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Modified Cuttlefish Swarm Optimization with Machine Learning-Based Sustainable Application of Solid Waste Management in IoT

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Abstract: The internet of things (IoT) paradigm roles an important play in enhancing smart city tracking applications and managing city procedures in real time. The most important problem connected to smart city applications has been solid waste management, which can have adverse effects on society's health and environment. Waste management has developed a challenge faced by not only evolving nations but also established and developed counties. Solid waste management is an important and stimulating problem for environments across the entire world. Therefore, there is the need to develop an effective technique that will remove these problems, or at least decreases them to a minimal level. This study develops a modified cuttlefish swarm optimization with machine learning-based solid waste management (MCSOML-SWM) in smart cities. The MCSOML-SWM technique aims to recognize different categories of solid wastes and enable smart waste management. In the MCSOML-SWM model, a single shot detector (SSD) model allows effectual recognition of objects. Then, a deep convolutional neural network-based MixNet model was exploited to produce feature vectors. Since trial-and-error hyperparameter tuning is a tedious process, the MCSO algorithm was applied for automated hyperparameter tuning. For accurate waste classification, the MCSOML-SWM technique applies support vector machine (SVM) in this study. A comprehensive set of simulations demonstrate the improved classification performance of the MCSOML-SWM model with maximum accuracy of 99.34%.

Keywords: sustainable applications; IoT; solid waste management; cuttlefish swarm algorithm; object detection; waste classification

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1. Introduction

With the rise of smart video surveillance, a large number of people-tracking applications, autonomous vehicles, facial detection, and fast and accurate object detection methods are in ever-growing demand [1,2]. The continuing development in the areas of computer vision (CV), image processing, and deep learning (DL) techniques have changed the way we think about various characteristics of daily life [3]. The DL methodology has provided a reliable basis for image recognition with reliable accuracy [4]. The prevalent image classification, the convolutional neural network (CNN), is a fascinating biological neural network that is composed of distinct layers, with the neurons of all the layers being strongly associated with the neuron in the subsequent layer [5]. The benefits of using a CNN are that they allow an independence between the feature extraction of preceding knowledge and a minimal design effort. CNN has made greater accomplishments in image recognition and classification [6]. The popularity and accuracy of CNN for image classification have been optimized due to the largescale system for learning and image processing, higher-speed GPUs, and the huge availability of public datasets of an image [7]. The idea of smart waste classification with waste and trash images has tremendous potential.

Owing to faster urbanization, currently, cities are facing significant challenges [8,9]. Amongst these challenges are those associated with the waste management system as the quantity of waste is directly proportional to the group of people living in urban regions. Waste management technology chiefly concerns the treatment and disposal of various kinds of waste [10] and therefore protects animals, human beings, and the surrounding areas [11]. An appropriate waste management technique could save money and result in less environmental pollution and improved air quality. Advanced regions of the world have been simultaneously implementing and discovering effective technologies for large-scale construction and effective waste management [12,13]. It is not possible to handle such a large quantity of waste in the forthcoming five years of the prevailing situation. Therefore, it is better to take each essential action needed for the effectual waste management [14] and to adopt the best practices and techniques to efficiently treat waste and obtain a healthier environment.

Gokulnath et al. [15] designed a new genetic approach and support vector machine (GASVM) to predict complex patterns, with the utilization of this approach offering improved results. Salama et al. in [16] developed a learning neural network with an ant colony optimization (LNNAC) model for the prediction of complex patterns in automated recognition processes. Next, Yadav et al. [17] have presented a new artificial neural network with a particle swarm optimization (PSO-ANN) model for resolving Troesch's problem. The authors in [18] introduced a new urban waste management technique which makes use of a cuckoo search-optimized long short-term recurrent neural network (CLST-RNN).

Malik et al. [19] have presented a network by which to classify litter into types identified from benchmark techniques. The network they utilized to classify litter was EfficientNet-B0. Their study presents an EfficientNet-B0-based approach to the tuning of detailed images to specific demographic regions and from there to effective classification. This kind of tuning method on transfer learning (TL) offers a modified approach to classification, one which is extremely optimized for specific regions. Alsubaei et al. [20] established an approach which mostly concentrates on the identification and categorization of lesser garbage waste objects in order to support an intelligent waste management system. In order to recognize an object, an improved RefineDet (IRD) technique with hyperparameter tuning process was employed. Secondly, a functional link neural network (FLNN) approach is executed to classify waste objects into several classes.

Verma et al. [21] have presented a DL-based intelligent garbage recognition method. An objective purpose of their work was to manage garbage efficiently. In order achieve this, automation was developed utilizing two CNN techniques and images of solid waste that were taken by drones. Both of the CNN techniques were trained on the gathered image dataset at distinct rates of learning, optimization, and periods. Yang et al. [22] have examined a new incremental learning structure, GarbageNet, in order to address the abovementioned challenges. Firstly, weakly-supervised transfer learning guarantees the ability of feature extraction. Secondly, to classify types of garbage, GarbageNet embeds them as anchors for reference and classifies the test instances by finding their nearest neighbors from the latent space. Thirdly, a considered collection of trained data were employed to suppress the negative outcomes of mislabeled data.

Kumar and Buelaevanzalina [23] have provided a visual geometry group–neural network (VGG16-NN) technique that is dependent upon the procedure of attention to classified recyclable waste. Their attention module was established in order to model the important data from the feature map and provide increased detail. This technique automatically extracts classification features, namely organic, recyclable and non-recyclable waste. Kumar et al. [24] have examined a new technique to waste segregation in order to achieve their effective recycling and disposal by employing a DL technique. The YOLOv3 technique was employed from the Darknet structure to train a self-made dataset.

In [25], the authors employ a DL-based classification and CC system for realizing higher accuracy waste classification, beginning with garbage collection. To assist the subsequent waste disposal, the authors subdivide recyclable waste into glass, plastic, cardboard or paper, fabric, metal, and other recyclable wastes. DL-based A CNN is employed to realize the task of classifying garbage. Uganya et al. [26] presented an automatic system for achieving an effectual and intelligent waste management scheme utilizing the IoT by forecasting the probability of waste items. The gas level, metal level, and wastage capacity were observed while utilizing IoT-based dustbins that could be located anywhere in city. Afterward, the authors presented techniques that had been tested by ML classifier approaches such as LR, linear regression, SVM, RF, and DT techniques. Though several models for waste classification are available in the literature, there is still a need to improve the performance of detection. At the same time, the trial-and-error hyperparameter tuning of the DL models is a tedious process. Therefore, metaheuristic optimization algorithms can be used for automated hyperparameter tuning.

