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Article

An Intelligent Hazardous Waste Detection and Classification Model Using Ensemble Learning Techniques

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Abstract: Proper waste management models using recent technologies like computer vision, machine learning (ML), and deep learning (DL) are needed to effectively handle the massive quantity of increasing waste. Therefore, waste classification becomes a crucial topic which helps to categorize waste into hazardous or non-hazardous ones and thereby assist in the decision making of the waste management process. This study concentrates on the design of hazardous waste detection and classification using ensemble learning (HWDC-EL) technique to reduce toxicity and improve human health. The goal of the HWDC-EL technique is to detect the multiple classes of wastes, particularly hazardous and non-hazardous wastes. The HWDC-EL technique involves the ensemble of three feature extractors using Model Averaging technique namely discrete local binary patterns (DLBP), EfficientNet, and DenseNet121. In addition, the flower pollination algorithm (FPA) based hyperparameter optimizers are used to optimally adjust the parameters involved in the EfficientNet and DenseNet121 models. Moreover, a weighted voting-based ensemble classifier is derived using three machine learning algorithms namely support vector machine (SVM), extreme learning machine (ELM), and gradient boosting tree (GBT). The performance of the HWDC-EL technique is tested using a benchmark Garbage dataset and it obtains a maximum accuracy of 98.85%.

Keywords: Hazardous waste; image classification; ensemble learning; deep learning; intelligent models; human health; weighted voting model

1 Introduction

Exposure to toxic and hazardous waste can cause significant impacts on the atmosphere and also on human wellbeing. When waste of any type, either from industries or households, decomposes, it can pollute the environment. To be more specific, mining wastes, sewage slug, electronic & electric wastes, and many others contaminate the environment and, in turn, affect human health in various forms [1]. Any hazardous or toxic substances entering the human body cause harmful effects in all groups, from fetuses, infants, teenagers, elders, and the elderly. However, the severity of these effects varies are the challenging factors due to the impact of toxic substances and hazardous wastes [2]. Inhalation, absorption, and dermal (skin) touch are the three main routes of exposure. Waste and the related risk have become an increasingly major challenge in ecological protections. There arises increasing attention in waste management across the globe, both in the developments of technology for minimizing the quantity and those associated with their economic and disposal uses. The primary cause for excessive waste production can be illogical material management.

The garbage gathering in landfilling might be employed as secondary raw material, the values of which are evaluated at hundreds of millions of dollars. 35% is iron, zinc, lead, and other metal; 25% of overall amounts of coal; and 40% is associated with the elements like slag, ash, aggregates, rock waste, etc. [3,4]. Constraining the amount of produced waste to levels which ensure balance among sanitary waste, raw material, and ecological is impossible without wide-ranging synchronization of technology also the way of people living with the working and formation of environmental structures in the region [5]. Action intended for decreasing the mass of generated waste and located in the surrounding must involve minimizing waste production from end to end, replacing traditionally used raw materials non-waste technologies/the use of modern low-waste, and recycling raw material [6]. The targeting scheme to solve the problems of waste generation polluted the natural environments are low and waste-free technology.

Techniques like Big Data, cloud computing (CC), Internet of Things (IoT), and artificial intelligence (AI) could be used for waste reduction [7]. Firstly, wet and dry wastes are segregating, and electromagnetic technique is employed for sorting iron comprising material. But, visual approaches are employed for segregating the plastic garbage [8,9]. In optical arranging, camera is applied for identifying distinct waste segments according to the visual properties, like texture/shape, color. The model makes triangle through the camera images over the base laser beam, it is also known as triangulation scanning [10]. Spectral imaging is an integration of computer image processing and spectral reflection measurement technologies.

This study concentrates on the design of hazardous waste detection and classification using ensemble learning (HWDC-EL) technique to reduce toxicity and improve human health. The HWDC-EL technique intends to detect the multiple classes of wastes, particularly hazardous and non-hazardous wastes. Moreover, the HWDC-EL technique derives an ensemble of three feature extractors using the Model Averaging technique namely discrete local binary patterns (DLBP), EfficientNet, and DenseNet121. Furthermore, the flower pollination algorithm (FPA) based hyperparameter optimizers are used to optimally adjust the parameters involved in the EfficientNet and DenseNet121 models. Lastly, a weighted voting-based ensemble classifier is derived using three machine learning techniques namely support vector machine (SVM), extreme learning machine (ELM), and gradient boosting tree

(GBT). The performance of the HWDC-EL technique is tested using a benchmark Garbage dataset and the results are scrutinized relating to different aspects.

2 Related Works

Hussain et al. [11] propose IoT based intelligent bins with machine learning (ML) and deep learning (DL) models for managing the garbage disposal also for predicting the air pollutants existing in the bin environments. The smart bins are related to IoT based servers, that carry out the necessary computations to predict the bin status also to predict air quality on the basis of realtime data. Researchers investigated conventional models (KNN) and logistic regression (LR) as well as a non-conventional method for making an alert message about status of the bin and predict the sum of air pollutants carbon monoxide (CO) existing in the atmosphere at a certain case. Cao et al. [12] proposed a recognition and garbage classification method on the basis of transfer learning (TL) approach that migrates the present InceptionV3 method recognition tasks on Imagenet datasets for the identification of garbage. Firstly, rise the dataset via data augmentation. Next, construct a convolution neural network (CNN) according to the source models and alter the NN parameter according to the training effects.

In Yang et al. [13], a CNN is trained by huge amounts of negative and positive samples. To adopt better for detecting objects, the topology of CNN is enhanced. The windows of suspicious hazardous articles are inputted to the enhanced CNN for detecting hazardous objects, and the false detection rate (FDR) is decreased when preserving the original detection rates. Ziouzios et al. [14] suggested a cloud-related classification method for automated machines in recyclable factories having ML model. Hua et al. [15] investigated with Keras, for creating a CNN, and OpenCV, to make realtime videos, which identify dangerous wastes from other recycling materials. With help of ML method, these models are capable of categorizing distinct recyclable material with an accuracy of around 90%. An object within the video receives predictions for three classifiers that include nonhazardous, batteries, and syringes waste. Adedeji et al. [16] suggested a smart waste material categorization system, i.e., presented by employing fifty layers residual net pretrain (ResNet-50) CNN models i.e., an ML tools and serve as an extractor, as well support vector machine (SVM) i.e., leveraged for classification.

