ILCNN: An Improved Lightweight Convolutional Neural Network Based Recycling Garbage Classification Strategy with Image Processing Technique

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Abstract: Domestic garbage has grown at an alarming rate in recent years, making the use of intelligent waste sorting technology an absolute necessity. Unfortunately, embedded garbage classification devices aren't a good fit for current garbage classification algorithms due to their high parameter counts and bad real-time performance. More and more people are using traditional garbage cans, which mean there's a growing need for effective segmentation and identification algorithms. Modern computer systems' increased processing power and more effective picture recognition technologies are in line with this desire. By utilizing an image processing logic known as Improved Lightweight Convolutional Neural Network (ILCNN), a new garbage classification procedure is established, which decreases the time and expenses associated with waste segregation. This helps to solve these challenges against test how well the suggested model works, it is compared against a standard deep learning model known as a Convolutional Neural Network (CNN). Reducing the need for human involvement and increasing efficiency in garbage segregation are the goals of automating the process. Using a publicly accessible dataset that included pictures of different kinds of garbage gathered from different places, we ran the various state-of-the-art deep learning models. On this dataset, we fine-tuned pre-trained ILCNN models using image augmentation approaches and transfer learning techniques. With its proposed ILCNN model, the network can classify and recognize garbage with great accuracy while using very little energy.

1 INTRODUCTION

Sorting garbage, sometimes known as garbage categorization, is the process of dividing waste into distinct groups according to its characteristics (Shanshan Meng, et al., 2020). Simplifying disposal is the primary goal of the project, which will lead to improved recycling, less environmental effect, and support for sustainability. (Sri Kruthika M, et al., 2024). It is common practice to classify waste into many types, such as: 1. Organic waste, which includes things like discarded food, yard trimmings, and paper goods. 2. Items that may be recycled include paper, cardboard, glass, specific types of plastic, aluminum, and metals. 3. Items that are considered hazardous garbage include old batteries, electronics, paints, solvents, pesticides, and certain chemicals. 4. Mixed garbage that cannot be recycled, including plastic bags, some forms of packaging, used diapers, and sanitary goods. 5. Industrial, medical, and construction-related garbage are examples of specialized waste streams. In most cases, communities and individuals need to be educated on the need of waste segregation, separate methods for collecting and labeling garbage, and facilities for proper disposal and recycling in order to sort garbage properly. (Yu Song, et al., 2023).

Governments, local authorities, corporations, and individuals all have a role to play in promoting efficient waste management systems and decreasing the environmental impact of waste. Extensive research has been conducted in the crucial and demanding area of object detection within computer vision. The objective of object detection is to identify and categorize all items. Its applications are practically endless: driverless vehicles, medical imaging, robot vision, intelligent video surveillance, remote sensing pictures, etc. (Yang Shen, et al., 2023).

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The quantity of domestic garbage has grown substantially in recent years due to rising urbanization and rising living standards. Incineration is the current gold standard for waste disposal; however, sorting waste before burning can help make better use of available resources. Conventional waste sorting involved transporting household waste to a treatment facility, where workers would stand on either side of a conveyor belt and manually sort the material by hand or with implements. Nevertheless, this method of garbage sorting requires a lot of workers, doesn't get the job done very well, and the pollution and smell coming from the treatment plant might be harmful to the workers' health (He Bai, et al., 2021).

The burden of post-recycling treatment can be substantially alleviated if sorting can be finished at the time of waste collection and recycled in separate bins according to distinct categories. There has been a rise in the visibility of intelligent garbage cans, recycling bins, and machine vision-based intelligent garbage categorization systems owing to advancements in AI technology (Yujin Chen, et al.,2023).

The goal of this project is to create software that can analyze gathered photographs and identify cases of abandoned garbage. Create a computer vision model that can sort waste by material, including paper, metal, glass, cardboard, and rubbish. To make recycling the waste materials as easy as possible and the worker's health may be harmed by the physical labor (Zhichao Chen, et al.,2022).

As a result, this study uses a self-constructed rubbish dataset for rubbish detection and classification for a small, efficient classification model. To enhance the spatial feature perception of the network model, we apply the Improved Lightweight Convolutional Neural Network (ILCNN) attention mechanism. Highly efficient and effective models across a range of tasks are produced by EfficientNet through the application of a compound scaling approach, which balances the depth, breadth, and resolution of the models. Efficiency in terms of parameters and computing cost allows it to attain extremely excellent performance (Kishan PS, et al., 2021).

