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A smart waste classification model using hybrid CNN-LSTM with transfer learning for sustainable environment

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Abstract
Waste collection, classification, and planning have become crucial as industrialization and smart city advancement activities have increased. A recycling process of waste relies on the ability to retrieve the characteristics as it was in their natural position, and it reduces pollution and helps in a sustainable environment. Recently, deep learning (DL) methods have been employed intelligently to support the administration's strategized waste management and related procedure, including capture, classification, composting, and dumping. The selection of the optimum DL technique for categorizing and forecasting waste is a long and arduous process. This research presents a smart waste classification using Hybrid CNN-LSTM with transfer learning for sustainable development. The waste can be classified into recyclable and organic categories. To classify waste statistics, implement a hybrid model combining Convolutional neural networks (CNN) and long short-term memory (LSTM). The proposed model also uses the transfer learning (TL) method, which incorporates the advantage of ImageNet, to classify and forecast the waste category. The proposed model also utilises an improved data augmentation process for overfitting and data sampling issues. An experimental analysis was conducted on the TrashNet dataset sample, with 27027 images separated into two classes of organic waste 17005 and recyclable waste 10 025 used to evaluate the performance of the proposed model. The proposed hybrid model and various existing CNN models (i.e., VGG-16, ResNet-34, ResNet-50, and AlexNet) were implemented using Python and tested based on performance measuring parameters, i.e., precision, recall, testing and training loss, and accuracy. Each model was created with a range of epochs and an adaptive moment estimator (AME) optimisation algorithm. For the proposed method, the AME optimisation achieved the best optimisation and accuracy and the least modelling loss for training, validation, and testing. The proposed model performed the highest precision of 95.45%, far better than the existing deep learning method.

Keywords Smart waste · Classification · Sustainable development · Deep learning · CNN-LSTM · Transfer learning

Extended author information available on the last page of the article

1 Introduction

Waste management applies to all such practices and activities needed to conquer from its origins to closure. Waste can be in the form of a solid, liquid, or gas. Recycling refers to the act of turning waste material back into new products. This idea frequently takes the recycling of energy from discarded items into consideration. A recycling process of content relies on retrieving the characteristics as it was in their natural position. It's an environmentally friendly substitute to "traditional" waste management, which can retain components and reduce emissions of greenhouse gases. Reprocessing helps to decrease the consumption of new resources and eliminate the loss of feasibly valuable resources, which reduces energy consumption, environmental pollution, and air, water and land pollution.

Various procedures are employed to determine how to deal with all forms of waste, including natural, manufacturing, and domestic. Household waste includes paperboard, glass, plastic, sheets, and organic waste [1]. The absorption of non-recyclable landfill waste all over the universe, along with the long and complex duration it takes for the majority of its components to biodegrade, have a massive effect on our surroundings in the twenty-first century if we, as little more than a society, do not act quickly to preclude this from transpiring. Furthermore, among all of the best-known potential consequences to individuals, waste buildup can enable disease transmission by viruses like mosquitoes, flies, and various other pests [2]. Regarding destroying the elegance of natural ecosystems, forest destruction, and terrain profession to give sufficient area to open dumps, water and soil can often be highly strung and heavily polluted because of the harmful pesticides in untreated wastewater components. In addition, pollution can affect the local ecosystem, food supply, farming, and industries, inevitably increasing illnesses and other problems for people and the planet's ecological processes [3].

Sustainable disposal of waste attempts to reduce the volume of solid garbage dumped in landfills or by burn. The hierarchical structure of waste management focuses on prevention, reduction, recycling, composting, recovering energy, and, subsequently, cure for waste disposal, which is the foundation of a sustainable waste management strategy. Waste accrual has become a more severe problem in the past few years for three principal reasons. The first concern is the limitation of recyclable waste items, although industries have been working to develop more environmentally friendly and renewable materials for a long time [4].

The second main factor is overpopulation, which is currently one of the most prominent issues. The reality that a substantial number of individuals require a wide range of materials implies a very complicated logistical problem when attempting to handle waste generation, resulting in a higher percentage of merchandise that can be reprocessed but instead ends up in an ocean and landfill, impacting the families and communities of millions of marine animals. At last, the third possibility is our lack of engagement as a civilization in climate change or other environmental issues [5].

Waste management is a critical global phenomenon. Since such an earth's population and requirement of higher living standards criteria increase, so does the level of waste produced [7]. Researchers are becoming greatly worried about waste processing and its possible repercussions and therefore are attempting to find solutions. The method of transforming industrial waste into new substances and entities is called "Recycling" [6]. To address these waste management challenges, some innovative, cutting-edge techniques such as Artificial intelligence (AI), Machine Learning (ML), and Deep Learning (DL). Among the most famously accepted methods in environmental studies is the DL technique. DL makes a model capable of learning complicated selective activities to help agro-industrial waste management [7]. A DL method is successfully utilised in the Sustainable waste management research area. DL is a broad subset of ML techniques, including various analytical tools and strategies for implementing ANN with object classification. Consequently, different CNN approaches have been incorporated into studies to detect and locate unauthorized dumps utilising roadside object data and extremely high-resolution aerial image graphs [7].

Many renowned researchers worldwide have made significant efforts to achieve Sustainable waste management utilising DL methods. SWM has widely used DL features to solve various problems, including waste identifiers and separation, actual bin-level sensing, and waste management forecasting. DL approaches are capable of identifying and learning features actively from images. This distinguishing feature has significantly improved image recognition and tracking [8].

A deep learning method, i.e., CNN, performs excellently in image identification and categorization assignment, i.e., Waste classification. However, the most significant problem with the CNN model occurs within model training because of the gradient disappearing issues and sometimes gradient explosions issues along with data loss, which may cause the model's poor performance. To overcome this issue in this research, we utilize a CNN model with LSTM and Transfer learning. Both temporal and spatial dimensions can be used to teach characteristics to a CNN. An LSTM network analyses data from sequences by cycling through time steps and discovering the long-term relationships among them. A CNN-LSTM network employs convolution and LSTM combined layers to acquire knowledge from the training information. That can be more efficient for image data prediction and classification [9]. Currently, The classification of waste is fraught with several difficulties.

- **Complexity:** It stems from the fact that waste materials are extremely diverse in their composition, physical properties, and possible environmental effects. Accurately classifying those calls for both specialized knowledge and in-depth investigation.
- **Subjectivity:** It refers to the fact that waste classification can sometimes be open to debate and differ from one regulatory body or expert to another.
- **Insufficient Data**: Inaccurate waste classification can be hampered by insufficient data about the waste materials.
- **Traditional methods**: of waste classification can be time-consuming and expensive, particularly for large volumes of waste. This is especially true when the volume of waste is large.
- **Emerging Waste Streams**: New types of waste, such as electronic waste and certain plastics, present new challenges when classifying them properly because of the complex nature of their components.

Deep learning techniques, which are a subfield of artificial intelligence, have the potential to improve waste classification and find solutions to problems. In this paper, we proposed a hybrid model focused on CNN-LSTM, which further uses ImageNet weights with a transfer learning method to categorize waste data. Furthermore, we cover the proposed hybrid Model CNN-LSTM technique with TL and the datasets utilised to evaluate the hybrid model in recognizing and classifying waste categories, such as recyclable and organic waste. The proposed model's performance is tested on the Kaggle waste dataset and compared with existing CNN models (i.e., VGG-16, ResNet-34, ResNet-50, and AlexNet). Each model was created with a range of epochs and an adaptive moment estimator (AME) optimisation algorithm [10].

The complete research article is organized as follows: Section 2 covers the related work in waste recognition and classification by various machine learning deep learning-based models. Section 3 covers the materials and methods, Section 4 covers the experimental results and discussion and Section 5 covers the conclusion and future work.

2 Related work

Waste management plays an important role in the sustainable development of the country. Waste management is a hot area of research. This section covers the analysis of existing research in waste management.

