Process Safety and Environmental Protection 152 (2021) 482–494

Contents lists available at ScienceDirect

Process Safety and Environmental Protection

journal homepage: www.elsevier.com/locate/psep

Artificial intelligence-based solution for sorting COVID related medical waste streams and supporting data-driven decisions for smart circular economy practice

Nallapaneni Manoj Kumar[a], Mazin Abed Mohammed[b], Karrar Hameed Abdulkareem[c], Robertas Damasevicius[d,*], Salama A. Mostafa[e], Mashael S. Maashi[f], Shauhrat S. Chopra[a]

[a] *School of Energy and Environment, City University of Hong Kong, Kowloon, Hong Kong*
[b] *College of Computer Science and Information Technology, University of Anbar, 11, Ramadi, Anbar, Iraq*
[c] *College of Agriculture, Al-Muthanna University, Samawah 66001, Iraq*
[d] *Faculty of Applied Mathematics, Silesian University of Technology, Gliwice 44100, Poland*
[e] *Faculty of Computer Science and Information Technology, Universiti Tun Hussein Onn Malaysia, 86400 Batu Pahat, Johor, Malaysia*
[f] *Software Engineering Department, College of Computer and Information Sciences, King Saud University, Riyadh 11451, Saudi Arabia*

A R T I C L E I N F O

Article history:
Received 4 March 2021
Received in revised form 17 June 2021
Accepted 17 June 2021
Available online 19 June 2021

Keywords:
Medical waste streams
Smart circular economy
COVID waste management
Waste sorting
Feature fusion
Machine learning

A B S T R A C T

Waste generation is a continuous process that needs to be managed effectively to ensure environmental safety and public health. The recent circular economy (CE) practices have brought a new shape for the waste management industry, creating value from the generated waste. The shift to a CE represents one of the most significant challenges, particularly in sorting and classifying generated waste. Addressing these challenges would facilitate the recycling industry and helps in promoting remanufacturing. But in the COVID times, most of the generated waste is getting mixed with conventional waste types, especially in the global south. The pandemic has resulted in colossal infectious waste generation. Its handling became the most significant challenge raising fears and concerns over sorting and classifying. Hence, this study proposes an Artificial Intelligence (AI) based automated solution for sorting COVID related medical waste streams from other waste types and, at the same time, ensures data-driven decisions for recycling in the context of CE. Metal, paper, glass waste categories, including the polyethylene terephthalate (PET) waste from the pandemic, are considered. The waste type classification is done based on the image-texture-dependent features, which provided an accurate sorting and classification before the recycling process starts. The features are fused using the proposed decision-level feature fusion scheme. The classification model based on the support vector machine (SVM) classifier performs best (with 96.5 % accuracy, 95.3 % sensitivity, and 95.9 % specificity) in classifying waste types in the context of circular manufacturing and exhibiting the abilities to manage the COVID related medical waste mixed.

1. Introduction

A new revolution in the era of Industry 4.0 has been seen with the emergence of the circular economy (CE) (Rossi et al., 2020; Zheng et al., 2020). The CE is primarily backed by the service-based circular business model (CBM), digital assets, resource management approaches, well-organized take-back systems, and autonomous refurbishment systems (Oghazi and Mostaghel, 2018). However, the shift to circular business practices is yet to be realized at the fullest level as this shift represents significant challenges (Viva et al., 2020). Upon considering the waste management industry as a case of observation, the CE has bought a new shape for this industry by creating value for the generated waste. Also, a market for remanufactured products is ensured under circular business practices (Bianchini et al., 2019). Overall, the potential has made the industries put more effort into circularizing the waste. But the smooth operation of the waste circularization system depends on many aspects, e.g., if any sought of disruption occurs, it will affect the process's whole course. Considering the issue with the mixed waste types would cause a delay in recycling or remanufacturing operations. This has become difficult and more complicated due to adverse global events like the COVID pandemic.

* Corresponding author.
E-mail addresses: mnallapan2-c@my.cityu.edu.hk (N.M. Kumar), mazinalshujeary@uoanbar.edu.iq (M.A. Mohammed), khak9784@mu.edu.iq (K.H. Abdulkareem), robertas.damasevicius@polsl.pl (R. Damasevicius), salama@uthm.edu.my (S.A. Mostafa), mmaashi@ksu.edu.sa (M.S. Maashi), sschopra@cityu.edu.hk (S.S. Chopra).

https://doi.org/10.1016/j.psep.2021.06.026
0957-5820/

The pandemic has resulted in a colossal infectious waste generation (Haque et al., 2021). Its handling is not easy due to the mixed waste streams at the source level, where less awareness was there. It has become the most significant challenge raising concerns over waste management in the context of CBM. On the other side, waste generation (i.e., either infectious waste and non-infectious) is happening continuously across the globe. Most of the generated waste is at the domestic level and healthcare unit level. These healthcare units have already had explicit instruction on segregating their waste considering the waste management guidelines. Hence, there should not be a problem unless this waste is put under the CE practices of recycling and recovering the material. However, on the other side, the waste coming from the domestic sector is mostly going for recycling. Given the lockdown conditions, the waste produced at the domestic level is said to increase and is mixed with COVID waste, whereas the waste segregation at the domestic level again depends on awareness. Considering the case of the global south, the practice rate of waste segregation at the source level is meagre. On the other side, the open dumping of waste still exists in many countries. With COVID, the waste coming to recycling centres will be of mixed types. Hence, handling will become more challenging, particularly raising fears and concerns over sorting and classifying.

1.1. Pandemic and waste management

While the beneficial impacts of national lockdowns like clean rivers and brighter sky by COVID-19 are visible throughout the world (Girdhar et al., 2020), the same cannot be said about proper waste management. The epidemic has modified the nature of waste production, causing challenges for decision-makers and sanitation staff (Tripathi et al., 2020; Sharma et al., 2020; Kulkarni and Anantharama, 2020). A higher amount of non-contaminated products of the same type are created by the excretion of a large range of medicinal and hazardous material, like contaminated gloves, uniforms, and other safety equipment. Incorrect recycling activities can contribute to specific municipal solid waste infection with the virus, and there is always a transmitting danger. Therefore, safe treatment and final management of this waste are essential factors for successful emergency response. The successful control and storage of biomedical and sanitary contaminants, in addition to adequately detecting, collects, sorting, stowing, shipping, stored, and disposal of, and the related essential aspects of disinfection, personal safety, and education. Therefore, policymakers have agreed that medical, domestic, and other dangerous waste disposals will be regarded as an immediate and vital public utility to reduce future secondary safety and environmental impacts (UNEP, 2020).

The need for food delivery services and consumer items to increase the development of traditional packaging waste plastic is on the rise with global lockdowns and the closure of foodstuffs from around the world (Tenenbaum, 2020). Because of the coronavirus epidemic, plastic waste prevention and control has been transformed into an immense obstacle for waste management companies (Kaufman and Chasan, 2020). Besides that, the market for the required health logistics globally will improve plastic waste packing from the medical sector. Moreover, citizens may opt to use single-plastic items in reaction to established health care issues, which undermines the limits on its usage set out by other countries.

The COVID pandemic has devastated the food production system, which poses several threats and repercussions. The threat of national lockdowns in several countries has contributed to the excessive storage of foodstuffs and other foodstuffs, resulting in a disturbing cycle of waste management development (Ferronato and Torretta, 2019). The need for robust supply chain growth was illustrated with imagery and media reports dumping foods and milk as fruits at the regional dumpsite and on sidewalks by farmers due to a fragmented distribution network (Neel, 2020). Therefore, more efforts should be put into the segregation and separation of the collected household waste. Municipal solid waste includes different types of waste such as discarded food, plastic, textiles, paper, wood, metals, glass and electronic waste. Proper segregation extremely determines the sustainability and smoothness of the waste recycling process. Waste management and recycling include many processes such as collection, washing, separation, and safe disposal of toxic and dangerous waste. To perform these activities efficiently, a complex waste monitoring system is required. For COVID-19-based waste management and sorting, machine learning (ML) offers decision support and automation (Mutlag et al., 2020). Computer-aided systems may learn to conduct such functions as classification, forecasts, and identifying trends in waste management and recycling. Various algorithms and mathematical methods for interpreting sample data are being used to train these models.

Waste management through productive storage, the study seen as a significant global function for green ecological sustainability (Okewu et al., 2017). The organization will support the production of waste through recycling and reuse the materials disposed of. To enhance recycling and will the environmental impact, effective selective processing is also introduced. This problem is especially relevant in developing countries, where the waste management is a serious problem for their urbanization and economic development. Knowing that a substantial part of the waste produced in large cities is recyclable, it needs to know and implement methods of reuse that might provide benefits or reduce environmental problems. The presence of methods or templates that help sort garbage has become essential for correcting these objects. While there are various recycling categories, people may also be confused or do not fully know how to decide the proper garbage bin to dispose of each garbage. To minimize the effects of improper disposal of domestic waste, integrated methods based on machine learning techniques aimed at the proper classification of waste in recycling categories are suggested. Ways in which humans have treated solid waste over the years are all based on the initial strategy of eliminating it. Population development has been the key driver in the increase in the generation of such waste. It should then be minimized personally to maintain the balance.

1.2. Key contributions and the objectives

This study highlights the immediate problems and structural issues confronting the emerging COVID problem in waste management and classification. This study further provides unique perspectives into the changes in complexities of emerging foreign biomedical waste management activities. It seeks to identify novel ways to resolve emerging disaster problems, thus proposing feasible improvements in current procedures to prevent and fix similar concerns in any future pandemics. This study also contains suggestions useful in implementing effective waste management mechanisms and classification in the pandemic and post-pandemic environment for decision-makers and regulators.

The main objective is to develop an automated method for waste sorting to improve the CE practice. This will have not only a positive environmental impact but also positive economic outcomes. Besides, the proposed system has a great community appeal to improve the disposal of garbage. So, the study investigates the different types of machine learning to categorize waste images into four classes: metal, paper, glass, and COVID related medical waste.

