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Artificial intelligence with earthworm optimization assisted waste management system for smart cities

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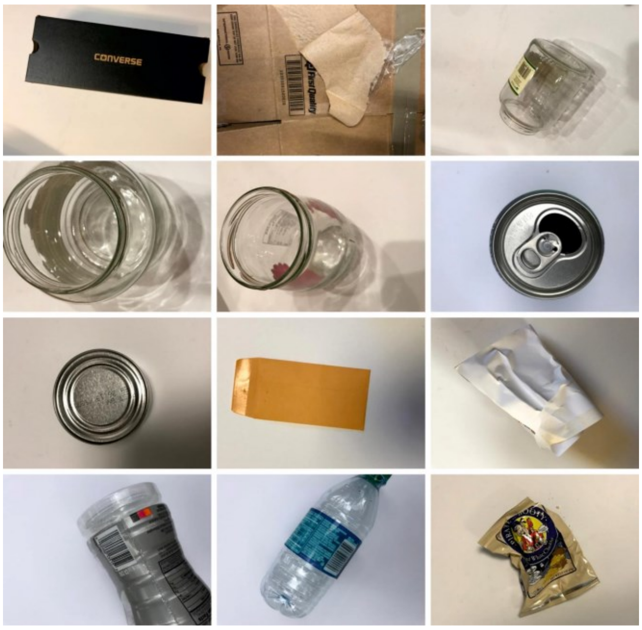
Graphical abstract



Abstract

In recent days, massive quantity of waste materials gets considerable increased with increasing population. Proper management of waste materials becomes essential to reduce environmental degradation and improve quality of life in smart cities. Waste management helps to collect and treat waste materials from society. Smart waste management is a new frontier for local authorities assisting in reducing municipal solid waste and improving community recycling rate. Appropriate classification of waste objects necessitates the design of automated waste classification models based on artificial intelligence (AI) and computer vision (CV) based approaches. With this motivation, in this study, an automated artificial intelligence with earth worm optimization assisted waste management and classification (AIEWO-WMC) model is proposed for smart city environment. The proposed technique intends to recognize and categorize waste objects using the DL techniques. The proposed model primarily derives a RetinaNet based object detection module to identify the existence of waste objects in the images. To improve the classification performance, Adagrad optimizer is applied. Moreover, earthworm optimization with stacked autoencoder (SAE) algorithm is applied for the classification of waste objects. To assuring the improvised results of the AIEWO-WMC technique, comprehensive experimentation is performed on standard dataset and the obtained values indicated the supremacy of AIEWO-WMC model over the other techniques with increased accuracy of 99.15%.

Keywords: Computer vision, smart city, stacked auto encoder; parameter tuning; artificial intelligence, retinanet, waste management, deep learning

1. Introduction

In smart cities, the plan of insightful waste administration is another fringe for neighborhood specialists meaning to limit civil strong waste and further develop local area reusing rate. Since cities spent significant expenses for overseeing waste openly puts, smart city waste administration programs bring about improved execution (Vishnu etal., 2021). The fast blast in urbanization, worldwide populace rate, and industrialization have acquired thought, related to climate corruption. With the worldwide populace developing at a disturbing rate, there has been horrendous corruption of the conditions, bringing about astounding circumstances. As indicated by the report (2019), India annually produces north of sixty two million tons (MT) of strong waste (Abuga and Raghava, 2021). The worry was expanded towards the need for isolation of waste based on biodegradable and non-biodegradable ways of behaving (Cheela *et al.*, 2021).

The waste management framework prevalently verifies the removal and treatment of various kinds of waste. In this way, it shields people, creatures, and environmental factors (Shah *et al.*, 2021). Sufficient waste administration methods can set aside much cash, which will prompt better air quality and less natural contamination. All the while, the high level locales are finding and carrying out a few productive methods for effective waste adminis-tration and thinking of colossal valuable outcomes (Aithal, 2021). It will be difficult to oversee such an immense measure of waste in the forthcoming five years under the current circumstance. In this manner, it is smarter to make every one of the fundamental moves expected for the powerful administration of waste. Hence, we should take on the best procedures and practices to treat waste proficiently to have sound climate (Roshan and Rishi, 2021). Successful waste isolation will uphold the fitting reusing and removal of this waste as indicated by its biodegradability. Along these lines, present day times direct the advancement of a smart waste isolation plot for suggesting the previously mentioned reason for natural remains. The isolation of wastes is consequently, looking for thought from a few academicians and scientists all over the planet.