A deep learning-based hybrid waste classification model is presented in [11]. They divided garbage into seven different groups employing SVM with CNN deep learning model. The proposed hybrid SVM-CNN model performed better than the existing CNN with 83% precision. RecycleNet, a framework that can precisely optimize waste, is presented in [12]. This model uses a sophisticated CNN architecture for certain recyclable product categories. The proposed system altered the existing linked patterns and skipped the dense block patterns. Although the proposed RecycleNet received a score of 87.58% in precision in the TrashNet image data. The proposed model also decreased the number of characteristics from seven million to approximately three million.

Applying the ResNet architecture [13] introduced a DNN-TC approach that intelligently categorizes waste in smart waste sorting equipment. To reduce complexity, two completely interconnected layers were added to the ResNeXt-101 general framework. Further, the pre-trained weights of ResNeXt-101 from the ImageNet database [14] were imported throughout the training phase, resulting in a better outcome of 94% precision over the TrashNet data. The DNN-TC method achieves better than ResNeXt-101 for identifying plastic and recycling in their test. However, the author does not explain why DNN-TC performs worse for metal, paper, and plastic when compared to ResNeXt-101.M-b Xception, a unique connection expansion-based network optimisation approach for garbage digital image recognition, which was introduced in [15]. The TrashNet collection produced the best outcomes 94.34% accuracy rate. While their system boosts resilience and accuracy rate compared to earlier approaches, it also raises processing costs and variable potential.

A deep CNN categorizes the local features from the waste image file [16]. To increase classification performance, the characteristics of a pre-trained classifier are altered in this article to use the waste dataset after it has been introduced and pre-trained upon this ImageNet massive image dataset. To classify waste, several investigators have developed modified CNN models. Hybrid CNN architecture was designed in [17] and assessed the model's effectiveness using two open waste datasets. A wide range of typical CNN techniques was evaluated. A VGGNet-19 achieved the highest precision at 92.9%. The proposed CNN technique performed faster and only managed a 90% accuracy rate.

Linen, plastics, biological refuse, and glassware waste were the four class descriptors used by [18] to assess an unnamed Deep CNN with 4600 self-acquired waste photos. They obtained an f-score of 69% and 85% for each category. A modified CNN-based waste categorization framework is offered in [19] to categorize organic and inorganic waste. The gathered waste can be divided into various categories using a flap. After that, the computerized order aids in the time employed on cleanliness. The organizations can simultaneously organize and manage the generated waste too. An image enhancement and a modified CNN for waste classification frameworks were addressed in [20]. Researchers executed research primarily focused on finding organic waste. The proposed model achieved 87.98% accuracy, which was the best compared to existing CNN models.

The expanding world accomplishment of reducing emissions has made recycling waste identification and classification a crucial step in advancing the growth of a sustainable society. A deep learning-based Model is discussed in [16] for a smart classification of recyclable material. The proposed model utilises ResNet and Transfer learning. The proposed model achieved an accuracy of 90.17% over the traditional CNN model. The method for determining if an image includes waste or doesn't was created by [17]. They made a trash app for Android mobile devices. A CNN programme recognizes the trash area of the image termed GarbNet. After GarbNet optimisation, precision was 87.69%, and specificity was 93.45%. The research also accessed the GarbageIn images database, a waste-sensitive repository comprising real-world, geotagged photos. Table 1 presents a summarized analysis of recent research in the field of waste management.

Compared to the findings of previous studies on this domain shown in Table 1, these models cannot gain the maximum level of accuracy in predicting waste. In the work cited by [11], the various machine learning models, i.e., DenseNet-169 and XGB, are being applied with 88.9%. Meanwhile, [20] tried RNN with Agriculture Waste with a 91.3% accuracy level. ResNet50 Model was integrated into [13] on Household Waste but gained 91.89% accuracy. In [39], the authors applied the ND-CNN (GoogleNet) to Industrial Waste but did not achieve a sufficient accuracy level (92.48%).

3 Materials and methods

This section covers the discussion on existing methods and the proposed method.

3.1 Dataset

This research utilises an online Kaggle waste dataset [31]. The dataset consists of 27025 images separated into two classes of organic waste (O: 17005) and recyclable waste (R: 10020) was used to test the proposed model. An improved data augmentation technique was applied to enhance the waste image quality. Considering recyclable waste in the environment is random and irregular, measures of colour space transformation, rotation, flipping, and noise injection have been taken to augment the image sample [32]. The details are discussed in Section 3.4.1. Figure 1 presents the image categories and sample images in the dataset.

3.2 Proposed hybrid model

This research presents a smart waste classification using Hybrid CNN-LSTM with transfer learning for sustainable development. The waste can be classified into recyclable and organic categories. Implement a hybrid model that combines CNN with LSTM to classify waste statistics. Transfer learning is also used by the proposed model, which incorporates the advantage of ImageNet, to classify and forecast the waste category [21]. Figure 2 presents the architecture of the proposed hybrid model.

Table 1 Summary of waste management research

Reference	Model used	Waste type	Waste dataset	Accuracy result	Transfer learning	Optimisation algorithm
[11]	DenseNet-169 and XGB	Industrial Waste	Kaggle dataset	88.9%	Im-Break	Chimp optimisation
[12]	RNN	Agriculture Waste	Self-made dataset	91.3%	Im-Break	Shuffled Frog-Leaping
[13]	ResNet50 Model	Household Waste	Self-made dataset	91.89%	Im-Break	Stochastic gradient descent
[14]	AlexNet Model and VGG16 Model	Industrial Waste	Kaggle dataset	89.98%	Im-Break	Genetic
[15]	GoogleNet	Plastic and liquid waste	Ocean Waste dataset	88.9%	None	Gradient Descent
[16]	ResNet-152	Agriculture waste	Kaggle waste dataset	87.78%	None	Adaptive Learning Rate
[17]	Darknet NN	Household and Industrial Waste	Self-made dataset	89.9%	None	Genetic
[18]	Lightweight NN	Water waste	Kaggle waste dataset	91.78%	None	Gradient Descent
[19]	ResNet-152	Solid, Liquid Waste	Self-made dataset	89.21%	None	Adaptive Learning Rate
[20]	ND-CNN(GoogleNet)	Industrial Waste	Kaggle l Waste data	92.48%	ImageNet	Genetic
Proposed model	CNN-LSTM with Transfer learning	Solid waste	Kaggle waste dataset	95.45%	ImageNet	AME