Nowakowski et al. [17] investigate an image detection scheme for the classification and identification of waste electronic and electrical equipment's from an image. The primary objective is to assist data interchange about the wastes to be gathered from individual or waste gathering points, thus using smartphones and wide acceptance. A new technique of identification and classification with neural network (NN) is presented to image analyses: a DL-CNN has been used for classifying the types of e-waste, and a fast region based convolution neural network (RCNN) method has been employed for detecting the size and category of the waste equipment in an image. Chu et al. [18] recommends a sorting waste disposal model manually of an individual in urban public areas. Though several models are available in the literature, there is still a need of ML and DL models to effectively handle the massive quantity of increasing waste. Therefore, waste classification becomes a crucial topic which helps to categorize waste into hazardous or non-hazardous ones and thereby assist in the decision making of the waste management process.

3 The Proposed Model

In this study, a novel HWDC-EL algorithm can be extracted for hazardous waste classification and detection. The HWDC-EL algorithm intends to detect the multiple classes of wastes, particularly hazardous and non-hazardous wastes. The overall working of the HWDC-EL technique involves two major stages namely ensemble learning based feature extraction and weighted voting based classification. Fig. 1 exemplifies the overall block diagram of proposed HWDC-EL model. The detailed operational principle of these processes is discussed in the succeeding sections.

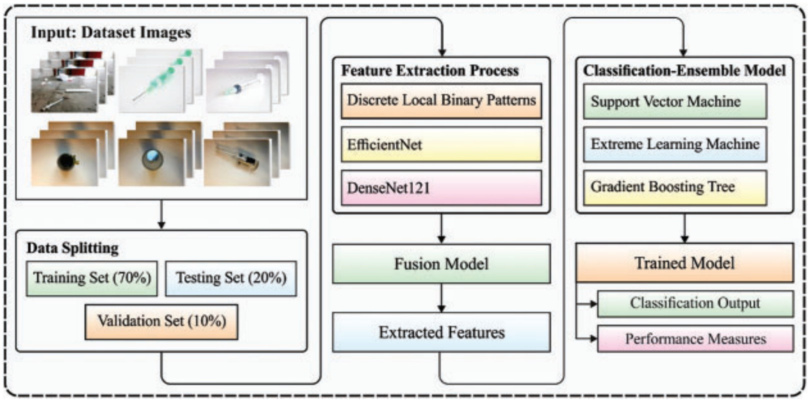

Figure 1: Overall block diagram of HWDC-EL model

3.1 Design of Ensembling Learning Based Feature Extraction Process

At the initial stage, the input images are fed into the feature extractor for generating a feature vector set. In this study, an ensemble of 3 feature extraction algorithms like DLBP, EfficientNet, and DenseNet121 algorithms are employed by Model Averaging technique.

3.1.1 DLBP Model

Local binary pattern (LBP) model provides a descriptors for few images with the gray level of all the pixels. In classical versions, pixels are deliberated by the eight nearby to him, thus forming a square of 3×3 pixels. Next, for all these 8 adjacent, their relationships having central pixels are calculated: when the grey levels are higher compared to the central pixels, they were interchanged with one, or else with zero [19]. The resulting binary patterns are later converted into a decimal value. The *LBP* operators are calculated by:

$$LBP\left(x_{c'}y_{c}\right) = \sum\nolimits_{p \in P} 2^{\mathrm{p}} * q\left(i_p - i_c\right), \tag{1}$$

whereas P represents a pixel closer to the central ones, i_c & i represents the grey level of central pixels as well as pth neighbors correspondingly, and $q\left(z\right)$ indicates a quantization operator determined by:

$$q\left(z\right) = \begin{cases} 1, z \geq 0 \\ 0, otherwise \end{cases} \tag{2}$$

It is noted that the numbers of neighbor and the radius are parameter which is altered and aren't static.

DLBP model is proposed by Kobayashi [20], as an altered form of LBP. It aims for discovering, per pixels patch, the optimum thresholds divide pixel inside it. The thresholds are acquired by minimalizing a remaining error computed by:

$$\varepsilon(\tau) = \frac{1}{N}\left\{\sum\nolimits_{i|I(r_i)\le\tau}(I(r_i)-\mu_0)^2 + \sum\nolimits_{i|I(r_i)\le\tau}(I(r_i)-\mu_1)^2\right\}. \tag{3}$$

With:

$$\mu_0 = \frac{1}{N_0}\sum\nolimits_{i|I(r_i)\le\tau} I(r_i) \ \ and\ N_0 = \sum\nolimits_i \mathrm{q}(\tau - I(r_i)), \tag{4}$$

$$\mu_1 = \frac{1}{N_1}\sum\nolimits_{i|I(r_i)\le\tau} I(r_i) \ \ and\ N_1 = \sum\nolimits_i \mathrm{q}(I(r_i) - \tau). \tag{5}$$

A residual error $\varepsilon(\tau)$ is later organized as an intraclass difference σ_{W}^2. The optimal thresholds are maximizing the difference among classes σ_B^2 of the pixel, patch is evaluated by:

$$= \sigma - \sigma_{\mathrm{W}}^2. \tag{6}$$

When the threshold can be established, the weight of all the pixels patch on last histogram are assessed as:

$$\omega = \sqrt{\frac{\sigma_B^2(\gamma^*)}{\sigma^2 + \mathrm{C}}}, \tag{7}$$

whereas C indicates a constant that serve for managing this case whereas σ^2 is closer to 0 and might result in fluctuation of the weighted votes.

3.1.2 EfficientNet Model

EfficientNet [21] is a type of CNN which employs an exclusive scaling method scales each dimension, viz., width, and resolution implementing compound coefficients. The EfficientNet outperforms various other advanced models on ImageNet datasets classification tasks and doesn't saturate when the number of trainable parameters is increased. Here, the EfficientB7 model is used.

3.1.3 DenseNet121 Model

Dense Convolutional Network (DenseNet) is a class of neural networks where every layer obtains input from each layer behind it and forwards its own feature map to each succeeding layer. In DenseNet, each layer acquires the knowledge of each preceding layer in a feedforward manner. A DenseNet using L layer has L(L + 1)/2 connection compared to just L connection in a traditional convolutional network [22].