The contributions of this paper can be summarized as follows:

- To the author's best knowledge, this is the first study on COVID waste management and classification using machine learning techniques.

- The feature-fusion based approach is proposed to obtained features required for waste classification. At the same time, Artificial Neural Network (ANN), Support Vector Machine (SVM), and k-Nearest Neighbor (k-NN) classifiers are used as classifiers to automate waste type recognition.
- The system efficiency is evaluated in the real-world scenario using an absolute waste image dataset.

The organization of this study as follows: section 2 does critical reviews of the related literature. Then, section 3 presents the proposed waste classification framework and methods. The dataset and waste classification results are described in section 4. Finally, section 5 presented the discussion and conclusions, along with future work.

2. Review of digital technologies enabling waste management

Considering the strengths of the internet-of-things (IoT) technology (Yunana et al., 2021; Maskeliunas et al., 2019), researchers investigated and created different waste management technologies. A primary device that defines the full range of waste bins was implemented, collects data, and transfers data via a wireless network to reduce electricity usage and optimize running time (Folianto et al., 2015). Yet, the concept also has specific vague process issues. To boost waste reduction, the Smart Towns application program has already launched (Pardini et al., 2019a), but it only relies on data collection, and technology from many organizations is part of the framework. On the other side, other methods are focused on applying waste disposal techniques for optimal operation. In Bueno-Delgado et al. (2019), the authors propose a waste management process to use Long Range Wide Area Network (LoRaWAN) communication protocol and road improvement in remote regions. An IoT-based system was also set up, but all waste bins' coordination and management were not rendered explicit by the program. The study presented a new method for monitoring smart bags validity and selecting a client in Philadelphia, the United States of America (USA), using logistic regression and genetic algorithm (GA) techniques. The study has no technologies for data transfer from the wastebasket to other systems. For example, the maximizing algorithms for the nearest neighbor, optimized colony, the genetic algorithm, and the optimized particulate swarm methods for IoT-based waste were established (Akhtar et al., 2017). In Hannan et al. (2018), the researchers suggested an approach for controlling an IoT technology-enabled waste network, which was a self-supporting, robotic-handed vehicle used to gather trash, although no algorithms the researcher reused to automate waste collection. In Jaid Jim et al. (2019), the device was tracked in real-time and interfaced with the IoT framework for an integrated waste management network. The study offered an IoT infrastructure system incorporating application integration, data processing, and management rather than waste collection design and optimisation. In Popa et al. (2017), the data was extracted using the Radio-frequency Identification (RFID) technology and transmitted via a wireless network; a way to collect food was provided. The drawbacks of this new tech have been intense in the long term, especially given that management in a large area is the Objective of the global buildings. Ultimately, the researcher's algorithm-based findings are not adequately explicit, and the researcher is not relevant to a particular system, including a region. In Awe et al. (2017), the authors suggest a Faster Region-based Convolutional Neural Networks (R-CNN) developmental project that categorizes waste into three categories: paper, recycling, and waste disposal. SVM and Convolutional Neural Network (CNN) were introduced by Yang and Thung (2016a) to categorize waste into six groups. A Google Net vision program has been established by Rad et al. (2017) to map and identify urban waste. The report states that the accuracy for multiple forms of waste varies from 63 % to 77 %. Donovan (2016) suggested using Google's Tensor Flow and recording video to recycle waste instantly. This is, indeed, no theoretical outcome as a research effort to date. A solution to identify if an image has garbage or not was developed by Mittal et al. (2016). They developed a waste application for android smartphones. The CNN called GarbNet that identifies the waste portion of the image. The accuracy attained after GarbNet optimization was 87.69 %, with a specificity of 93.45 %. The study also provided a Garbage In Images (GINI) database that is a waste-sensitive database with geo-tagged images obtained in the actual world. Yang and Thung (2016b) stated that waste classification could be classified as a specific topic, in which a new central database was established with 400–500 images per waste image class.

The development of Wireless Sensor Networks (WSN) and the IoT powered by Artificial Intelligence (AI) has led to the arrival of IoT-enabled smart cities (Anagnostopoulos et al., 2017) and Industry 4.0 (Felsberger and Reiner, 2020). The industrial processes supported by sensors and other smart devices can achieve higher performance in solving industrial tasks such as waste sorting (Pardini et al., 2019b). Several IoT based models have been proposed for waste management, including smart bins to detect and evaluate the type of waste through sensors installed in waste bins (Hong et al., 2014; Abdullah et al., 2019), cloud data encryption and decryption method for an automated waste collection system (Cotet et al., 2020), a smart sensor-based infrastructure for waste separation and on-time collection (Esmaeilian et al., 2018), optimization techniques for minimizing the vehicle route, operational cost, and carbon emission (Hannan et al., 2020), lightweight communication protocol for a waste management system (Jaikumar et al., 2020), a robotic arm for waste segregation (Kansara et al., 2019), and a decision support system for effective waste management and disposal (Banias et al., 2011). The advantage of IoT is that it integrates technologies required for waste management: identification technologies, data acquisition, spatial technologies, and communication technologies, while AI methods allow for decision support (Vitorino de Souza Melaré et al., 2017).

The main issues and obstacles to waste recycling management and classification involve the governmental and budgetary measures; poor public oversight and budgeting for waste recycling management and classification; household education; the value of self-recovery in households; technology: ineffective recycling technologies (Windfeld and Brooks, 2015; Rajan et al., 2019; Sawalem et al., 2009). Thus, COVID waste management and classification using a decision level fusion scheme and machine learning techniques are proposed in this paper to solve the problems stated above.

3. Materials and methods

3.1. Circular manufacturing framework with AI-supported waste sorting and classification

In Fig. 1, the circular manufacturing framework is illustrated, where Fig. 1a represents circular manufacturing without proper sorting and classification of collected waste. In contrast, Fig. 1b represents the circular manufacturing enabled by AI and ML to facilitate automated waste sorting and classification. Considering the framework presented in Fig. 1, this study intends to address the waste management-related questions discussed in the above sections and explore a fusion decision-making model that yields confidence-based classification results. This paper also develops rules to link the confidence level to the decision to classify the output. For reasons described in the COVID waste classification, only one classifier is used in the proposed model. In comparison, the

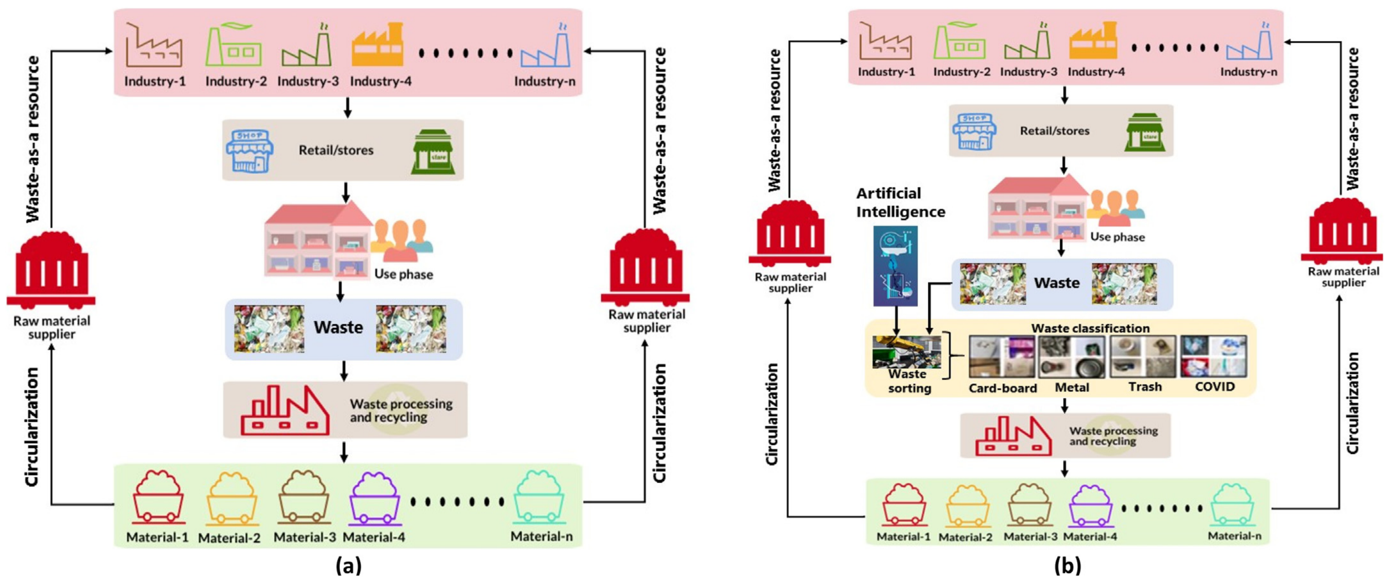

Fig. 1. Circular manufacturing framework; a) without proper sorting and classification of collected waste; b) AI and ML to facilitate automated waste sorting and classification.

