# Garbage Images Classification Using Residual Attention CNN and Hybrid Optimization Based on Firefly Algorithm

Ahmed T. Sadiq[1], Nadia M. G. Al-Saidi[2], Venus W. Samawi[3](✉), and Yeliz Karaca[4]

[1] Multimedia and Digital Media Department, University of Technology, Baghdad, Iraq
ahmed.t.sadiq@uotechnology.edu.iq
[2] Department of Applied Sciences, University of Technology, Baghdad 10066, Iraq
nadia.m.ghanim@uotechnology.edu.iq
[3] Department of MIS/Smart Business, Isra University, Amman 11622, Jordan
venus.samawi@iu.edu.jo
[4] University of Massachusetts Chan Medical School (UMASS), 55 Lake Avenue North, Worcester, MA 01655, USA
yeliz.karaca@ieee.org

**Abstract.** Garbage image classification has become an important application in recent years, as it supports waste sorting and identification, thereby helping environmental protection and recycling, and overcoming the problems of manual sorting. This paper presents a hybrid intelligent technique based on Residual Attention Convolutional Neural Networks (RACNN) with an improved Back-Propagation Neural Network (BPNN). The improvement in the BPNN is achieved using the Firefly Algorithm and the AdamW Optimizer for Fine-Tuning (BP-FF-AdamW) to ensure BPNN's regularization. A new chaotic function is used for weight initialization to control randomness and prevent the model from settling into local minima. The RACNN model is applied to images of garbage to extract complex, hierarchical features, bypassing the manual feature extraction stage. Furthermore, mathematical optimizations of the BPNN model, along with the use of the Firefly algorithm and chaotic sequences, enhance the learning process and produce a well-trained model capable of classifying garbage images. This integrated approach provides several effective intelligent learning features, in addition to mathematical optimizations, to improve the learning process and produce a well-trained model capable of classifying garbage objects. The developed blended approach is applied to the Garbage Dataset to test its classification ability. The achieved accuracy for classifying garbage objects is 96.5%.

**Keywords:** Waste classification · Residual Attention Convolutional Neural Networks · Deep Learning · AdamW Optimizer · Hyperparameter optimization · Fine-Tuning · Transfer learning · Computer Vision

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## 1 Introduction

Waste sorting is crucial for achieving sustainability and protecting the environment through encouraging resource reuse (recycling). The World Bank estimates that global waste will reach 2.59 billion tons by 2030 and 3.4 billion tons by 2050 [1]. The need to automate waste sorting is crucial because most people are still unaware of how to sort garbage [2]. Furthermore, humans who work in waste-sorting facilities do the hard, time-consuming work of sorting through waste. Various techniques are used to automate waste sorting, including sensor-based sorting, magnetic and density separation, and garbage image analysis and classification. In this paper, we focus on using garbage image classification to automate waste sorting. However, classifying garbage images is challenging for several reasons, including complex backgrounds, similar-looking categories, feature extraction and engineering, and low-quality images [3]. Therefore, we use deep learning (DL), specifically Convolutional Neural Networks (CNNs), for garbage image classification in waste sorting rather than traditional machine learning (ML) approaches.

Over the last ten years, DL has made significant strides due to significant improvements in computational power, enabled by Tensor Processing Units (TPUs) and Graphics Processing Units (GPUs), as well as architectural innovations. Furthermore, the explosion of big data and advances in underlying theory have played a crucial role in the development of DL [4, 5]. The development of DL has significantly advanced computer capabilities for interpreting visual data, such as object detection, image segmentation, and classification, thereby improving computer vision [6, 7]. One of the subfields of DL, which is primarily designed to analyze visual data, is CNNs. This is due to the shared weights and local connectivity employed by the convolutional layers in CNNs. CNNs are capable of performing feature extraction and improving image classification. These capabilities are useful for garbage image classification, which helps sort garbage for recycling, reducing time-consuming work and costs [8]. These capabilities are useful for classifying waste images, as they are used in sorting and recycling processes, thereby reducing time, effort, and costs. Furthermore, the integration of computer vision and deep learning technologies enables highly accurate automatic sorting and recognition of garbage objects in images, facilitating waste management and improving sorting results compared with human intervention [9, 10].

