method of human flow detection in crowded places by MV. The measurement of human body parameters is of great significance in sports, clothing and medical treatment. Traditional human body parameter measurement is complicated and requires a lot of human input. Arellano-González et al. [140] generated a new technique for measuring anthropocentric parameters based on a MV system. The results of the study showed that this technique had advantages in shortening sampling time, improving measurement accuracy and reducing equipment requirements compared with traditional measurement methods. Falling seriously affects the life safety of the elderly. Based on Microsoft Kinect® camera and Open CV library, Panahi et al. [141] developed a human fall recognition method based on machine vision. For human fall recognition, this method can achieve the recognition effect of the acceleration sensor.

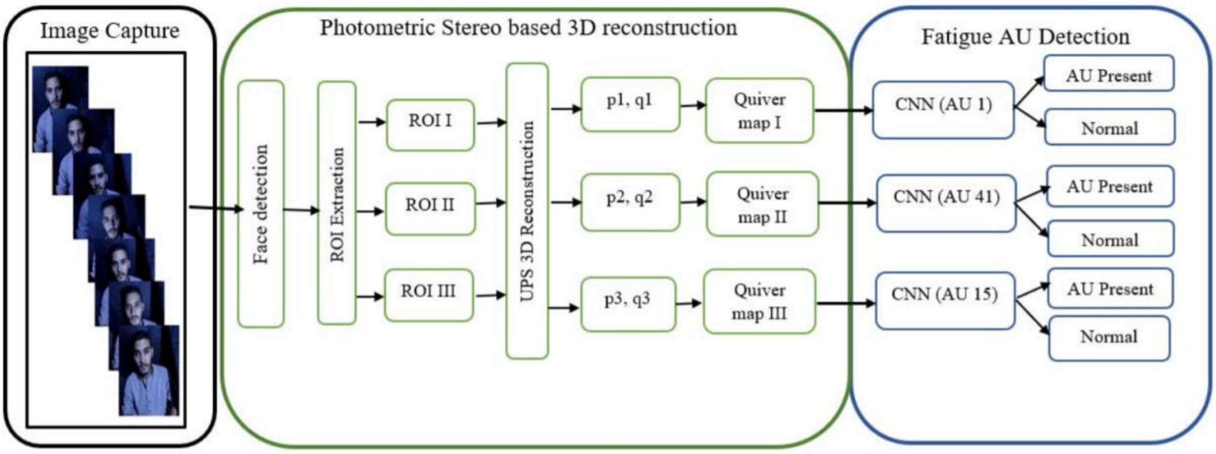


Figure 19. Framework of 3D facial action unit identification for fatigue detection [138].

Traffic plays an important role in the normal operation of human society. Road conditions, traffic facility management conditions, and vehicle driving technology have an important impact on traffic. Research on applying machine vision to these aspects has been widely carried out. Huang et al. [142] used MV to judge the degradation of ballast using the permeability of ballast as an index, and proposed a ballast inspection and maintenance method. The flowchart of the entire imaging-based ballast degradation analysis, including several preprocessing image enhancement techniques such as gamma adjustment, histogram equalization, and bilateral filtering is shown in **Figure 20**. Burghardt et al. [143] studied the impact of traffic signs of different materials and colors on machine vision recognition under different weather conditions in the laboratory. Yang et al. [144] proposed a new algorithm, which can eliminate the influence of oil and rust pollution on the track surface image recognition through denoising, and significantly improve the accuracy and processing speed of MV with an average accuracy of 97.11%, an average recall of 96.10%, and an average frame rate of 0.0064 s. Bridges play an important role in traffic. In order to ensure traffic safety, it is very important to detect the condition of bridges. Because it can simulate and reproduce the real scene, digital twin technology can be used to detect the condition of the bridge body. Dan et al. [145] studied a bridge parameter acquisition technology based on stress detection and machine vision, and relied on the acquired data for modeling to realize the digital twin detection of bridge conditions. Bridge cracks can be observed through drone photography and machine vision. Because there are problems in the clarity and other aspects of the photos taken by drones, traditional algorithms cannot analyze and judge them. Dan and Dan [146] have studied a new algorithm that can analyze the pictures taken by drones, and carried out experimental verification. Liu et al. [147] studied the impact of fog on the machine vision assisted driving system, determined the impact of fog and other adverse weather conditions on machine vision, and provided support for improving the safety of the machine vision assisted driving system.

