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Enhancing Smart City Waste Management through LBBOA based RIAN Classification

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Abstract: Effective trash management has become a top environmental priority, especially in urban areas with significant population growth where waste output is on the rise. As cities work to manage waste properly, innovative waste management programmes have the potential to increase effectiveness, cut costs, and improve the aesthetic appeal of public places. This article introduces SCM-RIAN, a powerful "Smart City Management and Classification System" built on the Internet of Things (IoT) and deep learning (DL) technologies. Convolutional neural networks are used in the waste classification model implemented within this smart city management and classification framework. This system for classifying waste is intended to categorise rubbish into several classes at waste collection sites, encouraging recycling. The Rotation-Invariant Attention Network (RIAN) is a unique approach presented for the categorization process to address a prevalent problem in smart city management (SCM). A Centre Spectral Attention (CSpeA) module built within RIAN isolates spectral bands from other categories of pixels' influence, reducing redundancy. As an alternative to the conventional 3 3 convolution, the Rectified Spatial Attention (RSpaA) module is also introduced to obtain rotation-invariant spectral-spatial data contained in SCM patches. The suggested RIAN for SCM classification is built on integrating the CSpeA, 1×1 convolution, and RSpaA modules. The Ladybird Beetle Optimisation Algorithm (LBBOA) is used to optimise hyperparameters. With improved results compared to other current models, this suggested SCM-RIAN achieved 98.12% accuracy (ACC) with high sensitivity (SEN), specificity (SPEC), and kappa index (KI) using the waste classification dataset.

Keywords: Smart city management, Rotation-invariant attention network, Center spectral attention, Rectified spatial attention, Ladybug beetle optimization algorithm.

1. Introduction

Numerous social and environmental concerns, the need for reliable infrastructure, and the possibility for technological improvements to improve quality of life are being faced by urban regions all over the world. Intelligent technologies have developed in response to these problems [1]. Cities are growing quickly thanks to factors including better connection and sophisticated automation, which is a reflection of the fourth industrial revolution that is still taking place in the twenty-first century. These elements have direct effect on the waste production brought on by urbanisation and population expansion [2]. The idea of "smart cities" is becoming more and more relevant, especially given that it is predicted that there will be 9.9 billion people on the planet by 2050, up from 7.8 billion in 2020 [3]. Smart cities incorporate a wide range of information and communication technologies, with the Internet of Things (IoT) playing a crucial role to efficiently managing public spaces and city services in a sustainable manner.

Although there are many obstacles to overcome, efficient waste processing and collection are crucial duties for big cities. As a result, smart waste management (SWM) has become a key idea in smart cities, calling for a multifaceted strategy [4]. SWM includes data gathering and processing from sensors on trash trucks, intelligent trash cans (SGBs), and other municipal infrastructure. It comprises providing incentives to residents, keeping an eye on the environment, classifying and separating waste, planning and optimising routes, providing information and decision assistance to many stakeholders, and managing waste as a whole. In order to construct a network of intelligent devices that are capable of measuring, computing, transferring, storing, and processing data, these systems are anticipated to heavily rely on IoT technology [5,6]. SWM systems with the use of ICT could be used to promote resource conservation, energy efficiency, and environmental safety [7].

Smart construction, medical care, waste management, navigation, technological advancement, energy management, networking, water management, and agriculture are just a few of the industries where IoT-based approaches have found applications. These approaches have improved services in contemporary cities around the world [8]. Waste management in smart cities poses a serious environmental concern that IoT might help solve [9,10]. It includes all phases of waste tracking, including generation, collection, transfer, and disposal, which can take place at landfills, disposal sites, or recycling facilities [11]. To address health and hygiene challenges while building smarter and safer communities, an IoT-based waste management system is necessary. An integrated strategy to waste management is presented in this work [12,13].

The paper at hand contributes significantly to the following areas;

- The SCM-RIAN (Smart City Management-Rotation-Invariant Attention Network) model is presented in this research as a novel approach to deal with the complex problems of waste management and recycling in contemporary urban settings.
- CSpeA and RSpaA modules are two cutting-edge methodologies that SCM-RIAN makes use of to improve waste classification in smart city management.
- The model's performance is further improved by the paper's use of the Ladybird Beetle Optimisation Algorithm (LBBOA) to tune hyperparameters.
- SCM-RIAN performs excellently when tested against a dataset for waste classification.

The remaining sections of the study are organised in the form of shadows: The relevant works, suggested model, the results and validation analysis, and the summary and conclusion are discussed in detail.

2. Related works

In this systematic study employing the PRISMA approach, Mohamed et al. [14] investigate the application of the Internet of Things (IoT) in the management of medical waste. Their studies centre on how IoT could improve waste monitoring and aid initiatives to hit net-zero waste goals. They support the use of digital surveillance tools, such as sensors for trash cans to track rubbish continuously. Despite the fact that few studies have looked at the possibilities of IoT in monitoring medical waste, the majority of studies have concentrated on problems with storage, transportation, or disposal. The report talks about these restrictions, examines the barriers to continued development, and offers suggestions based on some research. The digitalization of medical waste is growing and becoming a significant concern because to real-time monitoring and data exchange.

Farjana et al. developed a thorough IoT-based e-waste management technique [15]. This system manages efficient e-waste collection, sorting, and disposal. IoT devices with sensors provide real-time data on e-waste levels, which enhances the collection and disposal processes. The authors advocate recycling electronic waste while also emphasising the benefits of using machine learning to distinguish between various materials, such as metallic and plastic components. By anticipating the volume of waste and doing data analysis utilising cloud-based technologies, their strategy enhances waste pickup schedules and overall effectiveness.

Alzahrani et al. [16] employ blockchain technology wastewater management system for smart cities based on the IoT. Data storage for the development of wastewater reuse incentives is done via blockchain. The quantity and quality of reclaimed wastewater are used to determine token payouts, however there are concerns about potential data manipulation. The study makes use of anomaly detection methods to collect data from IoT sensor hacks. IoT sensors and quality indicators are used to measure the production and reuse of wastewater. According to simulations, wastewater will be managed more effectively and contain less moisture. Additionally, it will be reused and recycled.