This study develops a modified cuttlefish swarm optimization with machine learning-based solid waste management (MCSOML-SWM) in smart cities. In the MCSOML-SWM model, a single shot detector (SSD) model allows effectual recognition of objects. Then, a deep convolutional neural network (DCNN)-based MixNet model is applied to produce feature vectors and the hyperparameter tuning process is carried out by the MCSO algorithm. For accurate waste classification, the MCSOML-SWM technique applies a support vector machine (SVM) in this study. A comprehensive set of simulations were carried out to demonstrate the improved classification performance of the MCSOML-SWM model. In summary, the key contributions of the study are given as follows.

- An intelligent MCSOML-SWM technique composed of an SSD object detector, a MixNet-based feature extraction, an MCSO-based parameter tuning, and an SVM classifier is presented. To the best of our knowledge, the MCSOML-SWM model has never been presented in the literature.
- A novel MCSO algorithm is derived for hyperparameter tuning of the MixNet model.
- Hyperparameter optimization of the MixNet model using MCSO algorithm using cross-validation helps to boost the predictive outcome of the MCSOML-SWM model for unseen data.

2. The Proposed Model

In this study, a new MCSOML-SWM algorithm was established to identify different categories of solid waste to enable smart waste management. In the MCSOML-SWM model, the SSD model allows the effectual recognition of objects. Then, the DCNN-based MixNet model is applied to produce feature vectors and the hyperparameter tuning process is carried out by the MCSO algorithm. For accurate waste classification, the MCSOML-SWM technique applied SVM in this study.

2.1. Object Detection Using SSD Model

Primarily, the MCSOML-SWM model exploits the SSD model for the effective recognition of objects. Single shot multi-box detector is an SSD with a single and one-phase DNN intended for detecting objects in real time [27]. In contrast, the advanced method in two-phase processing, the fast region convolutional neural network (RCNN), makes use of the presented network to generate object proposals and categorize objects for real-time recognition rather than utilizing an external model, however, the entire procedure operates at seven frames per second. SSD improves the speed of the run time when compared with the preceding detector by removing the necessity for a proposal network. As a result, it creates some drops in mean average precision, which SSD compensates for by employing some developments involving default boxes and multi-scale features. This improvement allows SSD to obtain the fast RCNN using low resolution images which later accelerate the processing of SSD. Likewise, SSD is composed of a convolution filter to detect objects and to extract feature maps. SSD applies VGG16 as a base network for the extraction of feature maps. Next, it integrates six convolution layers in order to make predictions. Every prediction comprises an N + 1 score and bounding box for all the classes, whereby N refers to the class count and +1 to the additional classes with no objects. Rather than utilizing an RPN for box generation and for feeding the classifications to compute the class scores and object locations, SSD employs a smaller convolutional filter. Afterward, the VGG16 base network extracts features from the feature map, while SSD employs 3 × 3 convolutional filters for all the cells for predicting object. Every filter provides an output with N + 1 score for all the classes and four attributes for single boundary boxes. SSD is simultaneously different from previous methods in that it can predict multi-scale feature maps for independent detection instead of using one final layer. As explained above, SSD makes use of lower input images for object detection and therefore a lower resolution layer to identify largescale objects, while the initial layer is used to identify smaller objects gradually. In addition, SSD employs distinct scales of default boxes for instinctive visualization and distinct layers.

2.2. Feature Extraction

In this study, a MixNet model was applied to produce feature vectors. The Mixnet structure changes single convolution kernels with distinct kernels of various sizes, which led to an optimal accuracy and efficacy [28]. In the conventional method, the kernels are 3 × 3 in size, however, studies have demonstrated that integrating several kernels with sizes of 3 × 3, 5 × 5, 7 × 7, and 9 × 9 potentially enhances performance. Superior kernels do not always attain optimum outcomes, as the accuracy is dependent upon the dataset and the class of objects. Another thing to keep in mind is whether greater kernel sizes significantly improve the model size with further parameters, thus increasing the computation time.

The presented CNN structure, termed MixNet, offers an important benefit with respect to scalability. It is assumed that the general method seeks a balance amongst the accuracy and energy consumption of DL hardware. The kernel sizes utilized from every model begin with 3 × 3 and enhance by two every time they generate a division on the tensor in order to apply a novel kernel. For instance, when it is necessary to execute three distinct kernel sizes from the convolutional network, the sizes are 3 × 3, 5 × 5, and 7 × 7. For each of the kernels on a layer, the network can utilize the subsequent Equation (1) to determine the size of the kernels.

$$\text{Kernel size } = 2\text{i } + 1 \quad (1)$$

where i adds 1 to group size.

Next, the MCSO algorithm performs the hyperparameter tuning process [29]. Cuttlefish utilize three cell layers for altering the color of their skin, and the proposed technique was dependent upon these as the suggested cuttlefish algorithm CFA utilizes these procedures (visibility and mirror). It can thus be described as utilizing reflection and visibility for locating a novel solution (new).

$$newq = reflection + visibility \quad (2)$$

$$Q[k].points\ [s] = random * (upperLimit) + lowerLimit\ i = 1,2\ldots N;\ j = 1,2\ldots d \quad (3)$$

Whereas upper and lower limits represent the problem domain upper as well as lower boundaries, respectively, and *random* implies the arbitrary integer amongst Equations (2) and (3).

The researchers established a novel approach by integrating chromatophore cell stretch and shrink procedures, reflectivity in iridophores cells, and the visibility of images utilized by cephalopods to suit their backdrop.

$$reflection_s = A * I_1[k] \cdot Points\ [s] \quad (4)$$

$$visibility = W * (Bestpoints\ [s] - G_1[k] \cdot Points[s] \quad (5)$$

Gl refers to the group of chromatophore cells utilized to mimic a condition from the equation above. Afterward, the *I*th cell from the G_l group is *i*. Points [*j*] signifies the *j*th element of *i*th cell. Best points were utilized to indicate optimum solution points. Were the cell muscle to lengthen or rest, the reflection degree (*R*) was employed to determine the stretch range of scales. The pattern's ultimate visibility level was represented by letter V. Subsequently, the R and V values were computed:

$$A = random\ (\ ) * (a_1 - a_2)a_2 \tag{6}$$

$$W = random(\ ) * (w_2 - w_2) + w_2 \tag{7}$$

The random (0, 1) approach was utilized to find numbers amongst *zero* and one, which were picked at random.