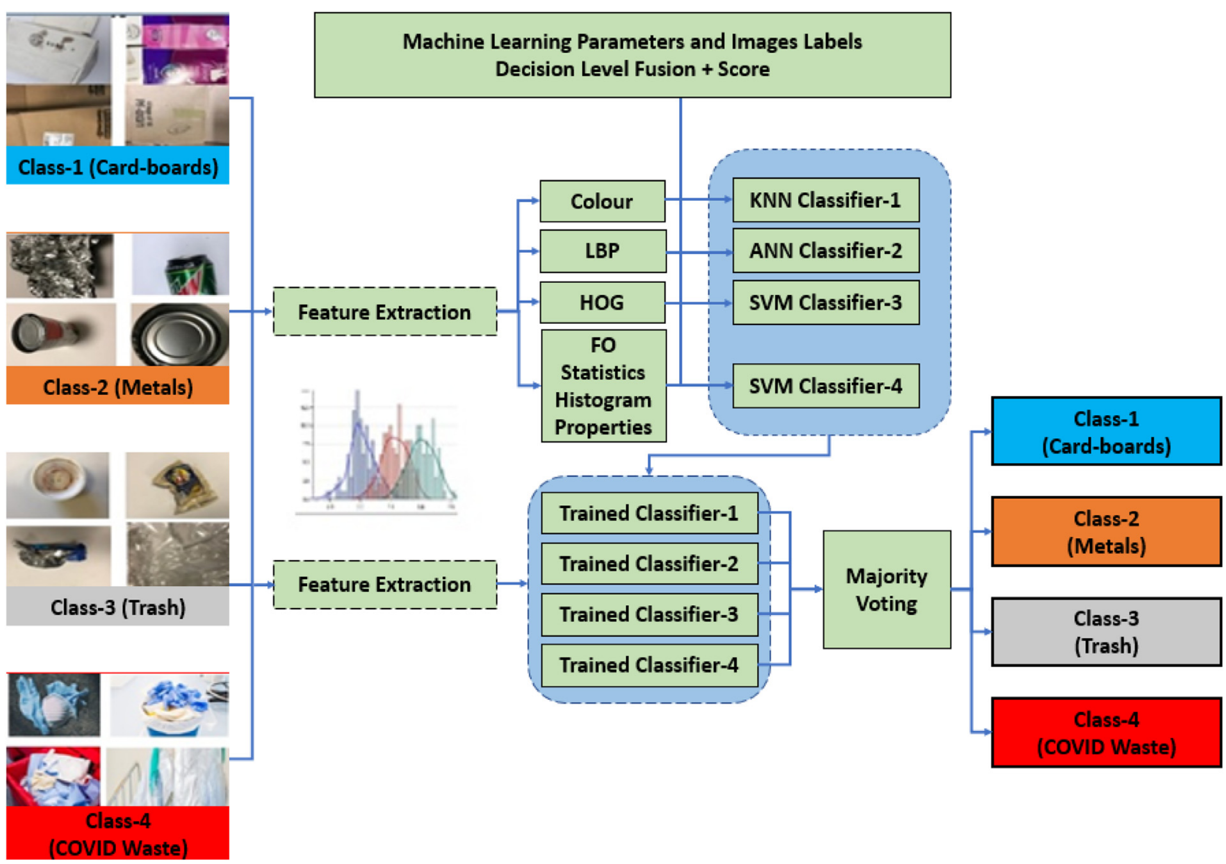

Fig. 2. The proposed COVID-19 waste classification and recycling approach.

grouping effects of two characteristics are only viewed in a pair way.

The proposed COVID waste classification and recycling approach is illustrated in Fig. 2 and explained in detail below. In the field of image processing, the features have a very significant role. Various techniques, such as binarization, thresholding, normalization, etc., have been used before obtaining any sample image features. Then, function extraction techniques have been proposed to find suitable characteristics for image recognition and classification. Feature extraction tools are effective in several processes of image processing, like character recognition. As characteristics define an image's action, they demonstrate their spot in terms of data storage, classification effectiveness, and processing time. The study would then analyze here numerous types of features, extraction, and the situation in which extraction methods are considered. Here in this study, the character identification extracts the featured after the preprocessing step. The primary purpose of pattern identification is to correct input data to one of the possible output groups. The feature selection and classified method can be categorized into 2 phases.

Feature extraction is a key step in the development of any pattern recognition and intends to extract information related to each group. In this procedure, features from alphabets are obtained to establish vectors of the features. The classifiers would then use these functional vectors to understand the input vector with both the target output vector. By looking at some of these features, it will become simpler for the algorithm to categorize the features in groups as it allows to differentiate fairly easily. The method to recover the most relevant data from raw image data is retrieving the functions.

In the classification process, the research processes have been used to recognize the above process's various steps. The following step is the feature extraction from the image of COVID-19 waste (these can be the most key features). These features can be in the field of space or frequency. The fully automated COVID-19 waste classification of the extracted features is additional and not the same now as the features extracted by the experts. In this paper, instead of measuring features, a focus on texture-related features is given importance. These characteristics can be saved efficiently in a vector and labelled by the classes to which they belong.

3.2. Texture analysis methods

The texture analysis concept provides a clear description by means of the texture content of regions in image analysis. Texture analysis attempts to assess instinctive properties characterized as a feature of the pixel intensity, for instance, in silky and in messy, rough, and soft terms. It was intended for combinations in the frequency or Gray stages to imply roughness. The texture analysis could be used to detect the boundaries of texture, called the known texture partition. Texture analysis can help if items are defined more through their texture than by frequency, and standard thresholding techniques could not be effectively used.

Here the texture of waste images of the COVID-19 and other waste groups is examined, and further investigation is done. The techniques analyzed include the first-order statistical features of the histogram image, Histogram of Greyscale (HoG), and Local Binary Pattern (LBP). An evaluation feature vector with each feature is produced, representing waste images fed to one of the classifiers (k-NN, ANN, and linear SVM) selected. Using the k-NN classifier, one must characterize the similarity/distance and removed histogram vectors from both the waste images when classified automatically in four groups. In this case, Euclidean distance is considered.

3.2.1. Histogram of grey scale intensity

The frequency task of the pixel intensity of the image pixels in grayscale is the image histogram. There are 256 different possible intensity positions in the 8-bit grayscale image. Consequently, the histogram shows 256 values showing the spread of pixels between those grayscale values (Wei et al., 2014). The histogram of image data shows distinctions in image luminosity. The comparison of histograms reveals a critical contrast that happens to differentiate between images of different waste groups, see Fig. 3.

The histogram of COVID-19 waste images allocates large portions of the waste scenario with a dim colouring that shows the closeness of strong texture within the image. Further, the histogram of the other kind of waste image does have a negative, exponential form clustered across the middle of the Grayscale on the one hand, with a slight mound showing that the waste images are near pure liquids. The third scenario is a waste scenario output, based on the used histogram that contains two isolated regions, in which the background is defined, through a far more common curve, near the middle of the dynamic range, in the waste to one hand of the greyhound because the waste situations have a dark environment.

3.2.2. The first-order (FO) statistics histogram properties

The first-order texture analytical techniques are used to measure the texturing process by utilizing image histogram or pixel occurrence chance. This approach's biggest benefit is that it can be conveniently represented using regular descriptive terms like variance and description (Lin et al., 2009). The effectiveness of this procedure to differentiate from one sort textures in different applications is also limited since the procedure may not recognize the spatial link and the interaction from pixels. The gray level becomes $0 \le i \le N_\delta - 1$ to give any image or texture phase, hence N_δ is the number of distinct gray rates. Suppose $N(i)$ is the pixel quantities. In that case, i and M are the total pixel quantities in an image, it takes the histogram or pixel case probability afterwards to be given and mostly evaluated using Eq. (1):

$$P(i) = \frac{N(i)}{M} \tag{1}$$

In total, seven features are measured that are typically used to describe image histogram attributes and later image texture. Such features are entropy, kurtosis, average, energy, variance, as skewness. If z is a random variable, $p(z)$ is the frequency of the image pixel, and L is the cumulative pixel of the image, then FO statistics highlighted are determined based on the Eqs. (3–8). In case the z is now a random component, based on the following features.

Entropy: This measure for the randomness of intensity frequencies, given in Eq. (2).

$$\boldsymbol{e} = -\sum_{\boldsymbol{i}=0}^{\boldsymbol{L}-1} \boldsymbol{p}(\boldsymbol{z_i}) \,\boldsymbol{log}_2 \boldsymbol{p}(\boldsymbol{z_i}) \tag{2}$$

Kurtosis: This measure for how to diminish the peak of conveyance curves, given in Eq. (3).

$$\boldsymbol{U} = \sum_{\boldsymbol{i}=0}^{\boldsymbol{L}-1} \boldsymbol{p}^2(\boldsymbol{z_i}) \tag{3}$$

Mean: Using Eq. (4), the mean is estimated. This measures the image or pictures medium level of intensity and shows picture brightness.

$$\boldsymbol{M} = \sum_{\boldsymbol{i}=0}^{\boldsymbol{L}-1} \boldsymbol{z_i}\, \boldsymbol{p}(\boldsymbol{z_i}) \tag{4}$$

Energy: This measure is used to calculate the intensity variety in the image, see Eq. (5).

$$\boldsymbol{E} = \sum_{\boldsymbol{i}=0}^{\boldsymbol{G}-1} [\boldsymbol{P}(\boldsymbol{i})]^2 \tag{5}$$

Skewness: Using Eq. (6), the Skewness measure is estimated. Unless the histogram becomes symmetric at the middle level, this value is 0. Therefore, if it is over or below, the mean is negative or positive.

$$\boldsymbol{\mu}_3 = \sum_{\boldsymbol{i}=0}^{\boldsymbol{L}-1} (\boldsymbol{z_i} - \boldsymbol{m})^3 \boldsymbol{p}(\boldsymbol{z_i}) \tag{6}$$

Standard Deviation STD: This measure characterizes the variety around the mean, and using Eq. (7), the standard deviation is measured.

$$\boldsymbol{\sigma} = \sqrt{\sum_{\boldsymbol{i}=0}^{\boldsymbol{L}-1} (\boldsymbol{z_i} - \boldsymbol{m})^2 \boldsymbol{p}(\boldsymbol{z_i})} \tag{7}$$