3.1.4 Hyperparameter Optimization

In order to tune the hyperparameters involved in the EfficientNet and DenseNet-121 models, the FPA is applied to it. The self-pollination, biotic pollination, cross-pollination, and abiotic pollination models are represented in optimization fields and induced in a flower pollination method. Flower reliability was determined as a precise solution that might be a visible one. In another case, local pollinations are performed within a smaller area of a unique flower was performed in shading water. Global pollination occurs with a possibility are called a switch possibility. Once the phases are removed, local pollination could be interchanged [23]. In FPA model, it consists of 4 rules as follows:

- Cross and Live pollinations are called global pollination as well as the carrier of pollen pollinator apply the levy fight.
- Self and Abiotic pollinations are denoted by local pollination.

- Pollinator is insect, i.e., capable of advancing flower constancy. It is determined as the production possibility to 2 employed flowers.
- The transmission of global and local pollinations can handled by a switch possibility.
- Henceforth, the 1st & 3rd rules are given below:
- $x_q^{t+1} = x_p^t + \gamma \times L(\lambda) \times \left(g_* - x_p^t\right)$ (8)

whereas $x_p^t =$ pollen vectors in iteration t; g_* indicates present optimal solutions from another present generating result; $\gamma =$ a indicates the scaling factors to control step size; also L represents strength of pollination i.e., associated with step-size of levy distribution. Levy flights are determined as a set of arbitrary computations that contain the length of all jumps which employs levy likelihood distribution using infinite variance. Next, L denotes a levy distribution as follows:

$$L \sim \frac{\lambda \times \Gamma(\lambda) \times \sin\dfrac{\pi\lambda}{2}}{\pi} \times \frac{1}{S^1 + \lambda} S \gg S_0 0, \tag{9}$$

whereas $\Gamma(\lambda) =$ standard gamma function. In local pollination, the 2nd & 3rd rules are formulated by:

$$x_p^{t+1} = x_p^t + \varepsilon\left(x_q^t - x_k^{\mathrm{t}}\right) \tag{10}$$

whereas x_q^t & $x_k^t = 2$ pollen from different flowers from related plants. In arithmetical form, while x_q^t & x_k^{t} come from the related species is chosen from homogeneous population, i.e., denoted by a local arbitrary walk and ε is included in a uniform distribution in range of zero and one.

3.1.5 Ensembling Process

The ensemble algorithm employed in this study is Model Averaging [24]. In this method, each classifier contribution will remain equal for computation of the final prediction. Unweighted averaging may be a reasonable ensemble to same base learner of similar performances.

3.2 Design of Weighted Voting Based Ensemble Classification Process

During classification procedure, the feature vectors were passed into classifier module which involves three models namely SVM, GBT, and ELM. In addition, a weighted voting based ensemble classification process is adopted to predict the final class of the applied input image.

3.2.1 SVM Classifier

Initially, SVM model was proposed by Vapnik in 1995, also it is becoming optimum method for classifying data. It contains a solid theoretical foundation depending upon the integration among basic risk minimalization principles. The major advantage of SVM is the high generalization ability and global optimization furthermore, it overcomes the over-fitting problem and provides sparse solutions compared with the present approaches like artificial neural network (ANN) in classification. In normal linear classification problems, e.g., 1, 2e must divide the group of trained data, $(x_i,\ y_i), i = 1, 2, \ldots, m$, m indicates the amount of provided observations, whereas $x_i \in R_n$ represent the feature vector also $y_i \in (-1,\ +1)$ indicates label vector. Binary classification problems are modelled as an optimization issue as given as follows:

$$Min: \frac{1}{2}\|w\|_2^2 + C\sum\nolimits_{i=1}^{m} \xi_i \tag{11}$$

Subjected to:

$$y_i (w \times x_i) + b \geq 1 - \xi_i, \xi_i \geq 0, \ i = 1, \ \ldots, m, \tag{12}$$

While C indicates the standardization variable; ξ_i the penalize relaxation variable [25]. Eq. (12) implies

$$w \times (\varnothing (x_i) + b \geq +1 \ if \ y_i = +1, \tag{13}$$

$$w \times (\varnothing (x_i) + b \geq -1 \ if \ y_i = -1.$$

It must be pointed out that the non-linear classifiers might be represented by

$$f (x) = sign \left(\sum\nolimits_{i=1}^{m} \alpha_{i^*} \times y_i \times K (x_i, y_i) + b^*\right), \tag{14}$$

whereas $f (x)$ represent the decision functions and bias b^* is evaluated using KKT condition; $K (x_i, y_i)$ signifies the kernel function which produces the inner products for this featured space. In this work, the subsequent radial basis function (RBF) is employed:

$$K (x, \ y) = \ \exp \left(-\gamma \|x - y\|^2\right), \tag{15}$$

whereas γ indicates the kernel variable. In order to attain an optimal efficiency, few SVM parameters need to be selected properly involving the standardization variable C and the kernel variable γ.

3.2.2 GBT Classifier

The term boosting mentions that a family of techniques which change weak learners to strong learners, kind that weak learners are only somewhat superior to an arbitrary selection, but strong learners have an almost perfect efficiency. The Gradient Boosting method has been ML approach which is utilized in combined regression as well as classification issues. These techniques generate the predictive method in the procedure of ensemble to weak predictive techniques that are commonly equivalent to decosopm tree (DT) under the specific case utilized. This technique creates the method in stages as other boosting techniques along with generalization these by optimizing random differentiable loss functions. There are several works which utilize AI approaches.

The ensemble can be created from the stage-wise procedure with gradient descent in function space. The last method is a function which gets as input the vector of attribute $x \in R^n$ for getting a score $F (x) \in R$ thus $F_i (x) = F_{i-1} (x) + \gamma_i h_i (x)$, in which all h_i refers the function which techniques a single tree and $\gamma_i \in R$ signifies the weight connected to the i-th tree, thus 2 terms are learned in the trained stage [26]. Conversely, a major reason for utilizing the GBT in contrast to another predictive technique are which ensemble techniques, mostly, are commonly the classifiers or regressors which supplies the optimum out-of-the-box outcomes. Also, assuming that the fundamental technique utilized for analyzing this issue is a typical DT, it is assumed that natural for utilizing their extension by means of ensemble technique.