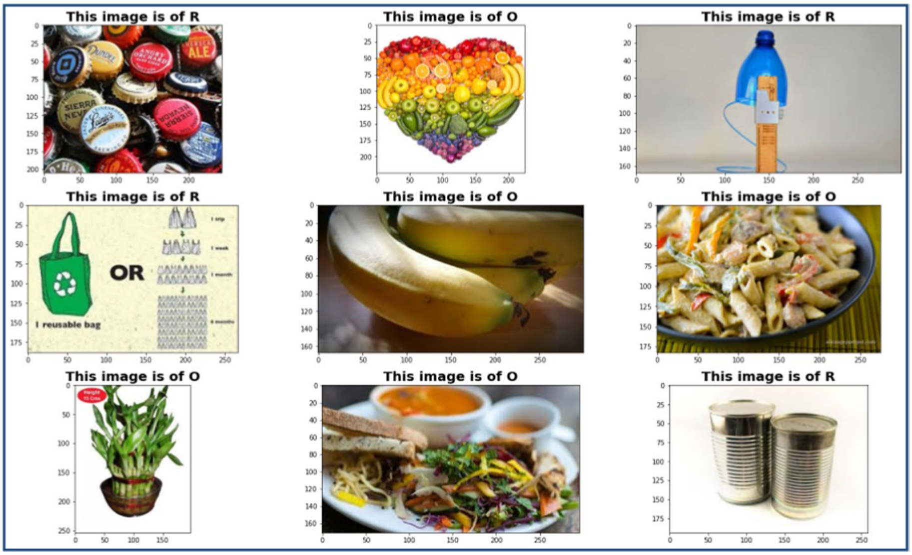


Fig. 1 Sample images in the dataset

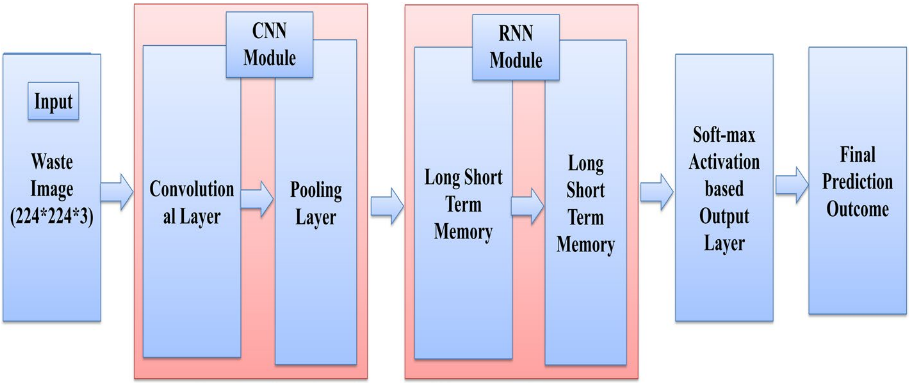


Fig. 2 Architecture of proposed hybrid model

3.3 Working of proposed hybrid model

This proposed model primarily consists of two segments: a separate autonomous RNN component and a CNN component with an image size of (224*224). In the proposed model, an independent, autonomous RNN component has two different LSTM layers, both of which are of batch shape 2048. However, the CNN is finally carried via a pre-trained TL model, i.e. ResNet-50, InceptionResNet-V2, until it achieves the final destination layer, i.e., Convolutional layer, that includes bottleneck functionalities; these all contain a batch size of 64 [22]. Figure 3 presents the working of the proposed Hybrid CNN-LSTM with the TL model.

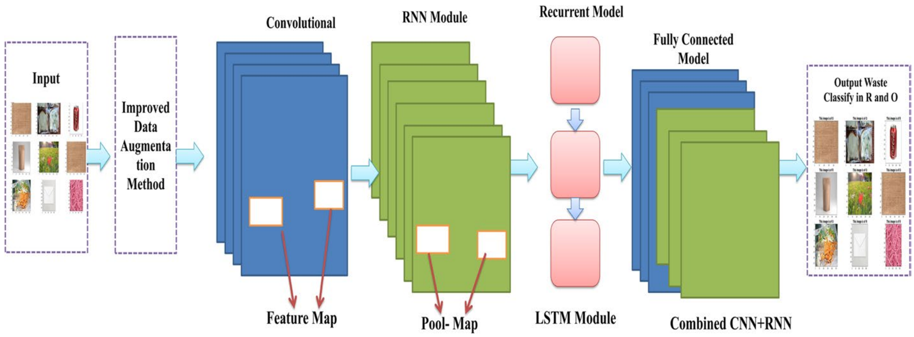


Fig. 3 Working of proposed hybrid CNN-LSTM with transfer learning

The components' results are combined through a variable size-based multiplication process. The result is procured further into the activation function (Soft-Max) and the categorisation layer of different classes for multi-class classifications. In the next phase, all the Convolutional layers with various filter strengths can recognise waste images with magnifying factors because every convolution operation may take images of a specific length [23]. The proposed hybrid model contains the following key components. a) LSTM layer with dense feature; b) SoftMax activation function c) fully connected layer component; e) Convolutional layer; f) pooling layer. The complete working of the model is as follows.

3.3.1 Improved data augmentation phase

To deal with data unbalancing and overfitting data augmentation phase is used. We utilise an improved data augmentation process in two steps, i.e., background modification (BackMod) and "ImageDataGenerator()" [24]. Figure 4 presents the architecture of the proposed improved data augmentation model.

The first phase performs an image background modification (BackMod). The idea besides this technique is to contextualise existing, classified waste. BackMod mainly analyses noise and other issues throughout the waste sample. The images within context subsequently allow waste analysers to concentrate on the aspects related to the waste images [25]. Figure 5 presents a data augmentation background enhancement process for waste images.

In the second phase, we undertake a multi-scale data augmentation process for the training waste data sample. Using a random combination of key features with a set of random methods, i.e., object rotation, flipping in both vertical and horizontal directions, object translation and intensity variation, this phase prevents unbalanced class and overfitting issues. A built-in Python Keras module, "ImageDataGenerator ()", was employed to achieve the augmentation feature on the image dataset [26, 27]. Figure 6 presents Data augmentation image flipping for recyclable (R) waste images.

Image frames were flipped in various angles, rotated vertically and horizontally, and the centre feature was selected as "True." We employed a data over-sampling technique combining the data augmentation by phases 1 and 2 to balance waste visuals of every class because the categories of waste statistics are unbalanced and reflect a Gaussian distribution [28].

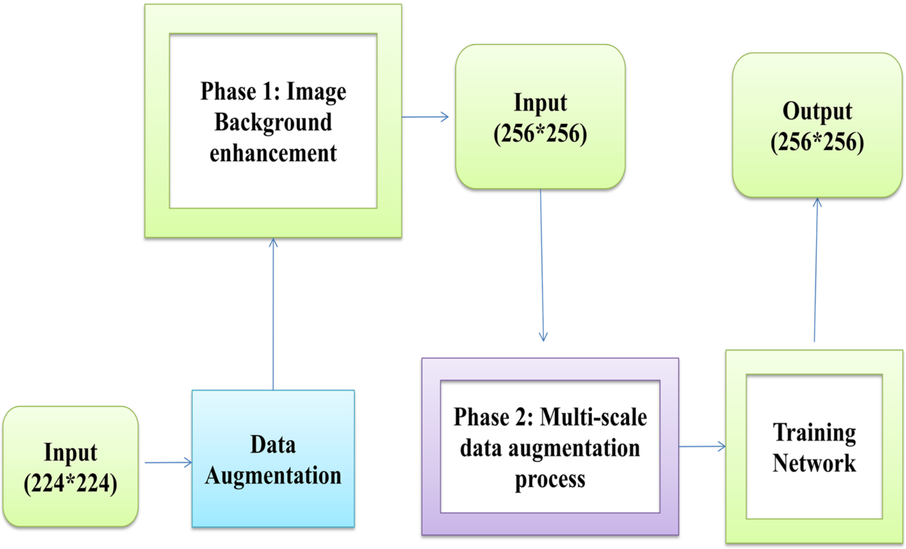


Fig. 4 Architecture of improved data augmentation model

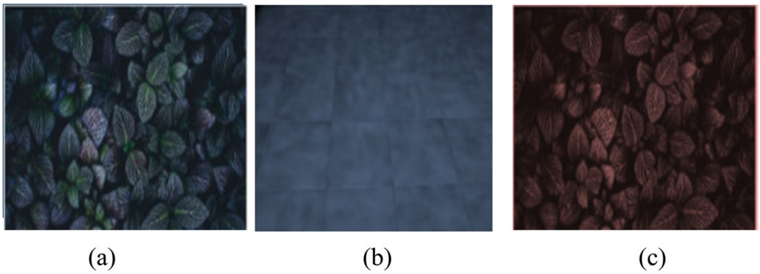


Fig. 5 Data augmentation background enhancement for waste images (Recyclable). **a** Input image, **b** process image and **c** output image

3.3.2 Parameter optimisation

The proposed model utilises an adaptive moment estimator (AME) based optimisation. AME becomes the next strategy that calculates adaptive learning scores of every factor. AME maintains an exponential decay mean of previous variations (*V*), comparable to motion, in contrast to an exponential decay mean of squared gradients (*S*). AME operates most like a massive ball experiencing internal friction instead of motion and can be visualised as a ball rolling downwards. As a result, AME favours a smooth minimum in the error function [29, 30].