- In order to enhance the recognition performance of the pre-trained MobileNetV3 model in waste classification tasks, a dataset was created that featured four typical forms of waste from homes.
- Instead of using SE-Net, the model is equipped with CBAM (Convolutional Block Attention Module) to improve its spatial perception of features. This allows it to adaptively emphasize or suppress distinct feature information based on the distribution of feature maps.
- The convolution layer employs the Mish activation function to enhance deep networks' information representation ability and generalization performance.
- In order to decrease the model's parameter, count and prevent overfitting, the classifier opts for global average pooling rather than a complete connection layer.

Waste categorization using deep learning algorithms, especially ILCNN can assist overcomes some of the problems that come with conventional machine learning methods. The following are some examples of how deep learning could help with these problems: Feature extraction, from unstructured data, deep learning systems may automatically learn feature hierarchies. Because of this, diverse machine learning models no longer require feature engineering that is done by hand and improving the model's capacity to distinguish between various forms of waste, ILCNN use convolutional layers to extract useful characteristics from rubbish images (Shoufeng Jin, et al., 2023).

Reduced requirement for massive volumes of labeled data is a result of size-transfer learning, which permits fine-tuning of pre-trained ILCNN models (e.g., trained on ImageNet) on smaller garbage classification datasets. The ability to generalize to new contexts and unknown data is strength of pre-trained models on big and varied datasets. Additionally, domain adaptation and data augmentation are two methods that can take model generalization to the next level. Considerations such as model complexity, processing resources, and classification accuracy determine the relative merits of the many deep learning models available for waste image categorization (Wei Liu, et al., 2023).

2 RELATED WORKS

Effective environmental sustainability and garbage management depend on correct garbage classification (Kirit Rathod, et al.,2024). Typical methods of waste classification rely on hand sorting. This might be a somewhat demanding and error-prone procedure that leads the government to carry out insufficient policy. In this research, we offer a garbage categorization method that uses deep learning and GCDN to automate and enhance the accuracy of the process. Shoe, green-glass, paper, cardboard, battery, biological, plastic, metal, brown-glass, white-glass, and waste are among the twelve types of trash that our system uses through an extra layer of convolutional neural networks (CNNs). Utilizing a publicly accessible dataset that comprises images of diverse waste materials gathered from numerous sites, we have educated many cutting-edge deep learning models. We applied picture enhancing methods before using transfer learning methods on pre-trained CNN models on this dataset. We obtained a training phase classification accuracy of 98.64% and a validation phase accuracy of 93.23% according to our results analysis. Experimental findings reveal that our approach effectively identifies garbage in challenging environments with different backgrounds and illumination levels. We also discuss some of the uses for our technology in smart garbage cans and recycling facilities to simplify environmental and consumer sorting of waste.

The appropriate categorization of garbage is crucial for efficient waste management and the long-term viability of the ecosystem. Using Convolutional Neural Networks (CNNs), this study (Al Mahmud Al Mamun, et al., 2024) thoroughly explores garbage categorization. Our goal is to develop a deep learning-based system that can classify waste with remarkable accuracy. Proving its efficacy in waste classification, the suggested CNN model attains a staggering 98.45% accuracy (Wenbo Liu, et al., 2024). The study covers all aspect, including data gathering and preprocessing, model creation, training techniques, and assessment. Results show that CNNs can transform waste management for the better and start a more environmentally friendly age.

Incorrect garbage classification may lead to environmental pollution by means of recycling. Designed on a convolutional neural network (CNN), an enhanced garbage sorting and recycling system is provided to effectively handle this problem. This article offers an approach based on a well-designed deep network topology to maximize the model parameters. With an aim of increasing the processing speed and accuracy in classification, it then employs the graphics processing unit (GPU) to achieve parallel processing and batch processing. With an accuracy of at least 94% and as high as 99%, the CNN-based garbage categorization system showed rather good performance according to the research. Direct outcome of the system design is better accuracy in garbage classification. Using autonomous feature learning and deep network architecture helps the system to more identify significant components in waste images. This guarantees efficient garbage recycling and helps to increase the accuracy of categorization results.

