**International Journal of Electrical and Computer Engineering (IJECE)**
Vol. 13, No. 3, June 2023, pp. 3407~3419
ISSN: 2088-8708, DOI: 10.11591/ijece.v13i3.pp3407-3419 

# A review of hyperspectral imaging-based plastic waste detection state-of-the-arts

**Owen Tamin[1], Ervin Gubin Moung[1], Jamal Ahmad Dargham[2], Farashazillah Yahya[1], Sigeru Omatu[3]**
[1]Faculty of Computing and Informatics, Universiti Malaysia Sabah, Sabah, Malaysia
[2]Faculty of Engineering, Universiti Malaysia Sabah, Sabah, Malaysia
[3]Digital Monozukuri (Manufacturing) Education Research Centre, Hiroshima University, Higashi-Hiroshima, Japan

**Article Info**

***Article history:***

Received Mar 16, 2022
Revised Sep 15, 2022
Accepted Oct 1, 2022

***Keywords:***

Hyperspectral
Imaging
Machine learning
Object detection
Plastic detection
Plastic waste

**ABSTRACT**

Plastic waste issues emerged from the build-up of plastics that negatively impacts the environment. As a result, plastic waste detection is proposed in many research studies to tackle the problems. Therefore, this paper aims to review hyperspectral imaging techniques and machine learning in plastic waste detection. Hyperspectral imaging techniques are found to be effective in detecting plastic waste and microplastics as they were able to capture plastic reflectance spectral by using the near-infrared sensor. However, the review also shows that hyperspectral imaging techniques were less efficient in capturing the electromagnetic spectrum of black plastics due to carbon-black absorption properties. Carbon-black strongly absorbs light in the ultraviolet and infrared spectral range of the electromagnetic spectrum, therefore not detected by the near-infrared sensor. This paper also reviews how machine learning can alternatively detect and sort all types of waste, including plastics. Multiple studies show that the machine learning model achieved good accuracy in detecting all types of plastics based on the waste dataset. Finally, it can be seen that the spectral information of plastic can be used as feature extraction for machine learning models for better plastic detection. It is hoped that this study will contribute to more systematic research on the same topic.



***Corresponding Author:***

Ervin Gubin Moung
Faculty of Computing and Informatics, Universiti Malaysia Sabah
Kota Kinabalu 88400, Sabah, Malaysia
Email: ervin@ums.edu.my

## 1. INTRODUCTION

Hyperspectral imaging (HSI) is a method that examines a broad spectrum of light. The spectrum extracted from every pixel in an image is used for object detection and localization. This method has been an active research area due to the reliability of its performance in a wide range of applications [1], [2]. HSI has aided researchers in the detection of cancer [3], agricultural [4], [5], and military equipment [6]. Researchers have looked towards HSI as a potential tool to solve the environmental problem due to the exponential growth of plastic waste around the world. Plastics are made of synthetic materials that make use of polymers and are simple and inexpensive to produce in large quantities in factories. This facilitates their widespread use. However, due to the negligence of humans, plastic was is not disposed of in an appropriate manner and instead winds up in landfills and the ocean. At this time, there have only been a handful of studies conducted on the detection of plastic using HSI technologies and machine learning. Both the emergence of HSI technologies and their implementation are still in their infancy at this point. Despite the fact that HSI technology and machine learning are widely available, there have not been many studies on the detection of plastic garbage. On the other hand, machine learning is typically utilized for the purpose of classifying and identifying several different types of garbage. Particularly when it comes to plastic, there is less of an emphasis placed on applying machine learning for single-class identification. Therefore, the purpose of this paper is to conduct a literature review on previous research on the detection of plastic waste based on hyperspectral imaging and machine learning in the hope of identifying current limitations or gaps found in the previous research. In addition to that, the performance of the deep learning model with regard to waste classification will also be presented in this work. The major contributions made by this paper are: i) to systematically review the recent application of hyperspectral imaging techniques in plastic detection; ii) to provide clear insights on the machine learning models used for waste classification and their performance; and iii) to identify the potential of incorporating near-infrared hyperspectral imaging techniques with machine learning models for waste classification.

This article is broken down into six sections. In section 1, we discuss the prior research, our motivation, and our contribution to the field. In section 2, we discussed the research methodology that was applied during the course of the study. In section 3, we cover an overview of hyperspectral imaging that is related directly to the detection of plastic. The results as well as the discussions are broken down in section 4. The limitations of this paper and suggestions for future research are discussed in section 5. Last but not least, the main conclusion is developed in section 6.

## 2. RESEARCH METHOD

The research questions constitute the most crucial stage in the process of getting started with this study. The research questions that are asked help to ensure that the correct path is taken and that the study meets its actual objective. This study is generated based on three research questions: i) how hyperspectral imaging technique is applied in plastic waste detection? ii) what is the electromagnetic spectrum of plastics that can be detected by a hyperspectral imaging system? and iii) what is the performance of a machine learning model in detecting plastic waste?

Once research questions are constructed, the next step is implementing the search strategy. The databases used in this study are Science Direct, IEEE Xplore, Springer, and Scopus. The first keyword generated from the databases is “hyperspectral imaging in plastic detection”, and the article year is set in the period of six years (2016 to 2022). Since the first keyword does not produce good results across the databases, the next following keywords are used: “plastic detection”, “machine learning in plastic detection”, and “deep learning in plastic detection”.

The final step is to establish inclusion and exclusion criteria for this study. It is imperative that this criterion be met in order to guarantee that the article that was searched is applicable to this research. Only articles with a scientific focus and written in English have been included. Because there is less of an emphasis placed on the detection of plastic waste, there is also an emphasis placed on the detection of general waste, which includes plastic. Research articles that did not focus on plastic waste were not considered for inclusion in this study.

## 3. REVIEW OF HYPERSPECTRAL IMAGING IN PLASTIC DETECTION

The term “hyperspectral imaging” refers to a type of spectral imaging that employs the use of multiple bands from the electromagnetic spectrum. Imaging spectroscopy can be broken down into the following categories: panchromatic, multispectral, superspectral, hyperspectral, and ultraspectral imaging. The range of spectral bands as well as the characteristics of each spectral imaging are presented in Table 1. The HSI takes measurements from continuous spectral bands, which enables the unique color characteristic of each individual object to be detected. HSI has the ability to differentiate the color spectrum of each pixel and can provide spectral details on images that only have two dimensions. The near-infrared (NIR) sorting method shows the best potential choice for material identification and classification when compared to trommel separators, Eddy current separators, induction sorting, X-ray technology, and manual sorting [7]. This is because the NIR sorting method is non-contact and non-destructive. The typical HSI sorting system for object detection on a conveyor belt is depicted in Figure 1.

This article also discussed the application of near-infrared hyperspectral imaging, also known as near-infrared hyperspectral imaging (NIR-HSI), in the process of waste reduction. In addition to this, it has been reported that NIR-HSI has been combined with other methods in order to differentiate numerous elements found in wood-based waste and two types of plastic waste polymers, namely polyvinyl chloride (PVC) and polyethylene terephthalate (PET). Approaches based on machine learning have also been used extensively to forecast the treatment of organic solid waste, various recycling processes, and solid waste management (SWM) [8]. Microplastics (MPs) are another form of waste that can be released into the atmosphere from plastic products. Using the HSI method, which involves investigating the chemical characteristics of airborne MPs, it is possible to identify these particles [9]. In addition to this, it can be found in water in the form of nanoplastics, which can be detected by high-tech systems such as satellites, autonomous vehicles, and remote operating systems [10]. Table 2 is a summary of a critical review of various existing techniques for the detection of plastic, including descriptions of theoretical models, findings, and limitations.

