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Internet of things enabled smart solid waste management system

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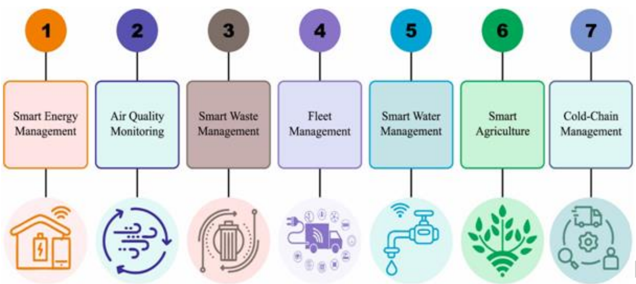
Graphical abstract



Abstract

The Internet of Things (IoT) paradigm roles a crucial play to enhance smart city applications by controlling and tracking city procedures in real-time. Among the most important problems connected to smart city application is solid waste management that is a negative impression on our people's health and environment. The standard garbage management procedure starts with waste generated by city populations and garbage removal bins at the source. Smart waste management utilizing IoT contains for instance analytics and group of data in sensors on smart garbage bins (SGBs), management of waste trucks and city structure, formation and optimization of garbage truck routes, and so on. This study introduces an Elitist Barnacles Mating Optimizer with Hybrid Deep Learning Model for waste classification (EBMOHDL-WC) in the IoT enabled sustainable environment. The presented EBMOHDL-WC system allows the IoT devices to proceed data collection process. Next, the EBMOHDL-WC technique uses MobileNetv2 model for extracting features and the hyperparameter adjustment of the MobileNetv2 technique was implemented by the EBMO technique, showing the novelty of the work. Finally, the waste classification procedure is performed using HDL classifier which integrates two DL models. The experimental evaluation of the EBMOHDL-WC technique is tested on garbage classification dataset from Kaggle repository. Experimentation outcomes of the EBMOHDL-WC technique exhibit competitive results over other techniques.

Keywords: Sustainability, waste management, smart city, deep learning, internet of things, barnacle mating optimizer

1. Introduction

The Internet of Things (IoT) is an ever-growing network of internet-connected devices that are presently being used globally. Notwithstanding the recent COVID-19 outbreak, the IoT industry was expanding, and it can be expected that approximately thirty billion IoT connection would be existed by 2025 (Dubey *et al.*, 2020). Modern smart sensors, big data, cloud computing (CC), web development tools, lightweight transmission protocols, and publicly-available server programs are the allowing technology that speeds up the deployment and development of domain-specific IoT systems (Sarc *et al.*, 2019). This interconnected device bridges the gap betwixt the digital and physical worlds to improve productivity, culture, and lifestyle. IoT is previously shown promising approaches toward domain-specific applications like Smart Grids, Smart Homes, Smart Cities, Agriculture, Wearables, Smart Supply chain Management, and Industrial Internet Telehealth. IoT has played a vital role in increasing smart city applications by real-time management and monitoring of city processes (Lin *et al.*, 2022). The major problem related to the smart city application is the disposal of solid waste that impact the nature and health of society. Solid waste can be generated due to animal and human activities and is usually thrown away as waste (Khoa *et al.*, 2020). Around 2.01 billion tons of urban solid waste are annually produced in the world, with minimum of 33% not being managed in an ecologically friendly way. Figure 1 depicts the overview of IoT-based sustainable applications.

The typical waste management technique initiates with garbage being disposed of in garbage dumps and produced by residents in cities at the point of construction (Viswanathan *et al.*, 2022). Corporations and Municipalities are struggling to maintain the outside bins to decide whether they are completely filled or not or when to clean them (Zhang *et al.*, 2019). The most serious problems of our time are the treatment, prevention, and tracking of those garbage's (Fayomi *et al.*, 2021). The traditional way of manually checking garbage in trash bins is a laborious process that needs more time, and money, and human labor is disregarded with current technology. Smart waste management (SWM) plays a crucial part in the smart city, and it needs a complex multi-criteria technique (Nowakowski. and Pamuła, 2020).