Reusing frameworks could create more successful outcomes by staying aware of modern turn of events. In this framework, the decay of waste is yet in view of human variables (Murugesan *et al.*, 2021). Be that as it may, the improvements in deep learning engineering and man-made brainpower innovation could prompt upgrading framework usefulness over human elements before long. In particular, human cerebrum control framework could be effectively and immediately communicated to the machine with artificial intelligence (AI) system. In these turns of events, it very well may be inevitable that reusing frameworks relying upon deep learning (DL) systems could be utilized in the waste grouping (Akbarpour *et al.*, 2021). The traditional waste arrangement depends to a great extent on manual choices, be that as it may, the weaknesses are inefficacy. Despite the fact that the current waste arrangement driven by Machine Learning (ML) strategies could work really, the order execution should be upgraded. By examining the current waste arrangement strategy relying upon deep learning technique, 2 potential explanations prompt the intricacy of upgrading the order execution (Zhang *et al.*, 2021; Kshirsagar *et al.*, 2021). At first, due to the unmistakable systems of DL strategies, they act in an alternate way on numerous datasets.

In this study, a novel AIEWO-WMC model is proposed for smart city environment, which mainly aims to recognize and categorize waste objects using the DL techniques. The proposed model primarily derives a RetinaNet based object detection module to identify the existence of waste objects in the images. To improve the classification performance, Adagrad optimizer is applied. Moreover, EWO algorithm with stacked autoencoder (SAE) model is exploited for waste object classification. To assuring the improvised results of the AIEWO-WMC technique, comprehensive experimentation is performed on standard dataset and the obtained values indicated the supremacy of AIEWO-WMC model over the other techniques.

2. Related works

In (Ali *et al.*, 2020), a novel IoT enabled intelligent waste management model has been developed. The developed framework assists with tackling the issues related to the executives of waste material and the IoT-based waste assortment for the smart city as examined previously. The presented framework can the assortment of waste successfully, location of fire in waste material, and estimate upcoming waste. In (Marques *et al.*, 2019), a multi-level IoT enabled waste management model is developed smart city management system is projected and challenge is employed as research to estimate the accuracy of the suggested technique. Outcomes demonstrated the idea of the framework, showing that it is capable of managing over 3902 waste bins at the same time. Cerchecci *et al.* (Cerchecci *et al.*, 2018) center around the acknowledgment of an IoT engineering to streamline waste administration with regard to Smart Cities. Specifically, an original typology of sensor hub in view of the utilization of minimal expense and low power parts is depicted.

Idwan *et al.* (Idwan *et al.*, 2020) reproduced a two-venture heuristic calculation of numerous trucks directing calculation to find the ideal course for the administration waste armada, utilizing smart dumpsters and specialist-based models. The smart dumpsters are outfitted with the sensors that action levels of waste and a regulator to send updates to the focal administration framework utilizing remote organization. Our objective is to further develop the waste assortment process by decreasing the clog out and about, the assistance time spent, and the general excursion length. AnhKhoa *et al.* (AnhKhoa *et al.*, 2020) proposed genuine grounds of Ton Duc Thang University (Vietnam) to assess the practicability and presentation of the framework performance. We inspect information moves on the LoRa and show the upsides of the presented architecture, which is carried out over a straightforward circuit planned with supplant capacity, less expense, and convenience. Our architecture saves time by tracing the finest course in the management of waste assortment.

Though several ML and DL models for waste classification are available in the literature, it is still needed to enhance the classification performance. Owing to continual deepening of the model, the number of parameters of DL models also increases quickly which results in model overfitting. At the same time, different hyperparameters have a significant impact on the efficiency of the CNN model. Particularly, the hyperparameters such as epoch count, batch size, and learning rate selection are essential to attain effectual outcome. Since the trial and error method for hyperparameter tuning is a tedious and erroneous process, Adagrad optimizer is employed in this work.

3. The proposed model

In this study, a novel AIEWO-WMC model is proposed for smart city environment, which mainly aims to recognize and categorize waste objects using the DL techniques. The proposed model primarily derives an Adagrad optimizer with RetinaNet based object detection module to identify the existence of waste objects in the images. Furthermore, EWO with SAE modelsisexploited for waste objectclassification.

3.1. Waste object detection using RetinaNet model

Primarily, the RetinaNet model has been developed for the identification and categorization of waste objects in the smart city environment (Wang *et al.*, 2019). The RetinaNet structure is comprised of feature pyramid network (FPN) detection backend and backbone. First, the image is processed by the backbone which generally is the ResNet structure. Now, it is noted to inform that even though MobileNet efficiency is on a bar with ResNet in the classification task, it is not accurate that MobileNet is a correspondence replacement for ResNet. From this assumption, utilizing MobileNet (Wang *et al.*, 2019) as a backbone for recognition process suffers from higher precision drop when compared to the classification. The major reason is that the confidence score of MobileNet-based backbone is minimized by trading off with low computational cost. Thus, it won't be a necessary selection of the backbone for higher accuracy object recognition network. The backbone and the subsequent FPN format an encoder-decoder-like network. The advantage of the FPN is that it combines the feature of successive layers from the coarsest to the optimum level that efficiently propagates the feature in distinct levels and scales to the following layer. Next, the multi-scale pyramid feature (P3-P7) is fed into the back-end in which two detection branches are utilized for object classification and bounding box regression. It should be noted that the bounding box and detective branches don't share weights. The weight of branch is distributed over the pyramid feature (P3-P7).