In recent years, high-performance image analysis has undergone a significant shift, driven by advances in DL-based technologies, especially CNNs [11–13]. Two factors are crucial for high-performance image analysis. The first is having sufficient training data in both quality and quantity, which next-generation camera systems and high-capacity storage devices ensure. The second factor is the need to develop a high-quality image classification model to achieve high accuracy in image analysis.

Existing studies on garbage classification show significant gaps remaining in this domain, as some research uses ML techniques while others use DL, particularly CNNs. Support Vector Machine (SVM) and Convolutional Neural Network (CNN) were trained on a self-collected dataset of 510 images, as compared in [14], to classify three types of waste: plastic, paper, and metal. SVM outperforms CNN in their study (94.8% vs. 83%). A dataset of 22500 waste-colored images with two classes, organic and recyclable, was used in [15] to train CNN and ResNet-50 architectures for waste classification and to compare the resulting accuracies. The custom CNN model achieves the best

accuracy, with 91.84%, outperforming ResNet-50, which achieves 81.34%. In [16], three Convolutional Blocks were utilized, each featuring distinct filter sizes and the Mish activation function. Three fully connected layers with Softmax activation were used to make multi-class predictions. The flattened output of the last MaxPool2D layer was used as input. DenseNet169 achieved the highest accuracy of 99.58%. The effectiveness of YOLOv5 was evaluated in [17] for trash detection, including plastic, paper, glass, metal, cardboard, and biodegradables. The study concluded that YOLOv5 is effectively able to identify various types of waste. In [18], transfer learning was used, leveraging a pre-trained DenseNet169 model to classify five datasets, achieving 82% accuracy. In [19], a garbage bin was designed that included both hardware and a mobile app. Afterward, a ResNet-34-based model was built, and its design was improved. Lastly, fake garbage data is used to test the proposed system's performance.

Recently, DL techniques have demonstrated excellent performance on computer vision tasks such as image classification, segmentation, and detection [20, 21]. Transfer learning enables superior performance despite limited data availability by utilizing pre-trained models [22, 23]. Since CNNs are the most suitable type of DL that use back-propagation (BP) as the main training algorithm, this means that CNNs encounter the primary challenges of BP, such as local minima and weight initialization. This study introduces an automated system that uses deep transfer learning for a five-class garbage image classification task. The main contribution is to address problems that occur when training CNNs with BP, such as local minima and weight initialization issues. Finally, evaluate the effectiveness of the proposed modified BP for training CNNs to classify images of garbage. For BPNNs to work better and more accurately in real-world applications, it is important to optimize them. To address important problems such as slow convergence, getting stuck in local-minima, and sensitivity to hyperparameters, many optimization methods have been developed. Although conventional methods such as Gradient Descent (GD) and its variants have yielded substantial advances, contemporary research has focused on hybrid techniques that combine metaheuristic algorithms with adaptive optimization strategies.

The main contributions of this work are abstracted as follows:

- Proposing a new chaotic map to be used for weight initialization to prevent poor initialization, which might slow down the training process or converge to a sub-optimal solution. Chaotic weight Initialization controls the randomness of the initial weight setting to accelerate convergence and prevent getting stuck in local minima.
- Utilizing the Residual Attention Convolutional Neural Networks (RACNN) with an improved Back-Propagation Neural Network. These methods have suffered from limitations, including fixed learning rates that often lead to suboptimal convergence. Additionally, the proper choice of learning is crucial, as a high learning rate may cause exceeding minima, while a low learning rate slows convergence.
- Using a gradient-based optimizer like AdamW provides a global search strategy, making it a good alternative to methods that are based on gradients. AdamW can reach suboptimal solutions too quickly, especially in high-dimensional search spaces such as those in deep learning. To adjust the learning rate, adaptive methods, including the Firefly algorithm and the AdamW optimizer for Fine-Tuning (BP-FF-AdamW)

are used. Unsuitable tuning may cause unstable updates or excessive regularization, thereby negatively affecting model performance.

The rest of the paper is organized into four sections: Section 2 presents the materials used for the methods in this work, including a detailed dataset description and model specifications. Section 3 explains the metrics used for performance measurement. In Sect. 4, the experimental results are presented, and our findings are discussed using performance measures. Section 5 concludes our work and proposes directions for future research to improve sustainable waste management practices.