3.2.3 ELM Classifier

ELM is proposed by Professor Huang, this approach employs single hidden layer feed forwared network structure, i.e., provided N trained sample and contain L standard NN method is formulated by:

$$\sum_{i=1}^{L} \beta_i G\left(a_i \times x_j + b_i\right) = O_j, j = 1, \ \ldots, \ N, \tag{16}$$

Whereas $G(x)$ represents the activation function of Hidden layer nod, β_i denotes the output weights among initial i node and link to the output neuron, $(a_i, \ b_i)$ signifies the input eight and the bias of input neuron, O_j indicates the actual output values of output neuron. Now $a(a_i, \ b_i)$ and β_i makes $\sum_{j=1}^{L} \|O_j - t_j\| = 0$ setups and could zero error estimate sample set $\{(x_i, \ t_i), \ i = 1, \ \ldots, \ N\}$ as:

$$\sum_{i=1}^{L} \beta_i G\left(a_i \times x_j + b_i\right) = t_j, j = 1, \ldots, N. \tag{17}$$

Eq. (17) is formulated by $H\beta = T$, now H denotes the hidden layer output matrix. Fig. 2 demonstrates the structure of ELM model. ELM does not t necessary to alter the early weight value in the procedure of training, it should workout the weight of output least square norm [27]. Hence, it is essential to make compromises among minimizing error and output weight. The equation is formulated by.

$$Minimize: \ \|\beta\| \tag{18}$$

$$Minimize: \ \sum_{i=1}^{N} \|\beta \times h(x_i) - t_i \tag{19}$$

Like LSSVM, the optimization problems are expressed in the following:

$$Minimize: \ L = \frac{1}{2}\|\beta\|^2 + C\frac{1}{2}\sum_{i=1}^{N} \|\zeta_i\|^2 \tag{20}$$

$$s.t.: h(x_i)\,\beta = t_i^T - \zeta_i^T, \ i = 1, \ \ldots, \ N$$

Now $\zeta_i = [\zeta_{i,1}, \ \ldots, \ \zeta_{i,m}]^T$ denotes the error vector about trained instances among the true and output values of initial m output nodes. Also, C represents the normalization variable that are the penalty factors employed for weighing structural and empirical risks, also controls overfitting by setup the parameters, for achieving an optimal classification result.

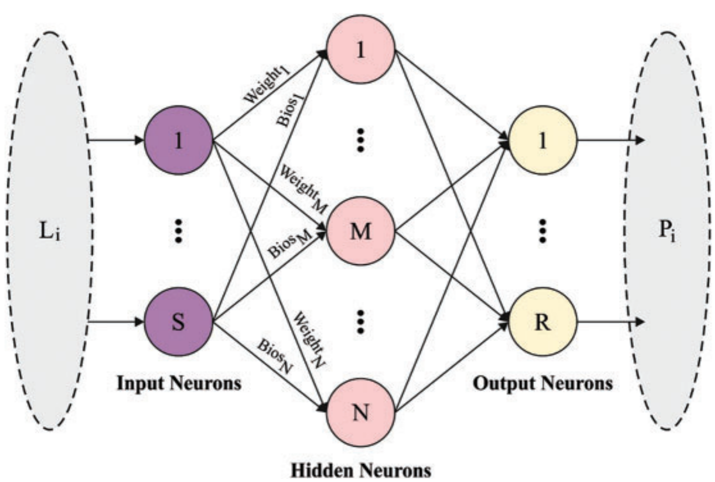

Figure 2: ELM structure

Using Moore Penrose generalized inverse matrix H^T of the hidden layer output matrix H, they could attain the solutions $\hat{\beta} = H^T T$, whereas $T = [t_i, \ldots, t_N]$. ELM has fast training speed and optimal generalization efficiency, but in handling data with imbalanced class distribution, it could not attain a better result hence it is essential for introducing the weight concept in ELM, as well create WELM model.

3.2.4 Weighted Voting Based Ensembling Process

At the weighted voting-related ensemble technique, the ML approaches were compiled. The voting technique was trained with all individuals' vectors and the respective 10-fold crows validation accuracy is later evaluated as FF [28]. Given the amount of classes as n and D base classifier algorithms to vote, the predictive class c_k of weighted voting to all instances, k can be determined as:

$$c_k = \arg\max_j \sum_{\mathrm{i}=1}^{D} \left(\Delta_{\mathrm{ji}} \times w_{\mathrm{i}}\right), \tag{21}$$

where Δ_{ji} implies the binary variables. If the ith base classifier algorithm classifies the instance k as to jth class, later $\Delta_{\mathrm{ji}} = 1$; else, $\Delta_{\mathrm{ji}} = 0$. w_{i} refers the weight of ith base classifier technique in an ensemble. Next, the accuracy was demonstrated as:

$$Acc = \frac{\sum_k \{1 | c_k \text{ is the true class of instance } k\}}{\text{Size of test instances}} \times 100\%. \tag{22}$$

4 Performance Validation

This section analyses the performances of the HWDC-EL algorithm on the garbage classification dataset and some Hazardous images collected from Google (available at https://www.kaggle.com/asdasdasasdas/garbage-classification). The dataset includes two major classes namely Non-hazardous and hazardous. In addition, plastic, paper, metal, and glass waste comes under Non-hazardous class whereas Syringes come under Hazardous class. Fig. 3 shows the sample test images. The classification results are investigated in three ways namely training, testing, and validation datasets. Each class holds a set of 260 images and the dataset includes a total of 1300 images. The parameter setting is given as follows: learning rate: 0.001, activation function, sigmoid, momentum: 0.4, and error: 0.001.

Fig. 4 shows the confusion matrix of the HWDC-EL method on the applied 70% of training dataset. The figure portrayed the HWDC-EL technique has proficiently categorized 172 instances into Plastic, 174 instances into Paper, 174 instances into Metal, 175 instances into Glass, and 175 instances into Syringe.