$$\left(V_t\right) = \left\{(\gamma_{1*}V_{t-1}\right) + (1-\gamma_1) * g_t\} \tag{1}$$

$$\left(S_t\right) = \left\{(\gamma_{2*}S_{t-1}\right) + (1-\gamma_2) * g_{t^2}\} \tag{2}$$

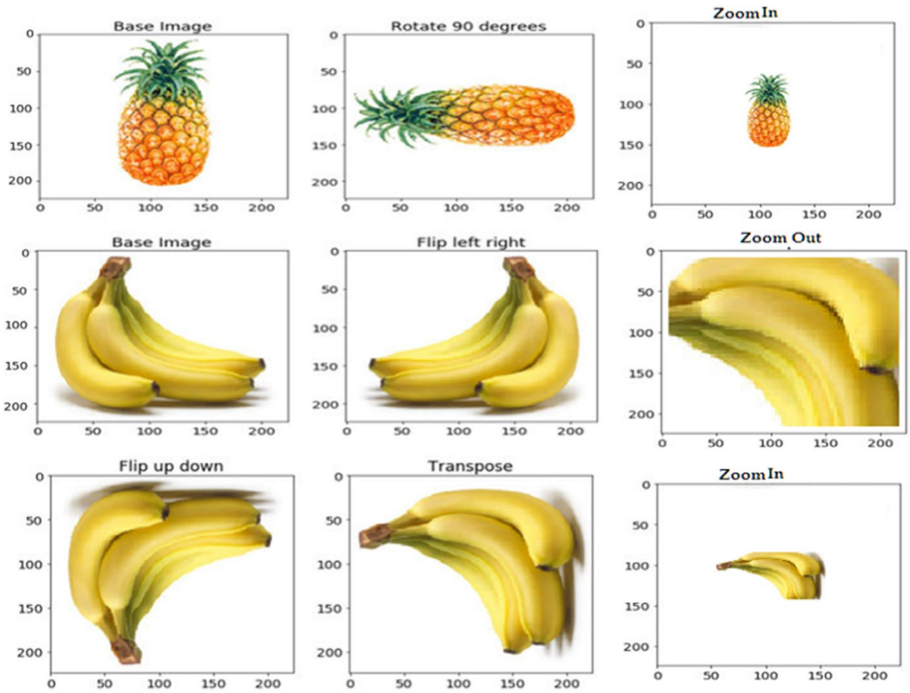


Fig. 6 Data augmentation image flipping for recyclable (R) waste images

where V and S are the vectors, g_t Gradient descent, γ optimisation. AME method helps to fine-tune the hyperparameters and improve prediction accuracy. DL methods were trained, optimised, and fine-tuned using hyperparameters. To avoid overfitting during the initial training phase and fine-tuning the parameters, we utilised feature check-pointers, callbacks, and loss-tracking features, and the optimal feature model's weights got retained [31]. Optimisation techniques were used to finalise the proposed model, i.e., training rates, changing epochs, and hyperparameters with the degree of tolerance "1e-2". Next, to identify the waste classes, we utilise a fine-tuned model created employing these ideal parameters. Table 2 presents the parameters used to implement the proposed model [32].

Table 2 Parameters for CNN model (Pre-trained model)

Parameters	Details	Value
Window size	Used for pooling layer	2
No. of epochs	Used for epoch cycle	100 and 200
No layers in LSTM	Used by LSTM model	2
Batch size	To proceed with the data	32
Activation function	Used for model activation	SOFTMAX function
Learning rate	It defines model learning	0.001
Batch normalisation	Used to Normalisation of batches	Yes
Optimizer	Used for Optimisation	Adaptive moment estimator

3.3.3 LSTM module

The LSTM scheme was created by [33] to address the problems associated with the training process, which contains lengthy dependencies that arise from the gradient constraints in CNN. An LSTM model consists of several sequentially linked sub-networks called "memory blocks". The block is designed to maintain its status over time despite controlling the overall data stream via "non-linear gating" components. Figure 7 presents the working of the LSTM model. An LSTM model contains various flags, i.e., yield value h (t), input X (t). In LSTM architecture, all the output blocks are recurrently linked with all the gates and input blocks.

An LSTM computing is achieved by mapping all the input sequence $X=(X_1....X_n)$ with all the output $Y=(Y_1, ...Y_n)$. The computing equations are as follows:

$$f(t) = \gamma[\mathrm{W_f} * [(\mathrm{h_{t-1}}, \mathrm{x_t}) + \mathrm{b_f}] \tag{3}$$

$$i(t) = \gamma[\mathrm{W_i} * [(\mathrm{h_{t-1}}, \mathrm{x_t}) + \mathrm{b_i}] \tag{4}$$

$$\mathrm{O}(t) = \gamma[\mathrm{W_o} * [(\mathrm{h_{t-1}}, \mathrm{x_t}) + \mathrm{b_o}] \tag{5}$$

$$\mathrm{C}(t) = f(t) * \mathrm{C}_{(t-1)} + i(t) * (\tan(\mathrm{h})[\mathrm{W_C} * [(\mathrm{h_{t-1}}, \mathrm{x_t}) + (\mathrm{b_C})] \tag{6}$$

$$\mathrm{h}(t) = O(t) * \{(\tan(\mathrm{h})[\mathrm{C}(t)]\} \tag{7}$$

$$\gamma^{\mathrm{O}} = \gamma[\mathrm{W_o} * [(\mathrm{h_{t-1}}, \mathrm{x_t}) + (\mathrm{b_o} + \mathrm{b_f} + \mathrm{b_i})] \tag{8}$$

In the above equations (Eqs. 1 to 4) *i* (*t*) denotes input activation function, *f* (*t*) Forget Gates and O (*t*) Output gates. Similar parameters b_f, b_i, and b_o represents a bias value towards a forget Gate's input and output. Also W_f, W_i, and W_o represents weigh parameters

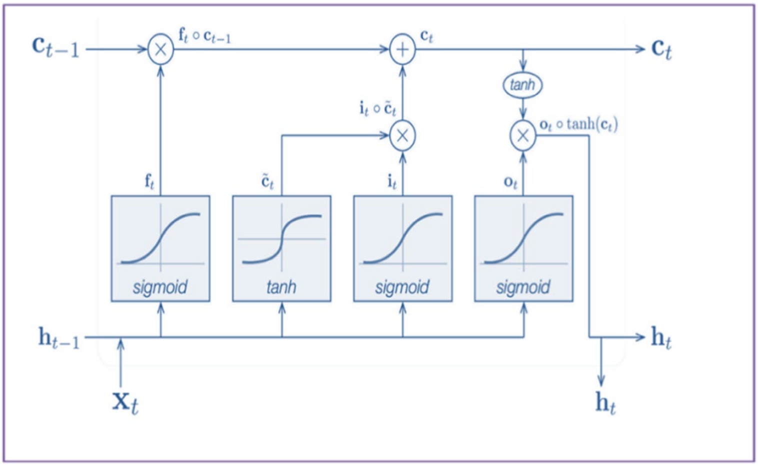


Fig. 7 LSTM model

towards Forget Gates input and output. Equation 5 represents the calculation of hidden layer outputs. Also, Eq. 6, h (*t*) denotes a hidden layer, γ represents a sigmoid activation function [34, 35].

3.4 Transfer learning

It is a deep learning approach that employs the ideas of field and assignment to transmit knowledge amongst multiple physical conditions. It has a margin distribution function M_x (x,y) among a source domain (S_d), Image labelling (I_L), and a source component (S_c), ImageNet (I_s) [36, 37]. Additionally, there is an objective domain (O_d), a Waste database (W_d), and a target activity (T_a), an appropriate label, for the identification and classification of all the possible recyclable waste (R_d). With the knowledge acquired from I_s and I_L, the T_L method aims to learn the objective probability distribution OP_T(x,y) in W_d. An ImageNet model contains over 12 million images with 1000 + classes in different categories. In this research for the classification of recyclable waste, we applied TL models with hybrid CNN-LSTM, and it helps to select pre-trained characteristics of the ImageNet and achieve higher accuracy [38–40].

