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ORIGINAL RESEARCH
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An IoT aware nature inspired Multilayer Hybrid Dropout Deep-learning paradigm for waste image classification and management

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ABSTRACT

In this manuscript, the combination of IoT and Multilayer Hybrid Dropout Deep-learning Model for waste image categorization is proposed to categorize the wastes as bio waste and non-bio waste. The input captured images are pre-processed and remove noises in the captured images. Under this approach, a Nature inspired Multilayer Hybrid Dropout Deep-learning Model is proposed. Multilayer Hybrid Dropout Deep-learning Model is the consolidation of deep convolutional neural network and Dropout Extreme Learning Machine classifier. Here, deep convolutional neural network is used for feature extraction and Dropout Extreme Learning Machine classifier for categorizing the waste images. To improve the classification accurateness, Horse herd optimization algorithm is used to optimize the parameter of the Dropout Extreme Learning Machine classifier. The objective function is to maximize the accuracy by minimize the computational complexity. The simulation is executed in MATLAB. The proposed Multilayer Hybrid Dropout Deep-learning Model and Horse herd optimization algorithm attains higher accuracy 39.56% and 42.46%, higher Precision 48.74% and 34.56%, higher F-Score 32.5% and 45.34%, higher Sensitivity 24.45% and 34.23%, higher Specificity 31.43% and 21.45%, lower execution time 0.019(s) and 0.014(s) compared with existing waste management and classification using convolutional neural network with hyper parameter of random search optimization algorithm waste management and classification using clustering approach with Ant colony optimization algorithm. Finally, the proposed method categorizes the waste image accurately.

KEYWORDS

nature inspired Multilayer Hybrid Dropout Deep-learning Model, DrpXLM classifier, HHOA optimization algorithm, waste image categorization

1. INTRODUCTION

Nowadays, the Internet plays an important role in technological advancement. IoT technology has better-quality of life to recognize the nearby environment over reconstruction [1, 2]. The IoT characterizes the most stimulating rebellion to monitor and manage waste information by real time presentation that place at every time. The air pollution is happened by the burning of waste and plastic [3, 4]. The creation of waste has increased intensely in

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modern periods. If the waste is not received properly, it may also pollute atmosphere. [5–7]. Hence, the categorization of waste is the first phase of waste management, to increase the amount of decomposable things and decrease the probability of pollution by other things [8, 9]. The prevailing of waste separation approaches is not fully resourceful [10, 11].

The classification of biodegradable and non-biodegradable waste is more important. The bio-degradable wastes are food, organic matter, etc. and the non-bio-degradable wastes are rubber, plastic, metal, etc. [12, 13]. Therefore, it is essential to separate the waste materials for decomposable efficacy [14, 15]. It supports to protect the people and the environment from the impacts of waste disposals. Automated sorting of waste is done through the machine learning approaches or in-depth learning approaches due to the advancement of technology [16, 17]. With the growth of deep learning and image processing algorithms, waste categorization is performed at high accurateness and in less time [18–23]. Waste categorization is an important step before the waste separation is done. Due to the improvement of deep learning and IoT, a lot of smart devices are collected [30].

In this manuscript, the combination of IoT and Multilayer Hybrid Dropout Deep-learning Model (MHDLS) is proposed to categorize the waste as bio waste and non-bio waste. At first, the great resolution camera captures the waste images and the sensors are used to notice these waste images. The input captured images are pre-processed [24]. Then, a Nature inspired Multilayer Hybrid Dropout Deep-learning Model (MHDLS) is proposed under this approach. MHDLS is the consolidation of deep convolutional neural network and Dropout Extreme Learning Machine classifier. Here, DCNN is used to feature extraction and DrpXLM classifier for categorizing the waste images. To improve the classification accurateness, the Horse herd approach is recycled to optimize the parameter of DrpXLM classifier. As a result, the proposed approach categorizes the waste image accurately.

The major contributions of this work are:

- The combination of IoT and Multilayer Hybrid Dropout Deep-learning Model (MHDLS) is proposed for waste image categorization
- This method classifies the exact waste images as bio waste or non-bio waste.
- At first, the great resolution camera captures the waste images and the sensors are used to notice these waste images.
- The input captured images are pre-processed. A certain filtering approaches are employed to eliminate noises in the captured image while pre-processing.
- Moreover, a Nature inspired Multilayer Hybrid Dropout Deep-learning Model (MHDLS) is proposed here [25, 26].
- MHDLS is the combination of deep convolutional neural network and Dropout Extreme Learning Machine classifier. In this, DCNN is used for feature extraction and DrpXLM classifier for categorizing the waste images
- To improve the classification accurateness, the Horse herd optimization algorithm (HHOA) [27] is used to optimize the parameter of the DrpXLM classifier

- The performance metrics of Specificity, Severity, Sensitivity, Accuracy, Precision, Recall, F-score are analyzed.
- Finally, the performance of the proposed method is compared with two existing methods, such as waste management and classification using convolutional neural network with hyper parameter of random search optimization algorithm (CNN-HRSA) [28] and waste management classification using clustering approach with Ant colony optimization algorithm (CA-ACOA) [29]

The rest of the manuscript is organized as follows: section 2 portrays the recent research works, section 3 illustrates the proposed method of waste image classification using MHDLS-HHO, section 4 exemplifies the outcomes and discussion, finally, section 5 concludes the manuscript.