The classification results obtained by the HWDC-EL technique on the detection of multiple classes on the applied 70% of the training dataset are given in Tab. 1. The results portrayed that the HWDC-EL technique has categorized all the waste objects effectively. For instance, the HWDC-EL technique has identified the 'plastic' class with the $prec_s$ of 0.9556, rec_{ll} of 0.9451, accuracy of 0.9802, and F_{score} of 0.9503. In addition, the HWDC-EL manner has identified the 'paper' class with the $prec_s$ of 0.9508, rec_{ll} of 0.9560, acc_y of 0.9813, and F_{score} of 0.9534. Followed by, the HWDC-EL methodology has identified the 'metal' class with the $prec_s$ of 0.9613, rec_{ll} of 0.9560, acc_y of 0.9835, and F_{score} of 0.9537. Besides, the HWDC-EL system has identified the 'glass' class with the $prec_s$ of 0.9459, rec_{ll} of 0.9615, acc_y of 0.9813, and F_{score} of 0.9537. Lastly, the HWDC-EL approach has identified the 'syringe' class with the $prec_s$ of 0.9669, rec_{ll} of 0.9615, acc_y of 0.9857, and F_{score} of 0.9642. In overall, the HWDC-EL technique has obtained an average $prec_s$ of 0.9561, rec_{ll} of 0.9560, acc_y of 0.9824, and F_{score} of 0.9560.

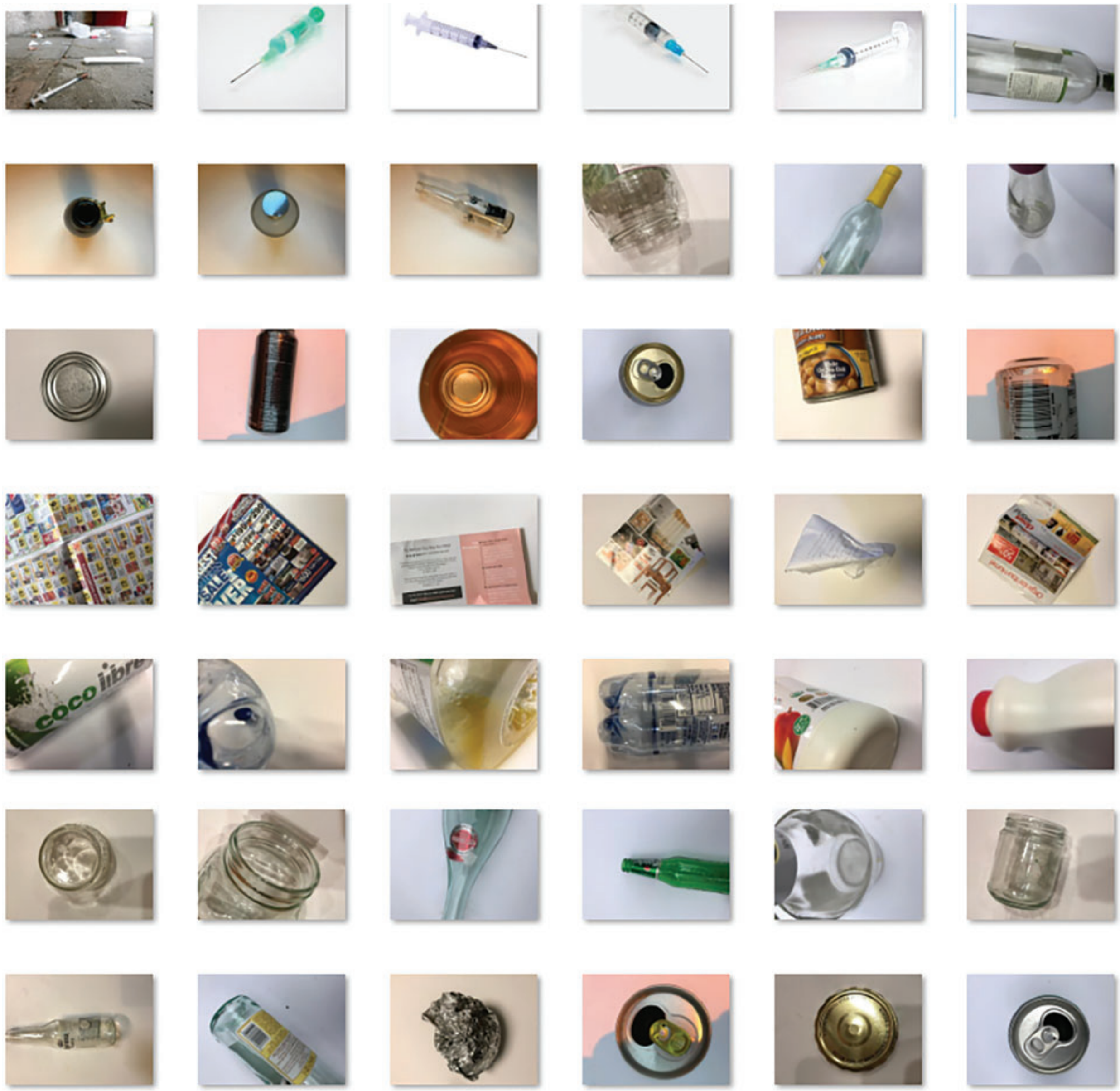

Figure 3: Sample test image

Fig. 5 showcases the confusion matrix of the HWDC-EL algorithm on the applied 20% of training dataset. The figure demonstrated the HWDC-EL approach contains has proficiently categorized 51 instances into Plastic, 49 instances into Paper, 50 instances into Metal, 50 instances into Glass, and 50 instances into Syringe.

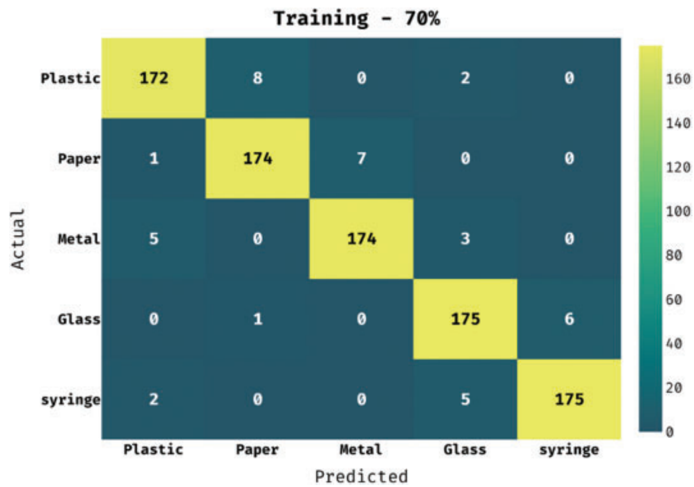

Figure 4: Confusion matrix of HWDC-EL model on training dataset (70%)