## 2 Methodology

The framework of the proposed approach relies on several intelligent techniques and mathematical enhancements. It outlines the theoretical foundation and mathematical formulations that guide each component of the methodology. The main stages of our proposed approach are presented in Fig. 1.

The proposed approach relies on several intelligent techniques and mathematical enhancements. The main stages include:

1- Dataset Acquisition.
2- Residual Attention CNN.
3- Improved BP-NN based on Firefly algorithm with AdamW optimizer for fine-tuning.

### 2.1 Garbage Dataset

The selected garbage image dataset, "A Comprehensive Image Dataset for Garbage Classification and Recycling," includes 19,762 clear images categorized into 10 classes [24]. Table 1 lists the 10 classes along with their training and test sizes. Partitioning the dataset into training and testing sets is achieved using 5-fold cross-validation to obtain more confident classification results. The dataset is considered comprehensive, but it is imbalanced because some classes have few images while others have many. Samples of images from the dataset are shown in Fig. 2.

The developed garbage classification model is implemented in two phases: training and evaluation. To accomplish the training phase, we need to carry out the following steps:

1. Fed the garbage images used for training into the RACNN for feature selection.
2. Initialize the BPNN weights using chaotic sequences.
3. Optimize BPNN weights using the Firefly algorithm to establish a well-optimized starting point.
4. AdamW is employed to fine-tune the model, enhancing stability and efficient learning.

At the end of the training phase, once the target convergence is reached, the evaluation phase starts.

During the evaluation phase, the developed model is assessed utilizing the test data. Performance metrics such as classification accuracy, recall, precision, F-score, and a confusion matrix are used to evaluate the effectiveness of the developed garbage classification model.