2. LITERATURE SURVEY

Among the previous investigation works on IoT applications, certain latest research is reviewed here, Ren et al., [30] have suggested two end-to-end Android malware recognition approaches depending on deep learning. When compared to other recognition approaches, the suggested system considers the benefit of its end-to-end method. This approach resamples the raw bytecodes of the classes.dex files of Android applications as input to deep learning models. Such methods were qualified and estimated on dataset contain 8K benevolent and 8K malevolent uses. Experimental outcome demonstrates that the suggested method has detection accurateness of 93.4% and 95.8% higher than the existing methods.

Lu et al., [31] have presented an ICT-based smart waste categorization which was distracted from bi-objective software design method to improve the waste gathering problems. The suggested SWCCS efficiently designed a novel multi-objective hybrid algorithm, which depends on whale optimization and genetic algorithm by better merging features and a fast, non-dominated categorization process. The suggested method was compared using two classic multi-objective algorithms. The suggested MOGWOA method was more efficient for improving the recognized approach.

Catarinucci et al., [32] have presented an advanced system capable of capturing and processing information involving door-to-door discrete waste gathering at setting of upcoming smart cities. The system consists of advanced RFID sensor-tag equipped by low-cost weight sensors and Cloud software system that handles the gathered information and satisfies several investors' outlooks. Initially the outcomes of both practical and presentation confirmation of the whole system were presented.

Rutqvist et al., [33] have presented real-life Smart Waste Management system. The presented method contains the existing physically planned process and its adjustment and conventional machine learning algorithms. Machine learning permits to enhance the categorization accurateness and recall of the previous physically engineered method from 86.8% and 47.9% to 99.1% and 98.2%. At last, the



presented method is likened with baseline existing physically engineered method, the presented method has good execution clarification increases the superiority of estimation for recycling containers.

Tsogbaatar et al., [34] have presented a deep ensemble learning outline for IoT irregularity identification and estimation with SDN. The DeL-IoT works deep and loaded auto encoders to remove manageable feature types of loading to collaborative learning method. The presented method provides effective recognition of irregularities, achieves flows animatedly, and predict short and long term device position for initial achievement. The presented method performs 3% better than the existing methods. The experimental outcomes show that the presented method has an improved and more dependable performance than other methods.

Alqahtani et al., [35] have presented an Internet of Things-Based Urban Waste Management method. IoT devices have been utilized for monitoring human activities and maintain waste management. All data from the city was gathered and managed at cuckoo search optimization in order to optimize long short-term recurrent neural network. The information notified the waste management centres of suitable activities, which should be reserved. The effectiveness of IoT-based waste management method was estimated through experimental investigation. The presented method consists of minimum error (0.16) and high accurateness (98.4%) and low execution time (15 min).

3. PROPOSED METHOD OF WASTE IMAGE CLASSIFICATION USING MULTILAYER HYBRID DROPOUT DEEP-LEARNING MODEL (MHDLS) WITH HORSE HERD OPTIMIZATION (MHDLS-HHOA)

In this manuscript, the combination of IoT and Multilayer Hybrid Dropout Deep-learning Model (MHDLS) for waste image categorization is proposed to categorize the wastes as bio waste and non-bio waste. Improper waste management increases the spread of illnesses and also pollutes the surrounding atmosphere. The several biodegradable waste mixtures produce poisonous gas that creates serious health risk. Biodegradable and non-biodegradable waste categorization methods help to have a healthy environment. At first, the great resolution camera captures the waste images and the sensors are used to notice those waste images. The input captured images are pre-processed. Certain filtering approaches are employed to eliminate noises in the captured images while pre-processing [24]. Then, a Nature inspired Multilayer Hybrid Dropout Deep-learning Model (MHDLS) is proposed under this approach. MHDLS is the consolidation of deep convolutional neural network (DCNN) and Dropout Extreme Learning Machine (DrpXLM) classifier. In which, DCNN is used to feature extraction and DrpXLM classifier for categorizing the waste images. To improve the classification accurateness, the Horse herd optimization

algorithm is recycled to optimize the parameter of DrpXLM classifier. Figure 1 shows the block diagram of waste image classification using MHDLS-HHOA.