2.3. Waste Classification Using SVM Model

For accurate waste classification, the MCSOML-SWM technique was applied SVM in this study [30]. An SVM is a binary classification, where the class label contains two values $+1$ and -1 and where several real time problems are allocated in various classes. Therefore, we employed a multiple class SVM. We created a set of binary classifiers $f^1, f^2 \ldots j^N$ for 1. Additionally, N classes were trained to distinguish a single class from the others. Multi-class classification was attained by integrating the classes based on the highest output that had previously employed the sign function argmax $g^k(x)$.

$$g^k(x) = \sum_{i=1}^{n} y_i \alpha_i^k k(x,\ x_i) + b^k \tag{8}$$

where $k = 1 \ldots N$. Thusly, $g^k(x)$ returns the signed real values indicating the distance from the hyperplane to the point x. These values are represented as confidence values. The higher the value, the more confidence there is that point x belongs to the positive class. Therefore, we should allocate x to the class which has the higher confidence value. Assume the standard dataset $\chi = \{x_1,\ x_2 \ldots x_m\} \in R^d$, that r represents the radius of hypersphere and that $c \in R^d$ is the center. The optimization issue is resolved by defining the minimal enclosing hypersphere.

$$Minimize\ r^2 \tag{9}$$

Subjected to $||\Phi(x_j) - c||^2 \leq r^2, j = 1, \ldots m$

$$L(c,\ r,\ \alpha) = r^2 + \sum_{j=1}^{m} \alpha_j \{||\Phi(x_j) - c||^2 - r^2\} \tag{10}$$

Set the derivative $\frac{\partial L(c,r,\alpha)}{\partial c} = 2\sum_{j=1}^{n} \alpha_j (\Phi(x_j) - c) = 0$. We attain the subsequent formula,

$$\sum_{j=1}^{m} \alpha_j = 1 \text{ and } c = \sum_{j=1}^{m} \alpha_j \Phi(x_j) \tag{11}$$

Thus Equation (10) becomes,

$$L(c,\ \gamma,\ \alpha) = \sum_{j=1}^{m} \alpha_j k(x_j,\ x_j) - \sum_{i,j=1}^{m} \alpha_i \alpha_j k(x_i,\ x_j) \tag{12}$$

which is the binary form of Equation (10).

The binary form of α is attained by resolving the optimization issue,

Maximize,

$$W(\alpha) = \sum_{i=1}^{m} \alpha_j k(x_i,\ x_j) - \sum_{i,j=1}^{m} \alpha_i \alpha_j k(x_i,\ x_j) \tag{13}$$

Subjected to

$$\sum_{i=1}^{m} \alpha_i = 1 \text{ and } \alpha_i \geq 0,\ i = 1 \text{ to } m.$$

Note that the Lagrange multiplier is non-zero as long as inequality constraints are equal for the solution. The complementarity condition is fulfilled by the optimum solution for α, $(c,\ \gamma)$ as follows,

$$\alpha_i\{||\Phi(x_i) - c||^2 - r^2\},\ i = 1\ldots m \tag{14}$$

Therefore, this shows that the training instances x_i lie on the surface of the optimum hypersphere respective to $\alpha_i > 0$.

$$f(x) = \mathrm{sgn}(r^2 - ||\Phi(x) - c||^2)$$

This denotes,

$$\begin{aligned} &= \mathrm{sgn}\ (r^2 - \{\Phi(x)\cdot\Phi(x)) - 2\textstyle\sum_{i=1}^{m}\alpha_i\Phi(x)\cdot\Phi(x_i)) \\ &\quad + \sum_{i,j=1}^{m}\alpha_i\alpha_j\big(\Phi(x_i)\cdot\Phi\big(x_j\big)\big)\}) \\ &= \mathrm{sgn}\ (r^2 - \{k(x,\ x) - 2\textstyle\sum_{i=1}^{m}\alpha_i k(x,\ x_i) \\ &\quad + \sum_{i,j=1}^{m}\alpha_i\alpha_j k\big(x_i,\ x_j\big)\}) \end{aligned} \tag{15}$$

Hence, the purpose of attaining a minimal enclosing hypersphere comprising each trained sample is fulfilled.

3. Performance Validation

The proposed model was simulated using Python 3.6.5 tool on PC i5-8600k, GeForce 1050Ti 4 GB, 16 GB RAM, 250 GB SSD, and 1 TB HDD. The parameter settings are given as follows: learning rate, 0.01; dropout, 0.5; batch size, 5; epoch count, 50; and activation, ReLU. In this study, the waste classifier results of the MCSOML-SWM method were tested using the TrashNet dataset [31], which includes 2527 samples under six classes as represented in Table 1. The class labels are glass, paper, cardboard, plastic, metal, and trash. The pictures were captured by placing the object on a white posterboard and using sunlight and/or room lighting. The pictures were resized to 512 × 384 pixels and the devices used were Apple iPhone 7 Plus, Apple iPhone 5S, and Apple iPhone SE.

Table 1. Dataset details.

Class	No. of Samples
Glass	501
Paper	594
Plastic	482
Cardboard	403
Trash	137
Metal	410
Total Number of Samples	2527

A set of confusion matrices formed by the MCSOML-SWM technique under diverse epochs are represented in Figure 1. The figure shows that the MCSOML-SWM system demonstrated improved waste classifier results under all epochs.