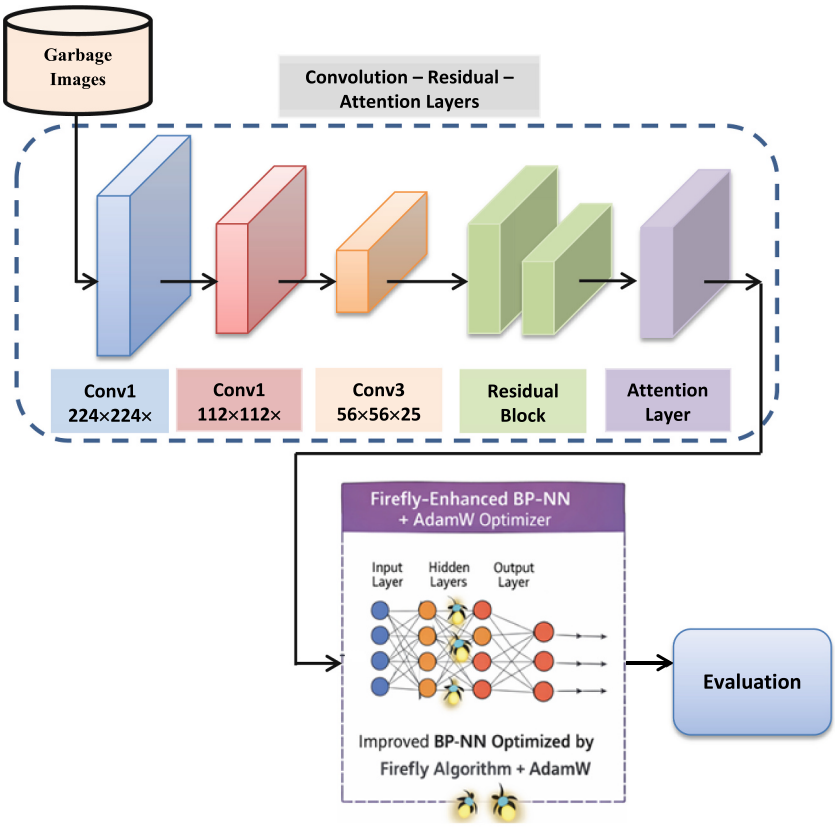



**Fig. 1.** Main stages of proposed garbage image classification (garbage classification Model)

### 2.2 Residual Attention Convolutional Neural Networks (RACNN)

The Residual Attention Convolutional Neural Network (RACNN) combines residual learning and attention mechanisms to improve feature representation and stabilize training. Residual connections help prevent gradient degradation by letting information flow directly between layers. Attention modules, on the other hand, adaptively emphasize useful spatial and channel features. This combination improves convergence, robustness, and discrimination, especially for classifying complex images. This makes RACNN an effective approach for learning deep hierarchical representations. Using RACNN will yield high-quality extracted/selected features. Because this type of CNN is very efficient in object classification. Another stage is an improved BP-NN based on the Firefly algorithm and the AdamW optimizer. Our proposed RACNN comprises 3 convolutional layers, 1 residual layer, and 1 attention layer. The fully connected layer in our RACNN is an improved BP-NN based on the firefly algorithm. Figure 3 illustrates the details of the RACNN of our approach. Using RACNN yields high-quality extracted/selected features. Because this type of CNN is very efficient in object classification. Another

**Table 1.** Garbage image dataset: classes and sizes

| Image Class | Training 80% | Testing 20% | Total |
|---|---|---|---|
| Trash | 757 | 190 | 947 |
| Shoes | 1581 | 396 | 1977 |
| Plastic | 1587 | 397 | 1984 |
| Paper | 1344 | 336 | 1680 |
| Metal | 816 | 204 | 1020 |
| Glass | 2448 | 613 | 3061 |
| Cloths | 4261 | 1065 | 5327 |
| Cardboard | 1460 | 365 | 1825 |
| Biological | 797 | 200 | 997 |
| Battery | 755 | 189 | 944 |




Trash Shoes Plastic Paper

**Fig. 2.** Samples of Garbage Image

stage is an improved BPNN based on the Firefly algorithm and the AdamW optimizer. The next sections provide details on RACNN and the improved BPNN.

The input image (RGB) of size 224-by-224 will be fed into two convolutional layers, then the residual process and attention. Flatten nodes will be entered to improve the BPNN.

### 2.3 Chaotic Weight Initialization

The primary goal of optimizing BPNN is to improve convergence speed, accuracy, and generalization. Using chaotic weight initialization improves convergence. The main purpose of applying chaotic initialization is to control randomness in weight settings, which helps prevent premature convergence to local minima. The weight initialization function is based on the chaotic maps given in Eq. (1), which generate highly unpredictable sequences that follow deterministic rules.

$$X_{n+1} = rX_n\left(1 - e^{-\delta X_n^2} + \gamma\right) \tag{1}$$

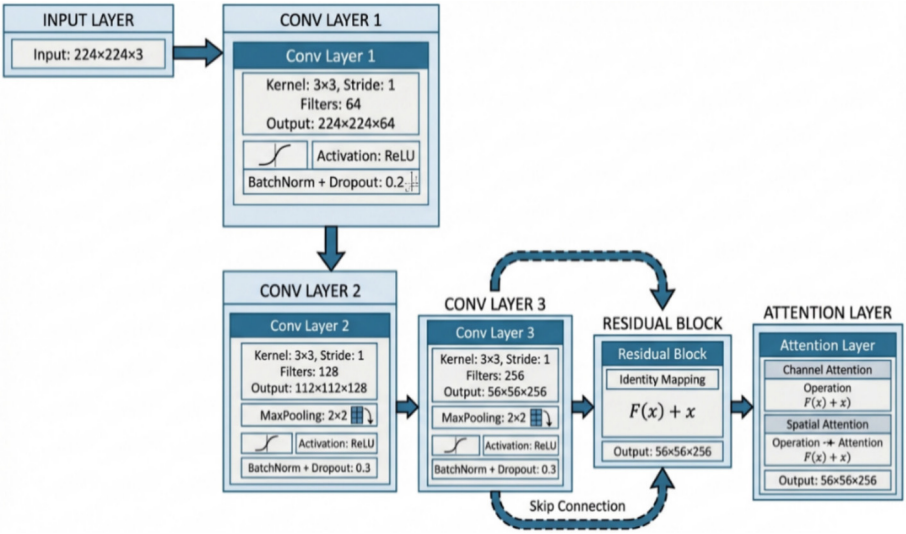
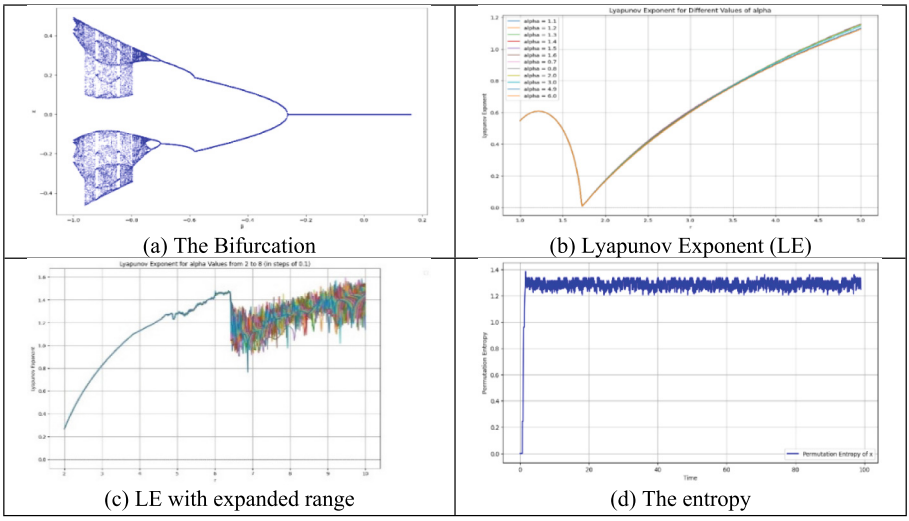