Ramya et al. [17] have developed a novel deep convolutional neural network (FHGO-based deep CNN) for the classification of electronic waste. They efficiently route e-waste photos using fractional Henry gas optimisation (FHGO), which ensures precise path prediction while consuming the least amount of energy. In addition to data augmentation, the team also employs feature extraction techniques such the local Gabor binary pattern (LGBP), histogram of oriented gradients (HOG), and grey level co-occurrence matrix (GLCM). The classification phase is then completed using deep CNN during FHGO training. One significant advantage is the method's higher degree of precision in comparison to alternatives.

In a different work by Al. Duhayyim et al. [18], a modified cuttlefish swarm optimisation with machine learning-based solid waste management (MCSOML-SWM) system is presented for smart cities. The major goals of MCSOML-SWM are to classify different types of solid waste and to promote cutting-edge waste management practises. This paradigm simplifies object detection by making use of a successful single-shot detector (SSD) concept. By utilising the MCSO approach, the MixNet model, which is based on a deep convolutional neural network, is utilised to produce feature vectors, which speeds up the laborious process of manually adjusting the hyperparameters. The MCSOML-SWM Support Vector Machine (SVM) approach is employed for precise trash categorization, and comprehensive simulations demonstrate its superior performance, achieving a maximum accuracy of 99.34% in categorization tests.

Furthermore, Thaseen Ikram et al. [19] developed an intelligent rubbish management model designed for smart cities. This model analyses, compiles, and deciphers data intelligently to enable sensible trash collection management decisions. It accomplishes this by combining a fuzzy inference engine with genetic algorithm (GA). The system includes a fuzzy inference engine to improve accuracy and adaptability while reducing errors under challenging operational circumstances. The cost of waste management is estimated using the Mamdani model, and the optimal set of rules for the fuzzy inference system (FIS) is chosen using GA. The model uses sensors to collect data, trains the FIS using fuzzy logic, and adds sensors to anticipate when smart bins would likely reach capacity. The genetic algorithm (GA) is used with fuzzy logic to identify important genes while preserving FIS interpretability. This deals with problems that the standard genetic algorithm has, like gene loss. This approach allows for the use of small, inexpensive sensors. The effectiveness of the model is verified using the Proteus simulator. The model had exceptionally high rates of overall accuracy, precision, and sensitivity (95.44%, 96.68%, and 93.96%, respectively). By correctly classifying recyclable items, this model minimises resource waste.

3. Proposed Methodology

The block diagram of the proposed SCM-RIAN is given below in figure 1.

3.1 Dataset description

A benchmark waste classification dataset that was provided from the Kaggle repository was used for the study of the experimental outcomes for the suggested technique [20]. There are the following numbers of photos in each class in this dataset:

- Class: Cardboard 393 pictures
- images of glass class: 491
- Metal category: 400 pictures
- paper type: 584 pictures
- Plastic category: 472 pictures
- Class of waste: 127 pictures

A selection of sample photos from this collection are offered for visual reference, as seen in Figure 2.

3.2 Classification

This section introduces the suggested RIAN. First, Section A provides an overview of RIAN. The CSpeA module's specifics are then introduced in Section B. Finally, Section C provides a detailed description of the RSpaA module.

3.2.1 Overview of RIAN

A typical 3D data format [21] for SCM typically consists of one spectral dimension and two spatial dimensions. Let's write the waste image as $X \in R^{W \times H \times C}$,, where $W \times H$ stands for the waste image's spatial dimensions and C for the number of spectral bands. When determining the landcover category for a specific pixel, represented by the notation $x^i \in R^C$ [22, 23], it is essential to take into account both the spectral and spatial information contained in X.