Table 1. Range of spectral band and characteristics for each spectral imaging

| Spectral imaging | Range of spectral bands | Range of electromagnetic spectrum | Characteristics |
|---|---|---|---|
| Panchromatic imaging | 1 to 2 | 450 to 900 nm | Capture only a single band of images that are displayed as one-dimensional (1D) or grayscale image |
| Multispectral imaging (MSI) | 3 to 15 | 250 to 2500 nm | Capture few spectral bands which contain both brightness and spectral information of the target being observed |
| Superspectral Imaging | 16 to 99 | 250 to 2500 nm | Capture more spectral bands than MSI (typically more than ten), enabling the sensor to capture the finer spectral characteristics of the target. |
| Hyperspectral imaging | 100 to 500 | 250 to 2500 nm | Capture hundreds of spectral bands for each pixel because they measure continuous spectral bands. |
| Ultraspectral imaging (USI) | 501 and more | 250 to 2500 nm | Capture more spectral bands than HSI and has the capability to present molecular absorption in two-dimensional (2D) display |

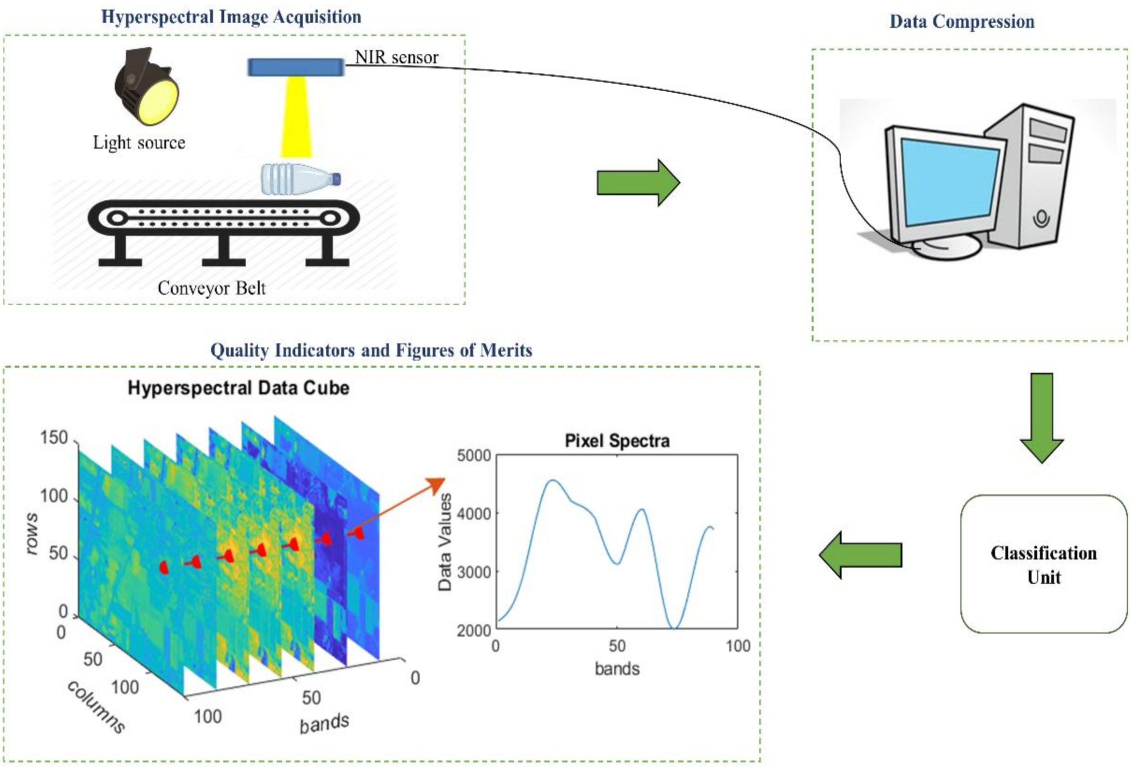


Figure 1. Typical HSI sorting system on a conveyor belt

A detection system that is both efficient and inexpensive for plastic waste is desperately needed. The results of Table 2 show that the NIR system, when combined with HSI techniques, offered superior options for the classification of plastic waste. The majority of studies demand for an increase in the collection of data on a variety of plastic types in order to improve plastic identification. NIR-HSI techniques were able to extract more electromagnetic spectrum from plastic, which further improved its capability in sorting systems. The establishment of a more comprehensive data collection system pertaining to plastic waste is one way in which this can be made possible. The lack of data regarding plastic waste can be remedied through the use of data augmentation techniques [11]. The augmentation technique aims to increase the data quantity by modifying existing data to train the model.

Table 2. Review of various existing techniques in plastic detection

| Ref. | Review Topics | Theoretical Model | Findings | Limitations |
|---|---|---|---|---|
| [7] | Review of existing waste management systems, techniques, and elements for material identification and categorization. | Partial least squares discriminant analysis (PLS-DA), artificial neural networks (ANN), support vector machines (SVM), linear discriminant analysis (LDA), k-nearest neighbors (KNN), and soft independent modeling by class analogy (SIMCA). | The NIR sorting method is the most suitable choice for material identification and classification among all the listed techniques because of its safe properties. | The study only looked at a few types of plastic and did not evaluate any others. |
| [8] | Review of artificial intelligence in solid waste management (SWM). | Linear Regression (LR), SVM, genetic algorithm (GA), ANN, and decision tree (DT). | Due to data shortage, traditional techniques based on mechanistic and rigid models are less suited for handling SWM issues. | Inadequate waste data, multiple artificial intelligence (AI) models that inhibit progress in implementing AI in SWM, difficulty mimicking most AI models, direct application of AI in tackling specific waste problems, and a substantial gap between AI research and the SWM sector. |
| [9] | Mini review of current studies of airborne microplastics. | Not mentioned. | The HSI method can be an alternative to study airborne MPs' chemical and quantification characteristics. | There is limited data on mass concentrations and the occurrence of airborne MP polymers due to a lack of standardization of analytical methodologies. |
| [10] | Review of marine pollutants presence and evaluation of remote and in-situ techniques for detecting plastic waste. | Not mentioned. | Satellite imaging is costly, but it may offer data for long-range surveillance. On the other hand, UAVs are a great way to improve resolution and reduce costs, but they cannot detect micro-and nanoparticles in the low range. | Introducing autonomous sampling systems demands a lot of energy, multiplex assays, sensor regeneration, and a detection limit that decreases ultra-trace pollutants. |
| [11] | Review of a tutorial on HSI analysis. | PLS. | The PLS classification accuracy can be improved by better-distributing samples on the conveyor belt, expanding the wavelength range, and using an HSI camera and appropriate multivariate imaging algorithms. | The minor distinction between pellets of the same plastic material impacts the pellet categorization rate. |
| [12] | Review of the mechanical and chemical recycling of SPW. | Not mentioned. | Contaminations and a mix of different kinds of plastic waste reduce product quality and increase the price of recycled materials. | Pollutants or the combination of different kinds of plastics in waste will influence product qualities, limiting scale economies and fluctuating costs for recycled materials. |

In light of the findings of recent research, it is recommended that waste plastic be dried in order to improve the effectiveness of Fourier transform near-infrared (FT-NIR) spectroscopy [12]. FT-NIR is used to identify and analyze materials at a wavelength ranging from 2,500 nanometers (nm) to 25 micrometers ($\mu$m), which falls within the mid-infrared spectrum. The performance of the NIR and FT-NIR systems in terms of classification can be negatively impacted when wet plastic waste is present. The greater the amount of an object's wetted surface, the higher the percentage of the object's pixels that will be incorrectly classified as a result of spectral shifts.