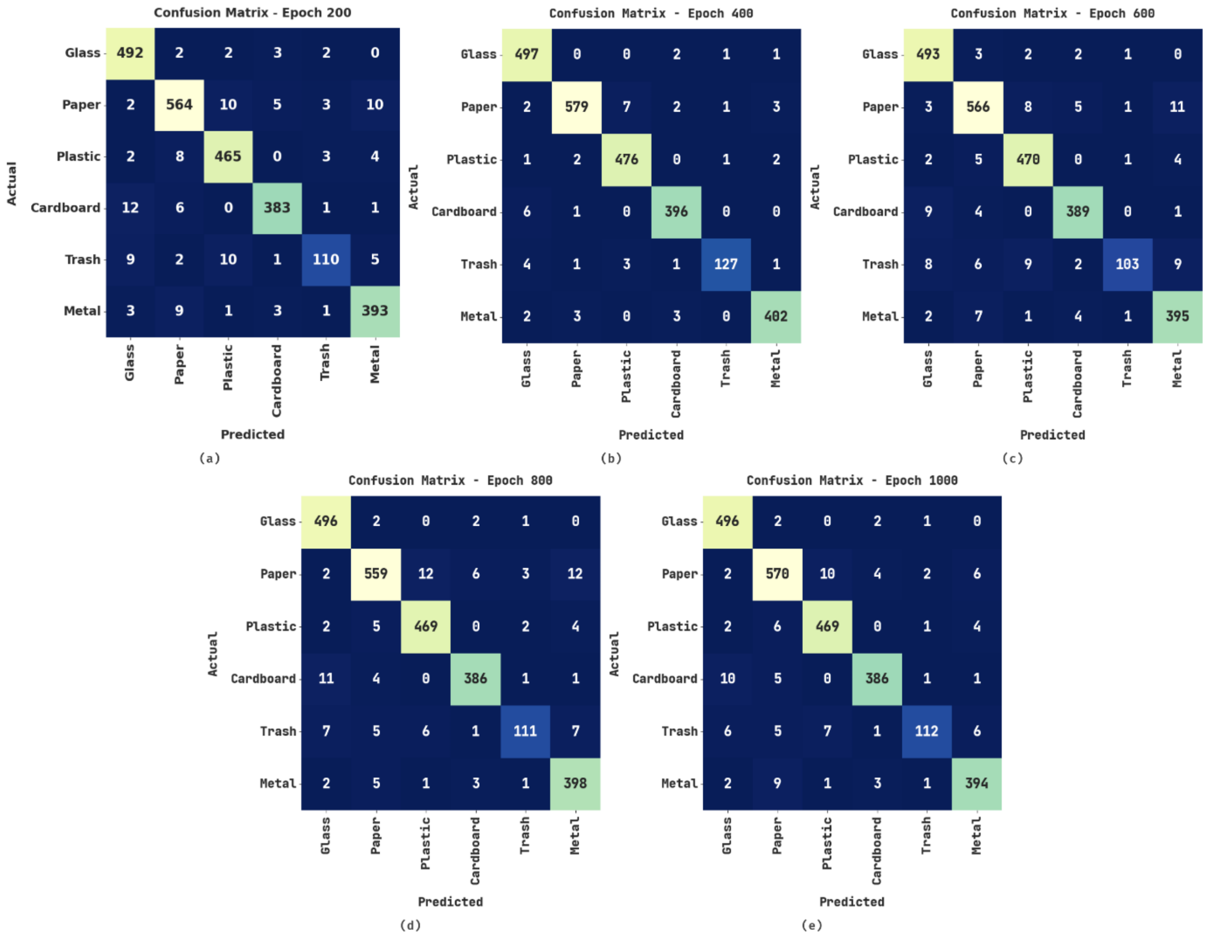

Figure 1. Confusion matrices of MCSOML-SWM approaches. (**a**) Epoch200, (**b**) Epoch400, (**c**) Epoch600, (**d**) Epoch800, and (**e**) Epoch1000.

Table 2 and Figure 2 highlight the waste classification outcomes of the MCSOML-SWM model on 200 epochs. The result shows that the MCSOML-SWM technique has provided improved outcomes under all classes. For example, in the glass class, the MCSOML-SWM method has offered outcomes for $accu_y$, $prec_n$, $reca_l$, F_{score}, and $Jaccard_{index}$ of 98.54%, 94.62%, 98.20%, 96.38%, and 93.01%, respectively. Additionally, for the paper class, the MCSOML-SWM approach provided outcomes for $accu_y$, $prec_n$, $reca_l$, F_{score}, and $Jaccard_{index}$ of 97.74%, 95.43%, 94.95%, 95.19%, and 90.82%, respectively. Furthermore, for the plastic class, the MCSOML-SWM method has provided outcomes for $accu_y$, $prec_n$, $reca_l$, F_{score}, and $Jaccard_{index}$ of 98.42%, 95.29%, 96.47%, 95.88%, and 92.08%, respectively.

Table 2. Result analysis of MCSOML-SWM algorithm with distinct class labels under 200 epochs.

Epoch-200					
Labels	$Accu_y$	$Prec_n$	$Reca_l$	F_{score}	$Jaccard_{index}$
Glass	98.54	94.62	98.20	96.38	93.01
Paper	97.74	95.43	94.95	95.19	90.82
Plastic	98.42	95.29	96.47	95.88	92.08
Cardboard	98.73	96.96	95.04	95.99	92.29
Trash	98.54	91.67	80.29	85.60	74.83
Metal	98.54	95.16	95.85	95.50	91.40
Average	98.42	94.85	93.47	94.09	89.07

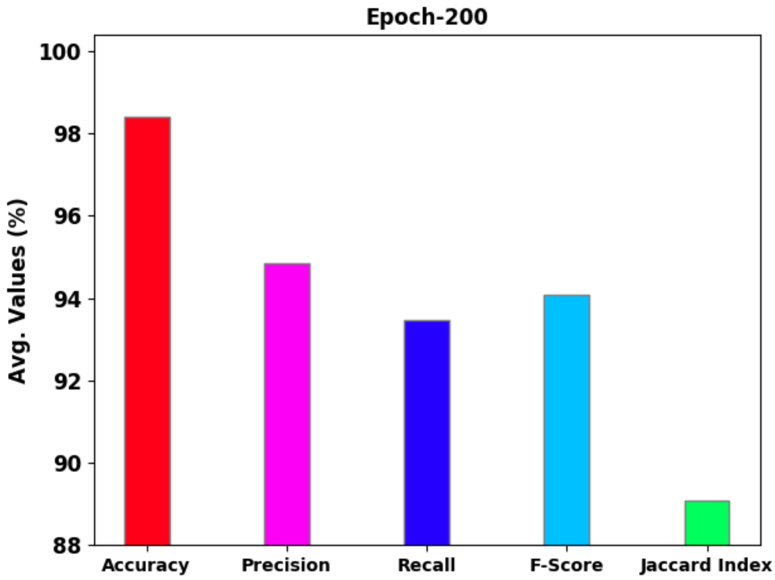

Figure 2. Average analysis of MCSOML-SWM technique under 200 epochs.

Table 3 and Figure 3 highlight the waste classification outcomes of the MCSOML-SWM method on 400 epochs. The results demonstrate that the MCSOML-SWM method has provided enhanced outcomes under all classes. For instance, in the glass class, the MCSOML-SWM model has offered outcomes for $accu_y$, $prec_n$, $reca_l$, F_{score}, and $Jaccard_{index}$ of 99.25%, 97.07%, 99.20%, 98.12%, and 96.32%, respectively. Furthermore, for the paper class, the MCSOML-SWM model has given outcomes for $accu_y$, $prec_n$, $reca_l$, F_{score}, and $Jaccard_{index}$ of 99.13%, 98.81%, 97.47%, 98.14%, and 96.34%, respectively. Moreover, in the plastic class, the MCSOML-SWM model has provided outcomes for $accu_y$, $prec_n$, $reca_l$, F_{score}, and $Jaccard_{index}$ of 99.37%, 97.94%, 98.76%, 98.35%, and 96.75%, respectively.