3.5 Performance measuring parameters

To measure the performance of the proposed model and various existing CNN model following performance-measuring parameters was calculated [41–43]].

$$Precision = \frac{[TruePositive]}{[TruePositive + FalsePositive]} \tag{9}$$

$$Recall = \frac{[TruePositive]}{[Orignallypostivedata]} \tag{10}$$

$$F1 - Score = 2 * \frac{[Precision * Recall]}{[Precision + Recall]} \tag{11}$$

$$Accuracy = \frac{[TruePositive + TrueNegative]}{[TruePositive + TrueNegativeon + FalsePositive + FalseNegative]} \tag{12}$$

Besides the above measures, the following parameters are widely used for performance analysis.

- **Training loss:** A training loss evaluates the model's performance across the training dataset and can be utilised to determine how well a deep neural network algorithm accurately reflects the training sets. A training loss is typically computed mathematically by summing the losses towards the training iteration [44].
- **Validation loss**: A similar measure, called a validation loss, is utilised to evaluate how well a neural network-based model performed on validation data. A validation loss is determined from the aggregate losses for each sample within validation data and is comparable to the training loss [45].

4 Experimental results and discussion

This section covers the experimental details and results analysis of the proposed hybrid model and existing CNN models, i.e., ResNet-50, AlexNet, ResNet-34 and VGG-16 models [40] at the waste dataset.

4.1 Experimental details

The implementation of the proposed Model and the existing Model was performed using Python programming. The hardware and software features in the implementation and operation include "Nvidia-GeForce" Graphics, "Google-Collaborator" with 52 GB of primary memory, Python, python libraries, and Linux 64-bit OS. For DL, the packages cuDNN-7.6.5, tensor-flow-V2.11.0, CUDA-V10.0 and Keras-V2.10 were utilised. For visualization, we mainly used matplotlib and Sea-born libraries [46–48].

Experimental results were performed for the proposed model and existing VGG-16, ResNet-34, ResNet-50, and AlexNet, using the TrashNet waste dataset. The dataset consists of 27025 images separated into two classes of organic waste (O: 17005) and recyclable waste (R: 10020) was used to test the proposed model. After fine-tuning the image parameters, the dataset was divided into 3 classes (Training: Validation: and testing).

An experimental analysis was performed for two dataset divisions. Experiment one used the dataset ratio of 80: 10: 10 (Training: Validation: Testing) and the number of epochs from 0-50. Similar to experiment 2 dataset ratio of 70: 15: 15 (Training: Validation: Testing) and the number of epochs from 0-100 were used. Table 3 presents an experimental parameters overview for the proposed model, and Figure 8 shows the sample experimental results (Organic and Recyclable).

Experiment 1 The dataset consists of 27025 images separated into two classes of organic waste (O: 17005) and recyclable waste (R: 10020) was used to test the proposed model. After fine-tuning the image parameters, the dataset was divided into 3 classes (Training: Validation: and testing). In experiment one, the dataset ratio was 80: 10: 10 (Training: Validation: Testing), and the number of epochs was 0, 30, and 50. The experimental results for experiment one are as follows.

Table 3 Experimental parameters for the proposed model

Model	Layer (type)	Output details	Parameters
	Conv-1d	(None, 28, 64)	192
	MaxPooling-1d	(None, 14, 64)	0
CNN	Flatten	(None, 896)	0
	Dense_4	(None, 50)	44,850
	None_1	(None, 1)	51
Total parameters of CNN	45093	Trainable: 45093	Non-Trainable: 0
	LSTM_7	(None, 50)	16800
LSTM	Droup_Out_5	(None, 50)	0
	Dense_16	(None, 25)	1275
	Dense_17	(None, 1)	26
Total parameters of LSTM	18101	Trainable: 18101	Non-Trainable: 0

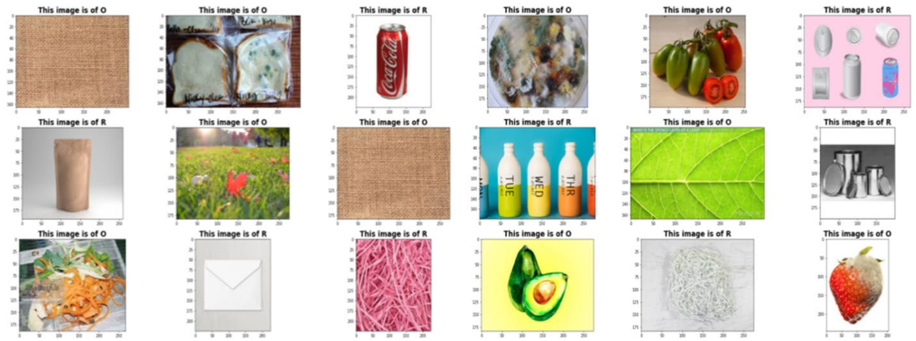


Fig. 8 Experimental results (organic and recyclable)

Training and validation accuracy and loss were calculated for dataset 80: 10: 10 (training: validation: validation: testing). Figure 9a presents training and validation accuracy results for the proposed model from 0–30-50 epochs. When the numbers of epochs are less, the training and validation accuracies are also less, but once the number of epochs increases, the accuracy results are increased for training and validation from 50 to 95%. A model with higher training and validation accuracy is always in demand, and the proposed model is fit. Figure 9b presents training and validation loss results for the proposed model from 0–50 epochs. Initially, the loss results are higher for epochs 0–30, but once we increase it up to 50, the loss % is also decreased, a fewer loss results show better performance.

Figure 10 presents a ROC graph of waste classification for experiment 1 for 50 epochs. A graph called the ROC represents how well an algorithm for classification works across all benchmarks. The graph is plotted among TPR and FPR. The ROC graph was plotted for various waste types, i.e., cardboard, glass, metal, plastics, and paper waste.

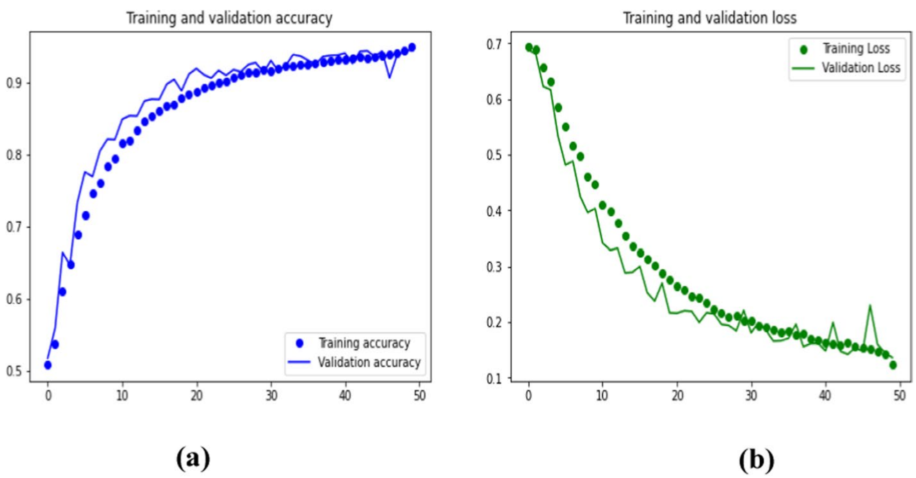


Fig. 9 **a** Training and Validation accuracy and **b** Training and Validation loss for the proposed model for 0–50 Epochs and dataset 80: 10: 10 (training: validation: testing)