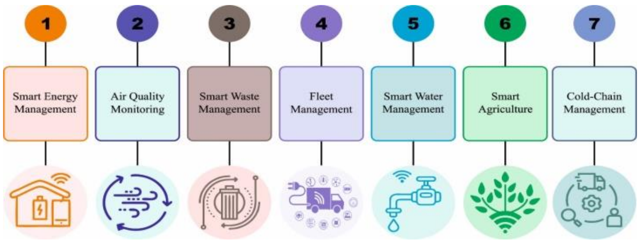


Figure 1. IoT based Sustainable Applications

SWM includes analytics and group of information in sensors on waste trucks and city structure; smart garbage bins (SGBs), data and decision support for consumers (citizens, dispatchers, and drivers); routes planning and optimization; waste classification and segregation; monitoring of the environmental situation; payments and benefits for citizens. At present, this technique is based mainly on IoT technologies (Bircanoğlu *et al.*, 2018), which form SWM systems comprising a massive amount of smart devices that interact with typical protocol, have virtual and physical features are intelligent (AI-based), and can process, measure, calculate, transmit, and store data. The usage of SWM system, viz., the use of information and communication technology (ICT) in waste management, might enhance the energy efficacy and environment protection of solid waste export, reduce resource consumption, and increase quality of life (Varudandi *et al.*, 2021).

This study introduces an Elitist Barnacles Mating Optimizer with Hybrid Deep Learning Model for waste classification (EBMOHDL-WC) in the IoT enabled sustainable environment. The presented EBMOHDL-WC algorithm allows the IoT devices to proceed data collection process. Next, the EBMOHDL-WC technique uses MobileNetv2 model for extracting features and the hyperparameter adjustment of the MobileNetv2 technique was executed by the EBMO technique. Finally, the waste classification procedure is performed using HDL classifier which integrates two DL models. The experimental evaluation of the EBMOHDL-WC technique is tested on garbage classification dataset from Kaggle repository.

2. Related works

Adedeji and Wang (2019) examine an intelligent garbage material classifier method that is established by utilizing the ResNet50 and CNN method is an ML device and assists as the extractor, and SVM is utilized for classifying the waste as to distinct groups/types namely plastic, glass, paper, metal, and so on. In (Wang *et al.* 2021), the authors employ the DL-based classification and CC system for realizing maximum accuracy waste classifier at an early stage of garbage group. To support the subsequent disposal of waste, the authors segment selective waste collection as to metal, plastic, glass, fabric, paper/cardboard, and other selective waste collection, an overall of 6 types. DL-based CNNs are executed for realizing the garbage classifier task. Latha *et al.* (2022) examine a novel approach identified as e-waste management by developing the dynamic CNN. It increases the classifier accuracy with support of correctly mapping the image feature. In the meantime, the group of wastes is optimized for reducing the time and distance. The e-wastes in the smart waste bin can be regularly observed by smartphone applications for collecting not wasting time.

Uganya *et al.* (2022) introduced an automatic system for achieving an effectual and intelligent waste management method utilizing IoT by forecasting the probability of garbage things. The garbage size, gas level, and metal level are observed constantly utilizing IoT-based dustbins that are located around town. Afterward, the presented approach is tested by ML classifier systems like linear regression, LR, SVM, DT, and RF techniques. Rahman *et al.* (2020) reveal an able structure of waste management methods dependent upon DL and IoT. The presented technique reduces an astute approach for sorting digestible and indigestible garbage utilizing a CNN, a general DL paradigm. This method also establishes an architectural proposal for smart trash bin which employs a microcontroller with several sensors. An IoT permits control of realtime data somewhere but Bluetooth supports short-range data observation by android applications.

In (Sivakumar *et al.*, 2022), an effort is aimed to progress a technique termed as SmartBin. The 2 distinct techniques are monitored for classifying solid wastes as non-biodegradable and biodegradable effectively. A primary method was dependent upon CNN and IoT, but the secondary system enhances many sensors to model established utilizing the primary method Sheng *et al.* (2020) establish a smart garbage management approach utilizing LoRa communication protocol and TensorFlow based DL technique. The bin contains many partitions for segregating the garbage comprising paper, metal, plastic, and common garbage subdivision are dependent on the servo motor. Waste classifier and object detection are complete in TensorFlow infrastructure with pre-training object detection method.

3. The proposed model

In this article, the EBMOHDL-WC technique was developed for sustainable waste management in IoT platform. The projected EBMOHDL-WC system exploited the IoT devices to ensure data collection process. The waste classification module incorporates MobileNetv2 feature extraction, EBMO based hyperparameter tuning, and HDL classifier. Figure 2 depicts the block diagram of EBMOHDL-WC approach.