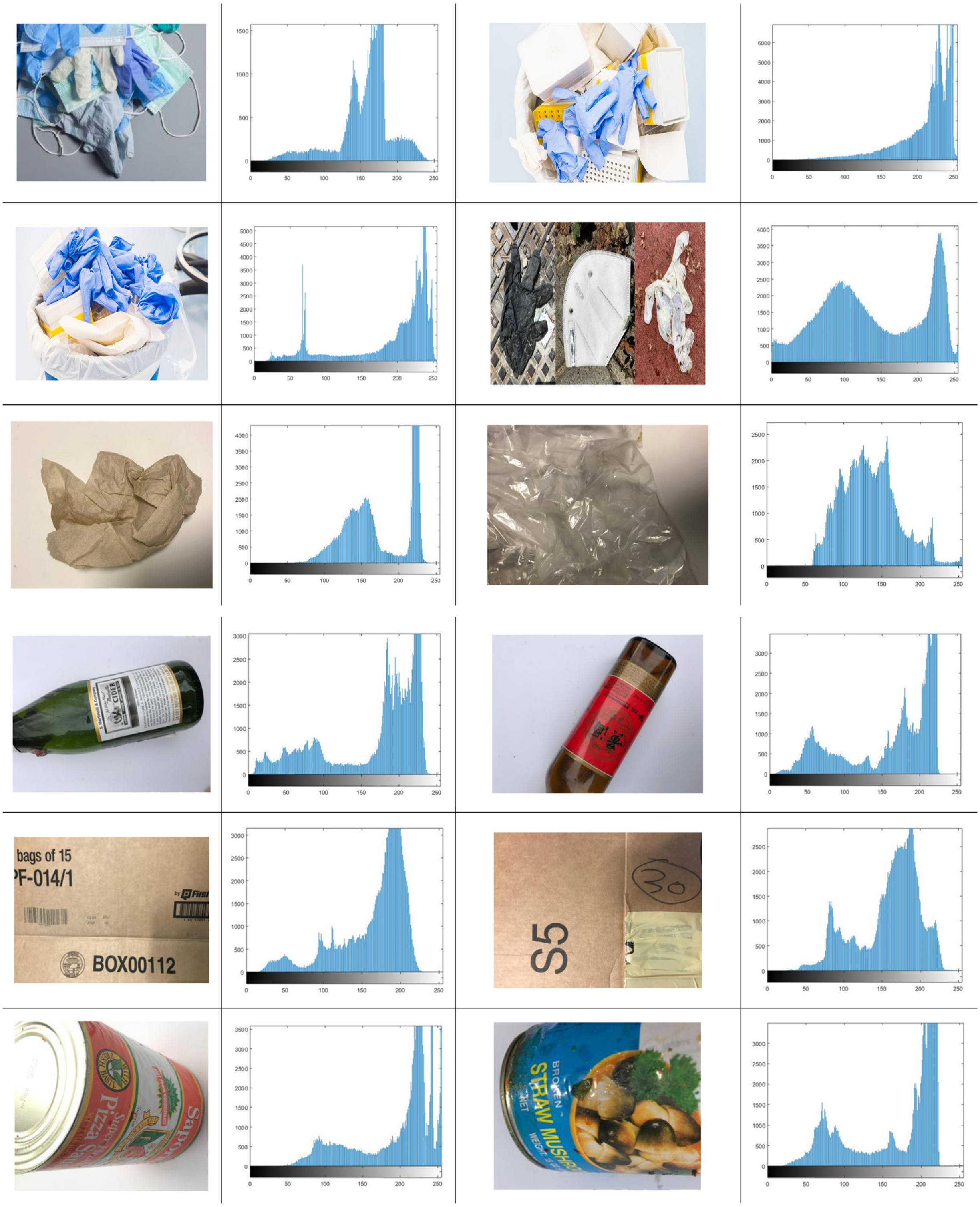

Fig. 3. Image histogram representation of COVID related medical waste and the trash image.

Smoothness: This measure characterizes the intensity relative smoothness using Equation (8).

$$\boldsymbol{R} = 1 - \frac{1}{1+\sigma^2} \tag{8}$$

3.2.3. *Local binary pattern (LBP) feature*

LBP is a local operator that can distinguish multiple texture forms. The initial LBP operator identifies each pixel of the image for an LBP code (Mohammed et al., 2020a). For the calculation of the LBP code, the central pixel value of 3/3 of the nearby pixel is compared, if the closest pixel value is smaller than the central one, that will carry the binary integer '0.' That feature acts for the eight-pixel neighbours, employing the pixel center as a boundary. When the next pixel is not assigned to the pixel with the most significant gray level than the middle of a pixel (or a comparable number of gray), it will take 0. The LBP functionality is generalized to include areas of varying sizes. A circle of the range R again from the inner

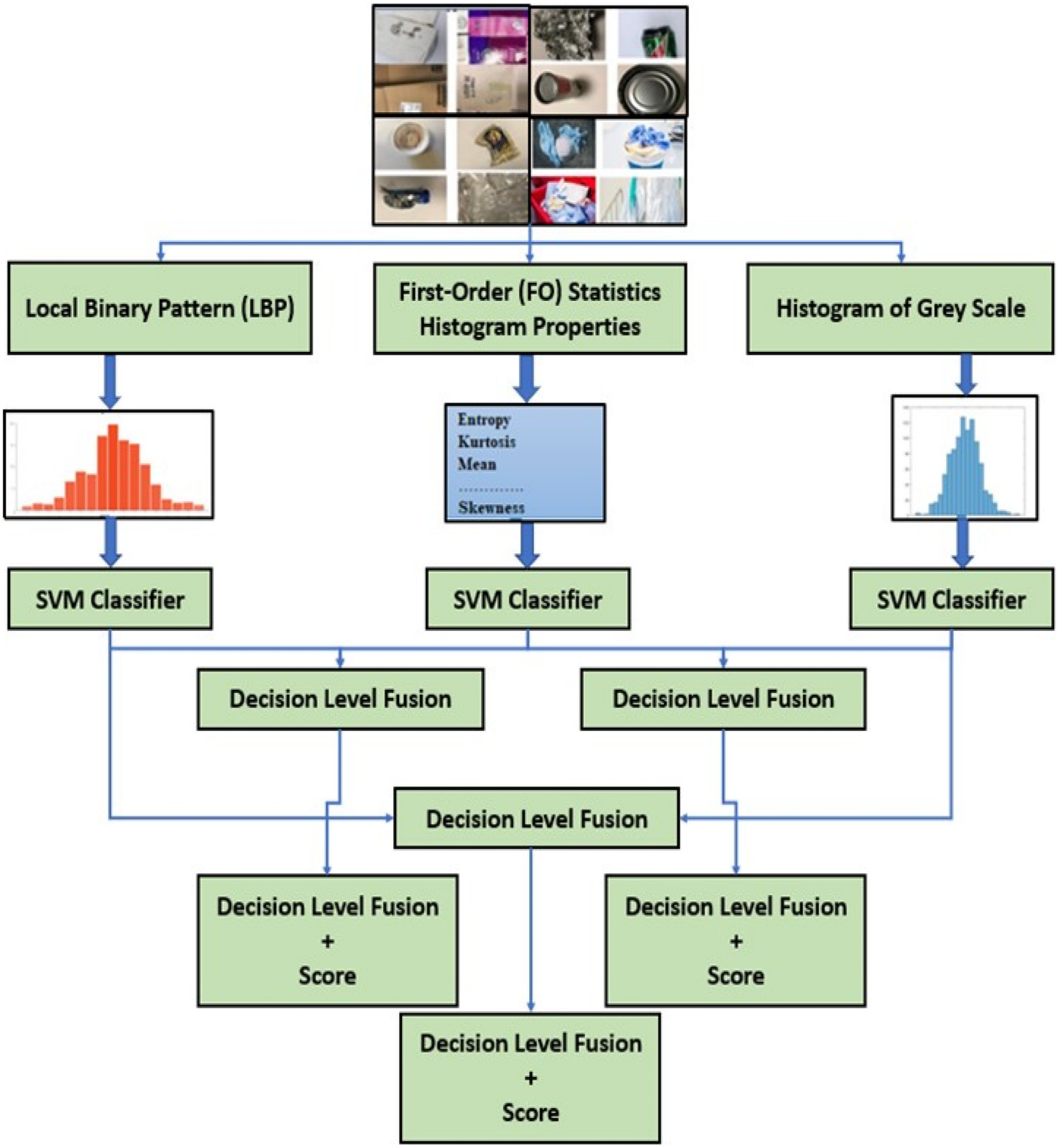

Fig. 4. The Decision level fusion of different features using SVM classifier.

pixel is formed in this case. LBP is especially used for the underlining texture of small waste images and comparisons amongst these cases. In hypothesis, the LBP replacements were increasing waste calculation by an 8-bit binary code, recognizing the gray value.

3.3. Decision-level fusion scheme

Fig. 4 illustrates the decision-level fusion of different features using an SVM classifier. The next phase is to incorporate the features taken from a COVID-19 waste image into the correct classification system, taking into account the final goal for a classification result/decision. As the study includes several types of wastes such as th COVID related medical waste streams, plastics, metal, and paper, a focus on using a classification algorithm for recognizing the types of waste is made. Any features extracted from the waste image are used for the multi-label classification of waste into COVID-19 and other classes. The classification results can be improved through better options utilizing various feature selection and fusion methods and classifiers. This mutual feature was used to improve classification precision by using fusion at different levels for certain image recognition issues. Fig. 5 summarizes the mechanisms of the proposed waste image feature fusion scheme presented in our study. In this study system, the evaluation of various fusion schemes is a key innovative feature of the proposed COVID-19 waste classification method. In this analysis, feature fusion is implemented in particular, at the pre-classification feature stage, at the post-classification measurement level, and even at the decision level after classification.