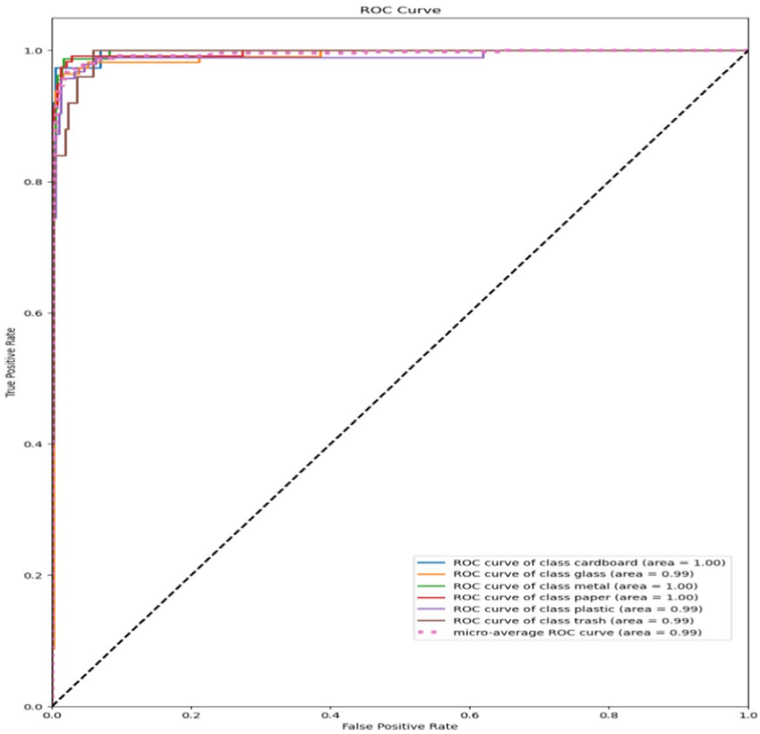
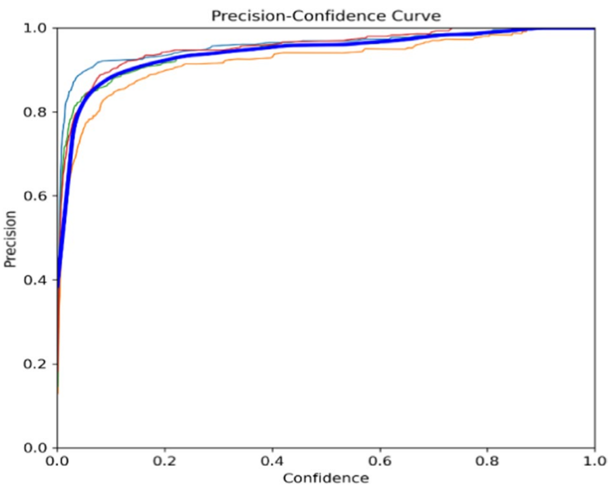


Fig. 10 ROC graph of proposed model for waste classification for 50 epochs

Figure 11 presents a Precision-Confidence (TPR) Graph for all waste classes. The graph is plotted among precision value and confidence results. A higher precision shows better performance. The graph is plotted for various waste types, i.e., carboard-0, glass-1, metal-2, plastics-3, and all classes-4.

Fig. 11 Precision-confidence graph for all waste classes



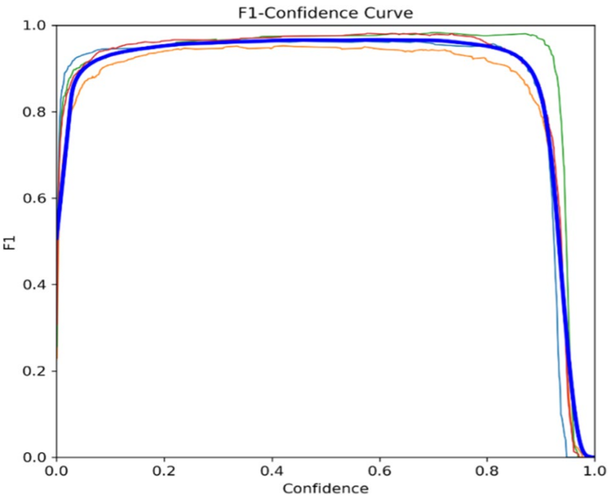


Fig. 12 Experimental results of the proposed model for the F1-Measure graph

Figure 12 presents an F1-Measure graph for all waste classes. The graph is plotted among the F1-score value and confidence results. A higher precision shows better performance. The graph was plotted for various waste types, i.e., carboard-0, glass-1, metal-2, plastics-3, and all classes-4.

Table 4 presents the error rate and total time comparison for the existing and proposed Models for 0, 30, and 50 epochs. The proposed model takes 4589 s for 30 epochs, and its error rate was also the lowest at 0.019578. Similar to the 50 epoch's error rate was 0.016578%, and the total time was 7586 s. A model with less error rate and time is always in demand; the proposed model achieved both factors. The proposed model takes 4589 s for 30 epochs, and its error rate was also the lowest at 0.019578. Similar to the 50 epoch's error rate was 0.016578%, and the total time was 7586 s. A model with less error rate and time is always in demand; the proposed model achieved both factors.

Similarly, Table 5 presents an experimental result comparison of experiment 1 for existing and proposed Models, i.e., Precision, Recall, F1-Score and Accuracy for 0–50 epochs and the 80:10: 10 dataset. The proposed model achieves a precision of 95.4%, recall of 94.3%, F1-score 93.1% and accuracy of 95.7%, which is best compared to all the existing methods.

Table 4 Error rate and total time comparison for existing and proposed model

Model	Transfer learning	Division details (training: validation: testing)	30 epochs error rate (%)	Total time (in seconds)	50 epochs error rate (%)	Total time (in seconds)
VGG-16	ImageNet	80: 10: 10	0.078871	7898	0.05159	13193
ResNet-34	ImageNet	80: 10: 10	0.071847	5478	0.062492	10172
ResNet-50	ImageNet	80: 10: 10	0.052381	6898	0.05717	11093
AlexNet	ImageNet	80: 10: 10	0.295718	4789	0.18788	8589
Proposed model	ImageNet	80: 10: 10	0.019578	4589	0.016578	7568

Table 5 Precision, recall, F1-score, accuracy results comparison for existing and proposed model for 50 epochs and 80:10: 10 (training: validation: testing) dataset

Model	Precision	Recall	F1-score	Accuracy
VGG-16 models	0.861	0.883	0.891	0.889
ResNet-34	0.883	0.892	0.906	0.891
ResNet-50	0.897	0.893	0.895	0.902
AlexNet	0.912	0.925	0.918	0.917
Proposed model	0.954	0.943	0.931	0.957

Experiment 2 The dataset consists of 27025 images separated into two classes of organic waste (O: 17005) and recyclable waste (R: 10020) was used to test the proposed model. After fine-tuning the image parameters, the dataset was divided into 3 classes (Training: Validation: and testing). In experiment two, the dataset ratio was 70: 15: 15 (Training: Validation: Testing), and the number of Epochs was 0–50-100. The experimental results for experiment 2 are as follows.

For dataset 70: 15: 15 (training: validation: testing), and epoch 0–50-100, training, validation accuracy and loss were calculated in experiment 2. Figure 13a presents training and validation accuracy results for a proposed model from 0–50 epochs. When the numbers of epochs are less, the training and validation accuracies are also less, but once the number of epochs increases, the accuracy results are increased for training and validation from 75% to 95.8%. A model with higher training and validation accuracy is always in demand, and the proposed model is the best fit. Figure 13b presents training and validation loss results for the proposed model from 0–50 epochs. Initially, the loss results are higher for epochs 0–20, but once we increase it to 50, the loss % also decreases. Fewer loss results show better performance.