3.1. Data collection process

At first, the projected EBMOHDL-WC system performs IoT-related camera sensor to gather data, and micro-controller was utilized to process it (Al Duhayyim *et al.*, 2022). The camera was attached on the micro-controller and is accountable to capture images of garbage. Generally, this method was initializing and preparing for image acquisition. It captures an image and sends it to micro-controller. Afterward getting the image, the micro-controller provides the image to previously trained CNN element and creates a response concerning that image.

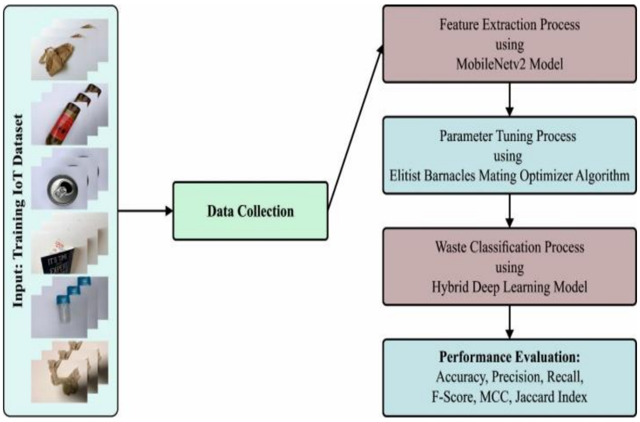


Figure 2 Block diagram of EBMOHDL-WC technique

3.2. Feature extraction process

At this stage, the features from the waste images are derived using MobileNet in this study. MobileNet is a CNN infrastructure which is a function to account requires. MobileNet is utilized on mobile phones (Rashid *et al.*, 2020). The common variance betwixt the mobilNet and CNN infrastructure are in the convolutional layer or layer with filtering thickness based on the input image. MobileNetV2 enhances method efficiency for optimum and is extremely utilized in assignment and develops the benchmark to distinct model size spectra. MobilenetV2 is an extracting feature which is highly efficient to object detection, for instance, for detecting it with a single shot detector lite. The bottleneck of MobileNetV2 encrypts in-between input as well as output but the inner layer encapsulates the model power for transforming in lesser level models such as pixels to superior level descriptors namely image types. MobileNetV2 utilizes pointwise convolutional and depth wise. MobileNetV2 utilizes depth wise and pointwise convolutional. Besides, MobileNetV2 also further 2 novel features like the primary linear bottleneck, and afterward shortcut connection betwixt bottlenecks. During the bottleneck subdivision, there are input and output betwixt the models, whereas the inner layer or layer covers the model capability for changing the input in the pixel levels towards the image classification is known. Therefore, shortcuts betwixt bottlenecks outcome in quicker training and optimum accuracy.

Followed by, the hyperparameter adjustment of the MobileNetv2 technique was executed by the EBMO system. BMO presented by Sulaiman *et al*. (2020) is a novel population-based meta-heuristic system simulated by how acorn barnacles replicate naturally. The 3 stages of BMO to optimize a provided challenge comprise initialized selection method and reproduction. During the initialized step, an array X including n solutions affected as barnacles can be generated. Mathematically, this array was determined as:

$$X = \begin{bmatrix} X_1^1 & X_1^N \\ \vdots & \vdots \\ X_n^1 & X_n^N \end{bmatrix} \quad (1)$$

whereas N implies the count of decision variables and n signifies the size of populations. All the cells viz., decision variable X^j for $(1 \le j \le N)$ of barnacles X_i for $(1 \le i \le n)$ was limited to upper as well as lower bounds written as ub and lb correspondingly. Lastly, the sorting approach was executed for placing an optimum barnacle at top of X.

The secondary step of BMO chooses parents termed as Dad and Mum for offspring generation. A major selective condition for his mom and dad is the penises size referred to as pl. The parents with longer pl can be chosen to mate under this stage. BMO implements exploitation procedure using pl -based selective randomly of individual's barnacle as parent and permits fertilization of barnacles by only another barnacles simultaneously. The exploration in BMO has required by sperm cast procedure that occurs if a barnacle chooses other barnacles to mate with index superior to its pl. Eq. (2) and Eq. (3) define this selective mathematical model.

$$barnacle_D = randperm(n) \quad (2)$$

$$barnacle_M = randperm(n) \quad (3)$$

whereas $barnacle_D$ and $barnacle_M$ are parents which are assumed for matting from population X of size n.