One alternative method to find plastics in large areas is to use remote sensing techniques like satellite imaging. However, the operational costs are quite high. The use of unmanned aerial vehicles (UAV) as a method for detecting plastic is a cost-effective alternative; however, this system is unable to identify microplastics when used at close ranges. On the other hand, hyperspectral imaging (HSI) techniques can be used to detect microplastics and can also be applied to studies that investigate the chemical and quantification characteristics of airborne microplastics. The subsequent part of this article will explain how an application of hyperspectral imaging can be used to detect general plastic, black-colored plastic, and microplastic.

## 4. RESULTS AND DISCUSSION

This section is divided into two subsections. The first subsection of section 4 presents a discussion on the use of hyperspectral imaging in the detection of waste plastics. In the second subsection, the findings from the conducted literature review of machine learning applications in plastic waste detection are covered.

### 4.1. Application of hyperspectral imaging

In this section, the various applications of hyperspectral imaging in detecting plastic waste will be explored. Subsection 4.1.1 will focus on the general application of hyperspectral imaging in detecting plastic waste, including the use of NIR spectroscopy and short-wave infrared (SWIR) hyperspectral imaging. Subsection 4.1.2 will delve into the specific application of hyperspectral imaging in detecting black plastic waste and the challenges that come with it. Finally, subsection 4.1.3 will explore the application of hyperspectral imaging in detecting microplastics and the potential for this technology in the recycling industry. Overall, this section will provide an in-depth look at the capabilities and limitations of hyperspectral imaging in detecting and sorting plastic waste.

#### 4.1.1. Application of hyperspectral in detecting plastic waste

Plastic is a synthetic material that is predominately composed of various types of polymers. Due to the molecular structure of the plastic, it was very easy to mold into a variety of different forms that could be used in daily life. And because of the relatively low cost of producing plastic, a brand-new plastic product was purchased to take the place of the older one. Because of this phenomenon, there has been a significant buildup of plastic objects in landfills, which is referred to as plastic waste. Identifying plastic waste through the use of hyperspectral imaging has been the subject of a significant number of studies. One of the studies separates virgin plastics from waste electrical and electronic equipment (WEEE) plastics by using data from NIR spectroscopy with a wavelength range of 900 to 1,700 nanometers (nm). The training data are made up of virgin plastics, and they are used to evaluate the effectiveness of the partial least squares discriminant analysis, the spectral angle mapper (SAM), and the partial least squares linear discriminant analysis (PCA-LDA). Virgin plastic is a material that has never been used or treated and is made from natural gas. The virgin plastic was selected to see how well the three classification systems execute with little training data, which could not entirely reflect the plastic waste obtained. PCA-DA outperforms SAM and PLS-DA in categorizing WEEE plastics based on pre-trained models in the virgin plastic spectrum. PLS-DA performs the worst because it can only examine the positions between categories in a subspace.

When virgin plastics were removed from the training data and WEEE plastics were added to the system, the performance of the SAM, PLS-DA, and PCA-LDA techniques saw a significant improvement. There are discernible differences between virgin plastics and WEEE plastics in terms of the NIR spectra, the composition, and the surface qualities of the materials. When compared to dark-colored plastic, it was found that NIR spectroscopy works best with light-colored plastic in the sorting system. Dark-colored plastic, on the other hand, cannot be analyzed using this method. In order to prevent misclassification and adequately account for changes in the impact of the coating and contamination on the surface, it is necessary to collect additional training samples from a variety of sources [13]. Another study uses short-wave infrared (SWIR) hyperspectral imaging to identify plastic samples specifically for low-density polyethylene (LDPE) and high-density polyethylene (HDPE) within 1,000 to 2,500 nm in the electromagnetic spectrum with resolution at 6.3 nm. This helps solve the difficulty of identifying both plastics through conventional recycling methods. The values for sensitivity and specificity for all of the various types of plastic samples, including LDPE and HDPE, fall somewhere in the range of 0.91 to 1. The proposed method has a great deal of potential for application in the classification of mixed plastics in an industrial setting on a large scale, particularly in the recycling industry.

The polystyrene sulfonate (PSS) polymer is also capable of spectra ranging from 1,320 to 1,850 nm, which can be determined using a near-infrared hyperspectral imaging (NIR-HSI) method to determine the thickness of Poly (3,4-ethylenedioxythiophene) (PEDOT). The conclusion drawn from the findings is that white-light interferometry has a lower root mean square error of prediction (RMSEP) than stylus profilometry does. Because of the more extensive measurement area, there is a difference in the results that is equal to 6 nm. Since NIR-HSI is able to identify even small labels and letterings, it can be applied to control the inline process of producing flexible substrates. NIR-HSI techniques based on the Fisher discrimination model in the sorting and characterization of plastic waste have also been carried out on 94 municipal waste samples. These samples primarily consisted of polyethylene, polystyrene, polypropylene, polyvinyl chloride (PVC), and acrylonitrile butadiene styrene (ABS). The proposed model consists of five linear functions that have the ability to predict unknown plastic with a precision of 100%. It was reported that the model could be implemented in the waste management system [14]. NIR-HSI methods have also been used to sort and classify six different types of construction waste. These methods include the random forest (RF) and the extreme learning machine (ELM), which were used, respectively, to identify trend and amplitude characteristics.

The HSI method based on modified PLS-DA, has the capability to recognize and categorize a variety of waste image types. The proposed method for detecting waste uses images obtained by NIR line-scanning hyperspectral cameras and is based on a model that is structured like a tree. Pixel-level prediction was applied to a number of different test images, and the result reveals that the proposed method achieved a non-error rate (NER) of 98%. Allocating each plastic sample according to the properties and installing an RGB camera on top of the existing hyperspectral camera will further enhance the classification of the proposed classification system [15]. This will allow for better edge and color detection of the images. In addition, it has been demonstrated that HSI methods can distinguish polymers from sink products using the sink-float process. The method known as Fourier transform infrared (FT-IR) spectroscopy has been utilized by the commercial sector throughout the process. Researchers continue to struggle with the challenge of determining whether or not PVC was present in the final stage of thermal valorization. Within a range of wavelengths that extends from 900 to 1,700 nm, NIR sensors are able to detect the amount of plastic pollution that is present. An SVM analysis was carried out in order to categorize and forecast the levels of plastic pollution present in the three soil samples. According to the findings, when compared to the other soil samples, the sample containing organic matter exhibited the highest response signal based on NIR spectroscopy, which was greater than 2% [16]. HSI has the ability to detect and sort PP and HDPE polymers based on the PLS model while operating within the same wavelength range of 900 to 1700 nm. Both sensitivity and specificity for PP and HDPE polymer items reached more than 90%, indicating that rigorous one-class classification models can solve more technological limitations and be an essential component for intelligent laboratory systems in the future [17].