3.1. Image acquisition

Here, the data set is collected from Trash Net dataset that is generated with Mindy Yang and Gary Thung at Stanford University [36]. TrashNet database consists of 2,527 images. From this, 2000 are taken for training and 527 for testing. In IoT, these waste images are captured by Raspberry Pi camera. The simulations are conducted in PC with Intel Core i5, 2.50 GHz CPU, 8 GB RAM and Windows 7. The proposed method is simulated in MATLAB.

Table 1 shows the Component used for Implement,

3.2. Pre-processing

Captured waste images contain excess noise while transmitting. The presence of unwanted interference can reduce the image quality. Hence, image pre-processing technique is the basic method for eradicating noises as well as raises the quality of captured input waste image. Gaussian, salt and pepper noise and the speckle noise are the various types of noise in image processing. These noises are generated due to image capturing and transmitting. Some of the filtering methods are deemed to de-noise the image, viz Lee, Khan, Weiner. Lee filter is employed to raise the intensity level of the imageries and remove the speckle noise.

3.3. Image extraction and classification using nature inspired Multilayer Hybrid Dropout Deep-learning model (DCNN+ DrpXLM)

Multilayer Hybrid Dropout Deep-learning Model (MHDLS) uses deep convolutional neural network and Dropout Extreme Learning Machine classifier. The DCNN is used for feature extraction and DrpXLM classifier for classifying the bio waste and non-bio waste. Initially, DCNN is trained through Softmax classifier of Cross-Entropy included class separation information is utilized from cost function. Softmax is detached and top features of the DCNN are used to train DrpXLM. The proposed DCNN+ DrpXLM is used for feature extraction and classification.

3.3.1. Extract image features using DCNN. In this section, DCNN is employed to remove the features of captured input image. Feature extraction method is achieved to remove stimulating features from new class by preceding network. Hence, deep convolutional neural network is used. The characteristic of DCNN is to resolve the problems of alteration sensitivity, and position sensitivity issues of captured images at feature extraction. DCNN is a type of multiple layer neural networks that contains input, convolutional, pooling and output layer. At first, the input image pixels are fed to the input layer. Then the convolutional layer removes the features of the image. Along with local correlation principle, data are desired at pooling layer. At last, the output layer plots the features labels.



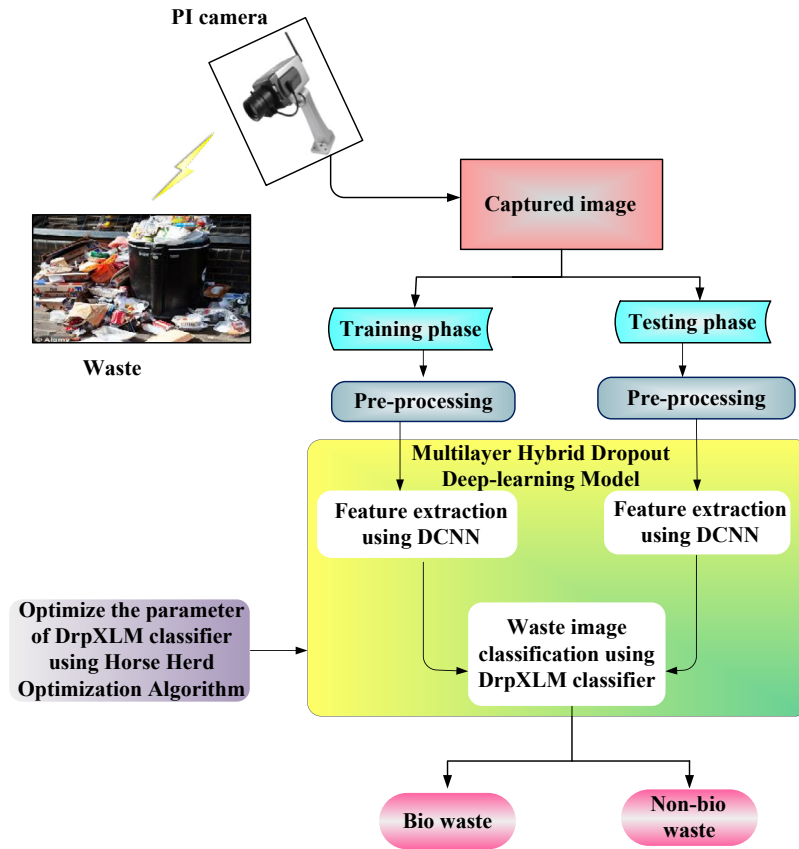


Fig. 1. Block diagram of waste image classification using MHDLS-HHOA

Table 1. Component used for Implement

Item	Model
Camera	Raspberry Pi
Sensor	HC-SR04
GPS Component	GY-NEO6MV2

Forward proliferation process. DCNN mapping the forward propagation approach defines the flow of information over total network from input to output layer. The non-linear function is included in the forward method to solve the linear effect. The non-linear activation function is engaged as output and the second layer can be formulated as,

$$\begin{aligned} w^k &= Z^k * y^{k-1} + a^1 \\ b^k &= \sigma(w^k) \end{aligned} \tag{1}$$