To successfully modify the hyperparameter involved in the RetinaNet model, the Adagrad optimizer is applied. Adagrad is a gradient-based optimization approach that adopts the learning rate to the parameter. Ada- grad enhanced significantly of SGD and utilized it to train largescale neural networks at Google. Then, gradient of objective function is represented as $g_{i,j}$, regarding the variable θ_i at time step t

$$g_{t,i} = \nabla_\theta J(\theta) \tag{1}$$

The SGD upgrade for each variable θ_i at each time step t become:

$$\theta_{t+1,i} = \theta_{i,j} - \alpha . g_{t,i} \tag{2}$$

In the upgrade rule, Adagrad adapts the learning rate at t time for all the variables θ_i according to the historical gradient that is estimated in the following:

$$\theta_{t+1,i} = \theta_{i,j} - \frac{\alpha}{\sqrt{G_{t,ii} + \varepsilon}} . g_{t,i} \tag{3}$$

$G_t \in R^{d \times d}$ represent a diagonal matrix in which all the diagonal elements i,i denotes the amount of the squares of the gradient regarding θ_i up to time step t, whereas ε indicates a smoothing term that evades division by zero. Figure 1 demonstrates the architecture of RetinaNet.

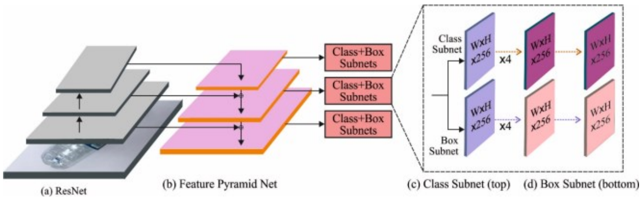


Figure 1. Structure of RetinaNet

3.2. Waste object classification using SAE

For proper identification and classification of waste objects, the SAE model is applied (Li *et al.*, 2016). The SAE is one of the deep learning techniques, commonly utilized in various fields, namely computer vision and traffic control (Li *et al.*, 2016). The SAE is considered unsupervised learning of information. It captures the inherent representation of the information by implementing the two-phase stochastic gradient method, viz., supervised finetune training, and unsupervised pre-training. The previous is utilized for initializing the biases and weights of hidden states to avoid the DL method from convergence to the local extremal. The last is utilized for training the weight and bias to attain the last feature of the input information. Assumed the data $\{(\chi^{(1)}, y^{(1)}), (x^{(k)}, y^{(k)})\}$, hidden layer h^i is attained from the autoencoder AE^i. In the AE^i, the input feature I^i is encoded as follows:

$$a^i = f(W_e^i I^i + b_e^i) \tag{4}$$

Whereas a^i denotes the activation, f indicates the nonlinear function, viz., the the *ReLU* and sigmoid function, b_e^i denotes the encoder bias vector, and W_e^i indicates the encoder weight viz. utilized for initializing the weight of theh^i hidden layer.Next, the activation is decoded to the output feature as follows:

$$O^i = f(W_d^i a^i + b_d^i) \tag{5}$$

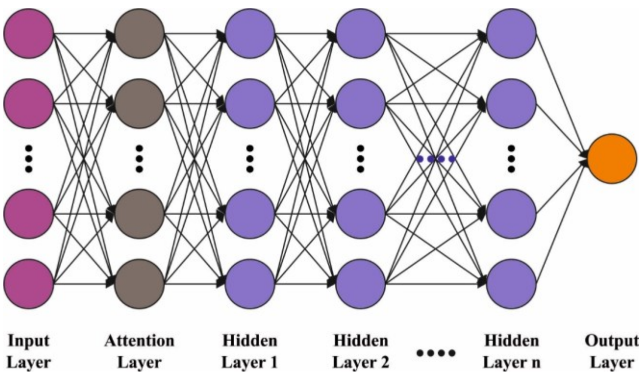


Figure 2. Framework of Stacked AutoEncoder

In which O^i denotes the activation, f indicates the non-linear function, b^i_e represent the decoder bias vector, and W_d^i signifies the decoder weight. Afterward the unsupervised pretraining of hidden layer, the deep structure stacked by the pretrained layer is trained on the labelled instance. The training can be implemented in a supervised manner for minimizing the overall loss function, namely the cross-entropy cost function and the squared error function. Even though the SAE has accomplished advanced performance, there are no strong actions to handle the uncertainty in the DL method. Here, the Bayesian model is developed for training the parameter that considers the uncertainties. Figure 2 showcases the framework of SAE.