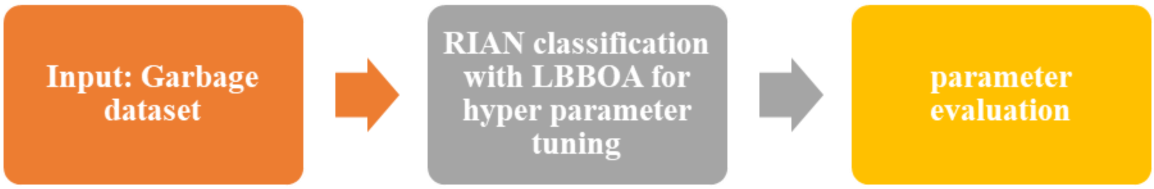


Figure 1. Block diagram

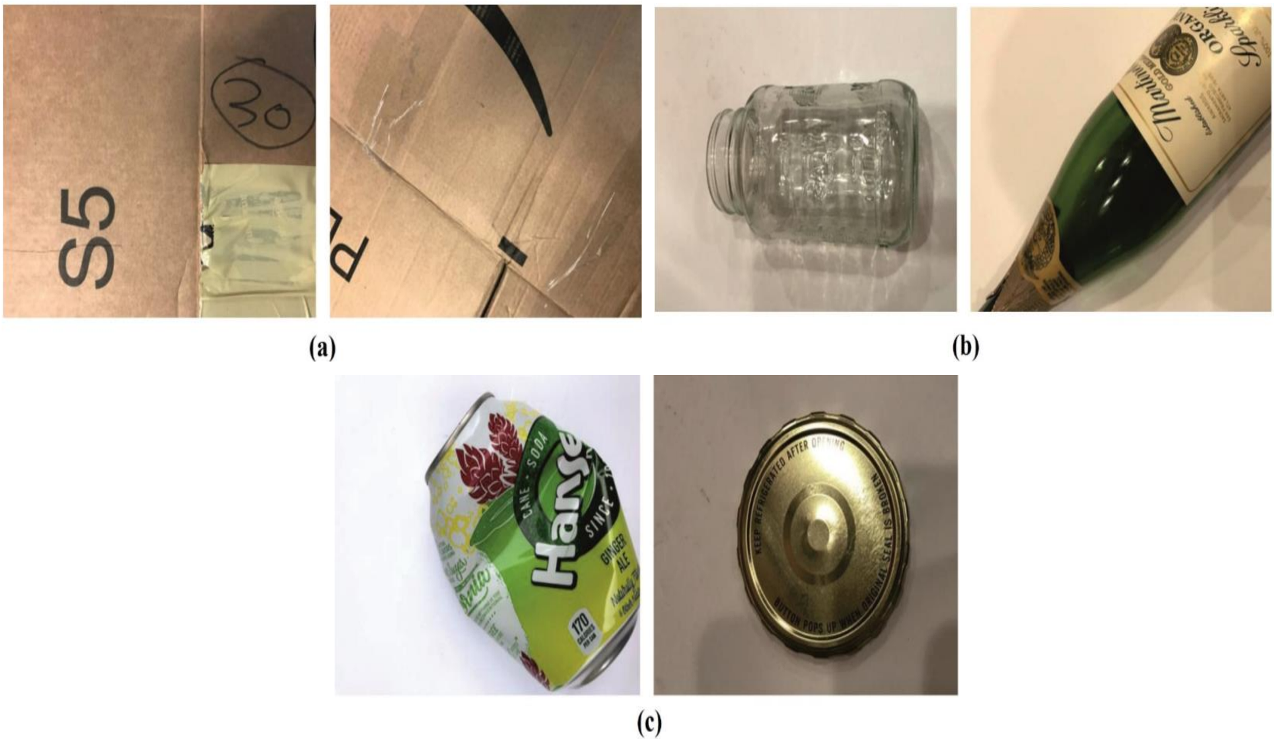


Figure 2. Sample images: (a) cardboard, (b) glass, (c) metal, and (d) paper.

Table 1. Detail of the proposed RIAN configuration

Layer	Shape of Output	Connected	Shape of Output	Kernels	Shape of input
Input	(K,K,C)	CSpeA	(K,K,C)	-	-
Spectral_Convlution-1	(K,K,64)	Element-wise-Addition-1	(K,K,64)	64	(K,K,64)
Spectral_Convlution-4	(K,K,64)	RSpaA-2	(K,K,64)	64	(K,K,64)
Spectral_Convlution-1	(K,K,64)	Spectral_Convlution-2, Element-wise-Addition-1	(K,K,64)	64	(K,K,C)
Spectral_Convlution-2	(K,K,64)	RSpaA-1	(K,K,64)	64	(K,K,64)
RSpaA-1	(K,K,64)	Spectral_Convlution-3	(K,K,64)	-	(K,K,64)
Element-wise-Addition-2	(K,K,64)	Spectral_Convlution-4, Element-wise-Addition-2	(K,K,64)		(K,K,64)
Fully_connection	(L)	Softmax	(L)	L	(1,1,64)
Global_Average_Pooling	(1,1,64)	Fully_connection	(1,1,64)	-	(K,K,64)
RSpaA-2	(K,K,64)	Spectral_Convlution-5	(K,K,64)	-	(K,K,64)
CSpeA	(K,K,C)	Spectral_Convlution-1	(K,K,C)	-	(K,K,C)
Spectral_Convlution-5	(K,K,64)	Element-wise-Addition-2	(K,K,64)	64	(K,K,64)
Element-wise-Addition-2	(K,K,64)	Global_Average_Pooling	(K,K,64)	-	(K,K,64)
Softmax (Output)	(L)	-	(L)	-	(L)

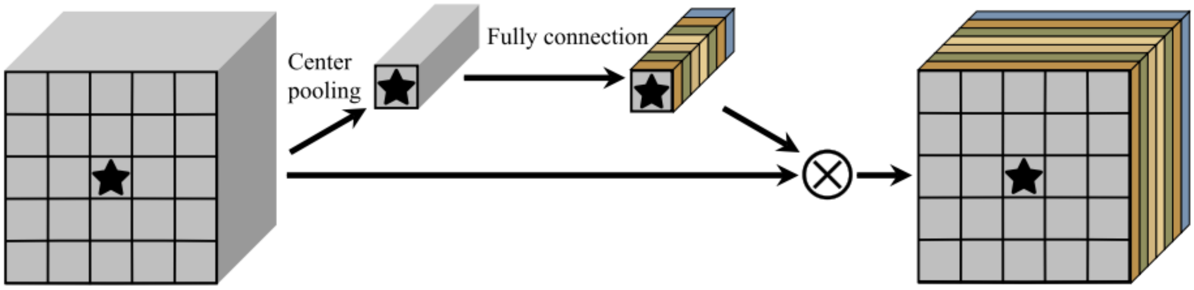


Figure 3. A demonstration of a CSpeA module

Waste images usually display a spatial smoothness pattern, in which adjacent pixels frequently fall under the same land-cover classification. We can use data from nearby pixels to improve the classification of pixel X_{i} [24]. To do this, we clip nearby pixels from the waste image X into a square region, resulting in the waste patch $X_i \in R^{K\times K\times C}$. The center pixel of this waste picture patch, designated by the letters KK, is called x_{i} . Importantly, every pixel that will be classified belongs to a certain waste image patch. The RIAN technique is then used to estimate the category of the pixel X_{i} using the information in the waste picture patch X_{i} . A representation of the CSpeA module is shown in Figure 3.

CSpeA Module for Spectral Band Reduction: To remove unneeded spectral bands, the CSpeA module is first applied to the waste patch X_{i}. The pipeline for processing data is streamlined in this step.

Spectral-Spatial Rotation-Invariant Extraction 2 residual blocks are employed to obtain spectral-spatial characteristics based on the waste patch X_{i} that are rotation-invariant. The ability of the model to handle different orientations is improved by these blocks.

Definition of Pixel Category: The last stage is to define the category of the pixel X_{i}, which is done using a linear softmax operation.

Within RIAN, each residual block consists of the following elements:

Each residual block's primary component, the RSpaA module, is critical for synthesizing rotation-invariant spectral-spatial information.

Utilizing rectified linear units (ReLU), spectral convolutions, each residual block employs two ReLU-based spectral convolutions. The initial spectral convolution concentrates on spectral property extraction from the block-specific input.

Spectral Convolutions: Two spectral convolutions are used in addition to the ReLU-based spectral convolutions. Notably, the residual block's second spectral convolution excels at generating highly discriminative spectral-spatial characteristics.