From the above equation, m denotes the k^{th} output layer and the $*$ indicates the convolution operation. If $k = 2$, $y^{2-1} = y^1$ specifies image matrix, which forms elements pixel. If $k > 2$, y^{k-1} specifies image feature matrix that extract as $(k-2)^{th}$ layer, Z^k, y^k and w^k refers weight matrix, bias matrix and weighted input of k^{th} layer, b^k final represents the actual output vector.

Backward proliferation process. The back propagation method is also known as supervised learning system that is

mostly employed for updating the parameter of Z^k and a^k . During the training of DCNN, the neurons make some mistakes and increase the time consumption. The cross entropy can be evaluated as,

$$F_0^M = \frac{1}{m} \sum_{j=1}^m \sum_{l=1}^M [s_l^K \ln b_l^K + (1 - s_l^K) \ln(1 - b_l^K)] \tag{2}$$

From equation (2), the total amount of training set can be denoted as m and the neurons that present in the output layer can be denoted as N , s_l^K represents the targeted value, b_l^K refers actual output value of k^{th} neuron of output layer. The error vector of every layer is calculated and output layer of l^{th} neuron of error vector can be formulated as

$$\delta^M = \frac{\partial F_o^M}{\partial w^m} \tag{3}$$

From equation (3), δ^M represents the error vector. In back propagation process, δ^M can be used to reversely reduce $\delta^M - 1$.

Class separation. To improve the efficiency of features removed images in DCNN method, the class separability figures are included with cross-entropy cost function from regularization duration and train DCNN. The class separability figures involve intra-class density and inter-class density that can be denoted as F_1 and F_2



$$F_1 = \frac{1}{2} \sum \|x_c^m - N_d\|_2^2 \tag{4}$$

$$F_2 = \frac{1}{2} \sum_d \|N_d - N_{d'}\|_2^2 \tag{5}$$

From equation (4) and (5), x_c^m indicates the original output value of m^{th} training samples that goes to m^{th} class. N_d and $N_{d'}$ the average output of training samples at d^{th} class.

$$F = F_o^M + \alpha F_1 - \beta F_2 \tag{6}$$

From equation (6), the weight parameter can be denoted as α and β . The determination of varying the cost function is to regulate Z^1 and a^1 that improve the network layer of classification. The error vector F_1 can be formulated as,

$$\delta_i^M = (1 - \frac{1}{m^d}) \sigma'(w^K) \Theta(X_d^M - N_d) \tag{7}$$

The error vector F_2 can be formulated as,

$$\delta_2^M = \frac{1}{m^d} \sigma'(w^M) \Theta \sum_d^A (N_d - N_{d'}) \tag{8}$$

At last, combining equation (3), (6)-(8) the new error vector of F and K^{th} output layer is formed and it is given below,

$$\delta' = \delta^M + \alpha \delta_1^K - \beta \delta_2^K \tag{9}$$

From the above equation, the error vector at every layer can be repetitively used (4) and the irregular features are detected

3.3.2. Categorize image using DrpXLM classifier. After removing features through the previously trained models, DrpXLM are trained on features removed through every deep model. Dropout Extreme Learning Machine (DrpXLM) classifier classifies the extract features of the DCNN. Here, the normal training of neural network using dropout. For each sample of mini batch, every node of network is detached through certain probability, then efficiently choose a dissimilar classifier for each sample. The dropout method introduces a linear neuron. The input image vector $J = (J_1, J_2 \dots J_m)$ and the output of linear neuron represent $R(J) = \sum_{j=1}^m z_j J_j$. The uniform distribution, $J_j (1 \leq j \leq m)$ are removed with equal probability 0.5, then it provides 2^m sub network contains empty network. The average output of 2^m sub network is expressed as,

$$F(T) = \frac{1}{2^n} \sum_M R(M, J) \tag{10}$$

From equation (10), N represents the set of all sub networks. If $\delta_j (1 \leq j \leq m)$ are m liberated Bernoulli random variables, and $q_i = Q(\delta_j = 1)$, $p_i = P(\delta_j = 0) = 1 - q_i$. Similarly, the probability of $J_j (1 \leq J \leq m)$ is removed. The linear neutron output is expressed as follows,