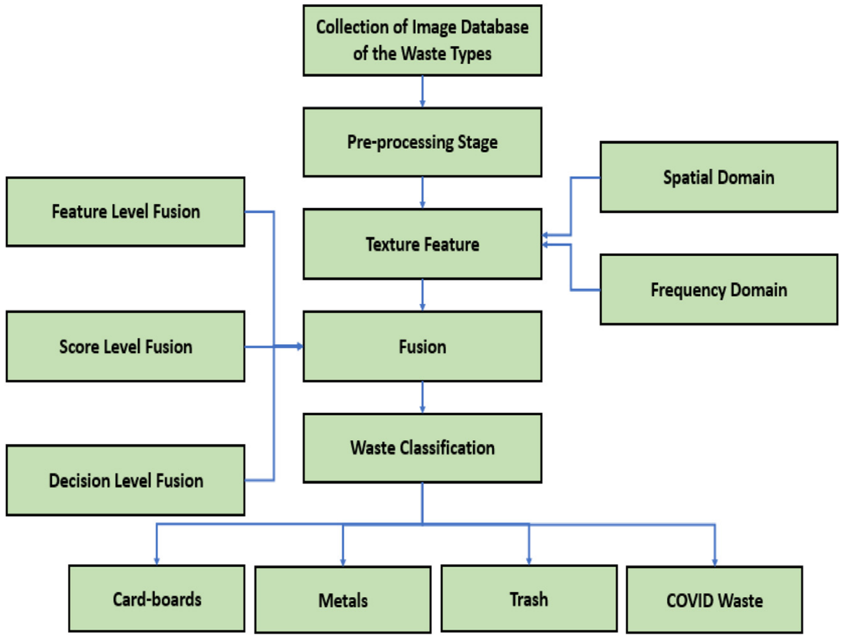

Fig. 5. The main steps of waste image-based sorting.

3.4. Classification methods

Throughout the area of image analysis, classification is an essential and difficult activity. Such distinction relies solely on the image, similarity, or texture of the items. Classification is a significant challenge in machine learning. This is a classification technique for at least two separate groups by labeling a related dataset for a certain marking to distinguish it from other groups. Two stages, preparation, and processing are carried out for image classification. For a classification algorithm, for instance, k-NN, SVM, ANN, respectively, a set of learning test images are used. If the classifier is qualified for such images, the class of an image is used to determine. The classification procedure is exact if the anticipated class is equal to the established class of the feature vector; otherwise, the pre-processing stage is accurate.

This model consists of selecting the correct classifier(s), introducing acceptable measurement conventions, and testing fusion methodologies. Two purposes are used to study effective classification techniques. First, using the elimination of the feature, the researcher ought to seek effective classifiers. Furthermore, the research needs to add effective waste classifiers to both of the two items, i.e. waste image classification or COVID-19 waste detection from earlier classification waste image situations. The spacing characteristic is large for the group of waste images, whereas the spacing characteristic for other types of waste images becomes low. The study is focusing on three specific approaches after a large analysis of existing classification techniques: k-NN, ANNs, and SVM. All classification strategies are important primarily for the kinds of features that the researcher has extracted for waste images, — for example, numerical quantity vectors, without planning further for practical vectors. Also, according to the analysis, the k-NN classifier has to be ideal for a specific portion with Euclidean size. The SVM classifier must, therefore, be suitable for a higher dimensional function area.

3.5. Fusion method

The findings of the use of a single classifier for classifying COVID-19 waste from different image texture-dependent feature vectors shown a variety of logical to high-precision features particularly by SVM. The integration of pattern detection in multi-schemes is a standard method for increased exactness. With each function system, the rating scores were averaged as per a guideline to presume a cumulative score being used for final ranking decisions. At the score point, the study uses the mentioned rules to fuse different combination for about the same three vectors (F1, F2, F3), and evaluate the trust rates by each combination. The SVM classification is implemented separately with each feature space and the signed scoring for each feature becomes reported. Instead, we take an average of three certified ratings for the three factors. The overall average sign defines the final rating, and then, as per the rules given, the overall average value becomes converted to a level of confidence. The process of the fusion system is seen in Fig. 6.

4. Dataset and results

4.1. Data collection

The data collection procedure was conducted manually as no data sets concerning waste materials were publicly available. The researchers used Flickr Content. However, the images in the Flickr Material Database show unadjusted material. This is impossible with recycled garbage since it is dirty, scratched, crumpled, and so forth. Apart from the ¨trash¨class with approximately 100 images, there are around 500 images in the dataset for each type of waste. In total, 2400 images are taken. The data collection process included the white poster board's application, the collection of waste and recycling images around Stanford, our residences, and the residences of relatives. Each image has different lighting and pose and does not change the data set. Below, Fig. 7 describes images from the four groups. Data augmentation techniques around each image relative to the size of each group were applied: random image rotation, translation and shearing. These image transformations have been selected to take place on different recycled material orientations.

4.2. Data preparation and pre-processing

Given that the data used for this study are a set of trash-related images, pre-processing of them had to be done to adjust to the format for the machine learning methods. The material images used

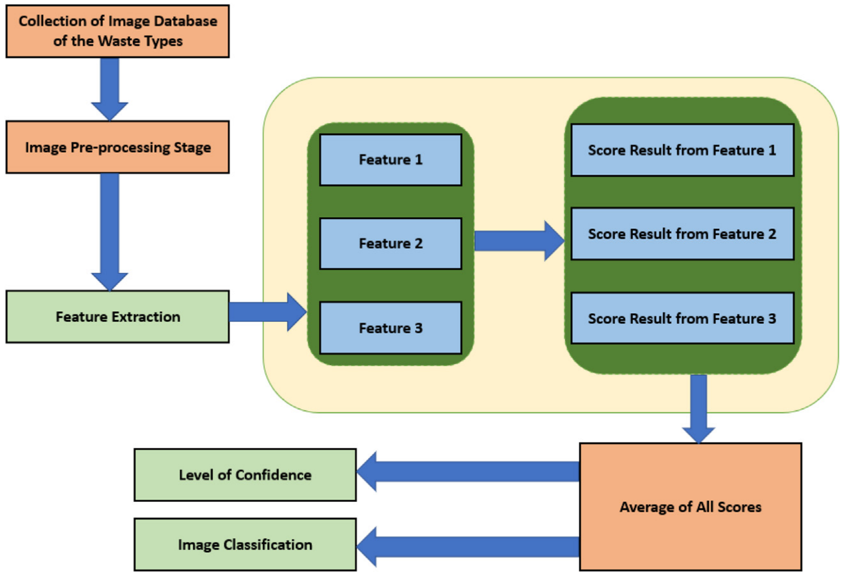

Fig. 6. The decision level fusion approach for COVID-19 waste classification.

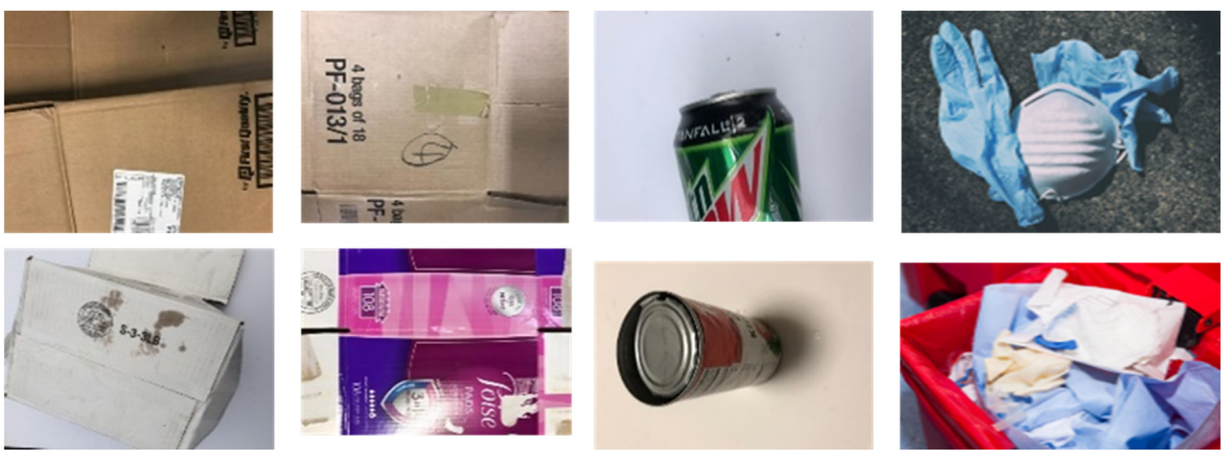

Fig. 7. Sample images of the trash dataset collection.

are 512 × 384 pixels in size each. Thus, the images are compacted to 10 % of their real size to reduce the time required for the images to process. The EBImage Package ReadJPEG function is used to extract features from those images and obtain Red, Green, and Blue values from each image pixel. Data would be separated where the training dataset contains 75 % of the data and the remaining 25 % used to verify the model's performance.

4.3. Results

The implementation of this study was carried out on a workstation with the following specification: Intel Core i5-8265U CPU@1.60 GHz with 8GB RAM and 64-bit Windows 10 operating system. The tool used for implementing the proposed model was on MATLAB (MathWorks Inc, USA).

The accuracy of the proposed method is analysed with and without pre-processing. For this study, 100 waste images are selected and repeated examination ten times. The evaluation part uses 20 images from each round, while the testing procedure utilizes 20 images. The overall accuracy is 93.83 % accuracy, 92.39 % sensitivity and 91.44 % specificity. The results are reported in Fig. 8. Without image pre-processing, the accuracy was 88.93 %, sensitivity 87.98 %, and specificity 86.73 %, which was lower than the performance achieved with pre-processing.

Error histogram with 20 bins has been presented in Fig. 9 and if closely observed, Fig. 9, showed the difference between the target values and predicted values after training and this difference is negative. Considering the help of a confusion matrix, the prediction results summary on a waste classification are provided. In Fig. 10, the confusion matrix for SVM classifier is given. This showed the number of correct and incorrect predictions with count values and broken down by each class of the waste type considered in this problem. The suggested ML classifier attained 96.5 % accuracy, 95.3 % of sensitivity, and 95.9 % of specificity.