The CSpeA Module for spectral band reduction, spectral convolutions for feature extraction, and the RSpaA Module for producing rotation-invariant spectral-spatial information make up the core elements of the RIAN system. The efficacy of the network in categorising waste images is influenced by all of these factors. In order to avoid introducing dependencies on nearby pixels and successfully prevent interference from other pixel categories during feature extraction, the spectral convolution uses convolutions with 1×1 spatial kernels. Refer to Table 1 for a complete configuration of the proposed RIAN.

3.2.2 CSpeA

Normally, waste materials have a wide range of spectral bands, however the trash patch X_{i} may contain redundant spectral data that could harm classification precision. It is crucial to either increase the useful spectral bands in the waste patch X_{i} or decrease the redundant ones in order to improve the classification results. Deep networks are frequently used in recent research projects to dynamically recalibrate the spectral bands within the waste patch X_{i}. This spectral attention module's goal is to produce an attention weight vector, as $\alpha \in R^{\mathrm{C}}$, that is specifically suited to the given classification task [25].

$$a = SpeA(X_i) \quad (1)$$

For the purpose of classifying trash images, the Spectral Attention Module, abbreviated as $SpeA$ (·) is essential in determining the importance of various spectral bands inside an image patch. Each spectral band is given attention weights by this module, expressed as, where lower values denote redundancy and larger values denote informativeness. The spectral bands of the waste picture patch X_i are to be calibrated using these attention weights. Current methods frequently use the waste image patch X_i global information to obtain their results. However, dealing with waste picture patches X_i poses a common problem in practise since these patches frequently contain conflicting pixels whose categories diverge from the core pixel x_i. Due to the fact that informative spectral bands differ for various pixel categories, this interference may affect how accurately attention weights are calculated.

The centre pixel of inputs is captured using the centre pooling during forward propagation. In the backward propagation of gradients, just the input's central pixel is returned to.

In this study, it present CSpeA, a simple strategy for decreasing the influence of overlapping pixels on their attention load. Centre pixel x_i within the waste picture patch X_i , where x_i denotes the pixel being considered for classification, is the only pixel used by CSpeA to calculate the attention weight. This technique successfully avoids the disruption brought on by pixels from several categories. The CSpeA procedure is described as follows:

Using a centre pool for the purpose of separating the central pixel x_i from the waste picture patch X_i, we developed a centre pooling mechanism that is similar to max pooling. During the process of forward propagation, the central pixel is taken from the inputs using the center pooling function. During the backward propagation phase, slopes of the outcomes are only returned to the central pixel of the inputs.

After central pooling, the attention weighted in a fully linked layer with an activation function that is sigmoid is only calculated using information from the central pixel, x_i. Recalibration of Spectral Bands: Using the attention weight that was collected, all of the pixels in the waste image patch's spectral bands are then recalibrated. The importance of spectral bands is adjusted during this recalibration procedure based on the calculated. The suggested CSpeA's formulation can be summed up as follows:

$$x_i = Center(X_i) \quad (2)$$

$$a = sigmoid(W_c x_i + b_c) \quad (3)$$

$$\hat{X}_i = a \otimes X_i \quad (4)$$

The following formulation uses:

- The centre pooling action is denoted by $Center(\cdot)$.
- The weight parameter of the completely linked layer is denoted by $W_c \in R^{C\times C}$
- The bias term is $b_c \in R^{C\times 1}$.
- Channel-wise multiplication is indicated by "$\otimes$"
- $\hat{X}_i \in R^{\mathrm{K\times K\times C}}$ refers to the X_i that has been calibrated.

3.2.3 RSpaA

The RSpaA module will be outlined in this article to improve the processing of rotation-invariant data by deep neural networks, particularly in rubbish photo categorization applications. The RSpaA module's main goal is to effectively combine the properties of nearby pixels to produce rotation-invariant spectral-spatial information. To make it simpler for readers to understand the RSpaA module, we first explain the standard spectral-spatial convolution.

Starting from a shallow feature tensor denoted by the notation $Y \in R^{\mathrm{K\times K\times C_{in}}}$, where Y has the characteristics of a channel depth of $\mathrm{C_{in}}$ and a spatial size of K × K, we can begin. To this input feature Y, the spectral-spatial compression technique is used. A variety of C_{out} kernels are employed in this operation. The spectral-spatial convolution's outcome is denoted by the symbol $Z \in R^{\mathrm{K\times K\times C_{out}}}$. Z's value at a certain point (i, j, or c) can be calculated using the following formula:

$$Z(i,j,c) = \sum_{m,n\in\Omega_k(i,j),1\le t\le C_{in}} W_c(i-m, j-n, t) \otimes Y(m,n,t) \quad (5)$$

The formula is written as $W_c \in R^{k\times k\times C_{in}}$, and $k\times k$ denotes the spatial dimensions of the kernels. Additionally, the set $\Omega_k(i,j) = \{m,n||m-i| \le k/2, |n-j| \le k/2, m \in Z^1, n \in Z^1\}$,. The word bias has been omitted from this portrayal, it should be highlighted.