Table 4 and Figure 4 highlight the waste classification outcomes of the MCSOML-SWM method on 600 epochs. The results show that the MCSOML-SWM approach has provided better outcomes under all classes. For example, in the glass class, the MCSOML-SWM technique has provided outcome for $accu_y$, $prec_n$, $reca_l$, F_{score}, and $Jaccard_{index}$ of 98.73%, 95.36%, 98.40%, 96.86%, and 93.90%, respectively. Furthermore, for the paper class, the MCSOML-SWM model has given outcomes for $accu_y$, $prec_n$, $reca_l$, F_{score}, and $Jaccard_{index}$ of 97.90%, 95.77%, 95.29%, 95.53%, and 91.44%, respectively. Furthermore, for the plastic class, the MCSOML-SWM model has given outcomes for the $accu_y$, $prec_n$, $reca_l$, F_{score}, and $Jaccard_{index}$ of 98.73%, 95.92%, 97.51%, 96.71%, and 93.63%, respectively.

Table 3. Result analysis of MCSOML-SWM algorithm with distinct class labels under 400 epochs.

Epoch-400					
Labels	$Accu_y$	$Prec_n$	$Reca_l$	F_{score}	$Jaccard_{index}$
Glass	99.25	97.07	99.20	98.12	96.32
Paper	99.13	98.81	97.47	98.14	96.34
Plastic	99.37	97.94	98.76	98.35	96.75
Cardboard	99.41	98.02	98.26	98.14	96.35
Trash	99.49	97.69	92.70	95.13	90.71
Metal	99.41	98.29	98.05	98.17	96.40
Average	99.34	97.97	97.41	97.67	95.48

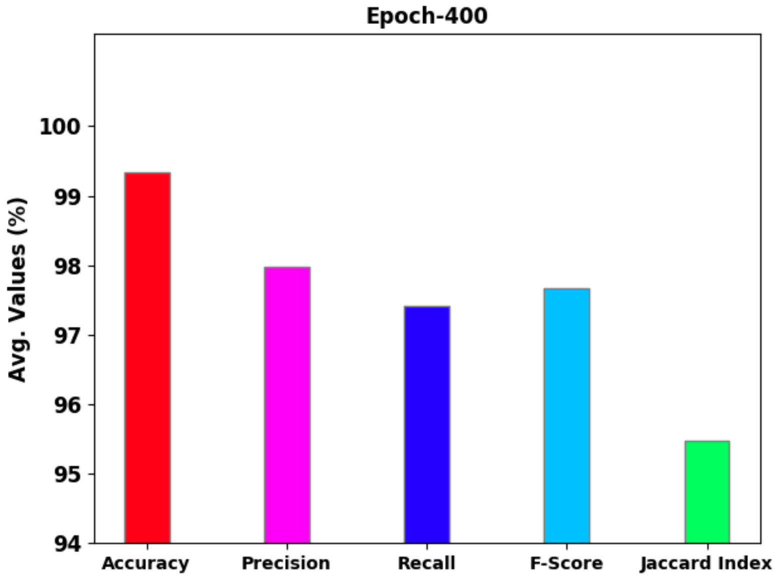

Figure 3. Average analysis of MCSOML-SWM methodology under 400 epochs.

Table 4. Result analysis of MCSOML-SWM algorithm with distinct class labels under 600 epochs.

		Epoch-600			
Labels	$Accu_y$	$Prec_n$	$Reca_l$	F_{score}	$Jaccard_{index}$
Glass	98.73	95.36	98.40	96.86	93.90
Paper	97.90	95.77	95.29	95.53	91.44
Plastic	98.73	95.92	97.51	96.71	93.63
Cardboard	98.93	96.77	96.53	96.65	93.51
Trash	98.50	96.26	75.18	84.43	73.05
Metal	98.42	94.05	96.34	95.18	90.80
Average	98.54	95.69	93.21	94.22	89.39

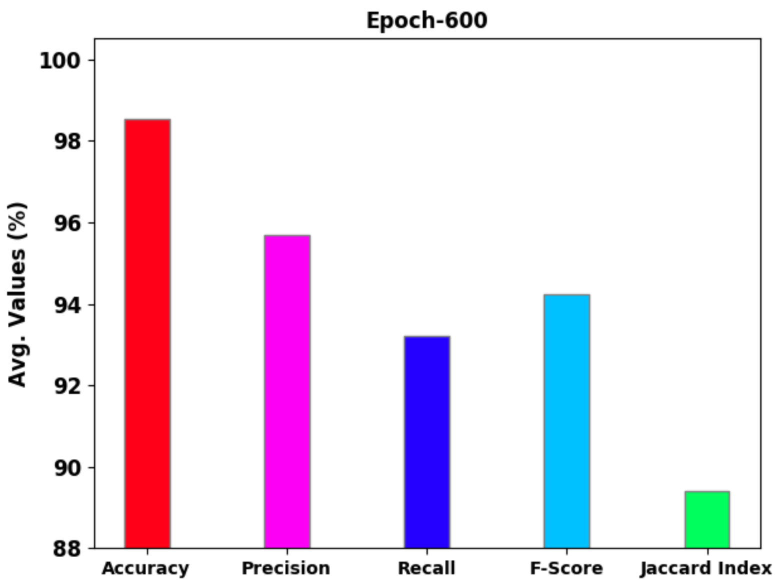

Figure 4. Average analysis of MCSOML-SWM approach under 600 epochs.

Table 5 and Figure 5 highlight the waste classification outcomes of the MCSOML-SWM system on 800 epochs. The results show that the MCSOML-SWM algorithm has provided better outcomes under all classes. For example, in the glass class, the MCSOML-SWM technique has offered outcomes for the $accu_y$, $prec_n$, $reca_l$, F_{score}, and $Jaccard_{index}$ of 98.85%, 95.38%, 99%, 97.16%, and 94.48%, respectively. Moreover, for the paper class, the MCSOML-SWM model has given outcomes for the $accu_y$, $prec_n$, $reca_l$, F_{score}, and $Jaccard_{index}$ of 97.78%, 96.38%, 94.11%, 95.23%, and 90.89%, respectively. Furthermore, for the plastic class, the MCSOML-SWM model has presented outcomes for the $accu_y$, $prec_n$, $reca_l$, F_{score}, and $Jaccard_{index}$ of 98.73%, 96.11%, 97.30%, 96.70%, and 93.61%, respectively.

Table 5. Result analysis of MCSOML-SWM algorithm with distinct class labels under 800 epochs.