Based on the previous studies, it can be seen that HSI techniques can be applied to detect plastic samples of various wavelengths in the NIR region. Table 3 presents the average NIR reflection spectra of different types of plastics according to the previous studies. The 1070 nm band is the lowest usable spectrum band of plastics from 330 to 2,500 nm, suitable for plastic detection due to apparent feature absorption. According to Moshtaghi *et al.* [18] by observing the spectrum range of NIR (850 to 900 nm), the spectrometer fails to detect a highly noticeable color and plastic reflectance. Therefore, the average reflection spectra of plastic waste are around 1084 nm to 1212 nm for wavelengths of 1,000 nm to 2,500 nm.

The plastics sample used to study their reflection spectra consists of colored and clear plastics in Table 3. The spectrum band information of plastic is helpful in identifying which reflection spectra are typical for plastic. This information can help separate plastic and non-plastic waste for detection and classification purposes. Different color plastics react differently in NIR light absorption and reflectance. Black plastics are known to absorb NIR light and are thus not detectable in most sorting systems. The following section discusses the implementation of HSI carried out by other researchers in detecting black plastic.

Table 3. Information on the spectrum band of plastics

| Ref. | Wavelength studied | Average NIR reflection spectra | Type of plastics |
|---|---|---|---|
| [13] | 900 to 1,700 nm | 1,084 nm, 1,278 nm, and 1,562 nm | PP, PS, ABS, and polycarbonate (PC) |
| [17] | 900 to 1,700 nm | 1,130 to 1,205 nm, 1,400 to 1,430 nm, and 1,660 nm | PE, PP, PVC, PET, PS, LDPE, and HDPE |
| [11] | 1000 to 1,700 nm | 1,212 nm | ABS, PS, and PP |
| [18] | 400 to 2,400 nm | 1,070 nm, 1,192 to 1,215 nm, 1,660 nm, and 1,730 nm | PET, PP, polyester (PEST), and LDPE |
| [14] | 1000 to 2,500 nm | 1,150 to 1,250 nm, 1,350 to 1,450 nm, and 1,650 to 1,750 nm | PET, PP, PVC, PS, PE, and ABS |

### 4.1.2. Application of hyperspectral in detecting black plastic waste

Black plastic is a form of plastic that gets its color from carbon black, a type of industrial pigment additive used for its durability and deep shade. The carbon black in the black plastic absorbs the NIR light emitted by the sorting sensor, making it difficult to sort into recycling categories. This problem will lead most black plastic directly to landfills. This phenomenon resulted in a huge abundance of black plastic objects in landfills, called black plastic waste. Most black plastic products are made from plastic parts of electronic and electrical equipment waste. Electronic components usually contain harmful chemicals such as flame retardants and heavy metals.

Several studies have shown that the use of mid-wavelength infrared (MIR) methods has the potential to overcome NIR technology limitations [19], [20]. Black or dark polymers can be recognized, sorted, and classified. Raman spectroscopy is a typical MIR spectroscopy that can extract spectrum information from black polymer materials. In the spectral region of 3.2 to 3.6 m, spectrometer methods under the photon-up-conversion approach detect black plastics faster and more sensitively than Fourier-transform infrared spectrometers (FTIR). On the other hand, pixels on the edges of the image are frequently reliable and can cause problems with the classification rate.

Another study looked into the possibility of using mid-wave infrared (MWIR) spectroscopy to sort black plastic and wood items that are difficult to sort with NIR due to low reflectance and signal range limitations. The MWIR absorption features in black and colorful pieces are nearly comparable. However, there is a considerable variation in reflectance. The distinction explains why reflection is determined not just by the color enhancer but also by the surface roughness of various samples. Because of the short integration period, a very low reflectance in smooth and flat black samples is noisy, and vice versa for clear models. However, the study is limited only to the color of the material and the surface of the texture. It ignores the distance between the camera and the subject, altering the MWIR reflectance [21].

#### 4.1.3. Application of hyperspectral in detecting microplastics

Microplastics are fragments of any plastic that are less than five mm in length. This microplastic pollutes natural environments by entering through various channels, including cosmetics, clothing, and industrial activities. The NIR-HSI method can detect microplastics in residual organic matter. The organic matter is filled with LDPE powder of six mussels' samples within the NIR spectrum's 1,000 to 2,500 nm range. The collected samples were filtered using nylon and cellulose filters. Results indicate that the cellulose filters outperform nylon filters because of the differences in porosity and hydrophilicity. The proposed method can detect MPs size as small as 80 mm, which overcomes the limitation of range detection faced by NIR spectroscopy.

HSI systems based on SVM algorithms can detect MPs in both seawater and seawater filtrate. The results show that the precision and recall values were 100% when the MP particle size was more significant than one mm and less than 80% for particle size less than one mm. The lowest values were when the particle size was between 0.1 and 0.2 mm. However, when the particles are less than 0.1 mm, the proposed system can easily misclassify the subject as non-plastic in the natural environment [22]. Another detection of MPs found in seawater filtrates from the Baltic Sea showed that the UmBio inspector is suitable for detecting MPs of particle size up to 300 µm due to the higher spectral resolution than Videometer and Malvern; inspector.

The NIR spectrum can detect MPs in the soil through HSI systems and chemometrics within 400 to 1,000 nm. The dataset consists of two-particle fields ranging from 0.5 to 5 mm of soil samples that contain various natural samples. The proposed method used a charged-coupled device (CCD) with a digitally regulated pan-tilt to acquire photos of soil samples. SVM attained a precision rate of 58% and 84% for black and white PE, in particle ranges of one to five mm.

Fresh leaves give the best accuracy rate in classification because of the large amount of chlorophyll and water that create strong absorption and reflectance in the NIR spectral region. However, the shadows present in the images are easily misclassified as black PE, which may influence the accuracy of black PE classification. Without addressing the whole composition of the soil, the soil's surface restricts the detection of MPs in the soil [23].

### 4.2. Machine learning models for plastic waste detection

Machine learning is a discipline of computer science that imitates human thinking and learning using data and algorithms. The machine can improve its accuracy and performance without human interference over a period of time. One of the most common uses of machine learning is image recognition. It is used to identify items, people, places, and digital photos, among other things. Several researchers have used machine learning models to sort waste images into multiple classes with larger sample sizes in a short period. Figure 2 presents the typical object detection model for waste detection in block diagrams.