$$R(J) = \sum_{j=1}^m z_j \delta_j J_j \tag{11}$$

The mathematical expression of equation (11) can be formulated as,

$$F(R) = \sum_{j=1}^m z_j F(\delta_j) J_j = \sum_{j=1}^m z_j q_j J_j \tag{12}$$

When $q_1 = q_2 = \dots = q_m = q$, then equation (12) can be modified as

$$F(R) = \sum_{j=1}^m z_j F(\delta) J_j = \sum_{j=1}^m z_j q_j J_j \tag{13}$$

The linear neuron has the bias a then the output of the linear neuron can be expressed as,

$$R(J) = \sum_{j=1}^m z_j \delta_j J_j + a \delta_a \tag{14}$$

where $q_a = Q(\delta_a = 1)$, equation (14) is known as the DrpXLM classifier. The input image sizes are decreased to avert the problem of over fitting when the process of classification. To get maximal accuracy with less execution time, the weight parameters of DrpXLM classifier are tuned by EGDO algorithm

3.4. DrpXLM parameter optimized with HHOA

HHO is employed to optimize the weight parameters of DrpXLM in the classification process. To acquire the optimum accuracy, computational time of HHO algorithm is used. HHO derives constant method and decreases over fitting. This optimization decreases the cost function utilizing simulations parameter, also develops the parameter in opposed path. The step by step procedures for DrpXLM-HHO are given below. Figure 2 depicts the flow chart of MHDLS-HHOA algorithm

Step 1: Initialization

Initialize the initial parameters based on the decision variables and constraints. The iterations and the decision variables are assessed to reduce the complexity. The input parameter is H_r and P_1 .

$$H_r = \{H_1, \dots H_k\} \tag{15}$$

$$P_1 = H_r \rightarrow \{1 \dots K_1\} \tag{16}$$

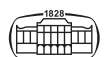
Step 2: Random generation

The constraints are generated randomly in the dimension along the process of domains in the search space from the initialization vectors present in HHO, the equation is,

$$X_v = X_{\min x} + \text{ran}(0, 1) \times (X_{\max x} - X_{\min x}) \tag{17}$$

Step 3: Fitness Function

The fitness function is to exploit that accuracy as well as to reduce the computation time and attain the objective function. The fitness value is estimated by the process of cost function. Then the cost function can be performed in two conditions:



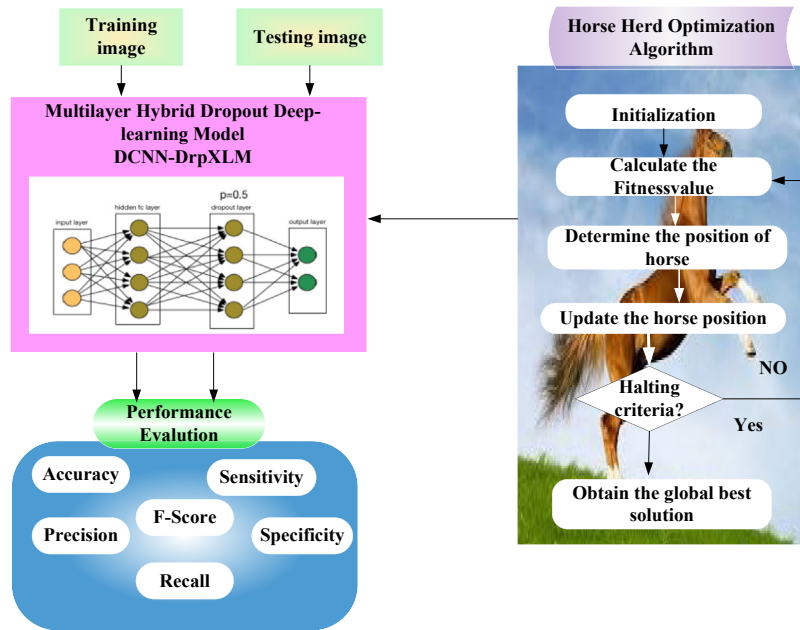


Fig. 2. Flow chart of MHDLS-HHOA Algorithm

1. If fitness value $(H_y) < \text{fitness}(H_y)$, $y \neq x$
 $P_1(H_y) > P_1(H_x)$

2. If fitness value $(H_y) = \text{fitness}(H_y)$, $y \neq x$
 $[P_1(H_y) - P_1(H_x)] \quad (y - x) > 0$

Let herd = $\{ \{H_1, \dots, H_k\}$, be a herd of k horses and P :
 herd $\rightarrow \{1, \dots, k\}$ a function