			Epoch-800		
Labels	$Accu_y$	$Prec_n$	$Reca_l$	F_{score}	$Jaccard_{index}$
Glass	98.85	95.38	99.00	97.16	94.48
Paper	97.78	96.38	94.11	95.23	90.89
Plastic	98.73	96.11	97.30	96.70	93.61
Cardboard	98.85	96.98	95.78	96.38	93.01
Trash	98.65	93.28	81.02	86.72	76.55
Metal	98.58	94.31	97.07	95.67	91.71
Average	98.58	95.41	94.05	94.64	90.04

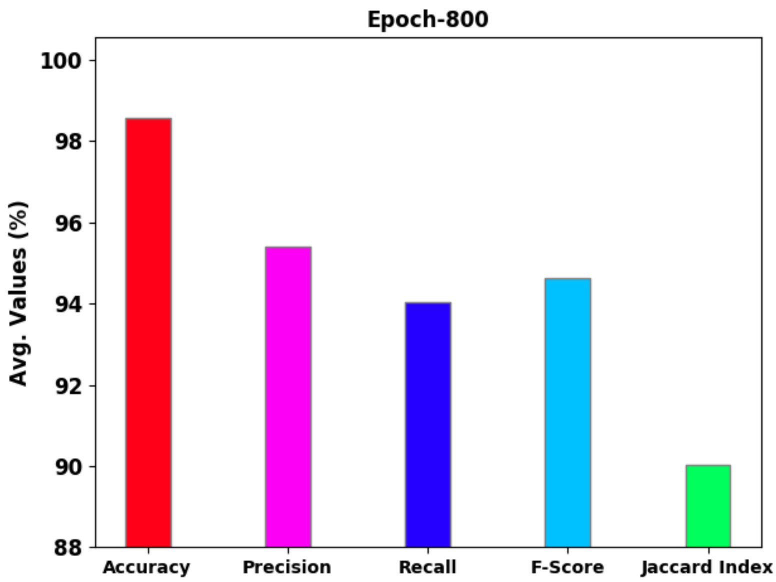

Figure 5. Average analysis of MCSOML-SWM algorithm under 800 epochs.

Table 6 and Figure 6 highlight the waste classification outcomes of the MCSOML-SWM algorithm on 1000 epochs. The results show that the MCSOML-SWM method has provided enhanced outcomes under all classes. For instance, in the glass class, the MCSOML-SWM model has presented outcomes for $accu_y$, $prec_n$, $reca_l$, F_{score}, and $Jaccard_{index}$ of 98.93%, 95.75%, 99%, 97.35%, and 94.84%, respectively. Furthermore, for the paper class, the MCSOML-SWM model has provided outcomes for $accu_y$, $prec_n$, $reca_l$, F_{score}, and $Jaccard_{index}$ of 97.98%, 95.48%, 95.96%, 95.72%, and 91.79%, respectively. Moreover, for the plastic class, the MCSOML-SWM model has given outcomes for $accu_y$, $prec_n$, $reca_l$, F_{score}, and $Jaccard_{index}$ of 98.77%, 96.30%, 97.30%, 96.80%, and 93.80%, respectively.

The training accuracy (TRA) and validation accuracy (VLA) accomplished by the MCSOML-SWM methodology on the test dataset are demonstrated in Figure 7. The results demonstrate that the MCSOML-SWM algorithm has accomplished the highest values of TRA and VLA. Additionally, the VLA seemed to be improved over the TRA.

Table 6. Result analysis of MCSOML-SWM algorithm with distinct class labels under 1000 epochs.

Epoch-1000					
Labels	$Accu_y$	$Prec_n$	$Reca_l$	F_{score}	$Jaccard_{index}$
Glass	98.93	95.75	99.00	97.35	94.84
Paper	97.98	95.48	95.96	95.72	91.79
Plastic	98.77	96.30	97.30	96.80	93.80
Cardboard	98.93	97.47	95.78	96.62	93.46
Trash	98.77	94.92	81.75	87.84	78.32
Metal	98.69	95.86	96.10	95.98	92.27
Average	98.68	95.96	94.32	95.05	90.75

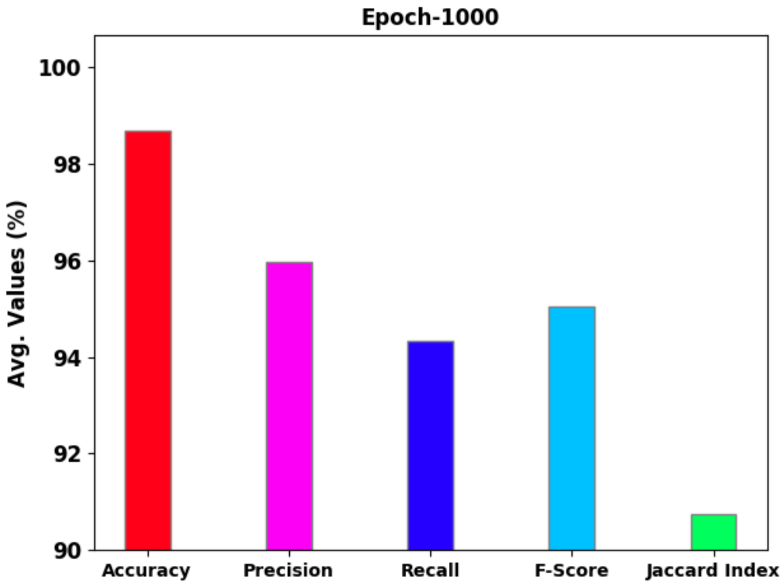

Figure 6. Average analysis of MCSOML-SWM methodology under 1000 epochs.

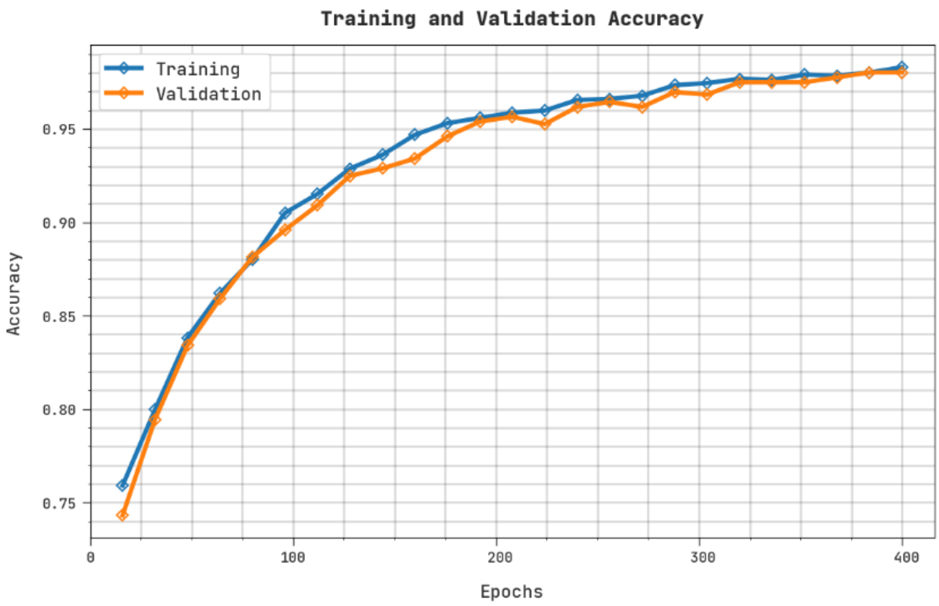

Figure 7. TRA and VLA analysis of MCSOML-SWM approach.