3.3. Parameter optimization using EWO algorithm

In order to effectually tune the SAE parameters, the EWO algorithm has been exploited (Ghosh and Roy, 2019). The EWO technique was utilized that is simulated in the reproductive procedure of earthworms (EW) to resolve optimized issues. The EW is a type of hermaphrodite and executes at all of them applyingfemale and male sex organs. Therefore, the sole parent EW generates a child EW by themselves. The reproduction_1 is determined as:

$$u_{i1,k} = u_{max,k} + u_{min,k} - \alpha u_{i,k} \tag{6}$$

The above equations describe the procedure of generating k^{th} element of child's EW *i1* in parent EW $i.u_{i1,k}$ and $u_{i,k}$ implies the k^{th} element of EW *i1* and $i.u_{max,k}$ and $u_{min,k}$ represents the effectual restriction of k^{th} element of every EW. α signifies the similarity factor which lies amongst zero and one, and it determines the movement in parents to child EW.

The Reproduction_2 employs an improved kind of crossover operator. Let, *M* be the amount of child EWs and it is 2, or 3 in most properties. The count of parent EWs (*N*) is any integer that is higher than 1. Uniform crossover was applied with *N*=2 and *M*=1. In 2 parent EWs P_1 and P_2 are chosen to employ roulette wheel chosen. It can be expressed as:

$$P = \begin{bmatrix} P_1 \\ P_2 \end{bmatrix} \tag{7}$$

Primarily, 2 offspring U_{12} and U_{22} are generated in 2 parents. *rand*arbitrary integer rangesfrom zero to one is complete and K^{th} element of U_{12} and U_{22} are generated as:

If $rand > 0.5$,

$$u_{12,k} = P_{1,k} \tag{8}$$

$$u_{22,k} = P_{2,k}$$

Then,

$$u_{12,k} = P_{2,k} \tag{9}$$

$$u_{22,k} = P_{1,k}$$

Lastly, the generated EW U_{12} in Reproduction-2 are demonstrated as (10). Consider that *rand*1 be another arbitrarynumber generated amongst zero and one.

$$u_{i2} = \begin{cases} u_{12} for rand1 < 0.5 \\ u_{22} else \end{cases} \tag{10}$$

Next, the generating EWs U_{i1} and U_{i2}, the EW U_i for next generation was calculated as:

$$u_i' = \beta u_{i1} + (1-\beta) u_{i2} \tag{11}$$

whereas β is termed as "proportional factor". It is employed to manipulate the proportion of u_{i1} and u_{i2} that global and local searching efficiency was recollected from balancing. It is offered as:

$$\beta^{t+1} = \gamma \beta^t \tag{12}$$

In which t signifies the current generation. Primarily at *t=0*, $\beta = 1$. γ implies the parameter that is outcome of cooling factor. The solution needs to exist run-away in local optimal. Thus, the "Cauchy Mutation" (CM) is executed. It improved the search capability of "EWO". The CM operator was determined under.

$$W_k = \left(\sum_{i=1}^{N_{pop}} u_{i,k} \right) / N_{pop} \tag{13}$$

whereas, W_k represents the weighted vector for K_{th} element of population *i* and N_{pop} implies the population size. The K^{th} element of last EW progresses:

$$u_i'' = u_i' + W_k * Cd \tag{14}$$

Here, *Cd* refers to the arbitrary number which is drawn in "Cauchy distribution" concerning =1. At the present, τ denotes the "scale parameter".

The EWO techniquemostlydescribes a fitness value to accomplish maximal classifier outcomes. It calculates a positive integer to illustratebetter results on the candidate solution. Now, decreasing the classification error rate istreated as the fitness function. The optimal solution holds minimum error rate and poorly achieved solutionsprovide highest error rate.

$$\begin{aligned} &fitness(x_i) = ClassifierErrorRate(x_i) \\ &= \frac{number\ of\ misclassified\ samples}{Total\ number\ of\ samples} * 100 \end{aligned} \tag{15}$$

4. Experimental validation

The proposed model is simulated using Python 3.6.5 tool on PC i5-8600k, GeForce 1050Ti 4GB, 16GB RAM, 250GB SSD, and 1TB HDD. The parameter settings are given as follows: learning rate: 0.01, dropout: 0.5, batch size: 5, epoch count: 50, and activation: ReLU.

The performance validation of the AIEWO-WMC model on the identification and classification of waste objects take place using a benchmark dataset from Kaggle repository (available at https://www.kaggle.com/asdasdasasdas/garbage-classification). The dataset holds instances under six class labels. Sample images are exemplified in Figure 3.