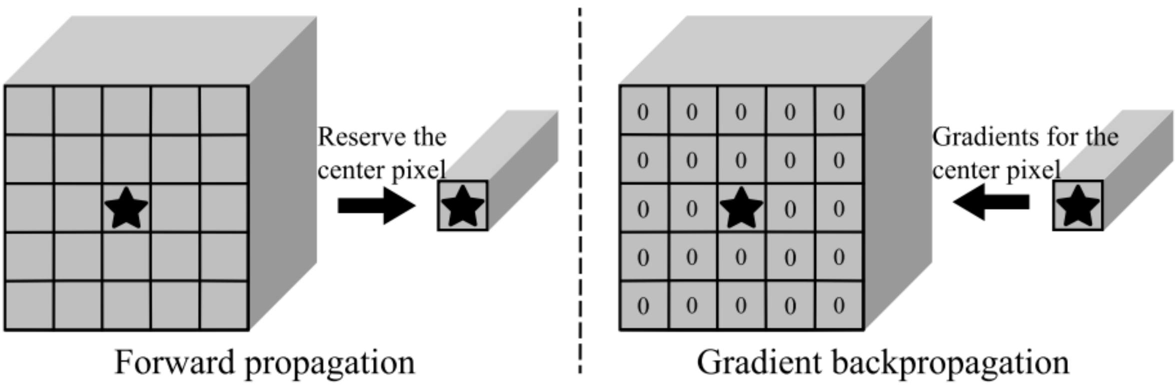


Figure 4. A scenario of centre pooling

The two primary parts of the spectral-spatial convolution in Equation (5) are spectral feature extraction (denoted as $\otimes$) and spatial aggregation (denoted as $\sum$).We execute element-wise multiplication between the local $k \times k \times C_{in}$ features and the $k \times k \times C_{in}$ convolutional kernels to calculate the spectral feature for each pixel. It is crucial to remember that the spectral-spatial convolution's W_c kernel lacks rotation invariance. As a result, in waste images, the spectral-spatial convolution may show sensitivity to spatial rotations. Spectral features from nearby pixels are immediately added to produce spectral-spatial information during the spatial aggregation step. This spatial aggregation technique does have certain drawbacks, though. Because it does not adaptively aggregate spectral qualities based on pixel content, neighbouring pixels may interfere. As a result, the output Z(i,j,c) may be impacted by conflicting pixel values. Additionally, the spectral-spatial convolution's ability to recover spectral-spatial features from a larger context inside the scrapped image patch is constrained by the convolutional kernels' constrained spatial size.

A new module named RSpaA is presented to take the place of spectral-spatial convolution in the construction of deep networks in order to solve its shortcomings. The RSpaA module consists of two crucial elements: The foundation of spectral-spatial convolution served as the basis for both spatial aggregation and spectral feature extraction. By using a spectral convolution operation with ReLU activation, we gather spectral characteristics in the spectral feature extraction section of the RSpaA module. Let C_{out} be the number of kernels employed in our studies, and let K represent the amount of kernels used for the spectrum convolution. Let the spectral characteristics of Y obtained by this spectral convolution be represented by $\bar{Y} \in R^{K \times K \times C_{out}}$. There are three main advantages to using spectral convolution for spectral feature extraction:

Due to the use of 1×1 kernels, spectral convolution is spatially invariant and resistant to waste image rotation. The preceding spectral-spatial convolution's SEN to spatial rotations is addressed by this characteristic. Efficiency of parameters: The number of weight parameters required by spectral convolution is much less than that of spectral-spatial convolution. This decrease in parameter complexity can improve both the model's performance and training. Implementation complexity is minimised and model creation is simplified because to the simplicity of spectral convolution.

The RSpaA module provides an adaptive method for aggregating the spectral properties of pixels during the spatial aggregation phase based on how similar the pixels are to one another. It specifically seeks to exclude pixels with low similarity and gather spectral features from those that show a high degree of similarity. The following sentence describes this procedure:

The following mathematical definition describes the spatial aggregate inside the proposed RSpaA:

$$Z(i,j) = \sum_{I \le m,n \le K} \beta_{ij}(\bar{Y}(m,n) \otimes \bar{Y}(m,n)) \quad (6)$$

where $\beta_{ij}(\bar{Y}(m,n) \in R^{1\times1}$ designates the closest pixel and The attention weight for all pixels is $\beta_{ij}(\bar{Y}(m,n)$ for the (i, j)-th pixel. The attention load of the (m, n)-th pixels corresponding to the (i, j)-th pixel in a wasted image patch is shown by $Z(i,j) \in R^{1\times1\times C_{out}}$. In this study, $\beta_{ij}(\bar{Y}(m,n)$ is calculated using the resemblance of images (m, n) and (i, j).

$$\beta_{ij}\left(\bar{Y}(m,n)\right) = \phi(\gamma(\rho(\bar{Y}(i,j),(\bar{Y}(m,n))))) \quad (7)$$

The term $\rho(\bar{Y}(i,j),\bar{Y}(m,n) \in R^{1\times1}$. in the equation (7) above stands for the similarity measure between Y(i,j) and Y(m,n). This similarity metric is crucial for figuring out how closely two pixels' spectral data are related. This similarity metric is calculated using the following two functions:

$\gamma(\cdot)$: Setting the attention weight of pixels whose similarity values are below a given threshold τ to 0 is the objective of this function, which serves as a corrected unit, The softmax activation $\varphi(\cdot)$ generates attention loads for each pixel by normalizing the similarity values.

Accurately determining pixel similarity becomes essential for achieving successful spatial aggregation. A number of operators have recently been developed to evaluate the similarity of 2 pixels within convolutional networks, including dot item, the distance from Euclid, and concatenation. The dot product stands out among these choices as a popular alternative with a track record of providing superior performance. Therefore, the operator used in this study to compute the similarity $\bar{Y}(i,j)$ and $\bar{Y}(m,n)$. $\rho(\bar{Y}(i,j),\bar{Y}(m,n))$, and the result is obtained as follows:

$$\rho\left(\bar{Y}(i,j),\bar{Y}(m,n)\right) = \sum \bar{Y}(i,j) \otimes \bar{Y}(m,n) \quad (8)$$

A high value of $\rho\left(\bar{Y}(i,j),\bar{Y}(m,n)\right)$ indicates a considerable resemblance between $\bar{Y}(i,j)$ and $\bar{Y}(m,n)$ according to Eq. (8). Using Eq. (8), we can calculate the similarity between all pixels and a specific pixel at coordinates (i, j) inside the waste picture patch X_i, designated as $S_{ij} \in R^{K\times K}$:

$$S_{ij}(m,n) = \rho(\bar{Y}(i,j),\bar{Y}(m,n)) \quad (9)$$

The RSpaA module's goal is to combine spectral characteristics from pixels with similar properties while reducing the impact of pixels with different properties. It add a corrected unit labelled as γ (·) to filter out different pixels while the spatial aggregation procedure is underway. By giving different pixels a low value, this unit effectively lowers the attention weights given to dissimilar neighbouring pixels to almost zero. The corrected unit's γ (·) formulation is expressed as follows:

$$\gamma(\mu) = \begin{cases} \mu, & \mu \ge \tau \\ \epsilon, & \mu < \tau \end{cases} \quad (10)$$

In this situation, a predetermined ratio v, which is in relation to the highest value of S_{ij}, determines the parameter τ. The attention weight also approaches zero since the value of ϵ is intentionally adjusted to -100.