**Fig. 3.** RACNN Layers Detail

where $X_n$ represents the initialized weight, and r = 5.8, δ = 8.9, γ = -1.59 ensures chaotic behavior.

This is done to avoid poor weight initialization and reduce the vanishing gradients risk. These parameters are chosen to ensure the system's chaotic behaviour. The dynamic behavior of the developed garbage classification model is explained in Fig. 4.



(a) The Bifurcation

(b) Lyapunov Exponent (LE)

(c) LE with expanded range

(d) The entropy

**Fig. 4.** The dynamic behaviour of the system (1).

### 2.4 Hybrid Optimization BPNN Based on Firefly Algorithm

In this stage, there are several sub-stages as follows:

a) **BPNN and Optimization:** A BPNN is a supervised learning algorithm that adjusts the W (weights) and b (biases) of a neural network to minimize the error function:

$$E(W, b) = \frac{1}{N} \sum_{i=1}^{n} \|y_i - \widehat{y_i}\|^2 \tag{2}$$

where $N$ is the number of training samples, $y_i$ is the true label of the ith sample, and $\widehat{y_i}$ is the predicted output. The weight updates are computed using gradient descent, where the parameters are adjusted iteratively:

$$W_{t+1} = W_t - \eta \nabla E W_t \tag{3}$$

Here, η is the learning rate and $\nabla E W_t$ is the gradient of the error function.

Conversely, the benefit of the Firefly algorithm lies in its ability to escape local minima and explore the search space effectively.

b) **Firefly and AdamW for Fine-Tuning:** The firefly algorithm (FA) is among the most widely used swarm-intelligence algorithms used. The firefly algorithm was developed by Xin-She Yang in 2008 [4], inspired by the natural behavior of tropical fireflies. FA mimics the flashing patterns and attraction behavior of fireflies. The purpose of these flashing lights is twofold: to attract mating partners and to warn potential predators. Clearly, these flashing lights and their intensity can follow certain rules, including physical laws. Essentially, FA employs the following three idealized rules. [25]:

- AS fireflies are unisex, they will be attracted to each other regardless of their sex.
- Attractiveness depends on brightness, decreasing as distance grows. Consequently, between two flashing fireflies, the less bright one moves toward the brighter. If no brighter fireflies exist, it moves randomly.
- The landscape of the objective function determines the brightness of a firefly.