Precision and recall results were calculated for 100 Epochs and dataset 70: 15: 15 (training: validation: testing). Figures 14 and 15 present the proposed Model for Precision and Recall experimental results. Graph 14 was plotted for precision Vs confidence, and Graph 15 for recall and confidence. A model which generates higher precision and recall can be treated as best.

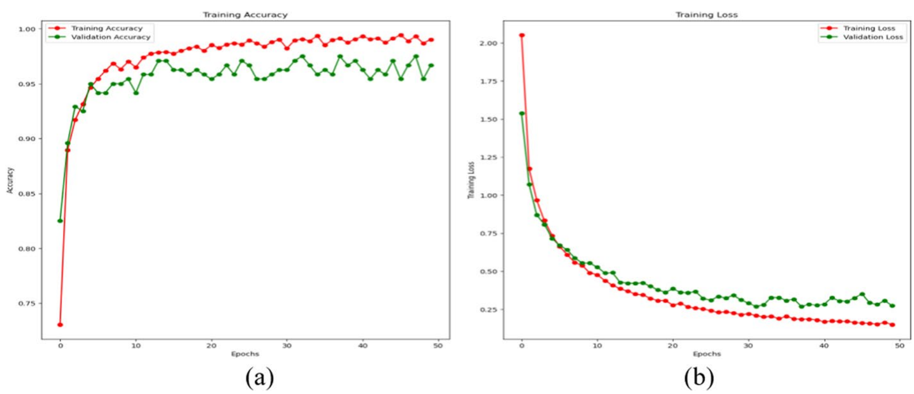


Fig. 13 Experimental results of the proposed model for Epoch 0–50 and dataset 70: 15: 15 (training: validation: testing), **a** training and validation accuracy and **b** training and validation loss

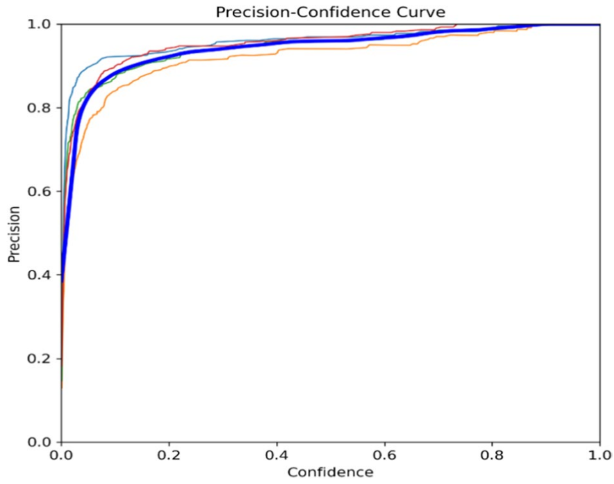


Fig. 14 Experimental results of the proposed model for precision value (100 Epochs and dataset 70: 15: 15 (training: validation: testing)

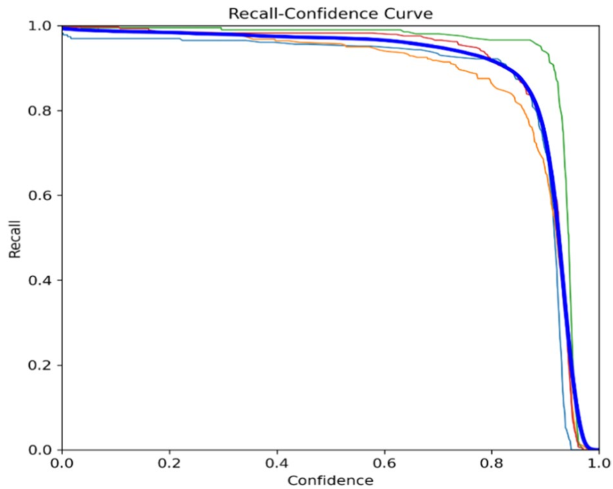


Fig. 15 Experimental results of the proposed model for recall (100 epochs and dataset 70: 15: 15 (training: validation: testing)

For dataset 70: 15: 15 (training: validation: testing), with 100 epochs, various performance measuring parameters, i.e., precision, recall, F-measure, training-loss, and validation-loss, were calculated for the proposed model. Figure 16 presents an experimental graph for all these results.

Table 6 presents the error rate and total time comparison for the existing and proposed Models for 50 and 100 epochs. The proposed model takes 4508 s for 50 epochs, and its error rate was also the lowest at 0.018181. Similar to the 100 epoch, the error rate was 0.032578, and the total time was 8508 s. A model with less error rate and time is always in demand; the proposed model achieved both factors. The choice of optimizer can significantly impact the accuracy of the proposed model. Different optimizers have strengths and weaknesses, and their performance can vary depending on the dataset's characteristics and the specific use case. Here are some general observations about the impact of different optimizers on the accuracy of the proposed:

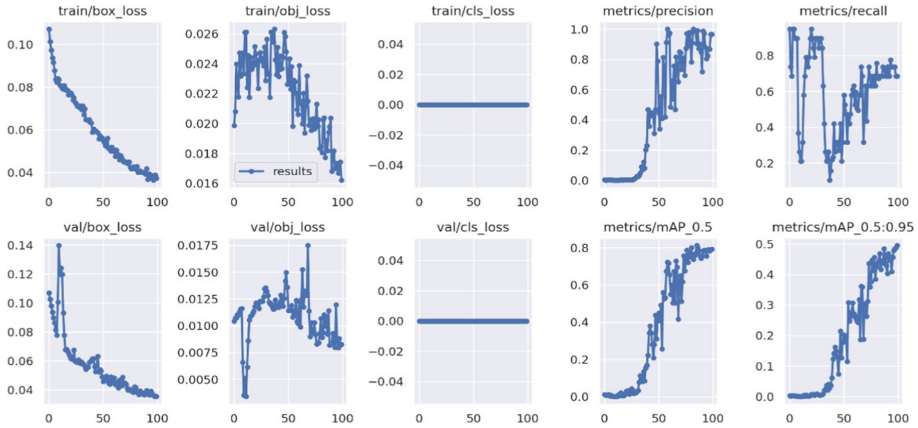


Fig. 16 Experimental results of the proposed model for various training and validation loss (for Epoch 0–100)

Table 6 Error rate and total time comparison for existing and proposed model

Model	Transfer learning	Division details (training: validation: testing)	50 epochs error rate (%)	Total time (in seconds)	100 epochs error rate (%)	Total time (in seconds)
VGG-16	ImageNet	70: 15: 15	0.04101	12103	0.08191	25193
ResNet-34	ImageNet	70: 15: 15	0.05287	10122	0.102107	20172
ResNet-50	ImageNet	70: 15: 15	0.4318	11901	0.851018	21091
AlexNet	ImageNet	70: 15: 15	0.1334	8280	0.25414	15580
Proposed model	ImageNet	70: 15: 15	0.018181	4508	0.032578	8508

- SGD is a simple optimizer that can work well for small datasets or simple models. However, it can slowly converge and get stuck in local minima.
- Adam is a popular optimizer that works well for most deep learning problems, including proposed. It can converge faster than SGD and can handle noisy or sparse gradients. However, it can be sensitive to the choice of hyperparameters and can sometimes overfit the data.
- Adagrad can work well for sparse data and can converge quickly. However, it can accumulate too much historical information and cause the learning rate to decay quickly, leading to slow convergence.
- Adadelta is similar to Adagrad, but it can handle the decay problem using a moving window of the past gradients. It can converge faster than Adagrad and requires fewer hyperparameters.
- RMSProp is a good optimizer for deep learning models, including the proposed model. It can handle the problem of vanishing or exploding gradients and adapt to different learning rates for different parameters. However, it can converge slowly and require careful tuning of the hyperparameters.

Table 7 presents an experimental result comparison for existing and proposed Models, i.e., Precision, Recall, F1-Score and Accuracy. The proposed model achieves a precision of 95.4%, recall of 94.3%, F1-score 93.1% and accuracy of 95.7%, which is best compared to all the existing methods. Figures 9, 10, 11, 12, 13, 14, 15 and 16 presents the experimental results for the proposed hybrid and existing models.