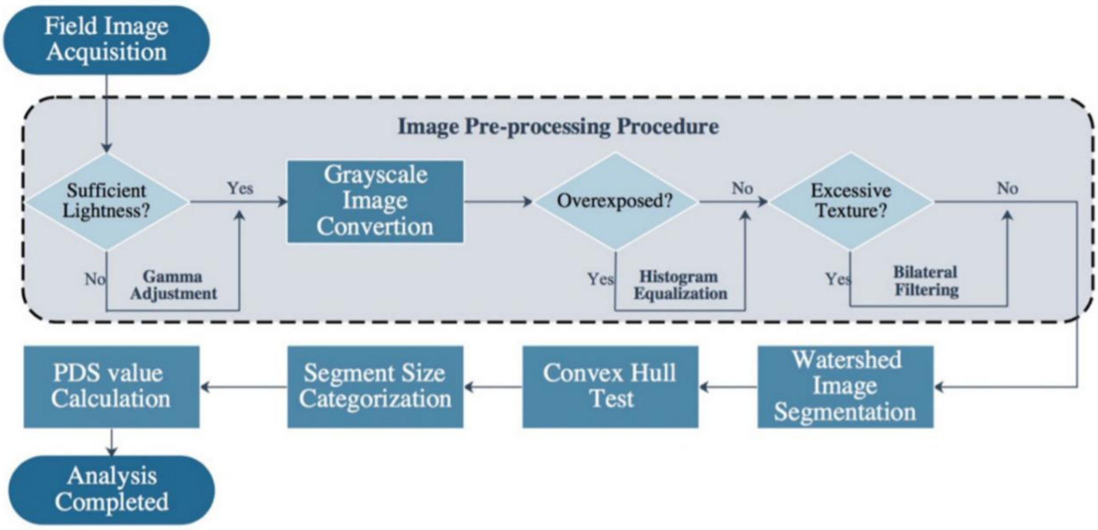


Figure 20. Flowchart of the imaging-based degradation analysis including preprocessing procedure [142].

There are a lot of time-consuming mechanical work in scientific research, such as Scanning Electron Microscopy (SEM) image analysis. The existence of these tasks has caused a lot of burden to scientific researchers and increased the cost of scientific research. Machine vision is used to analyze this type of image, which can reduce the workload of scientific researchers, reduce scientific research costs, and improve scientific research efficiency. Kim et al [148] studied the analysis method of SEM images based on machine vision and machine learning. The method has a good performance in determining particle size, particle size distribution and microscopic morphology of objects. Natova et al. [149] studied the application of machine vision and deep learning to identify transmission electron microscopy (TEM). This technology greatly improves the speed of TEM identification, and the identification time is about 2% of manual identification. Hendel et al. [150] applied machine vision to astronomical research, used machine vision and related algorithms to analyze space debris, and studied the evolution history of galaxies.

Table 5 briefly describes the work done on the functional application in other industries.

Table 5. Applications of machine vision in other industries.

Research direction	Authors	Method	Function	Research outcome
Human recognition	Sikander [138]	Photo-metric stereo	Predict driver fatigue	Improved the accuracy of driver fatigue identification by 95%
	Arellano [140]	Machine Vision	The measurement of human body parameters	Shorten sampling time, improve measurement accuracy and reduce equipment requirements
	Panahi [141]	Microsoft Kinect® camera and Open CV library	Human fall recognition	Achieve the recognition effect of the acceleration sensor
Traffic	Huang [142]	Machine Vision	Judge the degradation of ballast	Proposed a ballast inspection and maintenance method
	Yang [144]	New algorithm	Eliminate the influence of oil and rust pollution	Improve the accuracy and processing speed of MV
	D. Dan [145]	stress detection and machine vision	Bridge parameter acquisition	Realize the digital twin detection of bridge conditions
Research assistance	Kim [148]	machine vision and machine learning	Analyze SEM images	Perform good in determining particle size, particle size distribution and microscopic morphology of objects
	Natova [149]	machine vision and machine learning	Identify transmission electron microscopy (TEM)	improves the speed of TEM identification, the identification time is about 2% of manual identification
	Hendel [150]	machine vision	Analyze space debris	study the evolution history of galaxies