As a firefly's attractiveness is proportional to the brightness seen by adjacent fireflies, the variation of attractiveness β with the distance $r$ can be defined by using Eq. (4):

$$\beta = \beta_0 e^{-\gamma r^2} \tag{4}$$

where $\beta_0$ is the attractiveness at $r = 0$. The movement of a firefly $i$ is attracted to another, more attractive (brighter) firefly $j$ is determined by:

$$W_i^{t+1} = W_i^t + \beta_0 e^{-\gamma r^2} \left( W_j^t - W_i^t \right) + \alpha \varepsilon_i^t \tag{5}$$

where the second term is due to the attraction. The third term is randomization with α being the randomization parameter, and $\varepsilon_i^t$ is a vector of random numbers drawn from a Gaussian distribution at time $t$. Other studies also use the randomization $\varepsilon_i^t$ can be easily extended to other distributions, such as Lévy flights. It is worth pointing out that γ controls the scaling, while α controls the randomness. For the algorithm to converge properly, randomness should be gradually reduced, and one way to achieve this is to use

$$\alpha = \alpha_0 \theta^t \tag{6}$$

where $t$ is the index of iterations/generations. Here $\alpha_0$ is the initial randomness factor, and we can set $\alpha_0 = O(1)$ without losing generality.

The main steps of the Firefly algorithm are illustrated in Algorithm (1). Once the optimized weights are determined by the firefly algorithm, AdamW [26] is used for fine-tuning with adaptive learning rate control, which adjusts standard stochastic gradient descent by incorporating a history-sensitive learning rate as in Eq. (7):

$$W_{t+1} = W_t - \eta \frac{\widehat{m_t}}{\sqrt{\widehat{v_t} + \epsilon}} - \eta \lambda W_t \tag{7}$$

where η is the learning rate, $\widehat{m_t}$ is bias-corrected first moment (i.e., mean of gradients), $\widehat{v_t}$ is the bias-corrected second moment (i.e., variance of gradients) and λ is the weight decay coefficient.

**Algorithm (1): Firefly**

Input: Objective function f(x), number of fireflies $n$, max_iterations T
parameters: α (randomization), $\beta_0$ (initial attractiveness), γ (light absorption)
Initialize population of fireflies $X_i$ ($i$ = 1 to $n$) randomly
Evaluate brightness $I_i = f(X_i)$ for each firefly
For t = 1 to T do
  For i = 1 to n do
    For j = 1 to n do
      If $I_j > I_i$ then
        Compute the distance $r_{ij}$ between $x_i$ and $x_j$
        Compute attractiveness using Eq. (4)
        Move firefly $i$ towards firefly $j$ using $X_i = X_i + \beta * (X_j - X_i) + \alpha_t \epsilon_t$
          % where $\alpha_t$ is a parameter controlling the step size, while $\epsilon_t$ is a vector drawn from a Gaussian or other distribution.
      End If
    End For
    Evaluate new brightness $I_i = f(X_i)$
  End For
  Rank fireflies and update the best solution
End For
Output: Best solution found (X_best) and its fitness f(X_best)

## 2.5 Optimization Strategies

Unlike Adam, AdamW separates weight decay from the gradient update. Therefore, AdamW and the Firefly Optimization algorithm are chosen instead. This ensures weight decay acts as a true regularization force, not distorted by adaptive learning rates. Models trained with AdamW often perform better on unseen data than those trained with Adam. Also, AdamW has stable convergence, bias correction, and low memory cost. The adaptive learning rate works more effectively when integrated with the Firefly Algorithm for weight updates, while AdamW's weight decay proves more advantageous for very deep architectures. The firefly algorithm efficiently balances exploration and exploitation in

the search space, making it well-suited for deep learning optimization. The firefly algorithm's attraction-based updates lead to faster, more stable convergence. Combining the Firefly algorithm's global search abilities with AdamW's adaptive learning rates forms a strong hybrid approach that addresses the limitations of standalone gradient-based and evolutionary methods. This combination applies the strengths of both AdamW and the Firefly algorithm, offering a more effective and stable optimization strategy for this work.

## 3 Performance Evaluation Metrics

In this work, the confusion matrix will be used to indicate where the model's predictions are correct and where they are not. Therefore, it is considered a good performance evaluation metric. Four categories are used to construct the confusion matrix: true positive (TP), true negative (TN), false positive (FP), and false negative (FN) [10]. Moreover, four performance evaluation metrics are used to assess the developed garbage classification model [1, 9, 10]:

- ***Accuracy***: indicates the ratio of all correctly predicted samples to the total number of samples (see Eq. 8).

$$Accuracy = \frac{TP + Tn}{(TP + TN + FP + FN)} \tag{8}$$

- ***Precision***: indicates the ratio of all correctly predicted positive samples to the total predicted positive samples (see Eq. 9).