The destruction of past waste disposal methods is a logical result of the always faster rate of junk creation, which forces an unavoidable choice of garbage classification (Qingqiang Chen, et al., 2020). Also, much of interest is the accuracy of identification and the multi-category classification of waste. The present garbage classification systems lack diversity, low accuracy, and a single category emphasis that results in with an average accuracy of 64% and 92 frames per second, the paper proposes to detect 15 objects across 3 categories using the upgraded YOLOV4 network framework. The upgraded YOLOV4 fits well with embedded devices as they increase its capacity to recognize different waste kinds.

As the world population keeps growing today, pollution levels are also rising (Volkan Kaya, 2023). One main cause of environmental contamination is harmful compounds found in garbage. From incorrect waste management, damage to ecosystems and human health is considerable. Particularly as technology develops, the recyclability of the raw materials used to create waste products affects both national demands for resources and energy savings. As such, recycling facilities do a lot of traditional chores to re-use recyclable waste across different countries. These operations start with pre-processing and physical waste collecting, which depend on human labor. Apart from endangering people, this habit damages the surroundings as well.

This fact generates the need for an intelligent system competent of independently recognizing and classifying waste items. This work automatically sorted waste by material using powerful deep learning algorithms like Xception, InceptionResNetV2, MobileNet, DenseNet121, and EfficientNetV2S. Based on transfer learning methods, it also suggested two further algorithms: Xception_CutLayer and InceptionResNetV2_CutLayer. Using a dataset comprising six different kinds of garbage, we trained and assessed the suggested methodologies and deep learning techniques grounded on artificial intelligence. Utilizing the suggested Xception_CutLayer technique and 85.77% utilizing the InceptionResNetV2_CutLayer method, the study revealed that these methods exceeded the others in terms of classification success rate 89.72%.

3 METHODOLOGY

In order to manage waste and keep the environment sustainable, garbage categorization is crucial. The government's policies may be inadequate since traditional waste categorization systems sometimes rely on manual sorting, which is both labor-intensive and susceptible to human mistake. Unfortunately, embedded garbage classification devices are not a good fit for current garbage classification algorithms due to their high parameter counts and bad real-time performance. The volume of waste is causing cleanup to be quite a hassle. Waste separation, one of the desirable recycling activities, is by far the most important step in achieving low-cost recycling. When thinking about smart and automated cities, one of the efficiency challenges of waste management as it is currently done is that there are no developed systems for garbage collection. These past researches have lots of drawbacks such as:

- The current method of waste sorting is inefficient, requires a lot of workers, and may be harmful to their health due to the pollution and smell coming from the treatment facility.
- The computing demands on garbage classification devices are significant because large-scale models contain a huge number of parameters. Due to the high level of hardware limitation, these devices are both large and expensive.
- In the past, workers would stand on each side of a conveyor belt and physically sort household garbage as it came into the waste treatment facility. They would use their hands or equipment to separate the different types of waste.

In comparison to the current technology, Convolutional Neural Network (CNN), the suggested technique, Improved Lightweight Convolutional Neural Network (ILCNN) increases the model's recognition accuracy and streamlines waste management processes. The following figure 1 shows the system architecture and the following figure 2 shows the system flow diagram.

Intelligent garbage cans, recycling bins, and machine vision-based intelligent garbage sorting systems have recently made headlines, thanks to advancements in AI technology and suggested a network-based garbage categorization system that utilized deep learning to automate and enhance the accuracy of this procedure. To sort garbage into different types, such paper, cardboard, plastic, green-glass, etc., our system leverages an extra layer of enhanced lightweight convolutional neural networks (ILCNNs). A publicly accessible dataset including images of different kinds of waste gathered from different places has been used to train the various state-of-the-art deep learning models. Then, we utilized image augmentation and transfer learning strategies to this dataset to fine-tune the ILCNN models that had already been trained.