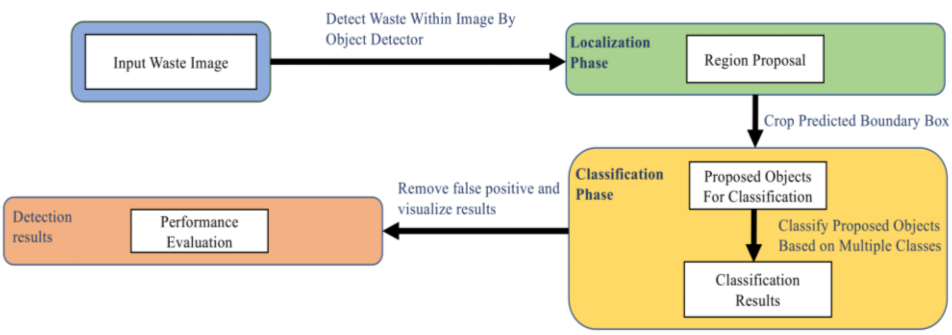


Figure 2. Block diagram illustrating a typical object detection model for waste detection

The object detector searches and locates possible waste regions within the input image. The detector then draws the boundary boxes around the proposed areas. Then, the boundary boxes are extracted and passed to the classifier to determine the types of waste. The irrelevant regions are removed to remove false-positive predictions. Then, the images showing all detected waste and its type are presented. Finally, the performance of the models is then presented with evaluation metrics. This section will explore numerous studies on deep learning for the classification, sorting, and identification of different ranges of waste.

**4.2.1. Deep learning**

Deep learning is a subfield of machine learning that attempts to model the way in which humans acquire knowledge. It assists data scientists in gathering, interpreting, and analyzing large amounts of data and has been used in various fields [24]–[26]. The most commonly used deep learning technique for classifying waste is the convolutional neural network (CNN) technique. A study utilized five CNN architectures; i) visual geometry group of 16 layers deep (VGG-16); ii) visual geometry group of 19 layers deep (VGG-19); iii) residual neural network (ResNet); iv) Inception; and v) Inception-ResNet, to classify and categorize 2527 waste images with a pixel size of 512x384 based on the TrashNet dataset. The results reveal that the ResNet performed better in waste classification based on a waste dataset with an accuracy of 88.6%. ResNet achieves such good performance due to the slightest standard deviation acquired and fewer epochs or periods to be trained, which makes the architecture much more stable than other CNN architectures [27].

A similar study is also conducted using four waste classifiers to identify and classify 9,200 waste images. They are i) VGG-16, ii) a 50-layers residual network (ResNet-50), iii) MobileNetV2, and iv) DenseNet-121. The performance of each waste classifier is then compared based on the histogram. The results also show that ResNet-50 performed the best among the four waste classifiers with more than 90% accuracy, which can be implemented in the recycling industry to sort a large amount of plastic waste [28].

A study was conducted on utilizing the ResNet network algorithm based on faster R-CNN and region proposal network (RPN) that can improve waste classification accuracy based on the target sample's size and location. The dataset consists of 816 images of waste collected from the sanitation department and non-waste based on the urban background, such as buildings and roads. The dataset parameter is based on the pre-trained common objects in context (COCO) model for better optimization due to the smaller dataset for training. The proposed method achieved an average precision of 89% with a detection speed of 6 seconds per image [29].

Another study investigated the deep learning performances of SVM with a histogram of oriented gradient (HOG) features, simple CNN, ResNet-50, and CNN with HOG features in the identification and classification of the waste image. A dataset consisting of 2527 images is collected with a pixel size of 384×512, categorized into six recycling categories. The results show that a simple CNN model performed the best among waste classifiers with a training and test accuracy of more than 90% with Adam and Adadelta optimizers due to the smooth convergence of the method [30].

The deep CNN model was trained using the ImageNet database. It is a dataset that has 1.2 million images and contains 1,000 different categories to categorize them into. During the process of preparing the dataset, augmentation techniques such as image translations and horizontal reflections were utilized. The techniques are utilized to enlarge the training samples by factors of 2,048 and alter the intensities of the RGB channels within the training images. The techniques aim to avoid storing the processed images on a limited disk size with little computation. Regularization methods such as dropout are implemented to minimize the overfitting problem in the fully connected layers of the system. However, it took five to six days to train the dataset because of the restricted memory of the graphics processing unit (GPU) used in the study [31].

AlexNet and SVM were employed to sort and classify 2,000 waste images into three classes: plastic, paper, and metal. Mean normalization techniques are employed as the pre-processing steps to all the images for brightness normalization. This approach allows two similar images of varying brightness to be treated as a single image. Both models' training sets are then implemented on a Raspberry Pi to compute the training accuracy. SVM performed the best with a classification accuracy rate of 94.8%. The limited GPU memory also affects the performance of the proposed system. This limitation leads to resizing the waste images to 32×32 and overfitting. Table 4 shows the details of several deep learning-based waste classification models.

The accuracy waste classification result obtained from Table 4 indicates that most deep learning models can classify the different types of waste into their respective classes. These findings show that deep learning models are becoming more effective and time-efficient for training waste images over the years. The dataset sets used for training significantly impact how well various deep learning models perform. The selection and size of the dataset are important in reducing overfitting and irrelevant feature extraction. Furthermore, the distribution of various types of waste classes in the dataset also impacts the performance of deep learning models. The imbalance of the distribution of different waste classes creates bias, which poses a challenge to deep learning models. Table 5 and Figure 3 show the number and percentage of papers that employ the classifier, respectively. This information may impact the selection of the deep learning model for future studies by indicating which classifier is usually utilized for waste classification.

Table 4. Performance of deep learning-based waste classification model

| Ref. | Study | Model | Results |
|---|---|---|---|
| [27] | Garbage detection based on the TrashNet dataset | ResNet, Inception, Inception-ResNet, VGG-16 and VGG-19 | Inception-ResNet performed the best with 88.6% accuracy. |
| [28] | Classification of municipal solid waste segregation | MobileNetV2, DenseNet-121, ResNet-50, and VGG-16 | ResNet-50 performed the best with 91.3% accuracy |
| [29] | Implementing deep learning models that can classify waste and non-waste | ResNet and RPN | The proposed model achieved an average of 89% accuracy rate. |
| [30] | Implementing deep learning model in classifying waste into six recycling categories | SVM with a histogram of oriented gradients (HOG) features, simple CNN, ResNet-50 and CNN with HOG features | The ResNet-50 model performed the best with training and test accuracy of 99.27% and 95.35%, respectively. |
| [31] | Using deep CNN to categorize 1.2 million waste samples based on ImageNet LSVRC-2010 dataset | CNN | CNN attained a rank one error rate of 37.5%, while the rank five error rates reached 17.0% |
| [32] | Waste classification based on the Gary Thung and Mindy Yang dataset | Pre-trained ResNet-50 is used as an extractor, and SVM is used as a classifier | The proposed model achieved an accuracy of 87%. |
| [33] | Implementing five deep learning models to identify waste samples for an automatic waste sorting system | Pre-trained SVM, AlexNet, RF, KNN, and VGG-16 | The VGG-16 method performed the best, with an accuracy of 93% |
| [34] | Web-based dataset for waste classification | CNN, ResNet-50, and VGG-16 | ResNet achieved a training accuracy of 95.94%. |
| [35] | Implementing a recycling waste classification model (CTR) known as the self-monitoring module (SMM) based on ResNet-18 for waste classification | ResNet-18 | The accuracy of ResNet-18 is 95.87%, which performed better than any other existing classifier based on the TrashNet dataset. |
| [36] | Implementing a CNN-based model that can classify waste into six recycling categories | MobileNet | The accuracy of MobileNet is 87.2% |
| [37] | Implementing a deep learning model that can classify waste into three categories | Faster R-CNN | The mAP of all the classifications of waste images reached about 0.683. The average precision for the paper is the lowest in the three recycling categories, with only 0.607 |
| [38] | Implementing a innovative lightweight neural network for waste classification systems | MobileNet-V3-small and ShuffleNet-V2 | The accuracy of both classifiers based on the TrashNet dataset is 96.10% |
| [39] | To create a new plastic waste categorization system based on recycling labeling | Singular value decomposition (SVD), Kernel PCA (KPCA), SVM, PCA, Laplacian Eigenmaps (LEMAP), and Fisher's linear discriminant analysis (FLDA) | The proposed method can identify and categorize plastic bottle types with 90% accuracy |
| [40] | Introducing mobile edge computing combined with deep learning to detect street garbage in urban areas | Faster R-CNN | The proposed model achieved a detection rate of 82% |
| [41] | Implementing a multilayer hybrid system (MHS) in the sorting and classification of 50 urban waste | AlexNet as feature extractor and multilayer perceptrons (MLP) as the classifier | The MHS model achieved an average accuracy rate of 94.9% compared to the CNN-only model of 83.9%. |
| [42] | Proposing an improved YOLO v2 model for garbage detection and recognition | Improved YOLO v2 | The proposed model achieved an average detection accuracy of 89.7%. |