$$\text{Precision} = \frac{TP}{(TP + FP)} \tag{9}$$

- ***Recall***: indicates the ratio of all correctly predicted positive samples to the total actual positive samples (see Eq. 10).

$$\text{Recall} = \frac{TP}{(TP + FN)} \tag{10}$$

- ***F1-Score***: is particularly useful for unbalanced datasets. It computes the harmonic mean of recall and precision (see Eq. 11).

$$\text{F1} - \text{Score} = 2 \times \frac{(\text{Precision} \times \text{Recall})}{(\text{Precision} + \text{Recall})} \tag{11}$$

## 4 Experimental Results

Before assessing the effectiveness of the proposed garbage classification model, it's useful to review the main parameters used during the training phase, which are shown in Table 2. The developed garbage classification model is applied to the test dataset, and confusion matrices, accuracies, precision, recall, and F-scores are calculated to assess the model's effectiveness. Table 3 summarizes the performance of the proposed model on the test dataset, reporting accuracy, precision, recall, and F1 Score. The results demonstrate consistently high values across all metrics, confirming the effectiveness, robustness, and reliability of the proposed RACNN with hybrid optimization in accurately classifying garbage images.

**Table 2.** Parameter description

| Parameters | Description/Value |
|---|---|
| Epochs | 300 |
| BP-NN Learning Rate | 0.005 |
| BP-NN Hidden Nodes | 500 to 600 |
| Dropout | 0.2 to 0.3 |
| Loss Function | Cross-Entropy Loss |
| Firefly Pop. Size | 50 |
| Max. Iteration Firefly | 500 |
| Firefly Learning Rate | 0.1 to 0.2 |
| Attractiveness | 0.9 |
| Light Absorption | 0.9 to 1.1 |
| Optimizer | AdamW |
| Chaotic Map | $r = 5.8$, $\delta = 8.9$, $\gamma = -1.59$ |

**Table 3.** The performance metrics of the developed garbage classification model

| Measure | Value |
|---|---|
| Accuracy | 96.5% |
| Precision | 95.5% |
| Recall | 96.7% |
| F1-Score | 96% |

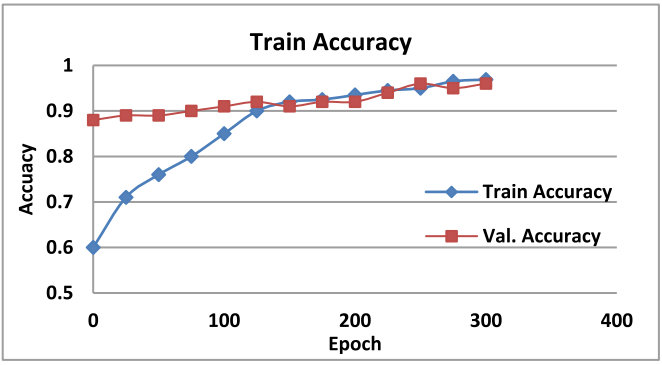



**Fig. 5.** Accuracy Training Chart

Figure 5 illustrates the training accuracy progression of the proposed model across epochs. The curve shows a steady and rapid increase in accuracy, followed by stable convergence, indicating effective learning. This trend confirms that the hybrid optimization strategy enhances training stability and enables the RACNN to achieve high classification performance without severe oscillations or overfitting.

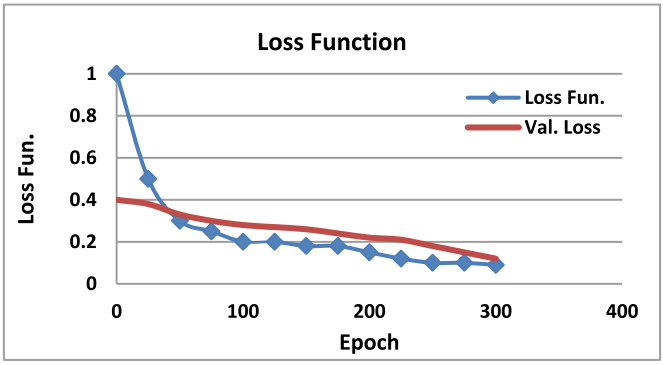



**Fig. 6.** Loss Function Chart

The training loss curve of the proposed model is shown in Fig. 6. The loss drops quickly in the early epochs and then stabilizes smoothly, indicating effective optimization, rapid convergence, and enhanced training stability achieved through the hybrid Firefly–AdamW optimization strategy, without noticeable overfitting.