The training loss (TRL) and validation loss (VLL) attained by the MCSOML-SWM methodology on the test dataset are portrayed in Figure 8. The results illustrate that the MCSOML-SWM method has accomplished minimum values of TRL and VLL. Particularly, the VLL shows lower values than the TRL.

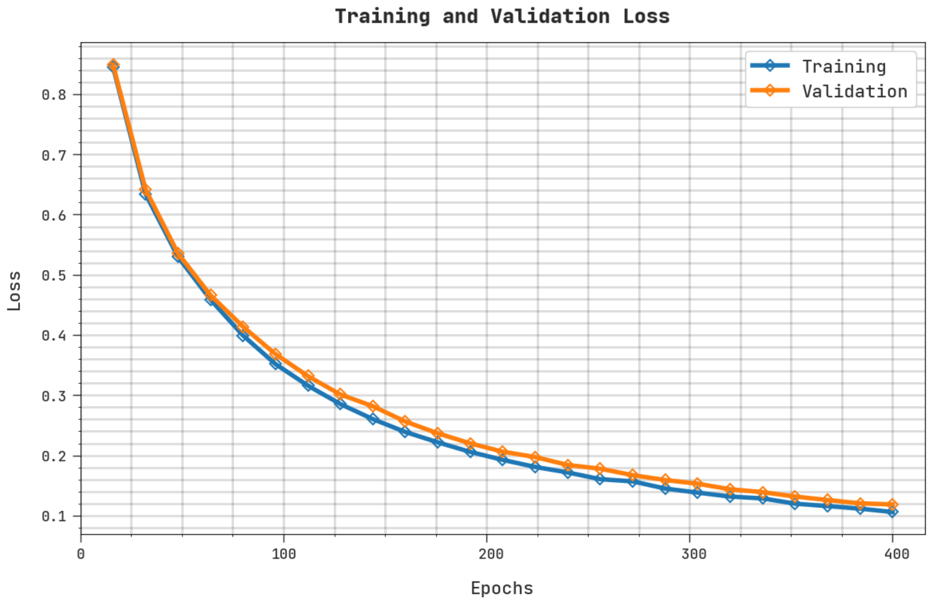

Figure 8. TRL and VLL analysis of MCSOML-SWM methodology.

A clear precision–recall assessment of the MCSOML-SWM approach on the test dataset is depicted in Figure 9. The figure shows that the MCSOML-SWM methodology has resulted in improved values of precision–recall values under each class.

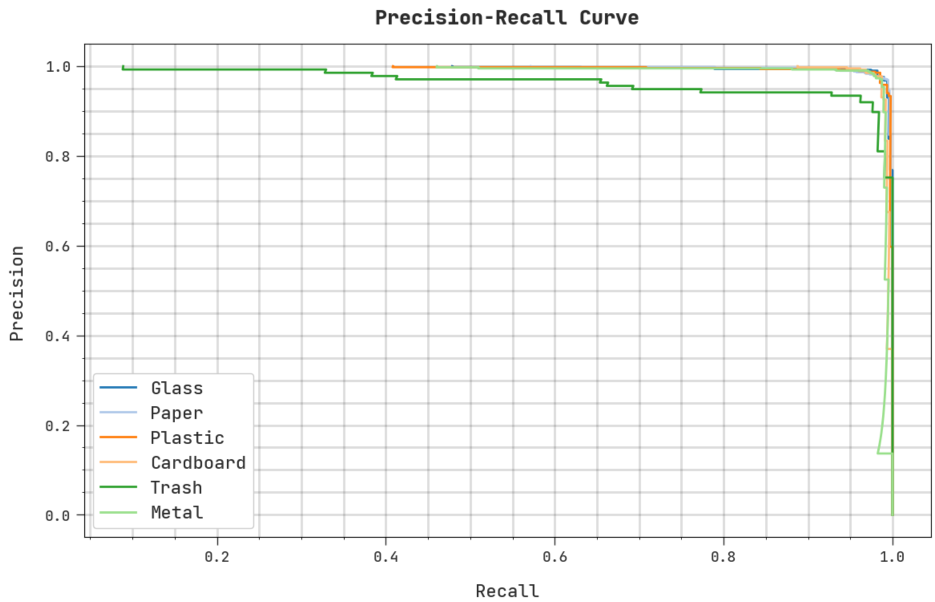

Figure 9. Precision–recall analysis of MCSOML-SWM method.

A brief ROC investigation of the MCSOML-SWM approach on the test dataset is depicted in Figure 10. The results signify that the MCSOML-SWM methodology has shown its capability in classifying distinct classes on the test dataset.

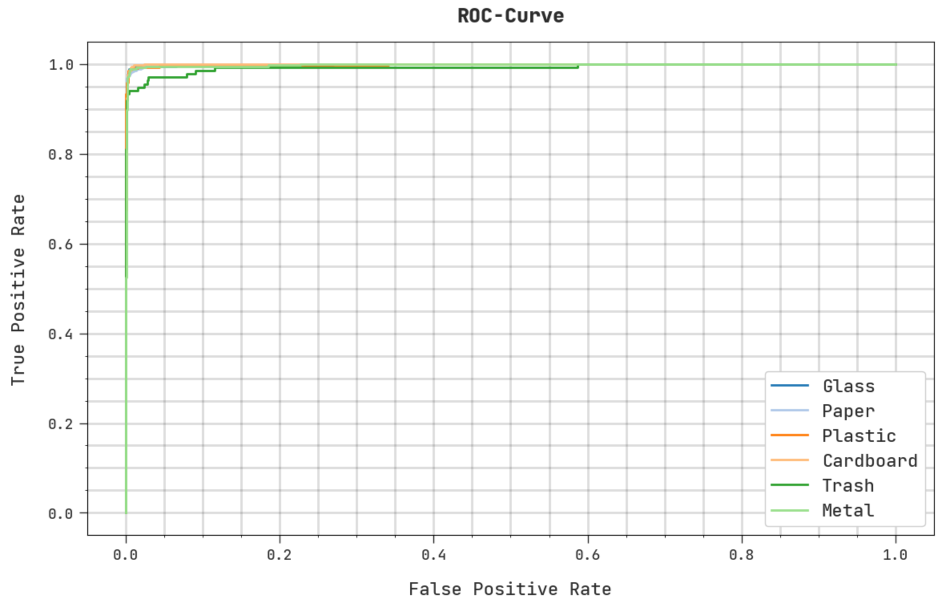

Figure 10. ROC analysis of MCSOML-SWM methodology.