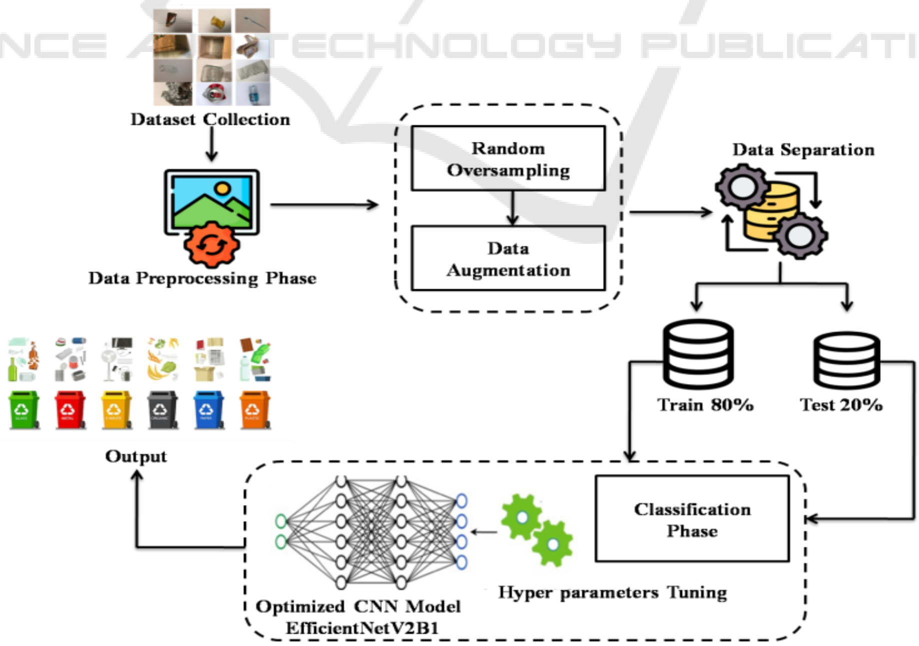


Figure 1: System Architecture.

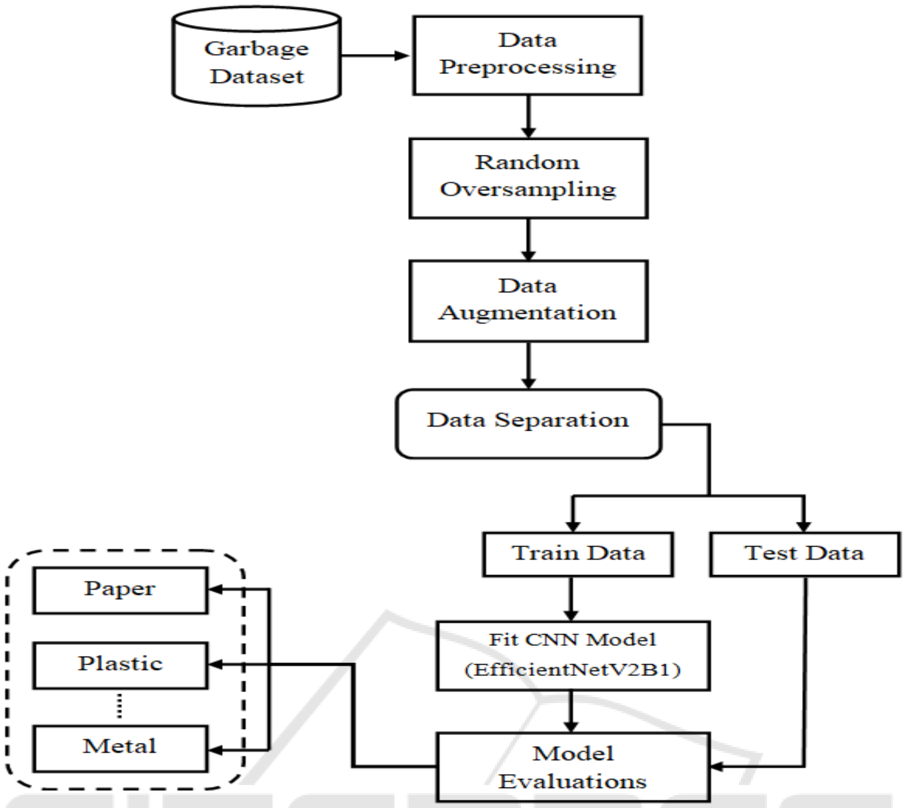


Figure 2: System Flow Diagram.

This improved its recognition performance in garbage classification tasks.

- The convolution layer makes use of the Mish activation function to enhance the deep network's information representation ability and generalization performance.
- To decrease the model's parameter, count and prevent overfitting, the classifier opts for global average pooling rather than a complete connection layer.
- In order to get the most out of the pre-trained model for garbage categorization tasks, we built it using four prevalent forms of household waste.