4.4. Decision level fusion

Instead of only having the score for specific items, the feature fusion system is focused on the choices taken with each part of the feature as a selection layout rather than on the final decision (Elhoseny et al., 2021). The simplest and most important criterion for a final decision will be focused on the category that earns the highest number of votes. At this stage, a multi-classification dilemma is handled (Abd Ghani et al., 2020). The same test setup is used for basic fusion-level scores for the fusion of three image

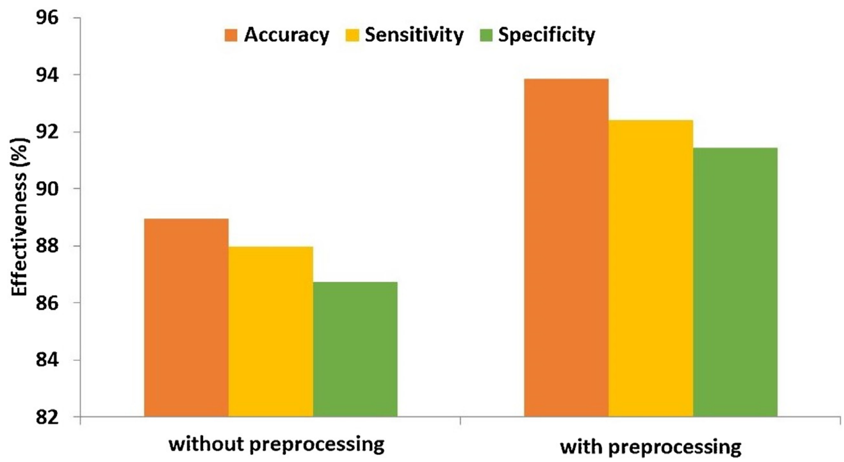

Fig. 8. The effectiveness of the pre-processing stage on waste images.

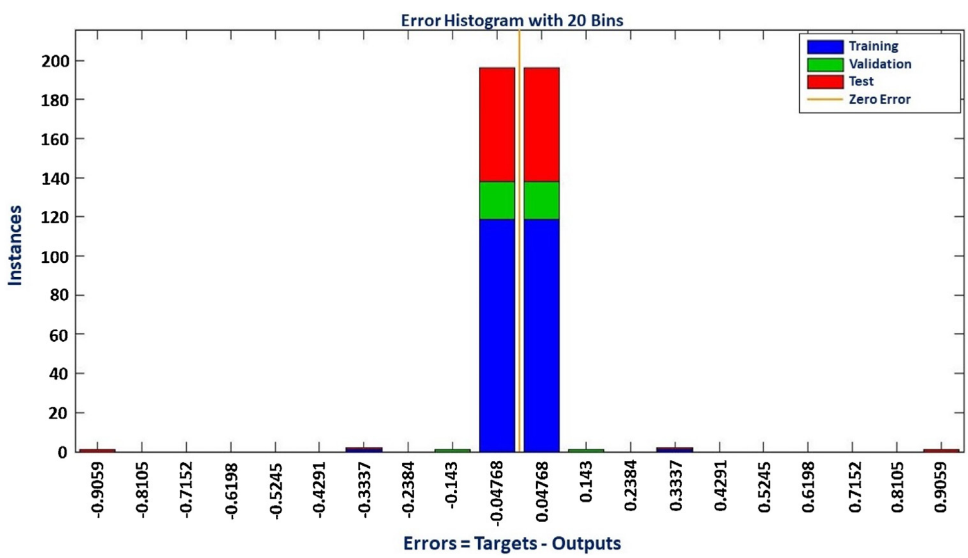

Fig. 9. Error histogram with 20 bins.

features (LBP, FO, HoG) at the decision-making stage, In the experiments, classifiers such as k-NN, SVM, and ANN are used. The results of these classifiers shown in Fig. 11 indicate the SVM classifier achieved an accuracy of 96.5 %, sensitivity of 95.3 %, and specificity of 95.9 %.

These findings indicate that the SVM classifier surpasses the majority rule for decision-dependent fusion compared to ANN and k-NN classifier (see Fig. 11). In the case of SVM, however, fusion based on decision reaches the required fusion stage. The majority voting based fusion significantly improves all forms of pattern classification. Feature fusion also increased the accuracy when two elements are combined instead of the three features.

The COVID-19 waste classification issue and challenge under investigation, as a multi-classification, is difficult since only two feature sets are usable as it is no longer practical to follow the majority voting criteria. The biggest obstacle is to combine only two grouping choices as all systems differ (Mohammed et al., 2020b; Mohammed et al., 2020c). The concept fusion system starts the SVM classification of the input pattern and incorporates the groups chosen by individual feature systems with the appropriate measured confidence level. The fusion system issues a final classification decision. Notice that, as per the final classification result by fusion, any SVM classification system with three rules controlling the location of the classification always needs a specific set of regulations for deciding the confidence level of the category. The feature fusion performance is shown in Fig. 12.

Depending upon the class outcome, the fused level of confidence can be set. When the two classifiers produce the same class outcome, it can be considered that the classifiers agree on the result. The fused level of certainty, which is otherwise called the level of confidence in the decisions, should always represent the true intensity of confidence. Setting the fused level certainty to medium is considered as a compromise in a situation where one prior level is high and the other is low. The combined confidence can also be set as a high level in a situation where one prior level is high, and the other is medium. Considering the more cautious step, it is necessary to consider the low confidence level too. Hence, we set the combined level of certainty to low in the situation where one level is low and the other is medium.

Suppose the two classifiers have a different class outcome. In that case, the arisen conflict needs to be resolved by having the fused decisions. Hence, it is important to have prior levels of confidence for having the final judgment in that situation. In the event of final class outcome determination, the decisions with high confidence will win. However, it reflects the overall strength of the prediction depending upon the class. Even in this case, the low confidence consideration is essential, like how it is done earlier for the situation with two classifiers having the same outcome.

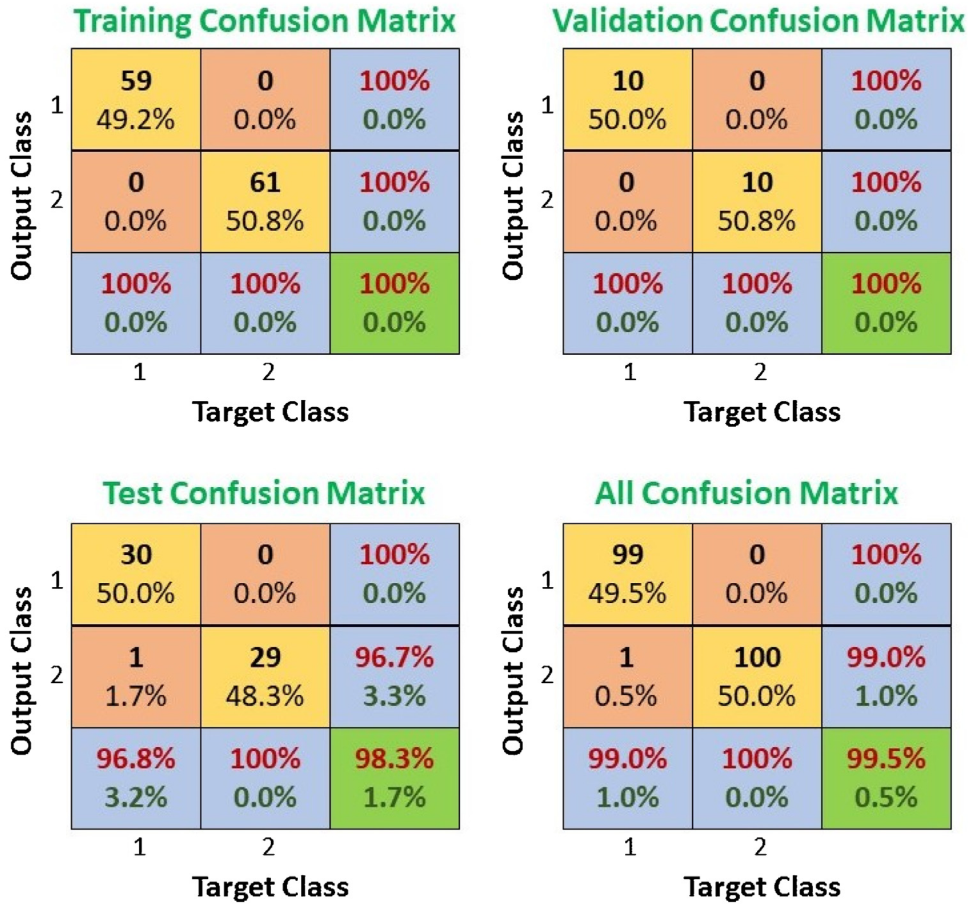

Fig. 10. Confusion matrix for SVM classifier for recognizing each class of waste in the binary classification setting.

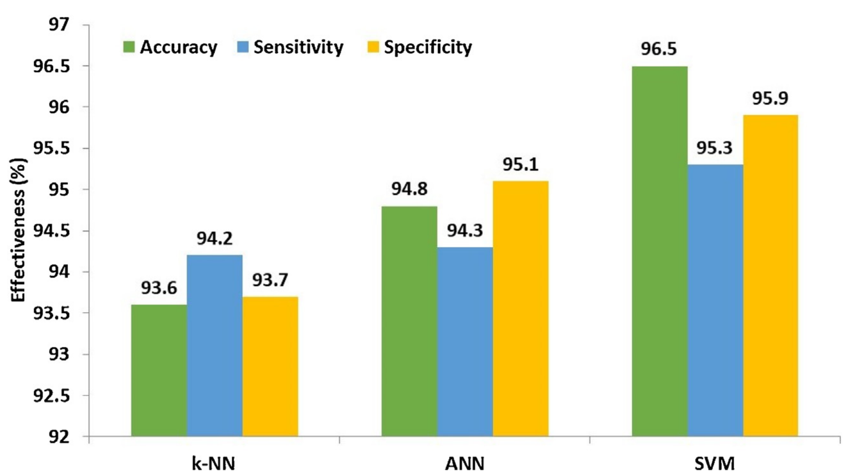

Fig. 11. The results of the decision level feature fusion.