Eventually, the Dad and Mum barnacles create offspring from the reproduction stage. The genotype frequency of these current barnacles can be assumed depending on Hardy-Weinberg rule in offspring generation. At this point, the predictable genotype frequency of 2 alleles D and M in parents demonstrated as $f(DD) = p^2$, $f(MM) = q^2$ (homozygotes) and $f(DM) = 2pq$ (heterozygotes) are utilized for computing genotypes to novel offspring. Eq. (4) properly reveals the generation of novel barnacles $X_i(T+1)$.

$$X_i^{\tau+1} = p \times X_{barnacle_D}^{\tau} + q \times X_{barnacle_M}^{\tau} \quad (4)$$

whereas p signifies the arbitrarily chosen interval [0,1], q is equivalent to $1-p$. These 2 values are assumed as the percentage features which a novel offspring X_i^{t+1} inherits in variable $barnacle_D$ of Dad and variable $barnacle_M$ of Mum. If $p = 0.4$, afterward the novel offspring obtains 40% features in Dad while 60% in Mom.

BMO changes to exploration procedure named as sperm cast procedure if indices of both mate barnacles exceeding than fixed pl value (Zamli *et al.*, 2022). In mathematical process, Eq. (5) determines this casting procedure.

$$X_i^{t+1} = rand() \times X_{barnacle_M}^t \quad (5)$$

whereas $rand$ () proceeds an arbitrary number in the interval of zero and one. In specific cases, the position upgrade can lead to the present solution position that is duplicated or out-of-boundary. For the purpose S -box, the objectivity condition dictates which all the items are uniquely determined in the range of [0-225] (viz., with no repetition). Therefore, in all the updates, the position of all the agents (for instance, item $is\ S\text{-}box$) was checked consequently. This elitist process led to an adaptive and exponential probability.

$$P_{elife} = e^{\frac{t - T_{\max iteration}}{T_{\max iteration}}} \quad (6)$$

During the primary part of population iterations, the P_{elite} probability has smaller results than EBMO for exploring the searching space arbitrarily and changing the present worse population. To the end of population iterations, EBMO inclines to concentrate on exploiting the recognized optimum candidate solution (viz., P_{elite} is huge) using swapping its respective position in any chosen dimensional. In order to effectively work the position upgrade iteration, novel $best_{agent}$ is presented. The iteration continues still Max fit eval is obtained. Finally, the global optimum agent $(best_{agent})$ is returned.

Algorithm 1: Pseudocode of BMO Algorithm

begin
Initialize $T_{\max iteration}$, $r\iota$ and $\text{Max}_{fit\ eval}$ ($i.e.,$ $\max fitness$)
Initialize the population of barnacles $X_i (i = 1, 2, \ldots, n)$
While (stopping criteria $not\ met\,(i.e.,\ t < T_{\max iteratio\tau\iota})$)
Generate Chebyshev map, $C_n (i = 1, 2, \ldots n)$,
$C_{n+1} = \cos(n \cos^{-1}(C_{\tau\iota}))$ with random initial position
for each member in population $(i.e.,\ i = 1, 2, \ldots, n)$
  Select parents (Dad and Mum) using Eq. (2) and Eq. (3)
  Set $p = C_{r\iota}(i)$ and $q = 1 - p$
  if the indexes of parents are equal to pl
    Generate offspring using Eq. (4)
  else
    Generate offspring using Eq. (5)
  End if
  Set $P_{elite} = e^{\frac{t - T_{max\ iteration}}{T_{\max iteration}}}$
  if $(rand() > P_{elite})$
    Find the *worst*
  $X_i^t = arg \min_{x_i^t \in X} fitness(X_i^t)$
    Update the worst $X_i^t = generate$
  $random\ X_i^t$
  else
    Find the *best*
  $X_i^t = arg \max_{x_i^t \in X} fitness(X_i^t)$
    Update *best* X_i^t *in random dimension*
    $X_i^t = swap\ \ (X_i^t,\ position\ \ p,\ \ position$
  $q)$ where $p \neq q$
  end if
end for
Update the best barnacle if found better than previous best 25. Set $t = t + l$
break while loop when fitness evaluation $\geq \text{Max}_{fit\ eval}$
end While
Return the global best X_i^t
end

The fitness choice is a critical aspect of the MBMO technique. The solution encoded was utilized to assess the aptitude (goodness) of candidate solutions. At this point, the accuracy value is an important criterion employed to design a fitness function.

$$Fitness = \max(P) \quad (7)$$

$$P = \frac{TP}{TP + FP} \quad (8)$$

From the expression, TP represents the true positive and FP denotes the false positive value.