$$\tau = v.\max(S_{ij}) \quad (11)$$

The rectified similarity is then normalised using the softmax activation $\varphi(\cdot)$, which yields the computation of the attention weight β_{ij}, where $\beta_{ij} = 1$.

$$\beta_{ij}(\bar{Y}(m,n)) = \frac{e^{\gamma(\rho(\bar{Y}(i,j),\bar{Y}(m,n)))}}{\sum_{1\le\hat{m},\hat{n}\le K} e^{\gamma(\rho(\bar{Y}(i,j),\bar{Y}(\hat{m},\hat{n})))}} \quad (12)$$

This can determine the spectral-spatial properties for each pixel in the waste image patch X_i by using equations (6) and (12). According to the suggested method, extracting spectral-spatial features is done via the RSpaA module by taking into account pixel similarity, making it insensitive to spatial rotations in the discarded image. The proposed RSpaA module's and the self-attention module that came before it both aim to enhance feature representations through the usage of pixel similarity. These two approaches, however, are very different from one another.

Spectral Feature Extraction: The RSpaA module extracts spectral information from the RSpaA input using a single spectral convolution operation. On the other hand, self-attention generally necessitates three distinct spectral convolution techniques, resulting in a higher number of weight parameters, when producing query, key, and value features.

Spatial Aggregation: A specialized unit is used in the spatial aggregate phase of RSpaA to eliminate contamination from various pixel categories. Self-attention is less successful at decreasing interference from other pixel categories because it combines the spectral properties of all pixels throughout the entire spatial domain.

The hyperparameters of RIAN are tuned using Lady Bug Beetle optimization algorithm [26].

4. Results and validation

4.1 Experimental setup

Using Python 3.6.5, the experiment incorporating the suggested technique was carried out. The proposed model was tested on a computer that met the following requirements:

- The MSI Z370-A Pro motherboard
- CPU: an Intel Core i5-8600k.
- GPU: A 4 GB VRAM NVIDIA GeForce GTX 1050 Ti16 GB of RAM, 250 GB of SSD, and a 1 TB hard drive.

Ten-fold cross-validation was used to provide reliable experimental validation. The following conditions were established for the experiments:

- Batch dimension: 128
- Rate of learning: 0.001
- Momentum: 0.2
- Optimizer: LBBOA

In the experiments, the suggested model was trained in these environments and evaluated there.

4.2 Performance Validation

The heat map analysis is shown in Figure 5 and identifies the items in the dataset. Figure 6 displays the results of a sample object detection on test photos using the suggested technique. In particular, the suggested method exhibits amazing ACC, obtaining a stunning 99% ACC in classifying glass, metal, and rubbish materials. The suggested method makes use of a confusion matrix to improve categorization, particularly after 1000 iterations.

Following are the categories that the matrix correctly identifies:

- 107 images were classified as waste with accuracy.
- 570 images were correctly identified as paper.
- 463 images were identified as plastic with accuracy.
- cardboard was precisely detected in 472 pictures.
- 472 images with the category "glass" are accurate.
- 380 images were correctly identified as metal.
- 372 pictures were identified as paper correctly.

These results highlight how well the suggested strategy for categorising waste objects performs in terms of effectiveness and accuracy (ACC).

4.3 Performance measure

The KI, SEN, SPEC, and ACC are a few examples of relevant performance metrics that can be used to assess a methodology's effectiveness. The regular evaluation of results and outcomes is different from a performance measure. The fundamental equations for calculating the waste detection's SEN, SPEC, ACC, and KI are given in Eqs. (13), (14), (15), and (16).

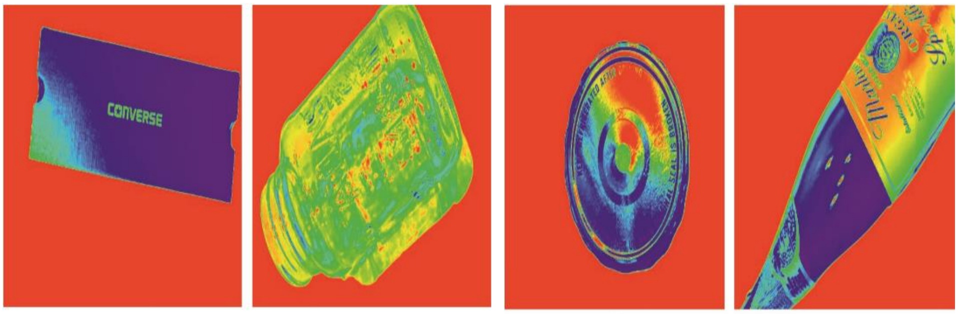
$$Sensitivity = \frac{TP}{TP+FN} \times 100 \quad (13)$$