A wide ranging comparison study of the MCSOML-SWM technique with other waste classifier models is portrayed in Table 7 and Figures 11 and 12. The comparison study demonstrated that the MCSOML-SWM model shows superior outcomes over other techniques. With respect to $accu_y$, the MCSOML-SWM method has demonstrated higher $accu_y$ of 99.34% whereas the GA-SVM, LNNAC, PSO-ANN, CLST RNN, and CNN models have depicted lower values for $accu_y$ of 85.08%, 90.58%, 95.20%, 98.58%, and 98.09%, respectively. Meanwhile, with respect to $prec_n$, the MCSOML-SWM model has established a high value for $prec_n$ of 97.97% while the GA-SVM, LNNAC, PSO-ANN, CLST RNN, and CNN methods have portrayed lower values for $prec_n$ of 88.18%, 88.68%, 92.95%, 97.08%, and 97.76%, respectively. Ultimately, with respect to $reca_l$, the MCSOML-SWM model has demonstrated high outcomes for $reca_l$ of 97.41% while the GA-SVM, LNNAC, PSO-ANN, CLST RNN, and CNN models have shown lower values for $reca_l$ of 84.15%, 90.13%, 94.20%, 97.28%, and 96.15%, respectively. Finally, with respect to F_{score}, the MCSOML-SWM model has established a high value for F_{score} of 97.67% while the GA-SVM, LNNAC, PSO-ANN, CLST RNN, and CNN models have portrayed lower values for F_{score} of 88.85%, 91.45%, 93.93%, 97.35%, and 95.09%, respectively.

Therefore, the MCSOML-SWM model has surpassed all the other waste classification models in the smart city environment.

Table 7. Comparative analysis of MCSOML-SWM attitude with existing methodologies [15–18].

Methods	$Accu_y$	$Prec_n$	$Reca_l$	F_{score}
MCSOML-SWM	99.34	97.97	97.41	97.67
GA-SVM [15]	85.08	88.18	84.15	88.85
LNNAC Model [16]	90.58	88.68	90.13	91.45
PSO–ANN Model [17]	95.20	92.95	94.20	93.93
CLST RNN Model [18]	98.58	97.08	97.28	97.35
CNN Model [18]	98.09	97.76	96.15	95.09

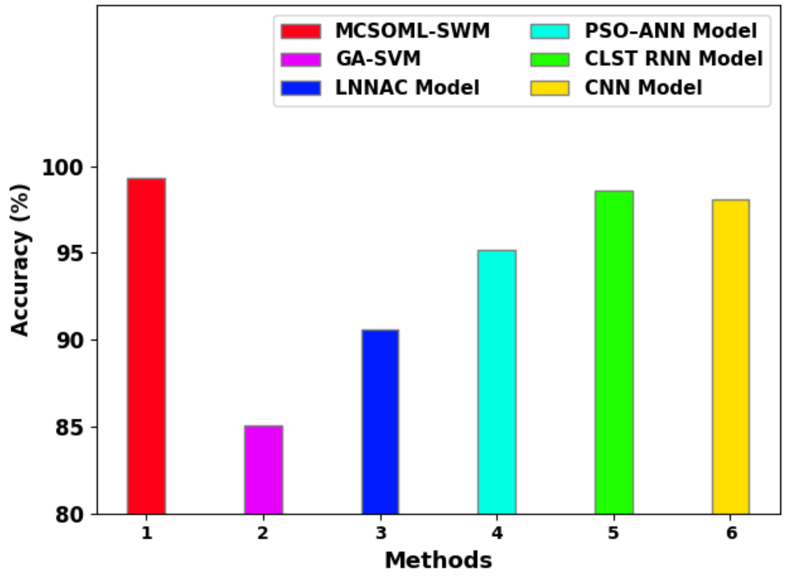

Figure 11. $Accu_y$ analysis of MCSOML-SWM with existing methodologies.

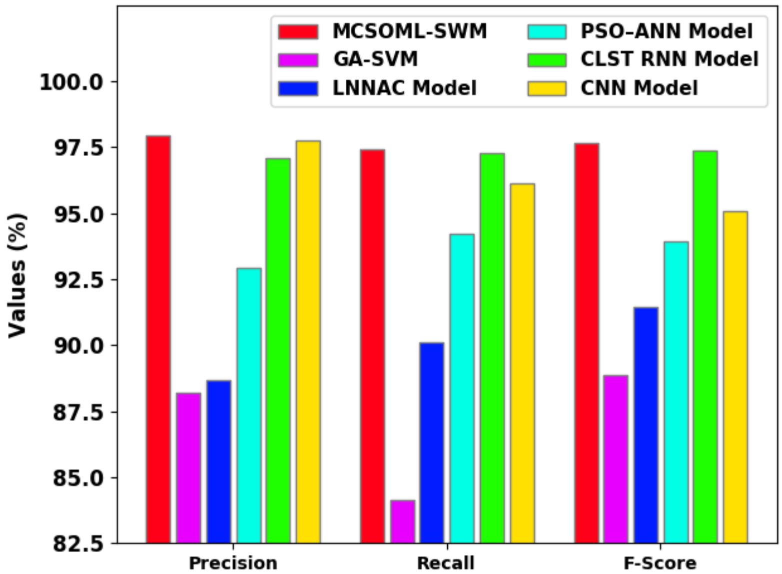

Figure 12. Comparative analysis of MCSOML-SWM with existing methodologies.

4. Conclusions

In this study, a new MCSOML-SWM system was established to identify different categories of solid waste to enable smart waste management. In the MCSOML-SWM model, the SSD model allows for the effective recognition of objects. A DCNN- based MixNet model is then applied to produce feature vectors and a hyperparameter tuning process is carried out by the MCSO algorithm. For accurate waste classification, the MCSOML-SWM technique applied SVM in this study. A comprehensive set of simulations were carried out to demonstrate the improved classification performance of the MCSOML-SWM algorithm. This widespread comparison study pointed out the improved performance of the MCSOML-SWM method over other DL algorithms. Thus, the presented MCSOML-SWM method may be exploited for effective waste management. In the future, hybrid DL classifiers may be integrated into the presented approach for improved performance.

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