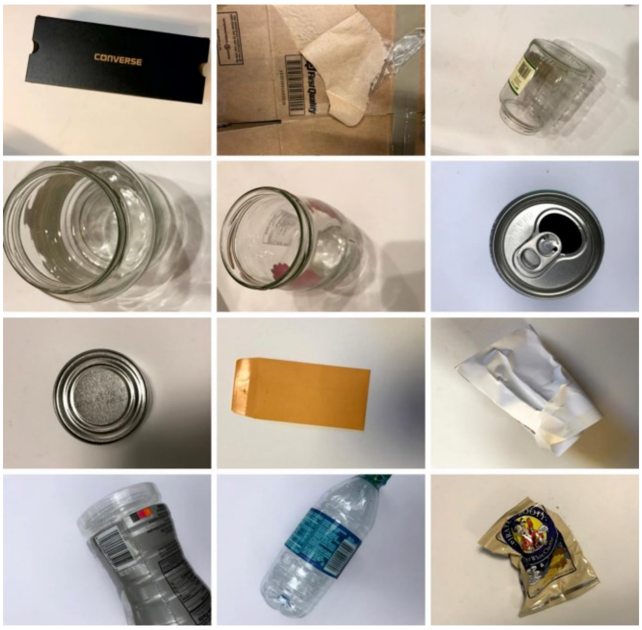


Figure 3. Sample Images

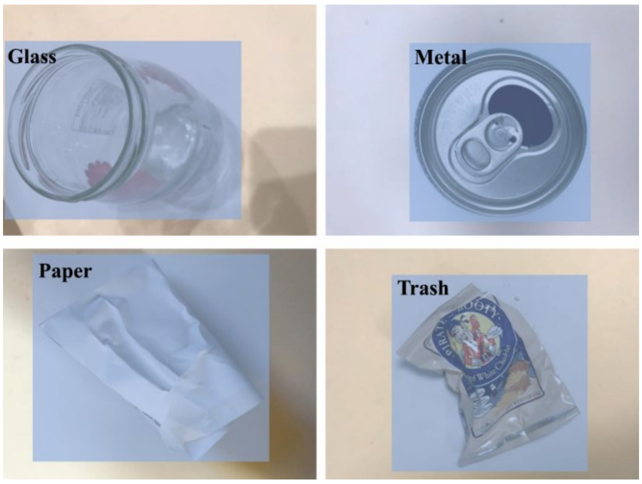


Figure 4. Visualization of Detected Objects

Figure 4 visualizes the results offered by the AIEWO-WMC model on the identification and classification of waste objects.

A set of three confusion matrices produced by the AIEWO-WMC model on the classification of waste objects is shown in Figure 5. The results implied that the AIEWO-WMC model has categorized all the objects effectively. For instance, on entire dataset, the AIEWO-WMC model has identified 396 instances into cardboard, 191 instances into glass, 400 instances into metal, 494 instances into paper, 473 instances into plastic, and 135 instances into thrash. In line with, 70% of training dataset, the AIEWO-WMC methodology has recognized 278 instances into cardboard, 327 instances into glass, 277 instances into metal, 355 instances into paper, 341 instances into plastic, and 90 instances into thrash. Along with that, on 30% of testing dataset, the AIEWO-WMC system has identified 118 instances into cardboard, 164 instances into glass, 123 instances into metal, 139 instances into paper, 132 instances into plastic, and 45 instances into thrash.

Table 1 and Figure 6 indicate the overall waste classification outcomes of the AIEWO-WMC method with distinct sizes of datasets. The experimentation result inferred the effective ability of the AIEWO-WMC model. For instance, with entire dataset, the AIEWO-WMC model has provided average $accu_y$, $prec_n$, $reca_l$, $spec_y$, and F_{score} of 99.34%, 97.67%, 98.09%, 99.60%, and 97.87% respectively. Along with that, with 70% of training dataset, the AIEWO-WMC algorithm has offered average $accu_y$, $prec_n$, $reca_l$, $spec_y$, and F_{score} of 99.28%, 97.45%, 97.83%, 99.56%, and 97.64% respectively. In line, with 30% of testing dataset, the AIEWO-WMC method has given average $accu_y$, $prec_n$, $reca_l$, $spec_y$, and F_{score} of 99.50%, 98.13%, 98.64%, 99.70%, and 98.37% correspondingly.