3.3. Waste classification process

For waste classification process, the HDL model is used. In the HCNN-LSTM paradigm, the CNN layer dealt with extracting the pattern in an automatic fashion. The series of features is again learned from the LSTM layer (Akilan *et al.*, 2019). The proposed method continuously adjusts the hyperparameter on the basis of outcome from the learning process of the LSTM and CNN techniques. The CNN approach is applied for extracting correlation that exists in the dataset and derives variable that is desired for the classification process that can be done using the class activation map. Eq. (9) characterizes the convolution function l for deriving a sequence of features. The convolution technique performs a product function on the trained data by using the feature mapping of size m_1^{l-1}. The kernel $K_{i,j}^l$ signifies different weights in all the regions to extract the considerable region of the feature mapping. Furthermore, the correlations amongst the nearby feature can be derived by the product operations. As well, the bias matrix B_i^l is exploited for modifying the weight from NN function. The product function can be performed on the amount of feature maps m_1^{l-1} and pass y_i^l to the succeeding convolution layer. For constructing non-linear decision boundaries, $f(z)$ in Eq. (10) represents an activation function as ReLU applied from l^{th} layer. The feature extraction can be done by multiple layers of convolutional function.

$$x_i^l = B_i^l + \sum_{j=1}^{m_1^{l-1}} K_{ij}^l * X_j^{l-1} \quad (9)$$

$$Y_i^l = g_i f\left(y_i^{l-1}\right), f(z) = \begin{cases} z \text{ if } z \geq 0 \\ 0 \text{ if } z < 0 \end{cases} \quad (10)$$

The pooling layer is applied to improve the classifier outcome and reduce the computation cost. Eq. (11) indicates the pooling layer function that allows to decrease overfitting and efficiently deriving features. T specifies the stride and R represents the size of pooling area.

$$p_{ij}^{l} = \max_{r\in R} Y_{i\times T+r,j}^{l-1} \tag{11}$$

In order to model the sequential data, the LSTM model is applied to store temporal data. The LSTM model is primarily applied for learning temporal information using the feature derived from CNN. Eq. (12) is defined by the three gate states that achieve the LSTM function that manages the sequential data as a continuous value within zero and one. All the cells hold forgotten input and output gates. Eq. (12) shows the output value of i, f, and o for all the gates. Furthermore, in order to collect long term data, the hidden state h_r of LSTM cell can be transcribed for all the r steps. Eq. (14) represents the hidden state of LSTM. Finally, Eq. (14) is defined by the cell state to transmit the state from existing to following one in the LSTM. Now, all the cells store the weight W vector and adjust the bias b vector values. The activation function σ such as sigmoid and hyperbolic tangents are applied for the generation of nonlinear decision boundaries.

$$\begin{pmatrix} i \\ f \\ o \\ g \end{pmatrix} = \begin{pmatrix} sigmoid \\ sigmoid \\ sigmoid \\ tanh \end{pmatrix} w^{l} \begin{pmatrix} h_t^{l-1} \\ h_{t-1}^{l} \end{pmatrix} + \begin{pmatrix} b_i \\ b_f \\ b_o \\ b_c \end{pmatrix} \tag{12}$$

$$c_r = f_t^{O} c_{t-1} + i_t^{o} g \tag{13}$$

$$h_t = o_t^{O} \sigma(c_t) \tag{14}$$

Eq. (15) shows the function of fully connected layer. The outcome of FC layer is classified into zero or one using the *softmax* function.

$$d_i^{l} = \sum_j \sigma\left(W_{ji}^{l-1}\left(h_i^{l-1}\right) + b_i^{l-1}\right) \tag{15}$$

$$P(c|d) = argmax_{c\in C} \frac{\exp\left(d^{L-1} w^{L}\right)}{\sum_{k=1}^{N_c} \exp\left(d^{L-1} w_k\right)} \tag{16}$$

Now C represents the class, L indicates the former layer index, and N_c shows the overall amount of classes.

Table 1. Details of dataset

Image Class	Number of Images
Cardboard	393
Glass	491
Metal	400
Paper	584
Plastic	472
Trash	127
Total Number of Images in Dataset	2467

4. Results and discussion

In this section, the waste classification outcome of the EBMOHDL-WC model was tested utilizing the waste classifier database in Kaggle repository (https://www.kaggle.com/datasets/asdasdasasdas/garbage-classification). The database contains 2467 instances with 6 classes as shown in Table 1. Figure 3 exhibits the sample images. 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.