Table 5. Review of classifiers employed for waste classification

| Classifier | References | Number of papers that employs the classifier |
|---|---|---|
| CNN-based | [30], [31], [34], [37], [40] | 5 |
| VGG-16 | [27], [28], [33], [34] | 4 |
| ResNet-50 | [28], [30], [32], [34] | 4 |
| MobileNet | [28], [36], [38] | 3 |
| SVM | [30], [33], [34] | 3 |
| AlexNet | [33], [41] | 2 |
| General ResNet | [27], [29] | 2 |
| DenseNet-121 | [28] | 1 |
| VGG-19 | [27] | 1 |
| ResNet-18 | [35] | 1 |
| Inception | [27] | 1 |
| Inception-ResNet | [27] | 1 |
| YOLO v2 | [42] | 1 |

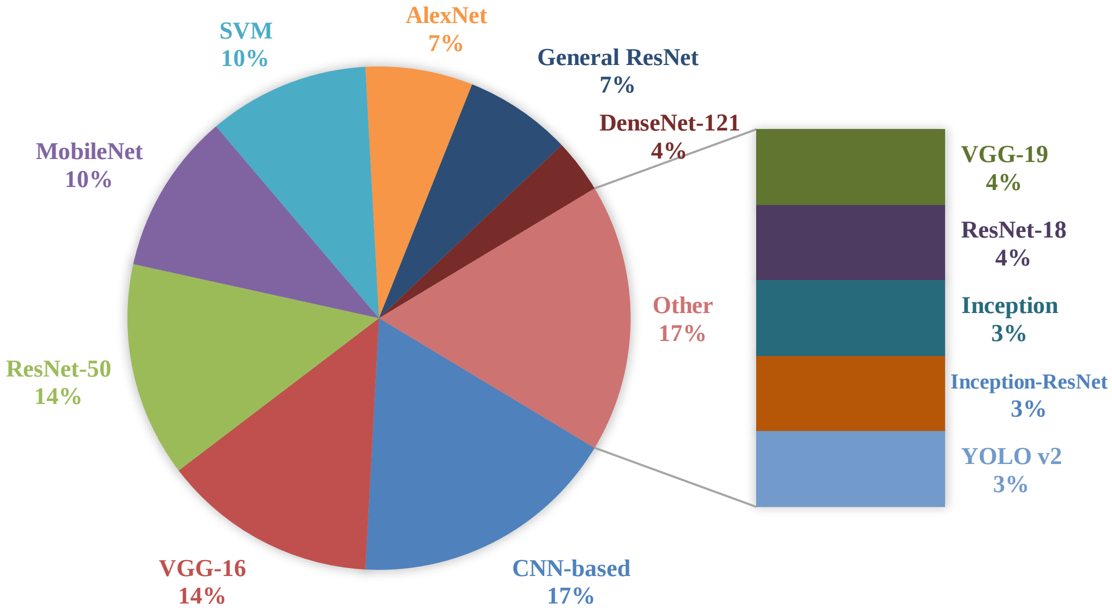


Figure 3. Percentage distribution of papers employing the classifier for waste classification

## 5. LIMITATIONS OF THE STUDY AND FUTURE WORK

This review combines both plastic waste detection and non-plastic waste detection review. Due to the scarcity of studies that use plastic waste as primary data, the majority of the literature reviewed in this paper focuses on general waste detection. The most significant limitation of HSI is the technologies' immaturity. HSI devices are costly, huge, and challenging to operate as they require knowledge to handle them. The study on plastic detection by the NIR-HSI technique is still considered new as researchers have only recently discovered the feasibility of the technique for plastic detection. The waste dataset used for training the machine learning models consists of an imbalance class. The imbalanced class can affect the performance of the models as the models are designed to work with an equal number of classes. Most of the dataset used for classification is based on a controlled lighting environment and a clean background. The model achieved high accuracy based on a controlled environment. However, the model will have difficulty detecting plastic waste in the natural environment. The future work that can be addressed this issue is to make HSI technique cheaper and user-friendly for plastic waste detection. The average reflection spectra of plastic waste do not exceed 1,300 nm. Therefore, selecting HSI devices that can work in the shorter NIR spectral range (less than 1,500 nm) can save cost. Creating a dataset solely on plastic waste images will generate more future studies for detection and classification purposes. Dataset consists of plastic waste images in an unclean state, and the natural environment can test the true capability of each machine learning model on detection performance. Another potential study is to utilize the plastic reflection spectra information as feature extraction for machine learning models. This feature extraction could help models detect plastic waste more accurately and effectively.

## 6. CONCLUSION

In conclusion, this paper reviewed hyperspectral imaging techniques for plastic waste detection and machine learning models for waste classification. The review reveals that hyperspectral imaging techniques provide a safe and effective method for plastic detection with high accuracy within a short period. The reflectance spectral of most plastics can be detected by a hyperspectral sensor, which makes it ideal for use in the plastic sorting system. However, the continuous production of black plastic still poses a problem to the environment, given the current near-infrared sorting system. Due to carbon black absorption properties, the current sorting method is less efficient in detecting black plastic. Although mid-wavelength infrared technology is introduced, it is very costly to implement in the sorting system compared to a near-infrared system. Given the lack of study provided, more research on mid-wavelength infrared technology for plastic detection can be explored. The review also reveals that the deep learning model has a high potential in classifying plastic efficiently regardless of color based on colored and grayscale images. This suggestion opens the possibility of exploring the implementation of deep learning models in detecting plastic waste based on near-infrared images regardless of color and spectral extraction. Most of the dataset used for classification is based on a controlled lightning environment, which may not reflect the actual condition of plastic waste. Therefore, introducing a database of realistic plastic images with the natural state in an uncontrolled environment can be useful for future studies of plastic detection by deep learning models.

## ACKNOWLEDGEMENTS

The article processing charge was funded by Kementerian Pengajian Tinggi Malaysia and Universiti Malaysia Sabah under grant code FRGS/1/2020/ICT06/UMS/02/1.