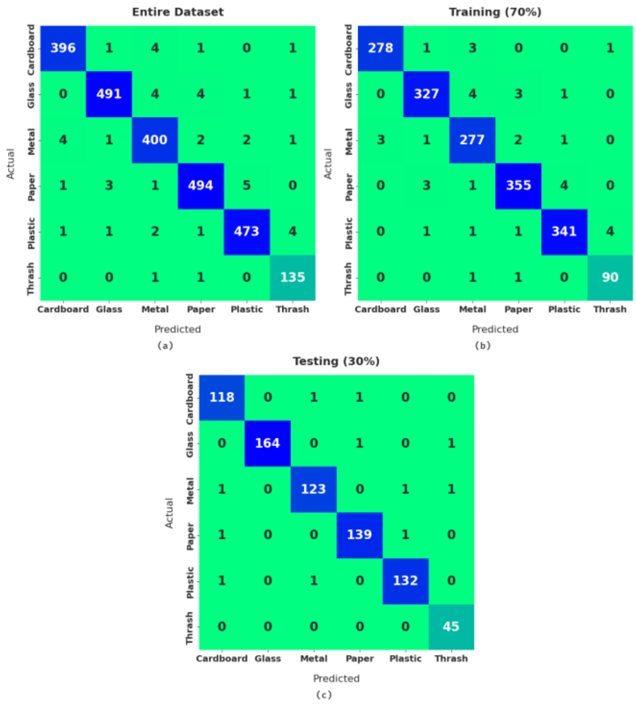


Figure 5. Confusion matrix of AIEWO-WMC technique under three datasets

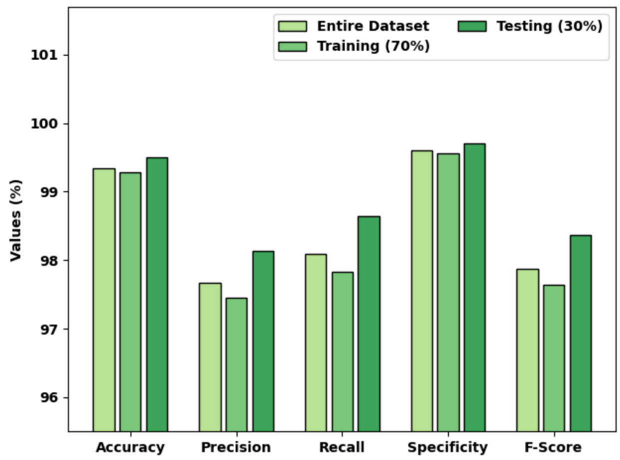


Figure 6. Result analysis of AIEWO-WMC technique with distinct measures

Figure 7 validates the training accuracy (TA) and validation accuracy (VA) offered by the AIEWO-WMC model. The figure exposed that the AIEWO-WMC approach has provided closer TA and VA values with an increase in epoch count. It is observable that the VA is certainly higher than TA.

Table 1. Result analysis of AIEWO-WMC technique with distinct measures

Classes	Accuracy	Precision	Recall	Specificity	F-Score
Entire Dataset					
Class 1	99.47	98.51	98.26	99.71	98.39
Class 2	99.34	98.79	98.00	99.69	98.40
Class 3	99.10	97.09	97.56	99.41	97.32
Class 4	99.22	98.21	98.02	99.53	98.11
Class 5	99.30	98.34	98.13	99.59	98.23
Class 6	99.63	95.07	98.54	99.70	96.77
Average	**99.34**	**97.67**	**98.09**	**99.60**	**97.87**
Training (70%)					
Class 1	99.53	98.93	98.23	99.79	98.58
Class 2	99.18	98.20	97.61	99.56	97.90
Class 3	99.00	96.52	97.54	99.30	97.02
Class 4	99.12	98.07	97.80	99.48	97.93
Class 5	99.24	98.27	97.99	99.56	98.13
Class 6	99.59	94.74	97.83	99.69	96.26
Average	**99.28**	**97.45**	**97.83**	**99.56**	**97.64**
Testing (30%)					
Class 1	99.32	97.52	98.33	99.51	97.93
Class 2	99.73	100.00	98.80	100.00	99.39
Class 3	99.32	98.40	97.62	99.67	98.01
Class 4	99.45	98.58	98.58	99.66	98.58
Class 5	99.45	98.51	98.51	99.67	98.51
Class 6	99.73	95.74	100.00	99.71	97.83
Average	**99.50**	**98.13**	**98.64**	**99.70**	**98.37**

Table 2. Comparative analysis of AIEWO-WMC approach with existing methods

Methods	Accuracy	Precision	Recall	Specificity	F-Score
IDRL-RWODC	99.15	97.40	93.23	92.15	90.26
CNN-MobileNetV2	88.66	97.43	92.39	96.85	91.74
CNN-VGG-16	88.04	96.40	92.33	90.31	91.96
CNN-ResNet50	86.26	97.31	90.25	92.43	89.41
CNN-RecycleNetV4	80.69	96.92	93.01	98.12	90.51
CNN-DenseNet121	94.60	97.32	94.05	90.37	88.97
AIEWO-WMC	99.50	98.13	98.64	99.70	98.37

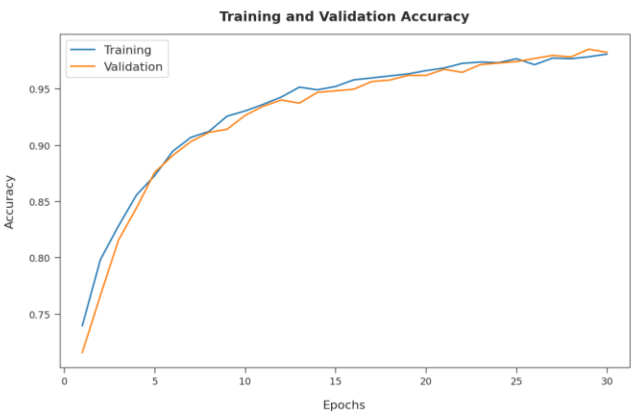


Figure 7. Accuracy graph analysis of AIEWO-WMC technique

Figure 8 depicts the training loss (TL) and validation loss (VL) provided by the AIEWO-WMC approach. The figure revealed that the AIEWO-WMC model has delivered lesser TL and VL with an increase in epoch count. It can be noticeable that the VL is lesser compared to TL.