$$Specificity = \frac{TN}{TN+FP} \times 100 \quad (14)$$

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \times 100 \quad (15)$$

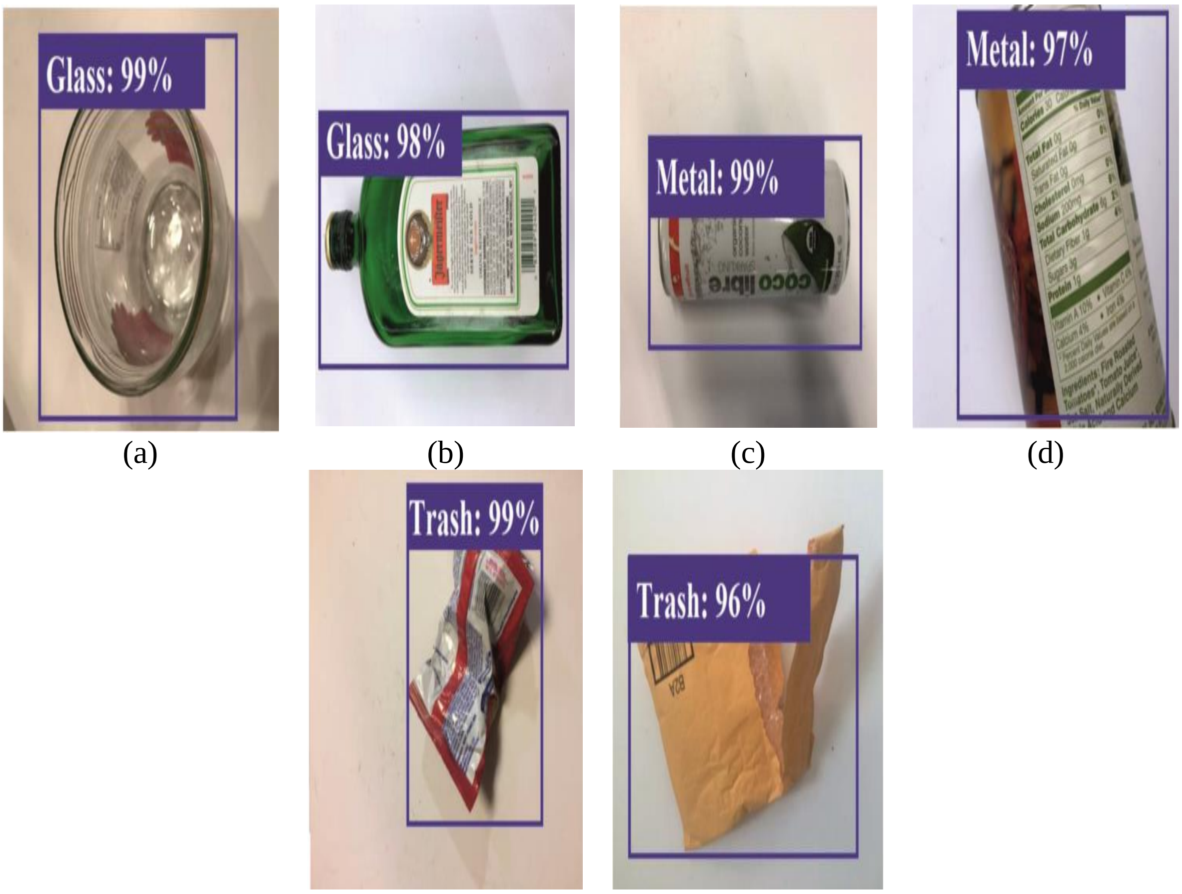
$$Kappa\ index = \frac{Accuracy - Accuracy_T}{1 - Accuracy_T} \quad (16)$$

The comparison of the projected classifier with the existing algorithms in terms of several metrics on datasets without LBBOA and with LBBOA is shown in Table 2 and Table 3.



(a) (b) (c) (d)

Figure 5. Heat map evaluation. (a) Cardboard, (d) glass.



(a) (b) (c) (d)

(e) (f)

Figure 6. detection of a sample object visualised. (a, b) Glass, (c, d) metal, and (e, f) trash.

Table 2. Analysis of suggested classifier in comparison to already-used methods without LBBOA

Methodologies	SPEC (%)	ACC (%)	SEN (%)	KI (%)
LSTM	76.55	72.03	72.33	76
RNN	83	87.33	86.95	79.86
CNN	88.4	92	91.77	81.45
Proposed RIAN model	**97.49**	**96.89**	97.34	**88**

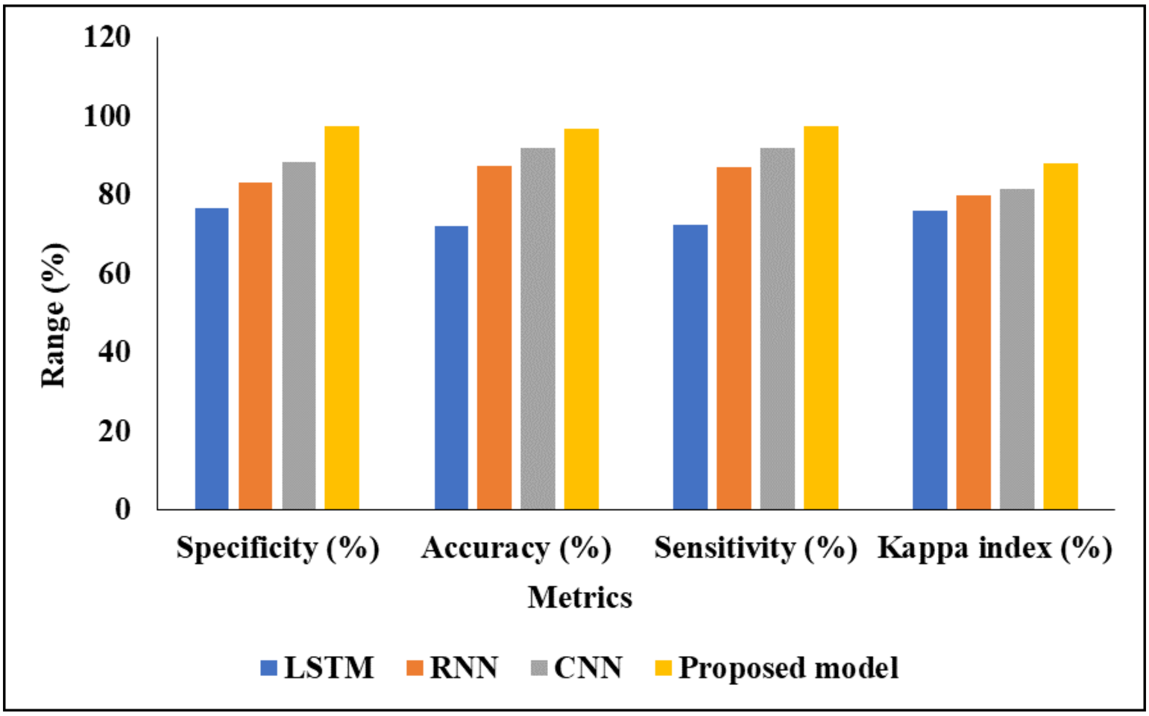


Figure 7. Classification analysis without LBBOA

Table 3. Analysis of suggested classifier in comparison to already-used methods with LBBOA

Methodologies	SEN (%)	SPEC (%)	ACC (%)	KI (%)
LSTM	85.43	75	91.22	79
RNN	89	83.50	90.89	80.08
CNN	94.76	87	93.98	83.44
Proposed RIAN model	**98.12**	**98.09**	**97.43**	**89.67**