Table 1: Result analysis of HWDC-EL model with different classes on training dataset (70%)

Classes	Precision	Recall	Accuracy	F-Score
Plastic	0.9556	0.9451	0.9802	0.9503
Paper	0.9508	0.9560	0.9813	0.9534
Metal	0.9613	0.9560	0.9835	0.9587
Glass	0.9459	0.9615	0.9813	0.9537
Syringe	0.9669	0.9615	0.9857	0.9642
Average	0.9561	0.9560	0.9824	0.9560

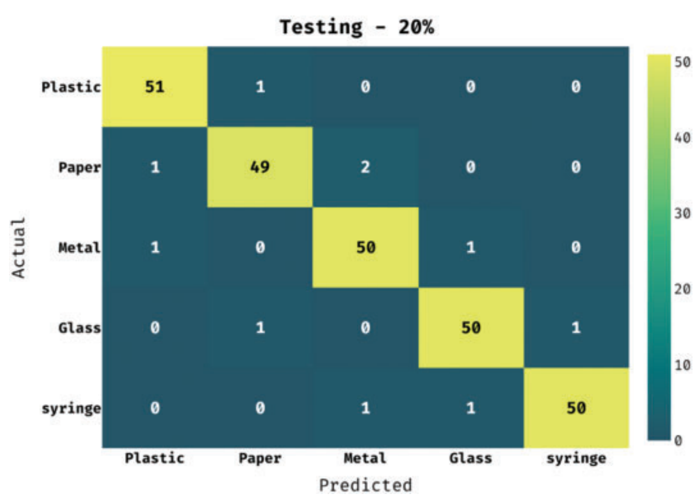

Figure 5: Confusion matrix of HWDC-EL model on training dataset (20%)

The classification results gained by the HWDC-EL method on the detection of multiple classes on the applied 20% of the training dataset are provided in Tab. 2. The outcomes exhibited that the HWDC-EL technique has categorized all the waste objects effectually. For instance, the HWDC-EL manner has identified the 'plastic' class with the $prec_s$ of 0.9623, rec_{ll} of 0.9808, acc_y of 0.9885, and F_{score} of 0.9714. Furthermore, the HWDC-EL system has identified the 'paper' class with the $prec_s$ of 0.9608, rec_{ll} of 0.9423, acc_y of 0.9808, and F_{score} of 0.9515. Afterward, the HWDC-EL algorithm has identified the 'metal' class with the $prec_s$ of 0.9434, rec_{ll} of 0.9615, accuracy of 0.9808, and F_{score} of 0.9524. Moreover, the HWDC-EL methodology has identified the 'glass' class with the $prec_s$ of 0.9615, rec_{ll} of 0.9615, acc_y of 0.9846, and F_{score} of 0.9615. Eventually, the HWDC-EL method has identified the 'syringe' class with the $prec_s$ of 0.9804, rec_{ll} of 0.9615, acc_y of 0.9885, and F_{score} of 0.9709. In overall, the HWDC-EL algorithm has gained an average $prec_s$ of 0.9617, rec_{ll} of 0.9615, acc_y of 0.9846, and F_{score} of 0.9615.

Table 2: Result analysis of HWDC-EL model with different classes on training dataset (20%)

Classes	Precision	Recall	Accuracy	F-Score
Plastic	0.9623	0.9808	0.9885	0.9714
Paper	0.9608	0.9423	0.9808	0.9515
Metal	0.9434	0.9615	0.9808	0.9524
Glass	0.9615	0.9615	0.9846	0.9615
Syringe	0.9804	0.9615	0.9885	0.9709
Average	0.9617	0.9615	0.9846	0.9615

Fig. 6 depicts the confusion matrix of the HWDC-EL manner on the applied 10% of training dataset. The figure demonstrated the HWDC-EL method has proficiently categorized 25 instances into Plastic, 26 instances into Paper, 24 instances into Metal, 25 instances into Glass, and 24 instances into Syringe.

The classification outcomes reached by the HWDC-EL method on the detection of multiple classes on the applied 10% of the training dataset are given in Tab. 3. The outcomes outperformed that the HWDC-EL method has categorized all the waste objects efficiently. For instance, the HWDC-EL algorithm has identified the 'plastic' class with the $prec_s$ of 0.9259, rec_{ll} of 0.9615, acc_y of 0.9769, and F-score of 0.9434. Likewise, the HWDC-EL approach has identified the 'paper' class with the $prec_s$ of 1.0000, rec_{ll} of 1.0000, acc_y of 1.0000, and F_{score} of 1.0000.

Also, the HWDC-EL method has identified the 'metal' class with the $prec_s$ of 1.0000, rec_{ll} of 0.9231, acc_y of 0.9846, and F_{score} of 0.9600. Similarly, the HWDC-EL technique has identified the 'glass' class with the $prec_s$ of 0.9259, rec_{ll} of 0.9615, acc_y of 0.9769, and F_{score} of 0.9434. Finally, the HWDC-EL methodology has identified the 'syringe' class with the $prec_s$ of 0.9231, rec_{ll} of 0.9231, acc_y of 0.9692, and F_{score} of 0.9231. In overall, the HWDC-EL approach has attained an average $prec_s$ of 0.9550, rec_{ll} of 0.9538, acc_y of 0.9815, and F_{score} of 0.9540.