Figure 9 illustrates the precision-recall analysis of the AIEWO-WMC technique. The figure designated that the AIEWO-WMC methodology has accomplished maximal precision-recall values on the distinct class labels.

Figure 10 demonstrates the ROC assessment of the AIEWO-WMC mode. The figure shows that the AIEWO-WMC method has gained improved ROC values on the distinct class labels.

A brief comparative examination of the AIEWO-WMC model with existing techniques is depicted in Table 2 (Duhayyim et al, 2022). Figure 11 provides a detailed comparative study of the proposed with existing models interms of $accu_y$. The obtained results showed that the CNN-RecycleNetV4 model has showcased lower performance with $accu_y$ of 80.69. At the same time, the

CNN-MobileNetV2, CNN-VGG-16, and CNN-ResNet50 models have resulted in moderate $accu_y$ of 88.66%, 88.04%, and 86.26% respectively. Though the IDRL-RWODC model has accomplished reasonable $accu_y$ of 99.15%, the AIEWO-WMC model has accomplished superior $accu_y$ of 99.50%.

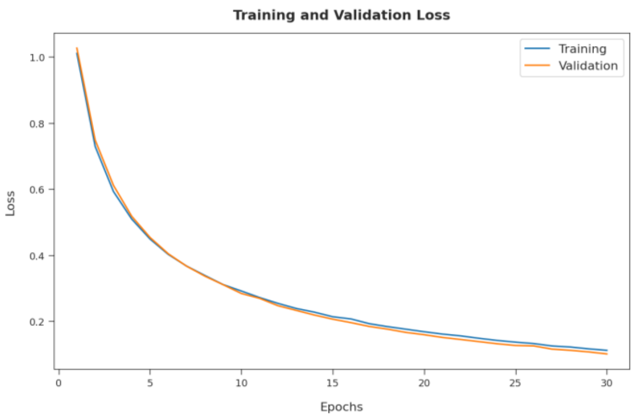


Figure 8. Loss graph analysis of AIEWO-WMC technique

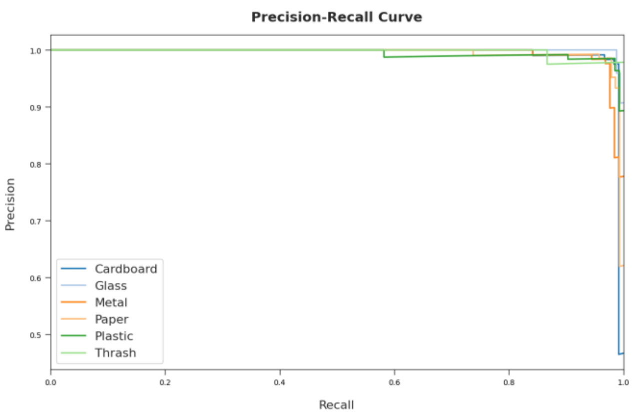


Figure 9. Precision-recall graph analysis of AIEWO-WMC technique

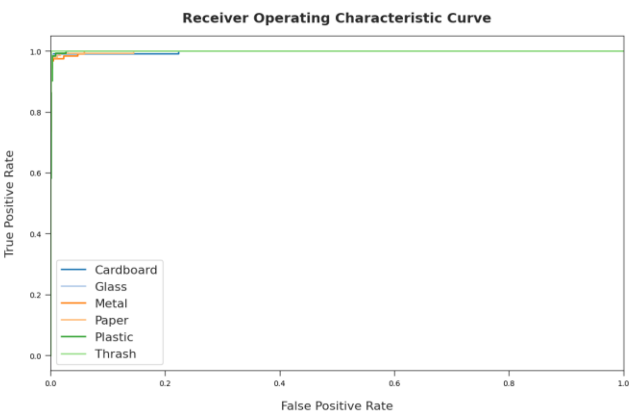


Figure 10. ROC curve analysis of AIEWO-WMC technique

Figure 12 reports an extensive comparative study of the AIEWO-WMC model with different models interms of $prec_n$ and $reca_l$. The figure portrayed that the CNN-VGG-16 and CNN-RecycleNetV4 models have shown poor outcomes with least values of $prec_n$ and $reca_l$. At the same time, the IDRL-RWODC, CNN-MobileNetV2, CNN-ResNet50, and CNN-DenseNet121 models have reached moderately closer values of $prec_n$ and $reca_l$. However, the AIEWO-WMC model has resulted in superior performance with maximum $prec_n$ and $reca_l$ values of 98.13% and 98.64% respectively.