Figure 3. Sample images

In Figure 4, the confusion matrices of the EBMOHDL-WC model on waste classification process are demonstrated. The figure pointed out that the EBMOHDL-WC model has identified six types of waste classes.

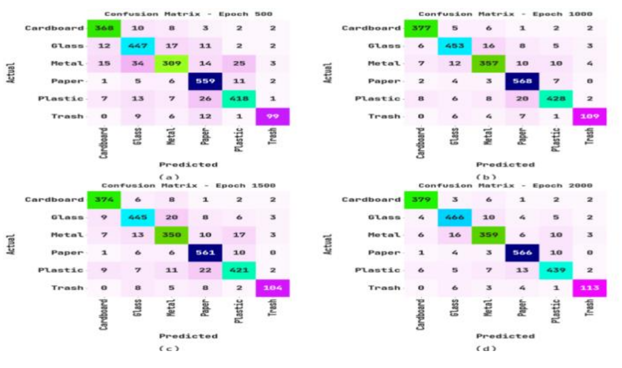


Figure 4. Confusion matrices of EBMOHDL-WC approach (a) Epoch 500, (b) Epoch 1000, (c) Epoch 1500, and (d) Epoch 2000

Table 2 reports overall waste classification results of the EBMOHDL-WC approach under varying epochs. The results implied that the EBMOHDL-WC system has identified six different types of waste. Figure 5 represents a brief classifier result of the EBMOHDL-WC model in terms of $accu_{bal}$, $prec_n$, and $reca_l$. The figure highlighted that the EBMOHDL-WC model has accurately categorized six waste classes. For sample, on 500 epochs, the EBMOHDL-WC system has attained average $accu_{bal}$ of 96.39%, $prec_n$ of 89.41%, and $reca_l$ of 87.36%.

Concurrently, on 1000 epochs, the EBMOHDL-WC approach has reached average $accu_{bal}$ of 97.64%, $prec_n$ of 92.65%, and $reca_l$ of 91.87%. Simultaneously, on 2000 epochs, the EBMOHDL-WC system has gained average $accu_{bal}$ of 98.04%, $prec_n$ of 93.89%, and $reca_l$ of 93.33%.

Table 2 Waste classifier outcome of EBMOHDL-WC approach with varying epochs

Class	Accuracy_{bal}	Precision	Recall	F-Score	MCC	Jaccard Index
Epoch-500						
Cardboard	97.57	91.32	93.64	92.46	91.02	85.98
Glass	95.34	86.29	91.04	88.60	85.72	79.54
Metal	94.53	87.54	77.25	82.07	79.07	69.59
Paper	96.31	89.44	95.72	92.47	90.12	86.00
Plastic	96.15	91.07	88.56	89.80	87.44	81.48
Trash	98.46	90.83	77.95	83.90	83.36	72.26
Average	96.39	89.41	87.36	88.22	86.12	79.14
Epoch-1000						
Cardboard	98.42	94.25	95.93	95.08	94.15	90.62
Glass	97.12	93.21	92.26	92.73	90.94	86.45
Metal	96.76	90.61	89.25	89.92	88.00	81.69
Paper	97.49	92.51	97.26	94.82	93.22	90.16
Plastic	97.20	94.48	90.68	92.54	90.85	86.12
Trash	98.82	90.83	85.83	88.26	87.68	78.99
Average	97.64	92.65	91.87	92.23	90.80	85.67
Epoch-1500						
Cardboard	98.18	93.50	95.17	94.33	93.24	89.26
Glass	96.51	91.75	90.63	91.19	89.02	83.80
Metal	95.95	87.50	87.50	87.50	85.08	77.78
Paper	97.08	91.97	96.06	93.97	92.08	88.63
Plastic	96.43	91.92	89.19	90.54	88.36	82.71
Trash	98.66	91.23	81.89	86.31	85.74	75.91
Average	97.14	91.31	90.07	90.64	88.92	83.02
Epoch-2000						
Cardboard	98.74	95.71	96.44	96.07	95.32	92.44
Glass	97.61	93.20	94.91	94.05	92.56	88.76
Metal	97.16	92.53	89.75	91.12	89.44	83.68
Paper	98.14	95.29	96.92	96.10	94.88	92.48
Plastic	97.53	94.00	93.01	93.50	91.98	87.80
Trash	99.07	92.62	88.98	90.76	90.29	83.09
Average	98.04	93.89	93.33	93.60	92.41	88.04