5. Discussion and conclusion

The COVID pandemic has devastated the food production system, which poses several threats and repercussions. The threat of national lockdowns in several countries has contributed to the excessive storage of food products and other packaging items related to processed foods, food deliveries etc., resulting in a disturbing cycle of waste management development (Albahli et al., 2021; Abdulkareem et al., 2021). The challenge of sorting and classification of waste is investigated in this study, considering the circular economy context, where recycling output is used as a resource to the industries. In such practices, sorting and classification will influence the recycling yields. Hence, an AI-based automated solution is proposed. The proposed model performance is verified by conducting the simulated experiments. Here, the classification is done using a decision level fusion scheme and machine learning techniques by aiming for the correct separation of waste in recycling categories—four trash categories such as glass, metal, COVID-19 waste, and plastic. The findings indicate that the proposed fusion scheme is significantly superior to the Single Best Performance Feature Scheme. The classification achieved 96.5 % accuracy, 95.3 % sensitivity and specificity of 95.9 % while using SVM as a classifier.

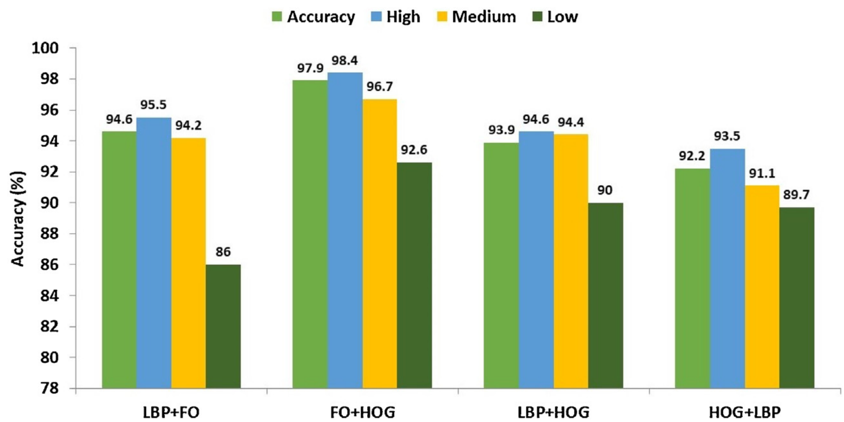

Fig. 12. Accuracy of the feature fusion.

However, SVM tends to be more computationally costly than other techniques, requiring better computational resources.

Overall, the results of these experiments revealed that this system could be considered for sorting and classifying waste at different scales. Considering the current waste management practices and waste segregation attitudes (that would vary from country to country), the system deployment can be done. A country with a well-planned waste segregation program may not need this solution at waste collection centres. However, this system can be deployed at the recycling centres whose waste is from mixed sources. Recycling centres having a supply chain that is not trusted worthy in terms of waste exchanges can be another potential client for this system. But in the case of countries in the global south, they have mostly poor waste segregation programs. Though some countries have guidelines on waste segregation, the implementation is lacking. In addition, only a minor percentage of the domestic sector follow the waste segregation guidelines in the global south. The rest are more inclined to open dumping in designated places as per the waste collectors advice. Such instances will lead to mixed waste, whether the waste is COVID one or other types. Hence, it is a must for recyclers to have this facility of sorting and classification. Deploying this system in the current waste management practices would benefit both developed nations and the global south. But upon comparing them, the most beneficial countries would be the ones in the global south. This system could change the waste management practices they have currently and enable recycling faster than usual.

The authors do acknowledge the current limitations of this study. For example, there could also be some other waste types (for example, food waste, textile waste, wood waste, electronic waste etc.) in the residential houses considering the lifestyle and country people live in are not included in the current study due to the unavailability of data sets. Also, this study is limited to digital technology development in CE. It does not account for the recycling yield or material recovery from the classified waste resources, which is the limitation of the presented model; however, such concepts can also be integrated, and the same will be presented as future work. Additionally, there is a possibility for improving the accuracy in SVM approaches through augmentation and fine-tuning, which will be investigated in future work. The other limitation is the data sets availability; if more data is available, deep learning approaches such as CNN tend to achieve better results.

Future research may also address non-black-box methods like deep-rough laws to include a comprehensible human law. Thus, the researcher recommends and finds the potential of models applied in a fully functional tool framework for stress evaluation of such models without losing their efficiency and robustness for the next job. However, with a multi-label image that is more complex and requires longer and more time, the researcher considers the usage of the waste labelling model. Overall, the proposed AI-based automated sorting and classifying solution would help recycle COVID-19 waste into valuable resources by eliminating fears among consumers.

Funding

This study was not funded.

Declaration of Competing Interest

There is no conflict of interests.

References

Abd Ghani, M.K., Mohammed, M.A., Arunkumar, N., Mostafa, S.A., Ibrahim, D.A., Abdullah, M.K., Jaber, M.M., Abdulhay, E., Ramirez-Gonzalez, G., Burhanuddin, M.A., 2020. Decision-level fusion scheme for nasopharyngeal carcinoma identification using machine learning techniques. Neural Comput. Appl. 32 (3), 625–638.

Abdulkareem, K.H., Mohammed, M.A., Salim, A., Arif, M., Geman, O., Gupta, D., Khanna, A., 2021. Realizing an effective COVID-19 diagnosis system based on machine learning and IOT in smart hospital environment. IEEE Internet Things J., 1, http://dx.doi.org/10.1109/jiot.2021.3050775.

Abdullah, N., Alwesabi, O.A., Abdullah, R., 2019. IoT-based smart waste management system in a smart city. In: Saeed, F., Gazem, N., Mohammed, F., Busalim, A. (Eds.), Recent Trends in Data Science and Soft Computing. IRICT 2018. Advances in Intelligent Systems and Computing, vol. 843. Springer, Cham, http://dx.doi.org/10.1007/978-3-319-99007-1_35.

Akhtar, M., Hannan, M.A., Begum, R.A., Basri, H., Scavino, E., 2017. Backtracking search algorithm in CVRP models for efficient solid waste collection and route optimization. Waste Manag. 61, 117–128.

Albahli, S., Algsham, A., Aeraj, S., Alsaeed, M., Alrashed, M., Rauf, H.T., Arif, M., Mohammed, M.A., 2021. COVID-19 public sentiment insights: a text mining approach to the gulf countries. Comput. Mater. Cont. 67 (2).

Anagnostopoulos, T., Zaslavsky, A., Kolomvatsos, K., Medvedev, A., Amirian, P., Morley, J., Hadjieftymiades, S., 2017. Challenges and opportunities of waste management in IoT-enabled smart cities: a survey. IEEE Trans. Sustain. Comput. 2 (3), 275–289.

Awe, O., Mengistu, R., Sreedhar, V., 2017. Smart trash net: waste localization and classification. arXiv preprint.

Banias, G., Achillas, C., Vlachokostas, C., Moussiopoulos, N., Papaioannou, I., 2011. A web-based decision support system for the optimal management of construction and demolition waste. Waste Manag. 31 (12), 2497–2502.

Bianchini, A., Rossi, J., Pellegrini, M., 2019. Overcoming the main barriers of circular economy implementation through a new visualization tool for circular business models. Sustainability 11, 6614, http://dx.doi.org/10.3390/su11236614.

Bueno-Delgado, M.V., Romero-Gázquez, J.L., Jiménez, P., Pavón-Mariño, P., 2019. Optimal path planning for selective waste collection in smart cities. Sensors 19 (9), 1973.

Cotet, C.E., Deac, G.C., Deac, C.N., Popa, C.L., 2020. An innovative industry 4.0 cloud data transfer method for an automated waste collection system. Sustainability 12, 1839.

Donovan, J., 2016. Auto-trash sorts garbage automatically at the techcrunch disrupt hackathon. In: Techcrunch Disrupt Hackaton, San Francisco, CA, USA, Tech. Rep. Disrupt SF, 2016.