Step 4: Position searching

Every herd has a centre position, which is equal to the average location of horses in herd, then weights are indicating rank of horse. Then the centroid position of herd is expressed as,

$$Hr_{\text{centre}} = \frac{\sum_{y=1}^k w_y H_{y.\text{rank}}}{\sum_{y=1}^K H_{x.\text{rank}}} \quad (18)$$

$H_{y.\text{rank}}$ represents the social motion vector of horse

Step 5: Update the position

The distance among the position of stallion and horse herd centre is calculated with Euclidean distance and it can be expressed as,

$$Dim_1(\text{Stallion}_1, \text{herd}_1) = \sqrt{\sum_{x=1}^{Dim} \text{stallion}_{1y} - \text{Herd}_{1\text{center}})^2} \quad (19)$$

From equation (17), dimension of the search space is denoted as Dim_1 . The horse updates its position using the below equation.

$$Vel_{y,x}^{T+1} = Vel_{x,y}^T + H_{y.\text{rank}} * (\text{Herd}_{1\text{centre},x}^T - Z_{y,x}^T) \quad (20)$$

From the above equation $T + 1$ is the new iteration. The above equation is represented as the updated position in every iteration. From this, the objective function is reached by reducing error and the computational time and the accuracy is increased.

Step 6:

The optimal parameter is chosen at Dropout Extreme Learning Machine classifier through the aid of Horse Herd optimization Algorithm (HHOA). Finally, Dropout Extreme Learning Machine classifier categorizes the waste images through the aid of Gradient descent optimization approach.

4. RESULTS AND DISCUSSION

Here, the simulation performance of IoT and Multilayer Hybrid Dropout Deep-learning Model (MHDLS) for waste image categorization is described. The proposed system is simulated in MATLAB. The performance metrics are examined. The performance is analyzed with two existing approaches, like waste management and classification using convolutional neural network with hyper parameter of random search optimization algorithm (CNN-HRSA) [28] and waste management and classification using clustering approach with Ant colony optimization algorithm (CA-ACOA) [29]

4.1. Dataset description

The data set of waste categorization identification contains two phases: (i) training and (ii) testing. For waste management



classification, two set of categorizations are done: Bio-waste and non-bio waste. Trash Net database consists of 2,527 images. From this, 2000 are taken for training and 527 for testing.

Table 2 shows the Data set description of waste categorization.

4.2. Performance metrics

The performance metrics, like Precision, Recall, F-Measure, Accuracy, Specificity are analyzed to validate the proposed method performance. To scale the confusion matrix, the values of True Negative, True Positive, False Negative, and False Positive are required.

- True Positive (PT): waste images are categorized as true as true.
- True Negative (NT): waste images are categorized as true as false.
- False Positive (PF): waste images are categorized as false as false.
- False Negative (NF): waste images are categorized as false as true.

4.2.1. Accuracy. This is the maximal value of false Accept rate and false reject rate

$$Accuracy = \frac{falseacceptrate + falserejectrate}{2} \times 100 \quad (21)$$

4.2.2. Sensitivity. It scales the quantity of real positives that is predictable exactly. It is expressed as,

$$Sensitivity = \frac{TP}{TP + FN} \quad (22)$$

4.2.3. Specificity. Specificity is nothing but true negative rate. This is formulated as

$$Specificity = \frac{TN}{FP + TN} \quad (23)$$

4.2.4. Precision. This is nothing but Positive predictive and this is formulated as,

$$Precision = \frac{TP}{TP + FP} \quad (24)$$

$$FDR = 1 - NPV = \frac{\text{number of false negatives}}{\text{number of true negatives} + \text{number of false negatives}} = \frac{\text{number of false negatives}}{\text{number of negative calls}}$$

Table 2. Data set description of waste categorization

Class	Total records	Training	Testing
Bio waste	1,200	900	300
Non-bio waste	1,327	1,100	227

Table 3. Confusion matrix of proposed MHDLS-HHOA method

Class	TP	FP	FN	TN
Bio waste	150	3	2	145
Non-bio waste	113	3	1	110

4.2.5. Recall. Recall is otherwise known as Sensitivity, and this is expressed as,

$$Recall = \frac{TP}{TP + FN} \quad (25)$$

4.2.6. F-score. The below equation shows F-score

$$F - Score = \frac{2 \times TP}{2 \times TP + FP + FN} \times 100\% \quad (26)$$

4.3. Confusion matrix of waste image classification

Table 3 illustrates the confusion matrix of two classification groups. The basic terms of confusion matrix are True positive (TP) shows that system classifies the waste as actually a bio waste. True negative (TN) shows that system classifies the waste as non-bio waste and actually it is non-bio waste. False positive (FP) shows that system classifies the waste as bio waste but it's actually non-bio waste. False negative (FN) shows that system classifies the waste as non-bio waste but it's truly a bio waste.