In the implementation phase, the original theoretical design for the project is turned into a functioning system. For this reason, this is the most important step in the design of a new system that the user will rely on and trust will work well. The implementation step will require planning everything out, research on the existing system and its shortcomings, devising a plan to switch to a new system, and reflecting on the effectiveness of that process.

3.1 Data Collection

Although the original MobileNet pre-trained model is trained on the ImageNet dataset, it is challenging to guarantee the effectiveness of transfer learning as the data in ImageNet does not entirely contain the images we need. To thus fine-tune the model, we require a dataset including garbage photos. There isn't yet a standard dataset for waste categorization projects. Though it has relatively few categories, which is not in line with the real state of residential garbage categorization in Indian, the garbageNet dataset for waste classification is still useful. Thus, this work generates a data set especially used for visual garbage sorting through network retrieval and laboratory real scene shooting, including many scenes such single object, multiple similar objects, complex background, and various interference situations such lighting and motion blur. With 4152 JPG photos overall, it is split into four categories: kitchen garbage, recyclable waste, hazardous waste, and other waste.

3.2 Data Preprocessing

Organize and preprocess the images. Among other preprocessing methods, this can involve scaling, normalizing, noise reduction, contrast enhancement, and other approaches.

3.3 Data Splitting

Three subsets made out of the dataset were validation, training, and testing. The training set is used to train the model; the validation set is used to fine-tune the hyper parameters; the testing set evaluates the performance of the produced model. This fundamental stage is needed in the development and application of machine learning algorithms for image classification chores. Open your preferred data analysis tool (python or C) then import the dataset for depicts categorization. One should verify if the dataset follows an ordered layout.

- Perform the necessary data preparation activities prior to data division. Examples of this are handling waste connected to missing images.
- Shuffling your dataset before beginning a machine learning project helps us to avoid our model from learning patterns that could be connected to the sequence of the data. A dataset could be shuffled both before and after the data loading process.
- The model gets trained with it. Validation set is used to adjust hyper parameters. Testing set: It helps to evaluate the performance of the final model.

3.4 Feature Extraction

Extract relevant information from the images and the deep learning methods could mean learning automatically features using convolution layers. Machine learning methods would extract features for traditional models using histograms of oriented gradients. Choose sensible model architecture. For deep learning techniques, this often involves ILCNN. Train the given model on the provided training set. Tune your chosen hyper settings based off of performance on the validation set. Training involves adjusting weights of the models so that the loss function is minimized. Assess the model using the test set. Common performance measures are accuracy and other related metrics. Every model can be optimized further to increase the performance of the model on the test set. This could mean tuning hyper parameters, collecting more data, using data augmentation, regularizing the model to prevent overfitting, etc. Assess model prediction and errors to understand the behavior of model. This phase may highlight the errors of the model and facilitate future development of the model.