4.2 Discussion

This research used a deep Convolutional neural network method to categorise waste into multiple classes. This research used a hybrid model that included CNN-LSTM and a trained TL model. Experimental results for proposed and existing models are as follows. The results were calculated in two experiments. Experiment 1 with 100 epochs and 70: 15: 15 (training: validation: testing) dataset. Table 3 presents the experimental parameters for the proposed model.

In experiment 1, the dataset consisting of 27025 images separated into two classes of organic waste (O: 17005) and recyclable waste (R: 10020) was used to test the proposed model. After fine-tuning the image parameters, the dataset was divided into 3 classes (Training: Validation: and testing). On the same dataset, the splitting ratio was 80: 10: 10 (Training: Validation: Testing) and the number of Epochs are 0–30 and 50.

Figure 9 presents Training and Validation Accuracy and Training and Validation loss for the proposed model for 0–50 in experiment 1. A Transfer learning model ImageNet was used for existing and proposed models. The proposed model utilises an LSTM layer which contains multiple Hyperparameters, including the rate of learning, the total number of hidden layers, and the epoch durations, which helps the proposed model to reduce the error rate and transfer learning aids to enhance the training time. We have also calculated a ROC graph for 50 epochs, a graphic that displays how well an algorithm is for classification across all the identification levels. Figure 10 presents the ROC graph of the proposed Model for Waste classification; the graph was plotted based on two parameters True Positive Rate and False Positives Rate.

Similarly, Fig. 11 presents the Precision-Confidence Graph for all waste classes for the proposed model. Figure 12 illustrates an F1-Measure graph for all waste classes. The graph is plotted among the F1-score value and confidence results. A higher precision shows better performance. The graph was plotted for various waste types, i.e., carboard-0, glass-1, metal-2, plastics-3, and all classes-4.

Table 4 presents the error rate and total time comparison for the existing and proposed Models for 0, 30, and 50 epochs. The proposed model takes 4589 s for 30 epochs, and its error rate was also the lowest at 0.019578. Similar to 50 epochs, the error rate was 0.016578%, and the total time was 7586 s. A model with less error rate and time is always

Table 7 Precision, recall, F1-score, accuracy results comparison for existing and proposed model for 100 epochs

Model	Precision	Recall	F1-score	Accuracy
VGG-16 models	0.852	0.879	0.881	0.871
ResNet-34	0.874	0.887	0.892	0.881
ResNet-50	0.885	0.878	0.881	0.895
AlexNet	0.902	0.915	0.903	0.908
Proposed model	0.941	0.938	0.921	0.941

in demand; the proposed model achieved both factors. The proposed model takes 4589 s for 30 epochs, and its error rate was also the lowest at 0.019578. Similar to the 50 epoch, the error rate was 0.016578%, and the total time was 7586 s. A model with less error rate and time is always in demand; the proposed model achieved both factors. Similarly, Table 5 presents an experimental result comparison of experiment 1 for existing and proposed Models, i.e., Precision, Recall, F1-Score and Accuracy for 0–50 epochs and the 80:10: 10 dataset. The proposed model achieves a precision of 95.4%, recall of 94.3%, F1-score 93.1% and accuracy of 95.7%, which is best compared to all the existing methods.

In experiment two on the same dataset, the splitting ratio was 70: 15: 15 (Training: Validation: Testing), and the number of Epochs was 0–50-100. Figure 13a presents training and validation accuracy results for the proposed model from 0–50 epochs. When the numbers of epochs are less, the training and validation accuracies are also less, but once the number of epochs increases, the accuracy results are increased for training and validation from 75% to 95.8%. A model with higher training and validation accuracy is always in demand, and the proposed model achieved the same.

Figure 13b presents training and validation loss results for the proposed model from 0–50 epochs. Initially, the loss results are higher for epochs 0–20, but once we increase it up to 50, the loss % is also decreased. Less loss results show better performance. Precision and recall results were calculated for 100 Epochs and dataset 70: 15: 15 (training: validation: testing). Figures 14 and 15 present the proposed Model for Precision and Recall experimental results. Graph 14 was plotted for precision Vs confidence, and Graph 15 for recall Vs. Confidence. A model which generates precision is always in demand. The proposed model achieved both. There are pros and cons to previous studies, and keeping them in mind lets researchers develop a method that can effectively address all drawbacks. Previous studies have somewhat addressed the problem of garbage categorization and management, but they all fall short in some way.

Some have proposed a hybrid strategy that combines elements of several different methodologies. Using a combination of Deep Learning algorithms (CNN-LSTM and Transfer Learning), the highest levels of accuracy have been attained. Over 94.1% accuracy was attained when sorting garbage.

Many suggested systems, too, provide a "machine learning and deep learning" mix as a solution [49–51]. The quest for a more precise and trustworthy system persists, nevertheless. The study's overarching goal is to understand better and implement automatic waste categorization systems, which aid in trash recycling. Various methods are available for sorting trash, but many need human intervention. The government, the people, and the business community may all benefit from implementing a completely autonomous system. The ultimate goal of this study is to develop a low-cost, fully automated waste management system that can efficiently classify garbage and return correct findings.

5 Conclusion and future works

For sustainable development of the environment, waste management is always in demand. Multiple research works using deep learning methods presented various waste prediction and classification research. This research proposed a hybrid waste recognition and classification model using CNN-LSTM with a Transfer learning feature. This research utilised an online TrashNet dataset sample, with 24705 images separated into two classes of organic waste (13880) and recyclable waste (10825) used to test the proposed model. An experimental analysis was performed for two dataset divisions. In experiment one dataset ratio of 80: 10: 10 (Training: Validation: Testing) and the number of epochs from 0–50, and in experiment 2 dataset ratio of 70: 15: 15 (Training: Validation: Testing) and the number of epochs from 0–100. Table 3 presents an experimental parameters overview for the proposed model, and Fig. 8 shows the sample experimental results (Organic and Recyclable).

The proposed hybrid model and various existing CNN models (i.e., VGG-16, ResNet-34, ResNet-50, and AlexNet) were implemented using Python and tested based on performance measuring parameters, i.e., precision, recall, testing and training loss, and accuracy. Each model was created with a range of epochs and an AME optimisation algorithm. For the proposed method, the AME optimisation achieved the best optimisation and accuracy and the least modelling loss for training, validation, and testing. The proposed model performed the highest precision of 95.45%, far better than the existing deep-learning method. When putting this paradigm into action, for instance, in a smart city initiative, there are many factors to consider. Autonomous vehicles equipped with a robotic arm and high-definition camera, as well as efficient operating cycles throughout a wide range of solid waste content areas, is one solution to these problems.

Finally, the proposed deep learning-based smart waste management and categorization framework can completely transform current methods for handling waste. These structures help contribute to a more sustainable and healthier future by lowering pollution levels, fostering a sustainable environment, and increasing the efficiency with which waste is processed. These systems are refined through continued advancements and research within this discipline, leading to more successful methods for dealing with the ever-growing difficulties associated with waste management within a rapidly altering ecosystem.

In future research, we will explore variables such as operational socio-economic factors and essential service expenditure that can affect waste generation. To create a waste management framework that can be better optimized and more economical additional research may be carried out to determine the significant aspects. The proposed model also has one limitation: it cannot sort the waste images based on the input; we will add this feature in the future.

Author contributions Umesh Kumar and Sarita: Problem statement, the key concept, design and initial draft preparation; Surjeet Dalal: Implementations, results analysis; Robertas Damaševičius: conceptualization and methodology.

Data availability The dataset is openly available on the Kaggle online website. The dataset is available from the corresponding author based on personal request.

Declarations

Conflict of interest The authors have no conflict of interest related to the research.

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