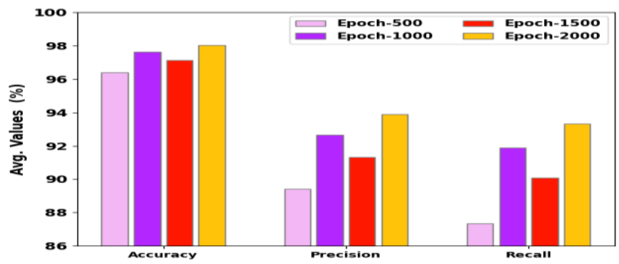


Figure 5 $Accu_y$, $Prec_n$, and $Reca_l$ outcome of EBMOHDL-WC approach with varying epochs

Figure 6 signifies a detailed classifier outcome of the EBMOHDL-WC algorithm with respect to F_{score}, MCC, and JI. The figure demonstrated that the EBMOHDL-WC approach has accurately considered 6 waste classes. For sample, on 500 epochs, the EBMOHDL-WC system has achieved average F_{Score} of 88.22%, MCC of 86.12%, and JI of 79.14%. Concurrently, on 1000 epochs, the EBMOHDL-WC algorithm has accomplished average F_{score} of 92.23%, MCC of 90.80%, and JI of 85.67%. Likewise, on 2000 epochs, the EBMOHDL-WC method has reached average F_{score} of 93.60%, MCC of 92.41%, and JI of 88.04%.

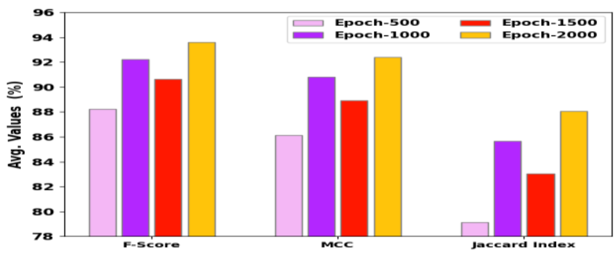


Figure 6. F_{score}, MCC, and JI outcome of EBMOHDL-WC approach with varying epochs

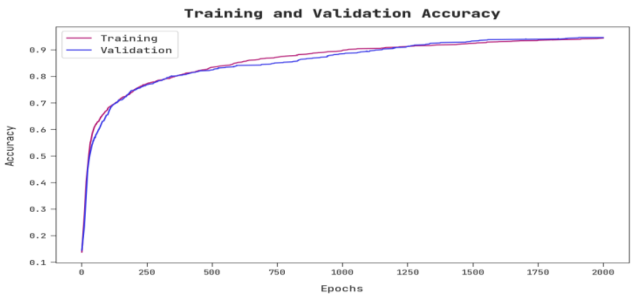


Figure 7 TACC and VACC outcome of EBMOHDL-WC approach

The TACC and VACC of the EBMOHDL-WC approach are investigated on waste classifier performance in Figure 7. The figure referred that the EBMOHDL-WC algorithm has shown better performance with enhanced values of TACC and VACC. It is noticeable that the EBMOHDL-WC system has reached maximal TACC outcomes.

The TLS and VLS of the EBMOHDL-WC technique are tested on waste classifier performance in Figure 8. The figure implied that the EBMOHDL-WC methodology has exposed optimum performance with minimal values of TLS and VLS. It is evident that the EBMOHDL-WC model has resulted in lesser VLS outcomes.

An evident precision-recall study of the EBMOHDL-WC approach in the test database is displayed in Figure 9. The figure stated that the EBMOHDL-WC system has led to higher values of precision-recall values in several epochs.

A comprehensive ROC exploration of the EBMOHDL-WC system in the test database is illustrated in Figure 10. The outcome referred that the EBMOHDL-WC algorithm has revealed its capability in classifying varying epochs.

Figure 8.TLS and VLS outcome of EBMOHDL-WC approach

In Table 3 and Figure 11, an overall comparison analysis of the EBMOHDL-WC approach on waste classification process is examined in detail (Al Duhayyim *et al.*, 2022). The experimental values indicated that the ResNet50, VGG16, and AlexNet models have obtained poor classification performance. At the same time, the MLH-CNN model has resulted in reasonable $accu_y$ of 91.94%, $prec_n$ of 91.28%, $reca_l$ of 91.30%, and F_{score} of 90.46%.