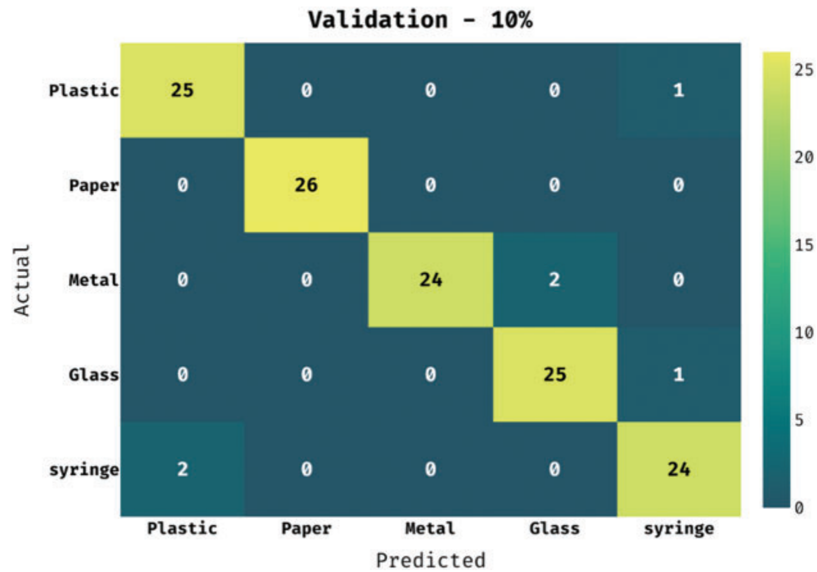

Figure 6: Confusion matrix of HWDC-EL model on training dataset (10%)

Table 3: Result analysis of HWDC-EL model with different classes on training dataset (10%)

Classes	Precision	Recall	Accuracy	F-Score
Plastic	0.9259	0.9615	0.9769	0.9434
Paper	1.0000	1.0000	1.0000	1.0000
Metal	1.0000	0.9231	0.9846	0.9600
Glass	0.9259	0.9615	0.9769	0.9434
Syringe	0.9231	0.9231	0.9692	0.9231
Average	0.9550	0.9538	0.9815	0.9540

Fig. 7 depicts the accuracy graph of the HWDC-EL method on the applied dataset. The figure depicted the HWDC-EL method has established an increasing training and validation accuracy. In addition, it is evident that the validation accuracy is superior to training accuracy.

Fig. 8 demonstrates the loss graph of the HWDC-EL technique on the applied dataset. The figure depicted the HWDC-EL technique has accomplished a reduced training and validation loss. Moreover, it is demonstrated the validation loss is lower compared to training loss.

The multi-class performance is converted into binary classes namely Hazardous and Non-hazardous waste. Fig. 9 shows the confusion matrices obtained by the HWDC-EL technique on binary classification process. On the applied training set of 70%, the HWDC-EL technique has effectually classified 179 instances into Hazardous and 721 instances into Non-hazardous waste. Moreover, on the applied training set of 20%, the HWDC-EL approach has effectively classified 51 instances into Hazardous and 206 instances into Non-hazardous waste. Furthermore, on the applied training set of 10%, the HWDC-EL methodology has efficiently classified 26 instances into Hazardous and 102 instances into Non-hazardous waste.

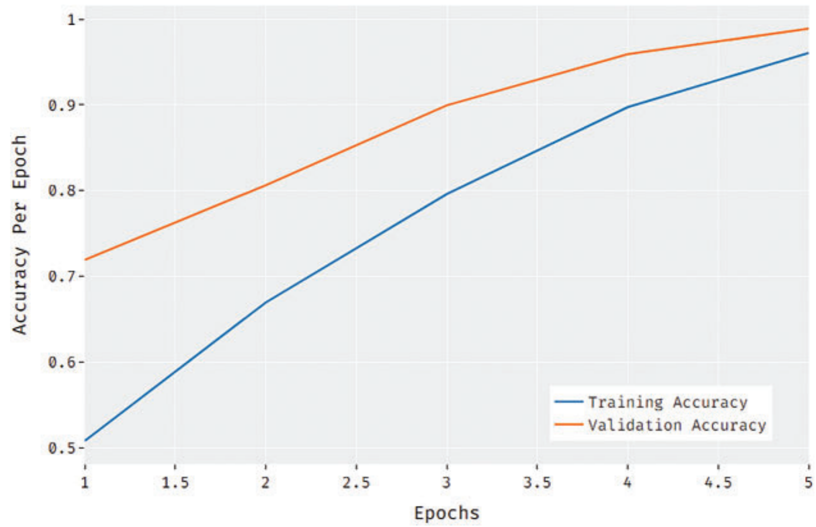

Figure 7: Accuracy analysis of HWDC-EL model

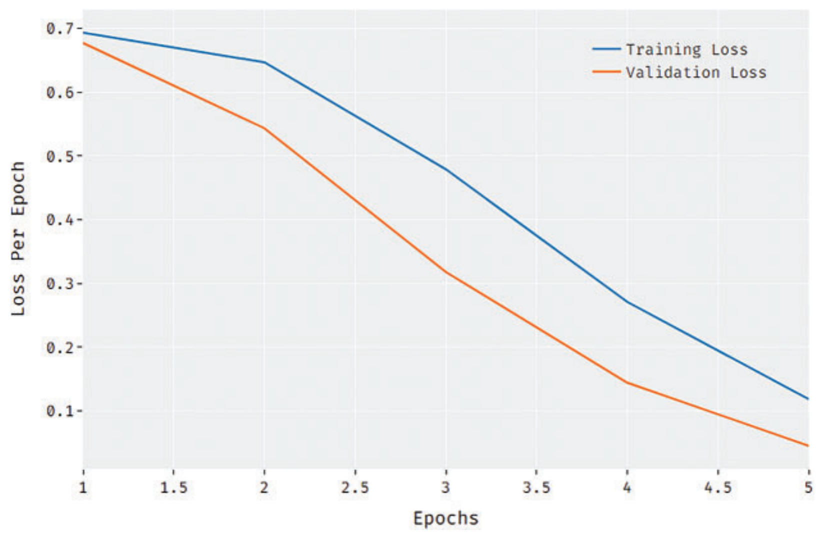

Figure 8: Loss analysis of HWDC-EL model

Tab. 4 grants the binary classification results analyses of the HWDC-EL method. On the training set, the HWDC-EL technique has obtained effective outcome with the recall of 0.9835, precision of 0.9624, F-score of 0.9728, and accuracy of 0.9890. Also, on the testing set, the HWDC-EL manner has gained effectual outcomes with the recall of 0.9808, precision of 0.9623, F-score of 0.9714, and accuracy of 0.9885. Besides, on the validation set, the HWDC-EL method has achieved efficient results with the recall of 1.0000, precision of 0.9286, F-score of 0.9630, and accuracy of 0.9846.