4.4. Simulation phase 1: performance comparison of various methods

Tables 4 and 5 tabulates the performance metrics of various methods. Here, the performance metrics, like accuracy, sensitivity, specificity, precision and f-score are analyzed. The performance of the proposed method is compared with existing waste management and classification using convolutional neural network with hyper parameter of random search optimization algorithm (CNN-HRSA) [28] and waste management classification using clustering approach with Ant colony optimization algorithm (CA-ACOA) [29].

Table 4 displays the performance metrics of Accuracy, Sensitivity, Specificity.

For the analysis of bio-waste, the MHDLS-HHOA accuracy is 18.75%, 24.05% is greater than existing methods. For the analysis of non-bio waste, the MHDLS-HHOA accuracy is 11.86%, 21.05% is higher than the existing CNN-HRSEA and CA-ACOA methods.

For the analysis of bio-waste, the specificity of MHDLS-HHOA system is 22.75%, 18.05% is superior to the existing methods. For non-bio waste, the specificity of the MHDLS-HHOA is 19.86%, 25.05% is higher than the existing CNN-HRSEA and CA-ACOA methods.

For the analysis of bio-waste, the sensitivity of proposed MHDLS-HHOA system is 17.75%, 22.05% is better than the existing models. For non-bio waste, the sensitivity of MHDLS-HHOA is 13.86%, 23.05% is better than the existing CNN-HRSEA and CA-ACOA models.

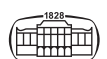


Table 4. Performance metrics of Accuracy, Sensitivity, Specificity

Methods	Accuracy (%)		Sensitivity (%)		Specificity (%)	
	Bio waste	Non-bio waste	Bio waste	Non-bio waste	Bio waste	Non-bio waste
CNN-HRSOA	78.43	88.43	65.43	88.43	71.43	78.43
CA-ACOA	76.43	74.43	68.43	88.43	75.43	77.43
MHDLS-HHOA (proposed)	98.65	98.67	99.65	97.65	99.65	97.65

Table 5. Performance metrics of Precision, F-Score, Recall

Methods	Precision (%)		F-Score (%)		Recall (%)	
	Bio waste	Non-bio waste	Bio waste	Non-bio waste	Bio waste	Non-bio waste
CNN-HRSOA	68.43	82.43	65.43	78.43	73.43	74.43
CA-ACOA	86.43	67.43	56.43	68.43	55.43	67.43
MHDLS-HHOA (proposed)	98.99	98.99	98.95	98.66	99.65	97.65

Table 5 displays the performance metrics of Precision, F-Score, Recall.

For the analysis of bio-waste, the precision of the MHDLS-HHOA method is 19.75%, 32.05% is greater than existing methods. For non-bio waste, the precision of MHDLS-HHOA is 28.86%, 17.05% is better than existing CNN-HRSOA, CA-ACOA methods.

For the analysis of bio-waste, the F-Score of MHDLS-HHOA method is 18.75%, 30.05% is greater than existing methods. For non-bio waste, the F-Score of MHDLS-HHOA is 22.86%, 13.05% is greater than existing CNN-HRSOA and CA-ACOA methods.

For bio-waste analysis, the Recall of proposed MHDLS-HHOA system is 21.75%, 34.05% is greater than existing methods. For non-bio waste analysis, the Recall of proposed MHDLS-HHOA system is 30.86%, 15.05% is better than existing CNN-HRSOA and CA-ACOA methods.

Figure 3 displays the performance metrics of execution time of waste image classification using MHDLS-HHOA approach. Here, the proposed method is analyzed with existing CNN-HRSOA and CA-ACOA methods. At node bio-waste, the proposed MHDLS-HHOA execution time is 74.46%, 68.23% is lower than the existing methods. At node non-bio waste, the proposed MHDLS-HHOA execution time is 58.27%, 64.49% is lower than the existing methods.