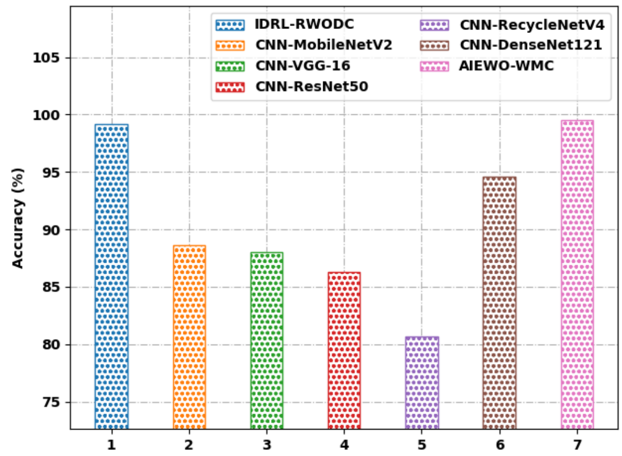


Figure 11. Comparative $accu_y$ analysis of AIEWO-WMC approach with existing methods

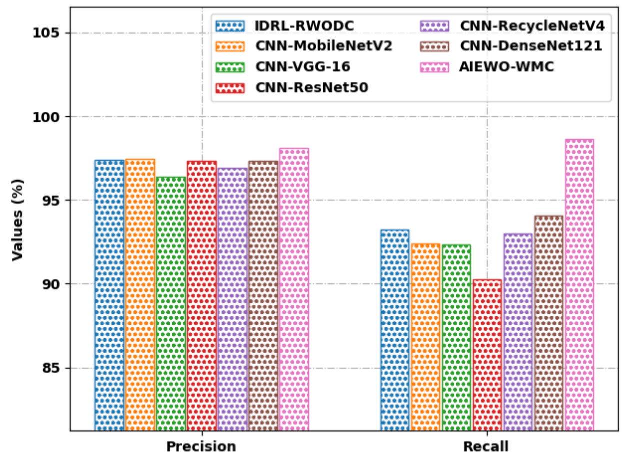


Figure 12. Comparative $prec_n$ and $reca_l$ analysis of AIEWO-WMC approach with existing methods

Figure 13 provides a comprehensive comparative study of the AIEWO-WMC model with existing approaches interms of $spec_y$ and F_{score}. The figure depicted that the CNN-DenseNet121, CNN-VGG-16, and CNN-ResNet50 models have exposed lower values of $spec_y$ and F_{score}. Meanwhile, the IDRL-RWODC, CNN-MobileNetV2, and CNN-RecycleNetV4 models have accomplished considerably nearer values of $spec_y$ and F_{score}. But the AIEWO-WMC model has accomplished better outcomes with higher $spec_y$ and F_{score} values of 99.70% and 98.37% respectively. These results ensured the enhanced performance of the AIEWO-WMC algorithm over the other recent methodologies.

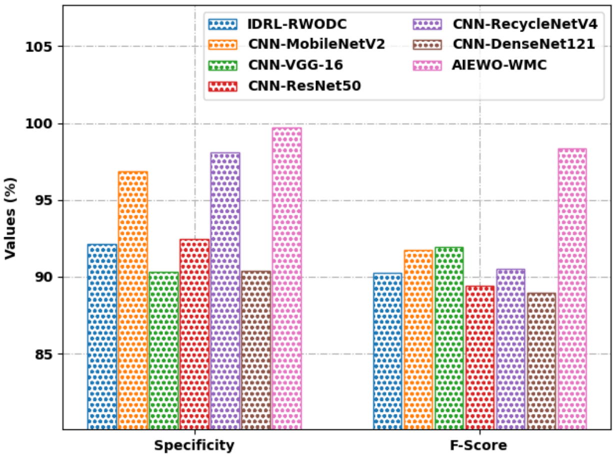


Figure 13. Comparative $spec_y$ and F_{score} analysis of AIEWO-WMC approach with existing methods

5. Conclusion

In this study, a novel AIEWO-WMC model is proposed for smart city environment, which mainly aims to recognize and categorize waste objects using the DL techniques. The proposed model primarily derives an Adagrad optimizer with RetinaNet based object detection module to identify the existence of waste objects in the images. Furthermore, EWO algorithm with SAE algorithm is exploited for waste objectclassification. To assuring the improvised results of the AIEWO-WMC technique, comprehensive experimentation is performed on standard dataset and the obtained values indicated the supremacy of AIEWO-WMC model over the other techniques. Thus, the AIEWO-WMC model can be treated as a powerful tool for waste management in smart city environment. In the future, hybrid DL algorithm can be derived to enhance the waste object detection efficacy.

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