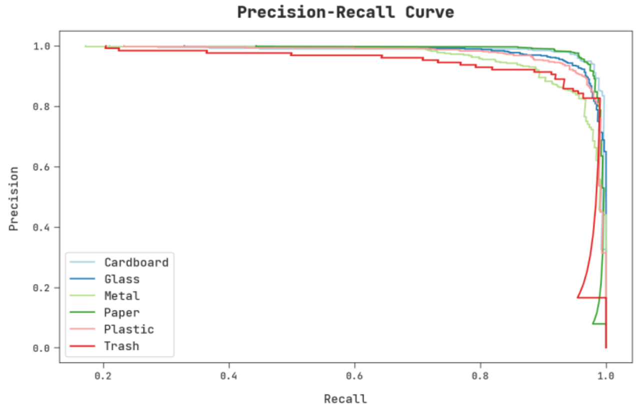


Figure 9. Precision-recall outcome of EBMOHDL-WC approach

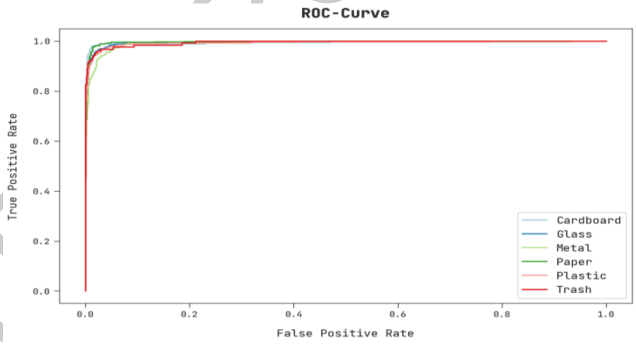


Figure 10. ROC outcome of EBMOHDL-WC approach

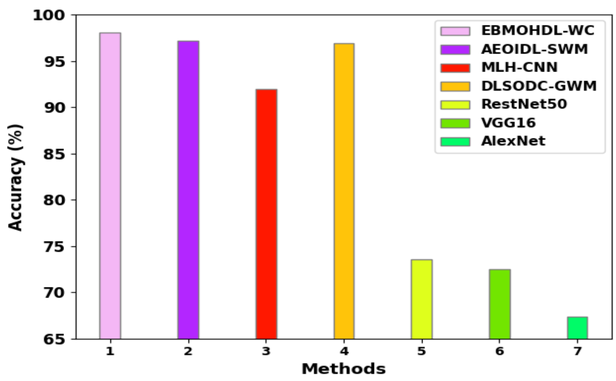


Figure 11. $Accu_y$ analysis of EBMOHDL-WC approach with other recent methodologies

Table 3. Comparative analysis of EBMOHDL-WC system with other recent methodologies

Methods	$Accu_y$	$Prec_n$	$Reca_l$	F_{Score}
EBMOHDL-WC	98.04	93.89	93.33	93.60
AEOIDL-SWM	97.14	92.09	91.48	91.72
MLH-CNN	91.94	91.28	91.30	90.46
DLSODC-GWM	96.93	90.30	90.92	91.81
RestNet50	73.55	71.75	72.06	71.62
VGG16	72.46	69.54	69.09	67.30
AlexNet	67.39	62.82	68.73	65.39

Contrastingly, the DLSODC-GWM and AEOIDL-SWM models have accomplished competitive performance. But the EBMOHDL-WC model has shown improved performance with $accu_y$ of 98.04%, $prec_n$ of 93.89%, $reca_l$ of 93.33%, and $F_{score} \frac{n!}{r!(n-r)!}$ of 93.60%. Thus, the EBMOHDL-WC model can be employed for maximum waste management process.

5. Conclusion

In this study, the EBMOHDL-WC technique has been developed for sustainable waste management in the IoT platform. The projected EBMOHDL-WC system exploited the IoT devices to ensure data collection process. Next, the EBMOHDL-WC technique uses MobileNetv2 model for extracting features and the hyperparameter adjustment of the MobileNetv2 technique was applied by the EBMO approach. Finally, the waste classification procedure is performed using HDL classifier which integrates two DL models. The experimental evaluation of the EBMOHDL-WC technique is tested on garbage classifier database from Kaggle repository. Experimentation outcomes of the EBMOHDL-WC technique exhibit competitive results over other techniques with accuracy of 98.04%. In future, the proposed model can be extended to the design of feature fusion based approaches to improve the classification performance.

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