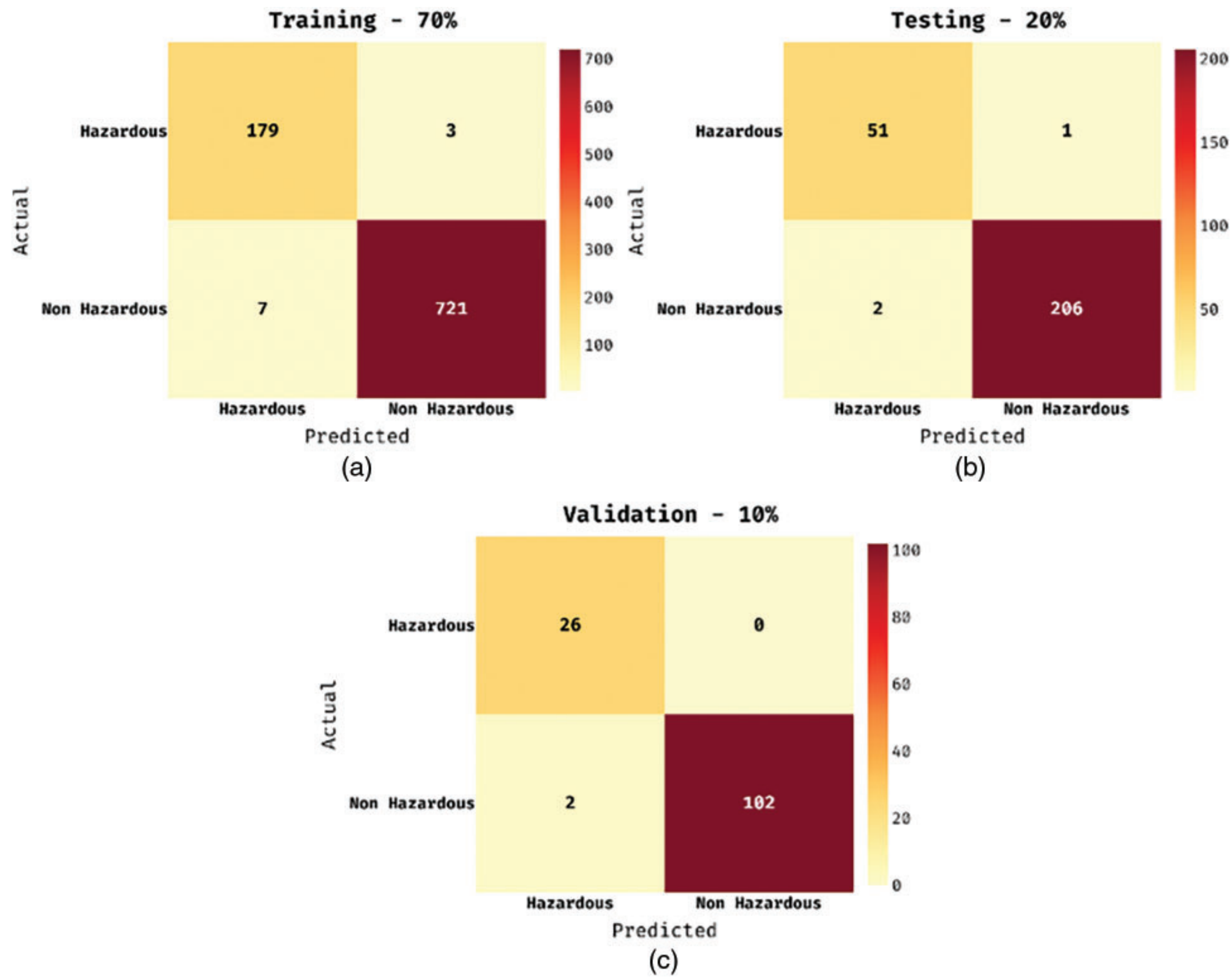

Figure 9: Multiclass analysis of HWDC-EL model

Table 4: Results of binary class on proposed HWDC-EL model

Dataset	Precision	Recall	Accuracy	F-Score
Training set	0.9624	0.9835	0.9890	0.9728
Testing set	0.9623	0.9808	0.9885	0.9714
Validation set	0.9286	1.0000	0.9846	0.9630

To assure the maximum classification performances of the HWDC-EL method, a brief comparison study is made in Fig. 10. The presented HWDC-EL technique has resulted in a maximum accuracy of 98.46% and 98.85% on the classification of multiclass and binary classes respectively. The HWDC-EL method has achieved maximum classification performances and was a proper tool for hazardous waste classification.

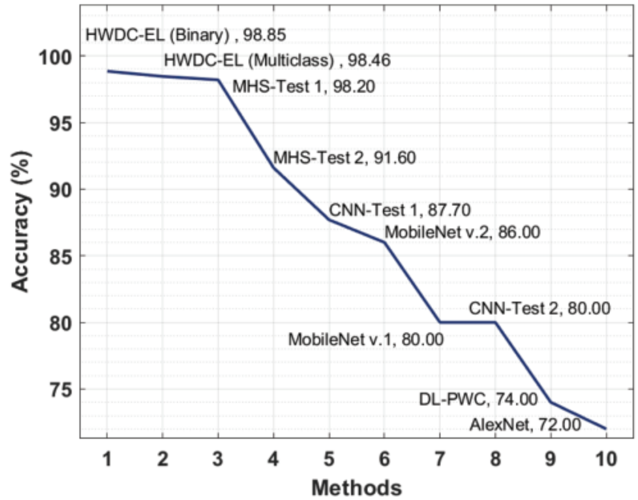

Figure 10: Accuracy analysis of HWDC-EL model with existing approaches

5 Conclusion

In this study, a new HWDC-EL system is derived for hazardous waste detection and classification. The HWDC-EL technique intends to detect the multiple classes of wastes, particularly hazardous and non-hazardous wastes. The HWDC-EL technique has derived an ensemble of feature extraction processes namely DLBP, EfficientNet, and DenseNet121. Moreover, hyperparameter optimization of EfficientNet and DenseNet121 algorithms takes place using FPA. Finally, a weighted voting based ensemble classifier is derived using SVM, ELM, and GBT models. The experimental validation of the HWDC-EL technique is validated by the use of a benchmark Garbage dataset and the results are inspected interms of diverse aspects. In future, the presented HWDC-EL technique was extended to the design of waste collection scheduling and route planning approaches.

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