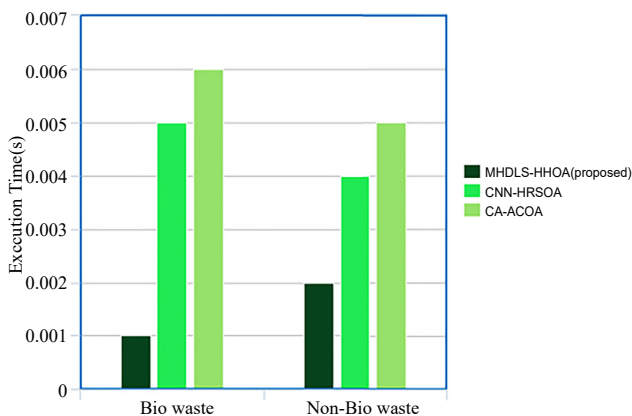


Fig. 3. Performance metrics of execution time

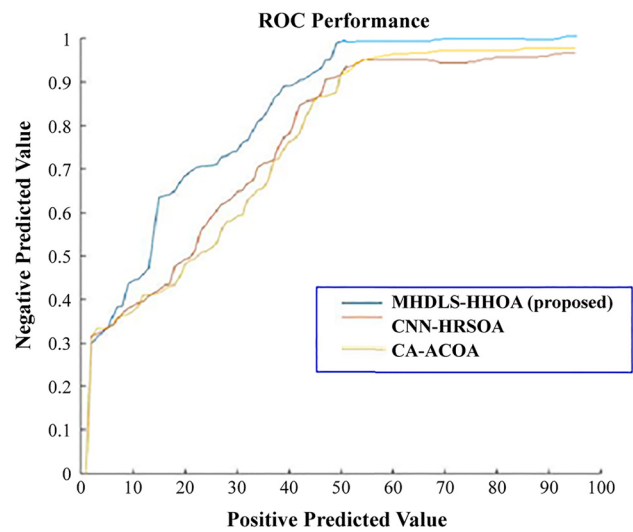


Fig. 4. ROC curve for detecting and classification of AD disease

Figure 4 depicts the ROC. Here, a total number of TPR is divided by overall count of false positive rate. The values are computed through the procedure of features between 0.0 and 1.0 values. TPR described from the proportion of positive data points appropriately predict positive. FPR described from the proportion of negative data points inappropriately predict positive.

5. CONCLUSION

This paper proposes the consolidation of IoT and Multilayer Hybrid Dropout Deep-learning Model to waste image categorization and to categorize the wastes as bio waste and non-bio waste. The input captured images are pre-processed and remove noises in the captured images. Then, a Nature inspired Multilayer Hybrid Dropout Deep-learning Model is proposed under this approach. Multilayer Hybrid Dropout Deep-learning is the consolidation of deep convolutional neural network and Dropout Extreme Learning Machine classifier. In which, DCNN is applied for feature extraction



and Dropout Extreme Learning Machine classifier is used for categorizing the waste images. To raise the classification accurateness, Horse herd optimization algorithm is recycled to augment the parameter of the Dropout Extreme Learning Machine classifier. The objective function is to maximize the accuracy by minimizing the computational complex. The simulation is done in MATLAB. The proposed Multilayer Hybrid Dropout Deep-learning Model and Horse herd optimization algorithm attains better accuracy 99.56%, better Precision 88.74%, better F-Score 92.5%, better Sensitivity 94.23%, better Specificity 91.45%, lower execution time 0.019(s) and the proposed system compared with existing systems, like waste management and classification using convolutional neural network with hyper parameter of random search optimization algorithm and waste management and classification using clustering approach with Ant colony optimization approach. At last, the proposed method accurately categorizes the waste image.

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NOMENCLATURE

Parameter	Parameter description	Parameter value
m	total amount of training set	
N	neurons that present in the output layer	
δ^M	error vector of every layer	
F_0^M	cross entropy	
x_c^m	original output value of m^{th} training samples	
α and β	weight parameter	
Z^k	weight matrix	$k = 2$
y^k	bias matrix	
w^k	weighted input of k^{th} layer	
b^k	final actual output vector	
s_l^K	targeted value	
b_l^K	actual output value of l^{th} neuron of output layer	
N_d and N_d	average output values of training samples in d^{th} class	
x_c^m	original output value of m^{th} training samples that goes to m^{th}	
α and β	weight parameter	
H_r and P_1	input parameter of horse herd optimization	
F	new error vector	
$H_{y.rank}$	social motion vector of horse	
Dim_1	dimension of the search space of horse	

S. No	Abbreviation	Description
1	MHDLS	Multilayer Hybrid Dropout Deep-Learning Model

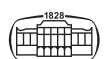
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S. No	Abbreviation	Description
2	IoT	Internet of Things
3	DCNN	DeepConvolutional Neural Network
4	DrpXLM	Dropout Extreme Learning Machine Classifier
5	HHOA	Horse Herd Optimization Algorithm
6	CNN-HRSGA	Convolutional Neural Network with Hyper Parameter of Random Search Optimization Algorithm
7	CA-ACOA	Clustering Approach with Ant Colony Optimization Algorithm
8	SWCCS	Smart Waste Categorization and Collection System
9	ICT	Information and Communication Technologies
10	MOGWOA	Multi-Objective Hybrid Algorithm Depending on Whale Optimization and Genetic Algorithms
11	RFID	Radio Frequency Identification Reader
12	SDN	Software-Defined Networking
13	DeL-IoT	Deep Ensemble Learning Framework For IoT

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