## REFERENCES

[1] M. Kanthi, T. H. Sarma, and C. S. Bindu, "Multi-scale 3D-convolutional neural network for hyperspectral image classification," *Indonesian Journal of Electrical Engineering and Computer Science (IJEECS)*, vol. 25, no. 1, pp. 307–316, Jan. 2022, doi: 10.11591/ijeecs.v25.i1.pp307-316.

[2] T. S. Reddy and J. Harikiran, "Hyperspectral image classification using support vector machines," *IAES International Journal of Artificial Intelligence (IJ-AI)*, vol. 9, no. 4, pp. 684–690, Dec. 2020, doi: 10.11591/ijai.v9.i4.pp684-690.

[3] S. Kothari, S. Chiwhane, S. Jain, and M. Baghel, "Cancerous brain tumor detection using hybrid deep learning framework," *Indonesian Journal of Electrical Engineering and Computer Science (IJEECS)*, vol. 26, no. 3, pp. 1651–1661, Jun. 2022, doi: 10.11591/ijeecs.v26.i3.pp1651-1661.

[4] K. Jhajharia and P. Mathur, "A comprehensive review on machine learning in agriculture domain," *IAES International Journal of Artificial Intelligence (IJ-AI)*, vol. 11, no. 2, pp. 753–763, Jun. 2022, doi: 10.11591/ijai.v11.i2.pp753-763.

[5] M. C. G. Baabu and M. C. Padma, "Semantic feature extraction method for hyperspectral crop classification," *Indonesian Journal of Electrical Engineering and Computer Science (IJEECS)*, vol. 23, no. 1, pp. 387–395, Jul. 2021, doi: 10.11591/ijeecs.v23.i1.pp387-395.

[6] A. W. Altaher and S. K. Abbas, "Image processing analysis of sigmoidal Hadamard wavelet with PCA to detect hidden object," *Telecommunication Computing Electronics and Control (TELKOMNIKA)*, vol. 18, no. 3, Jun. 2020, doi: 10.12928/telkomnika.v18i3.13541.

[7] M. Cesetti and P. Nicolosi, "Waste processing: new near infrared technologies for material identification and selection," *Journal of Instrumentation*, vol. 11, no. 9, Sep. 2016, doi: 10.1088/1748-0221/11/09/C09002.

[8] M. Abdallah, M. Abu Talib, S. Feroz, Q. Nasir, H. Abdalla, and B. Mahfood, "Artificial intelligence applications in solid waste management: A systematic research review," *Waste Management*, vol. 109, pp. 231–246, May 2020, doi: 10.1016/j.wasman.2020.04.057.

[9] Y. Huang, X. Qing, W. Wang, G. Han, and J. Wang, "Mini-review on current studies of airborne microplastics: Analytical methods, occurrence, sources, fate and potential risk to human beings," *TrAC Trends in Analytical Chemistry*, vol. 125, Apr. 2020, doi: 10.1016/j.trac.2020.115821.

[10] M. Farré, "Remote and in situ devices for the assessment of marine contaminants of emerging concern and plastic debris detection," *Current Opinion in Environmental Science and Health*, vol. 18, pp. 79–94, Dec. 2020, doi: 10.1016/j.coesh.2020.10.002.

[11] J. M. Amigo, H. Babamoradi, and S. Elcoroaristizabal, "Hyperspectral image analysis. A tutorial," *Analytica Chimica Acta*, vol. 896, pp. 34–51, Oct. 2015, doi: 10.1016/j.aca.2015.09.030.

[12] K. Ragaert, L. Delva, and K. Van Geem, "Mechanical and chemical recycling of solid plastic waste," *Waste Management*, vol. 69, pp. 24–58, Nov. 2017, doi: 10.1016/j.wasman.2017.07.044.

[13] X. Wu, J. Li, L. Yao, and Z. Xu, "Auto-sorting commonly recovered plastics from waste household appliances and electronics using near-infrared spectroscopy," *Journal of Cleaner Production*, vol. 246, Feb. 2020, doi: 10.1016/j.jclepro.2019.118732.

[14] Y. Zheng, J. Bai, J. Xu, X. Li, and Y. Zhang, "A discrimination model in waste plastics sorting using NIR hyperspectral imaging system," *Waste Management*, vol. 72, pp. 87–98, Feb. 2018, doi: 10.1016/j.wasman.2017.10.015.

[15] R. Calvini, G. Orlandi, G. Foca, and A. Ulrici, "Development of a classification algorithm for efficient handling of multiple classes in sorting systems based on hyperspectral imaging," *Journal of Spectral Imaging*, Dec. 2018, doi: 10.1255/jsi.2018.a13.

[16] Z. Qiu, S. Zhao, X. Feng, and Y. He, "Transfer learning method for plastic pollution evaluation in soil using NIR sensor," *Science of The Total Environment*, vol. 740, Oct. 2020, doi: 10.1016/j.scitotenv.2020.140118.

[17] M. Rani *et al.*, "Miniaturized near-infrared (MicroNIR) spectrometer in plastic waste sorting," *Materials*, vol. 12, no. 17, Aug. 2019, doi: 10.3390/ma12172740.

[18] M. Moshtaghi, E. Knaeps, S. Sterckx, S. Garaba, and D. Meire, "Spectral reflectance of marine macroplastics in the VNIR and SWIR measured in a controlled environment," *Scientific Reports*, vol. 11, no. 1, Dec. 2021, doi: 10.1038/s41598-021-84867-6.

[19] W. Becker, K. Sachsenheimer, and M. Klemenz, "Detection of black plastics in the middle infrared spectrum (MIR) using photon up-conversion technique for polymer recycling purposes," *Polymers*, vol. 9, no. 9, Sep. 2017, doi: 10.3390/polym9090435.

[20] L. Jacquin, A. Imoussaten, F. Trousset, D. Perrin, and J. Montmain, "Control of waste fragment sorting process based on MIR imaging coupled with cautious classification," *Resources, Conservation and Recycling*, vol. 168, May 2021, doi: 10.1016/j.resconrec.2020.105258.

[21] O. Rozenstein, E. Puckrin, and J. Adamowski, "Development of a new approach based on midwave infrared spectroscopy for post-consumer black plastic waste sorting in the recycling industry," *Waste Management*, vol. 68, pp. 38–44, Oct. 2017, doi: 10.1016/j.wasman.2017.07.023.

[22] J. Shan, J. Zhao, Y. Zhang, L. Liu, F. Wu, and X. Wang, "Simple and rapid detection of microplastics in seawater using hyperspectral imaging technology," *Analytica Chimica Acta*, vol. 1050, pp. 161–168, Mar. 2019, doi: 10.1016/j.aca.2018.11.008.

[23] J. Shan, J. Zhao, L. Liu, Y. Zhang, X. Wang, and F. Wu, "A novel way to rapidly monitor microplastics in soil by hyperspectral imaging technology and chemometrics," *Environmental Pollution*, vol. 238, pp. 121–129, Jul. 2018, doi: 10.1016/j.envpol.2018.03.026.