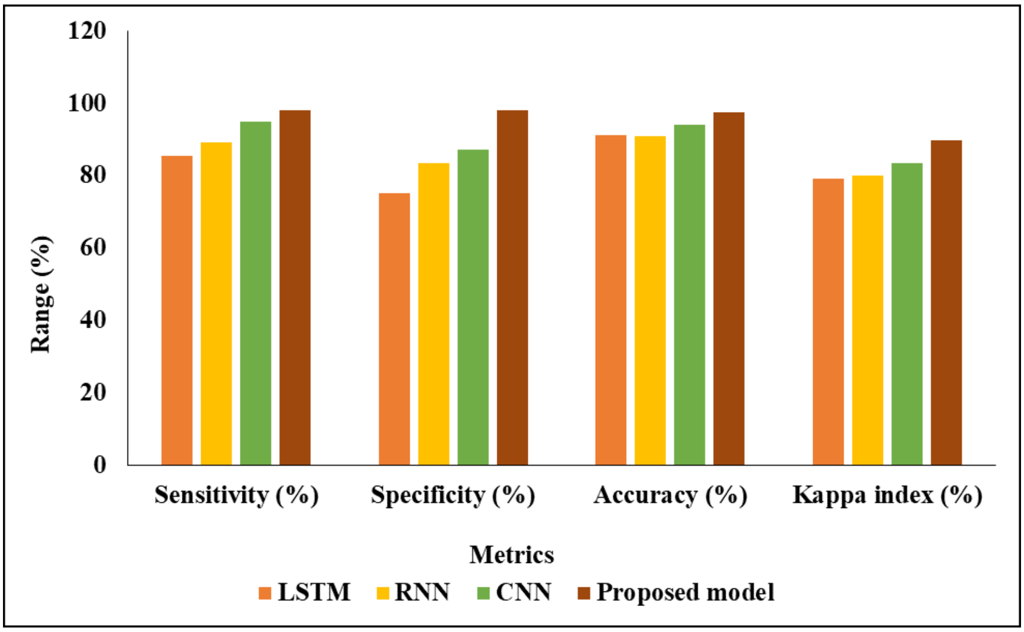


Figure 8. Classification validation with LBBOA

From table 2 and figure 7, the performance metrics of different models stand out in the analysis of classification without using the Ladybird Beetle Optimisation Algorithm (LBBOA). The SEN, SPEC, ACC, and KI of the LSTM are 76.55%, 72.03%, and 72.33%, respectively. With a SEN of 83%, a SPEC of 87.33%, an ACC of 86.95%, and a KI of 79.86%, RNN outperforms this. With a SEN of 88.4%, SPEC of 92%, ACC of 91.77%, and a Kappa score of 81.45%, CNN displays even better results. The proposed RIAN model, though, excels in this study and produces outstanding outcomes. RIAN has a remarkable Kappa value of 88%, SEN of 97.49%, SPEC of 96.89%, and ACC of 97.34%. These outstanding numbers highlight the RIAN model's effectiveness in classifying waste, making it a promising option for enhancing waste management in smart cities.

From table 3 and figure 8, the considerable improvements in the performance measures of many models in the thorough analysis that incorporates the Ladybird Beetle Optimisation Algorithm (LBBOA). With SEN of 85.43%, SPEC of 75%, ACC rate of 91.22%, and KI of 79%, LSTM achieves excellent results. With a SEN of 89%, SPEC of 83.50%, ACC of 90.89%, and a Kappa score of 80.08%, RNN maintains its advantage. With a remarkable SEN of 94.76%, SPEC of 87%, ACC rate of 93.98%, and KI of 83.44%, CNN improves even more on its previous performance. However, it is abundantly evident that the proposed RIAN model is the top performance in this thorough research. With unequalled SEN of 98.12%, amazing SPEC of 98.09%, extraordinary ACC rate of 97.43%, and increased KI of 89.67%, RIAN displays exceptional results. These exceptional measurements highlight the RIAN model's unmatched strength in the area of waste classification, categorically proving it as a highly promising and efficient solution ready to revolutionise waste management in smart cities. It is essential to include LBBOA while setting hyperparameters. To improve the model's classification performance, LBBOA tunes its parameters. With the help of this optimisation process, a model is created that is precisely calibrated to the distinctive features of the waste data, improving ACC and effectiveness.

5. Conclusion

In conclusion, the creation of an efficient waste management system has turned into a pressing environmental necessity, particularly in the context of expanding metropolitan regions. The SCM-RIAN is a potent and ground-breaking solution presented in this paper to tackle the complex problems of waste management and recycling in contemporary metropolitan settings. The study proposes RIAN as a cutting-edge and reliable classification method to address the problems inherent in smart city management (SCM). Redundancy is minimized via the RSpaA and CSpeA modules, which isolate spectral bands and minimize the impact of other pixel categories in obtaining rotation-invariant spectra-spatial properties from SCM patches. With the help of this novel method, trash classification is kept precise and flexible regardless of the spatial orientation. The dataset for waste categorization is used in this article to assess the results. SCM-RIAN's outstanding ACC rate of 98.12%, together with its high SEN, SPEC, and KI values, speak for itself. These exceptional results outperform those of current models, demonstrating the potency and effectiveness of SCM-RIAN as a cutting-edge solution to the difficult problems of SCM and categorization in waste. Utilising LBBOA, hyperparameters are tweaked. Adopting cutting-edge technology like SCM-RIAN will be essential in creating cleaner, more sustainable, and environmentally responsible cities in the future as metropolitan areas expand. In future, going to Create sophisticated analytics and visualisation tools so that waste management authorities may make decisions based on data by giving them actionable insights into waste trends.

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Authors Contribution Statement

The author K. Sankar performed the initial screening and defined the problem statement. Author V. Gokula Krishnan involved in manuscript preparation/writing and reviewing the literature. Author S. Venkata Lakshmi performed the data collection and analysis part of this research work. Author S. Kaviarasan performed the simulation work and generated the results and author A. Arockia Abins done the paper formatting and proof-reading works. All authors have contributed in this research work equally.

Has this article screened for similarity?

Yes

Conflict of Interest

The Authors have no conflicts of interest on this article to declare.

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