The research group generated a topology diagram, **Figure 21**, of this section and it is shown below:

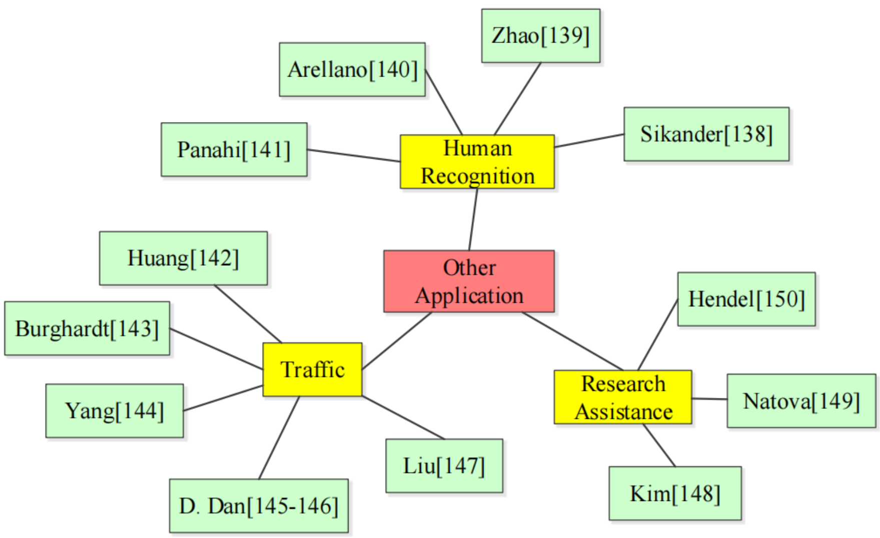


Figure 21. Topology diagram of other applications of machine vision.

7. Results

In this research, firstly, the group introduced the development of MV algorithm. Then the authors review the applications of MV in several areas, including agriculture, medicine, manufacturing, and so on. There are plenty of results are founded in this work:

- As the algorithm developed, MV could afford some work to reduce workload of human beings.
- Since MV is good at image classification, it has plenty of applications in the area of agriculture, especially in seed selection, fruit classification, pest identification, and so on.
- With the help of MV, the workload of doctors is reduced since the algorithm could do detection tasks and improve the accuracy of medical decision and treatment.
- In the field of manufacturing, MV is used in work-piece classification, defect detection, work-piece processing degree prediction, and so on.
- Besides, MV also has several applications in different areas. For example, it could be used in traffic to reduce the happen of accident. And MV can be used to analyze SEM images to help doing research. Moreover, MV could help to study the evolution history of galaxies.

8. Conclusion

Advancements in the MV field have been growing in every aspect of daily life, from research to manufacturing. Many organizations and academia continuously create a high number of unique solutions for refining high-quality and low-cost MV applications. And the applications of MV is growing sharply since the ability of image detection, classification, and processing. After summarizing the above articles, this team summarized the relevant applications of MV in agriculture, medicine, manufacturing, traffic, and so on. The research did a brief analysis based on the number of published paper, MV has more applications in medicine than other fields. But in agriculture, the number of MV applications develops fast. Thus, in future work, the group plan to focus on agriculture, because in this area, MV could do detection of the crop, then help farmers to irrigate or spread manure. MV is a useful tool to increase the harvest of crop. Today, MV has a profound impact on the daily life of everyone. This team completed this article to make a phased summary of the application of MV. It is evident that the current trends in the growth of MV technology will positively impact several utilizations in the mentioned areas in this research.

Funding: This work is supported by the Funding for Visiting Scholar project of ordinary undergraduate universities in Shandong Province in 2024 and Youth Fund of Shandong Agriculture and Engineering University (QNKJZ202301).

Conflict of interest: The authors declare no conflict of interest.

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