The confusion matrix of the testing dataset is shown in Fig. 7, illustrating the classification performance of the proposed model across all garbage categories. The strong concentration of values along the main diagonal indicates high correct classification rates, while small off-diagonal values reflect low misclassification, confirming the model's robustness and ability to distinguish between classes. The confusion matrix shows that most misclassifications occur when clothing is misidentified as trash, paper, or plastic.

The obtained experimental results are then compared with several benchmark DL models stated in previous research in terms of accuracy, precision, recall, and F1-score, as illustrated in Table 4. The comparison results show that the proposed RACNN with hybrid optimization outperforms the other DL models, demonstrating improved classification performance and better generalization than SqueezeNet, MobileViT, and ResNet.

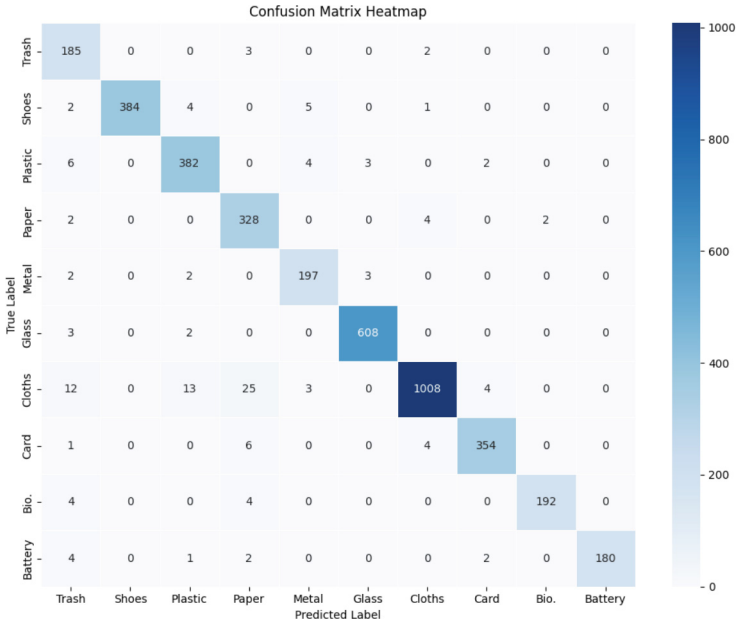



**Fig. 7.** Testing dataset confusion matrix

**Table 4.** Comparison between the proposed RACNN and other methods

| Model | Accuracy | Precision | Recall | F1-Score |
|---|---|---|---|---|
| SqueezNet | 92.8% | 92.9% | 92.8% | 92.8% |
| MobileViT | 95.5% | 95.5% | 95.5% | 95.5% |
| ResNet | 94.7% | 94.4% | 94.7% | 94.5% |
| The Proposed Model | 96.5% | 95.5% | 96.7% | 96% |

## 5 Conclusion

As more and more people care about protecting the environment and using resources sustainably, garbage classification is an urgent issue for everyone. The current classification methods depend too much on people doing the work, which can be affected by factors such as their quality, attention, and sense of responsibility. Fast, accurate automatic classification technology is very important and will be the only way for society to move forward. Using AI technology to sort trash can make sorting faster and cheaper, which is good for business. An effective garbage classification model that combines several intelligent and mathematical techniques. Starting with RACNN for feature selection. The BPNN with improved weights based on a new chaotic map is used to generate balanced, high-quality randomized weight values. The performance of this network is optimized through the Firefly gradient algorithm to establish a well-optimized starting

point. Our proposed approach achieved 96.5% accuracy on the test dataset; therefore, it is a promising approach in the important area of garbage image classification. Finally, the proposed technique uses fine-tuning with AdamW for stable, efficient learning. Using several evaluation metrics, our technique demonstrates high performance compared to several conventional models in the literature.

As future work, since trash comes in many shapes and sizes in real life. It would be interesting to learn more about how to build a robust data collection platform or augment datasets using adversarial learning. Moreover, the garbage classification system only works with a single object; we can design a simple, effective garbage-collection platform that shows multiple objects at once.

**Disclosure of Interests.** The authors declare no competing interests in this study.

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