Elhoseny, M., Mohammed, M.A., Mostafa, S.A., Abdulkareem, K.H., Maashi, M.S., Garcia-Zapirain, B., Mutlag, A.A., Maashi, M.S., 2021. A new multi-agent feature wrapper machine learning approach for heart disease diagnosis. Comput. Mater. Cont. 67 (1), 51–71, http://dx.doi.org/10.32604/cmc.2021.012632.
Esmaeilian, B., Wang, B., Lewis, K., Duarte, F., Ratti, C., Behdad, S., 2018. The future of waste management in smart and sustainable cities: a review and concept paper. Waste Manag. 81, 177–195, http://dx.doi.org/10.1016/j.wasman.2018.09.047.
Felsberger, A., Reiner, G., 2020. Sustainable industry 4.0 in production and operations management: a systematic literature review. Sustainability 12, 7982.
Ferronato, N., Torretta, V., 2019. Waste mismanagement in developing countries: a review of global issues. Int. J. Environ. Res. Public Health 16 (6), 1060.
Folianto, F., Low, Y.S., Yeow, W.L., April 2015. smartbin: smart waste management system. In: 2015 IEEE Tenth International Conference on Intelligent Sensors, Sensor Networks and Information Processing (ISSNIP), IEEE, pp. 1–2.
Girdhar, A., Kapur, H., Kumar, V., Kaur, M., Singh, D., Damasevicius, R., 2020. Effect of COVID-19 outbreak on urban health and environment. Air Qual. Atmos. Health, 1–9, http://dx.doi.org/10.1007/s11869-020-00944-1.
Hannan, M.A., Akhtar, M., Begum, R.A., Basri, H., Hussain, A., Scavino, E., 2018. Capacitated vehicle-routing problem model for scheduled solid waste collection and route optimization using PSO algorithm. Waste Manag. 71, 31–41.
Hannan, M.A., Hossain Lipu, M.S., Akhtar, M., Begum, R.A., Al Mamun, M.A., Hussain, A., et al., 2020. Solid waste collection optimization objectives, constraints, modeling approaches, and their challenges toward achieving sustainable development goals. J. Clean. Prod. 277, http://dx.doi.org/10.1016/j.jclepro.2020.123557.
Haque, M.S., Uddin, S., Sayem, S.M., Mohib, K.M., 2021. Coronavirus disease 2019 (COVID-19) induced waste scenario: a short overview. J. Environ. Chem. Eng. 9 (1), 104660, http://dx.doi.org/10.1016/j.jece.2020.104660.
Hong, I., Park, S., Lee, B., Lee, J., Jeong, D., Park, S., 2014. IoT-based smart garbage system for efficient food waste management. Sci. World J. 2014, 1–13.
Jaid Jim, A.A., Kadir, R., Mamun, M., Al, A., Nahid, A.A., Ali, M., 2019. A noble proposal for Internet of garbage bins (IoGB). Smart Cities 2 (2), 214–229.
Jaikumar, K., Brindha, T., Deepalakshmi, T.K., Gomathi, S., 2020. IOT assisted MQTT for segregation and monitoring of waste for smart cities. In: 2020 6th International Conference on Advanced Computing and Communication Systems, ICACCS 2020, pp. 887–891.
Kansara, R., Bhojani, P., Chauhan, J., 2019. Smart Waste Management for Segregating Different Types of Wastes., http://dx.doi.org/10.1007/978-981-13-1402-5_3.
Kaufman, L., Chasan, E., 2020. Cities wonder whether recycling counts as essential during the virus. In: Bloomberg Green, accessed 8.10.20 https://www.bloomberg.com/news/articles/2020-03-27/cities-wonder-whether-recycling-counts-as-essential-during-the-virus.
Kulkarni, B.N., Anantharama, V., 2020. Repercussions of COVID-19 pandemic on municipal solid waste management: challenges and opportunities. Sci. Total Environ. 743, 140693, http://dx.doi.org/10.1016/j.scitotenv.2020.140693.
Lin, P.H., Lin, C.C., Yen, H.C., 2009. Tri-histogram equalization based on first order statistics. In: 2009 IEEE 13th International Symposium on Consumer Electronics, IEEE, pp. 387–391.
Maskeliunas, R., Damaševicius, R., Segal, S., 2019. A review of internet of things technologies for ambient assisted living environments. Future Internet 11 (12), http://dx.doi.org/10.3390/FI11120259.
Mittal, G., Yagnik, K.B., Garg, M., Krishnan, N.C., 2016. Spotgarbage: smartphone app to detect garbage using deep learning. Proceedings of the 2016 ACM International Joint Conference on Pervasive and Ubiquitous Computing, 940–945.
Mohammed, M.A., Abdulkareem, K.H., Mostafa, S.A., Ghani, M.K.A., Maashi, M.S., Garcia-Zapirain, B., Oleagordia, I., Alhakami, H., Al-Dhief, F.T., 2020a. Voice pathology detection and classification using convolutional neural network model. Appl. Sci. 10 (11), 3723.
Mohammed, M.A., Abdulkareem, K.H., Al-Waisy, A.S., Mostafa, S.A., Al-Fahdawi, S., Dinar, A.M., Alhakami, W., Abdullah, B.A.Z., Al-Mhiqani, M.N., Alhakami, H., Arbaiy, N., 2020b. Benchmarking methodology for selection of optimal COVID-19 diagnostic model based on entropy and TOPSIS methods. IEEE Access 8, 99115–99131.
Mohammed, M.A., Abdulkareem, K.H., Garcia-Zapirain, B., Mostafa, S.A., Maashi, M.S., Al-Waisy, A.S., Subhi, M.A., Mutlag, A.A., Le, D.N., 2020c. A comprehensive investigation of machine learning feature extraction and classification methods for automated diagnosis of covid-19 based on x-ray images. Comput. Mater. Contin. 66 (3).
Mutlag, A.A., Khanapi Abd Ghani, M., Mohammed, M.A., Maashi, M.S., Mohd, O., Mostafa, S.A., Abdulkareem, K.H., Marques, G., de la Torre Díez, I., 2020. MAFC: multi-agent fog computing model for healthcare critical tasks management. Sensors 20 (7), 1853.
Neel, K., 2020. Punjab farmers start dumping vegetables due to curfew. In: Chandigarh News (Times of India) (accessed 8.8.20) https://timesofindia.indiatimes.com/city/chandigarh/punjab-farmers-start-dumping-vegetables-due-tocurfew/articleshow/74801554.cms.
Oghazi, P., Mostaghel, R., 2018. Circular business model challenges and lessons learned—an industrial perspective. Sustainability 10, 739, http://dx.doi.org/10.3390/su10030739.
Okewu, E., Misra, S., Maskeliunas, R., Damaşeviçius, R., Fernandez-Sanz, L., 2017. Optimizing green computing awareness for environmental sustainability and economic security as a stochastic optimization problem. Sustainability 9 (10), http://dx.doi.org/10.3390/su9101857.
Pardini, K., Rodrigues, J.J., Kozlov, S.A., Kumar, N., Furtado, V., 2019a. IoT-based solid waste management solutions: a survey. J. Sens. Actuator Netw. 8 (1), 5.
Pardini, K., Rodrigues, J.J.P.C., Kozlov, S.A., Kumar, N., Furtado, V., 2019b. IoT-based solid waste management solutions: a survey. J. Sens. Actuator Netw. 8 (1), http://dx.doi.org/10.3390/jsan8010005.
Popa, C.L., Carutasu, G., Cotet, C.E., Carutasu, N.L., Dobrescu, T., 2017. Smart city platform development for an automated waste collection system. Sustainability 9 (11), 2064.
Rad, M.S., von Kaenel, A., Droux, A., Tieche, F., Ouerhani, N., Ekenel, H.K., Thiran, J.P., July 2017. A computer vision system to localize and classify wastes on the streets. In: International Conference on Computer Vision Systems. Springer, Cham, pp. 195–204.
Rajan, R., Robin, D.T., Vandanarani, M., 2019. Biomedical waste management in Ayurveda hospitals–current practices and future prospectives. J. Ayurveda Integr. Med. 10 (3), 214–221.
Rossi, J., Bianchini, A., Guarnieri, P., 2020. Circular economy model enhanced by intelligent assets from industry 4.0: the proposition of an innovative tool to analyze case studies. Sustainability 12, 7147, http://dx.doi.org/10.3390/su12177147.
Sawalem, M., Selic, E., Herbell, J.D., 2009. Hospital waste management in Libya: a case study. Waste Manag. 29 (4), 1370–1375.
Sharma, H.B., Vanapalli, K.R., Cheela, V.S., Ranjan, V.P., Jaglan, A.K., Dubey, B., Goel, S., Bhattacharya, J., 2020. Challenges, opportunities, and innovations for effective solid waste management during and post COVID-19 pandemic. Resour. Conserv. Recycl. 162, 105052, http://dx.doi.org/10.1016/j.resconrec.2020.105052.
Tenenbaum, L., 2020. The amount of plastic waste is surging because of the coronavirus pandemic. In: Forbes (accessed 8.11.20) https://www.forbes.com/sites/lauratenenbaum/2020/04/25/plastic-waste-during-the-time-of-covid-19/#7c4e661f7e48.
Tripathi, A., Tyagi, V.K., Vivekanand, V., Bose, P., Suthar, S., 2020. Challenges, opportunities and progress in solid waste management during COVID-19 pandemic. Case Stud. Chem. Environ. Eng. 2, 100060, http://dx.doi.org/10.1016/j.cscee.2020.100060.
UNEP, 2020. BASEL: waste management an essential public service in the fight to beat COVID-19. In: The United Nations Environment Programme (UNEP) and The Basel Convention (accessed 8.10.20) http://www.basel.int/Implementation/PublicAwareness/PressReleases/WastemanagementandCOVID19/tabid/8376/Default.aspx.
Vitorino de Souza Melaré, A., Montenegro González, S., Faceli, K., Casadei, V., 2017. Technologies and decision support systems to aid solid-waste management: a systematic review. Waste Manag. 59, 567–584, http://dx.doi.org/10.1016/j.wasman.2016.10.045.
Viva, L., Ciulli, F., Kolk, A., Rothenberg, G., 2020. Designing circular waste management strategies: the case of organic waste in Amsterdam. Adv. Sustain. Syst. 4 (9), 2000023, http://dx.doi.org/10.1002/adsu.202000023.
Wei, Z., Lidong, H., Jun, W., Zebin, S., 2014. Entropy maximization histogram modification scheme for image enhancement. IET Image Process. 9 (3), 226–235.
Windfeld, E.S., Brooks, M.S.L., 2015. Medical waste management–a review. J. Environ. Manag. 163, 98–108.
Yang, M., Thung, G., 2016a. Classification of trash for recyclability status. In: CS229 Project Report, 2016.
Yang, M., Thung, G., 2016b. Classification of trash for recyclability status. In: CS229 Project Report, 2016.
Yunana, K., Alfa, A.A., Misra, S., Damasevicius, R., Maskeliunas, R., Oluranti, J., 2021. Internet of things: applications, adoptions and components - a conceptual overview. In: Hybrid Intelligent Systems. Springer International Publishing, pp. 494–504, http://dx.doi.org/10.1007/978-3-030-73050-5_50.
Zheng, T., Ardolino, M., Bacchetti, A., Perona, M., 2020. The applications of Industry 4.0 technologies in manufacturing context: a systematic literature review. Int. J. Prod. Res., 1.