[24] E. G. Moung, C. J. Hou, M. M. Sufian, M. H. A. Hijazi, J. A. Dargham, and S. Omatu, "Fusion of moment invariant method and deep learning algorithm for COVID-19 classification," *Big Data and Cognitive Computing*, vol. 5, no. 4, Dec. 2021, doi: 10.3390/bdcc5040074.
[25] M. N. Razali *et al.*, "Indigenous food recognition model based on various convolutional neural network architectures for gastronomic tourism business analytics," *Information*, vol. 12, no. 8, Aug. 2021, doi: 10.3390/info12080322.
[26] E. G. Moung, C. C. Wooi, M. M. Sufian, C. K. On, and J. A. Dargham, "Ensemble-based face expression recognition approach for image sentiment analysis," *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 12, no. 3, pp. 2588–2600, Jun. 2022, doi: 10.11591/ijece.v12i3.pp2588-2600.
[27] V. Ruiz, Á. Sánchez, J. F. Vélez, and B. Raducanu, "Automatic image-based waste classification," in *From Bioinspired Systems and Biomedical Applications to Machine Learning*, Springer International Publishing, 2019, pp. 422–431, doi: 10.1007/978-3-030-19651-6_41.
[28] C. Srinilta and S. Kanharattanachai, "Municipal solid waste segregation with CNN," in *2019 5th International Conference on Engineering, Applied Sciences and Technology (ICEAST)*, Jul. 2019, pp. 1–4, doi: 10.1109/ICEAST.2019.8802522.
[29] Y. Wang and X. Zhang, "Autonomous garbage detection for intelligent urban management," *MATEC Web of Conferences*, vol. 232, Nov. 2018, doi: 10.1051/matecconf/201823201056.
[30] S. Meng and W.-T. Chu, "A study of garbage classification with convolutional neural networks," in *2020 Indo-Taiwan 2nd International Conference on Computing, Analytics and Networks (Indo-Taiwan ICAN)*, Feb. 2020, pp. 152–157, doi: 10.1109/Indo-TaiwanICAN48429.2020.9181311.
[31] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "ImageNet classification with deep convolutional neural networks," *Communications of the ACM*, vol. 60, no. 6, pp. 84–90, May 2017, doi: 10.1145/3065386.
[32] O. Adedeji and Z. Wang, "Intelligent waste classification system using deep learning convolutional neural network," *Procedia Manufacturing*, vol. 35, pp. 607–612, 2019, doi: 10.1016/j.promfg.2019.05.086.
[33] B. S. Costa *et al.*, "Artificial intelligence in automated sorting in trash recycling," in *Anais do XV Encontro Nacional de Inteligência Artificial e Computacional (ENIAC 2018)*, Oct. 2018, pp. 198–205, doi: 10.5753/eniac.2018.4416.
[34] Y. Liao, "A web-based dataset for garbage classification based on Shanghai's rule," *International Journal of Machine Learning and Computing*, vol. 10, no. 4, pp. 599–604, Jul. 2020, doi: 10.18178/ijmlc.2020.10.4.979.
[35] Q. Zhang *et al.*, "Recyclable waste image recognition based on deep learning," *Resources, Conservation and Recycling*, vol. 171, Aug. 2021, doi: 10.1016/j.resconrec.2021.105636.
[36] S. L. Rabano, M. K. Cabatuan, E. Sybingco, E. P. Dadios, and E. J. Calilung, "Common garbage classification using MobileNet," in *2018 IEEE 10th International Conference on Humanoid, Nanotechnology, Information Technology,Communication and Control, Environment and Management (HNICEM)*, Nov. 2018, pp. 1–4, doi: 10.1109/HNICEM.2018.8666300.
[37] O. Awe, R. Mengistu, and V. Sreedhar, "Final Report: Smart trash net: Waste localization and classification," 2017. http://cs229.stanford.edu/proj2017/final-reports/5226723.pdf (accessed Feb. 1, 2022).
[38] Z. Yang and D. Li, "WasNet: A neural network-based garbage collection management system," *IEEE Access*, vol. 8, pp. 103984–103993, 2020, doi: 10.1109/ACCESS.2020.2999678.
[39] K. Özkan, S. Ergin, Ş. Işık, and İ. Işıklı, "A new classification scheme of plastic wastes based upon recycling labels," *Waste Management*, vol. 35, pp. 29–35, Jan. 2015, doi: 10.1016/j.wasman.2014.09.030.
[40] J. Sousa, A. Rebelo, and J. S. Cardoso, "Automation of waste sorting with deep learning," in *2019 XV Workshop de Visão Computacional (WVC)*, Sep. 2019, pp. 43–48, doi: 10.1109/WVC.2019.8876924.
[41] Y. Chu, C. Huang, X. Xie, B. Tan, S. Kamal, and X. Xiong, "Multilayer hybrid deep-learning method for waste classification and recycling," *Computational Intelligence and Neuroscience*, pp. 1–9, Nov. 2018, doi: 10.1155/2018/5060857.
[42] Y. Liu, Z. Ge, G. Lv, and S. Wang, "Research on automatic garbage detection system based on deep learning and narrowband internet of things," *Journal of Physics: Conference Series*, vol. 1069, Aug. 2018, doi: 10.1088/1742-6596/1069/1/012032.


## BIOGRAPHIES OF AUTHORS

**Owen Tamin** received his Bachelor of Applied Science (Hons) in Mathematical Modelling from Universiti Sains Malaysia (USM) in 2019. He is currently an active Graduate Research Assistant and has pursued his Master's study in Computer Science in Universiti Malaysia Sabah (UMS) since 2021. His research focuses on formulating plastic waste detection algorithm using machine learning. He can be contacted at email: owentamin1996@yahoo.com.

**Ervin Gubin Moung** is a senior lecturer in the Faculty of Computing and Informatics, Universiti Malaysia Sabah. He graduated from Universiti Malaysia Sabah (UMS) with a Bachelor of Computer Engineering in 2008, a Master of (Computer) Engineering in 2013, and a Ph.D. in Computer Engineering in 2018, all in that order. His research interests are concentrated on the field of computer vision and pattern recognition. He can be contacted at email: ervin@ums.edu.my.

**Jamal Ahmad Dargham** received his Bachelor of Science degree in Control Systems Engineering from the University of Technology in Iraq in 1984. He went on to receive his Master of Science degree in Control Systems Engineering from the University of Manchester in the United Kingdom in 1987. He then went on to receive his Doctor of Philosophy degree in Image Processing from the Universiti Malaysia Sabah in 2008. Since 1996, he has been working as a faculty member in the Faculty of Engineering at the Universiti Malaysia Sabah. His major areas of research interest are in Image Processing, more specifically in Biometrics and Engineering Education. He can be contacted at email: jamalad@ums.edu.my.

**Farashazillah Yahya** is a senior lecturer and researcher at the Faculty of Computing and Informatics, Universiti Malaysia Sabah. She obtained her Ph.D. from University of Southampton, United Kingdom. She has published several indexed papers on machine learning, big data, and cybersecurity topics. She can be contacted at email: fara.yahya@ums.edu.my.

**Sigeru Omatu** was born in Ehime, Japan in 1946 and completed their education at Ehime University in 1969. At Osaka Prefecture University, he first earned his Master's degree in 1971 and then his Doctoral degree in 1974. After that, he went on to work at the University of Tokushima as a Lecturer, Associate Professor, and Professor from 1974 until 1995. Now, he is working at Hiroshima University as distinguish Professor. His research areas are control theory, signal processing, neural networks, pattern classification, and smell measurement and its visualization. He can be contacted at email: omatu@rsh.oit.ac.jp.