3.5 ILCNN Architecture

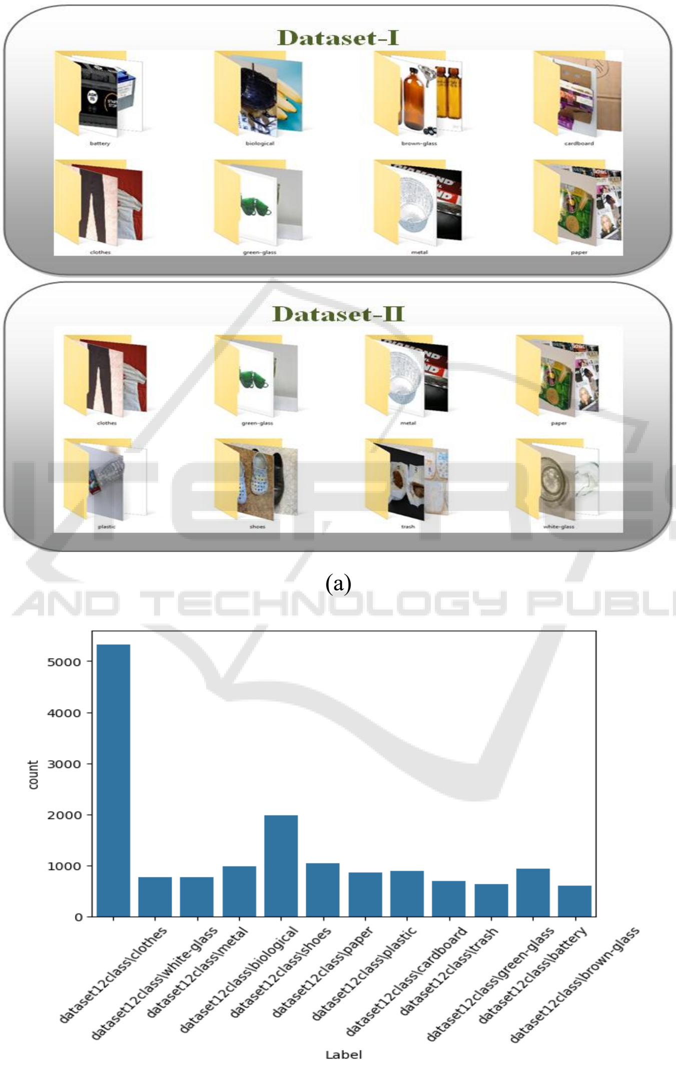
After preprocessing the image waste classification, we selected an ILCNN architecture that performs well for waste image classification. For classification, we selected EfficientNetV2B1, and included weights for this model pretrained from an EfficientNetV2B1-like dataset. These types of models can be found in deep learning utilities such as TensorFlow or Pytorch. We removed the previous classification head from EfficientNetV2B1 pretrained model and added our own classification head with the same number of garbage classes in our dataset. To extract hierarchical and discriminative features from the garbage images we utilized ILCNN layers. To tune the model weights during training we need to use an optimizer such, as Adam or SGD, and an appropriate loss function, such as categorical cross-entropy, for multi-class classification. Finally, to deliver the final waste classifications, we transferred the extracted features into the ILCNN architectural scheme, again by overlaying fully connected layers.

3.6 Training and Testing

After the model is developed, it has to be trained using a large number of images that have the necessary objects tagged. Keep in mind that in order for the EfficientNetV2B1 model to learn to differentiate between the different classes appropriately, the data must be balanced. Once the data is prepared, it has to be put into the EfficientNetV2B1 model. Dataset size determines whether this is best done in batches or in one continuous run. Next, a suitable optimizer, such as Adam or SGD, has to be used to train the model. In order for the model to learn to identify different objects in the images, its weights are modified continually during the training phase. After then, the testing set may be used to assess the model's correctness. There are a number of ways to evaluate the model's efficacy, including recall, accuracy, and F1 score. One way to measure the model's performance is to see how many photos it accurately labels. It is also possible to test the model on new data to determine how well it generalizes. The model's performance with unobserved data will be shown by this.

4 RESULTS AND DISCUSSION

The goal of this study was to evaluate the efficacy of the proposed scheme by cross-validating it with the traditional deep learning model, Convolutional Neural Network (CNN), and classifying waste as organic or recyclable using a deep learning-based model called ILCNN. The research demonstrated that ILCNN was capable of distinguishing between different types of garbage, thereby facilitating the development of more efficient recycling methods. This study suggested an automated classification method that utilizes ILCNN for efficient image recognition. Using an optimization method with a higher level of classification accuracy, the model that has been presented emphasizes the role of ILCNN in automating recycling tasks.



(a)

(b)

Figure 3: (A) Dataset View and (B) Data Visualization.

The objective of this investigation was to categorize photographs of waste products into seven categories: cardboard, glass, metal, organic, paper, plastic, and refuse. Transfer learning methods were employed to enhance the model's performance, thereby emphasizing ILCNN's adaptability in managing a variety of refuse categories. In a research article, an ILCNN model was presented that achieved a classification accuracy of 98.63% for a variety of refuse categories. ILCNN's proficiency in automating garbage categorization duties is illustrated by this remarkable precision. The results emphasize the effectiveness of ILCNN in accurately classifying waste products, and these studies collectively demonstrate the extent to which ILCNN automates garbage classification, thereby promoting more sustainable environmental practices and effective recycling methods. A clear and concise representation of the dataset view and the data visualization perspective is provided in the following figure, which is referred to as Figure 3.

The training accuracy and validation accuracy assessments of the suggested scheme known as ILCNN are depicted in the figure that can be seen below, which holds the designation Figure 4.

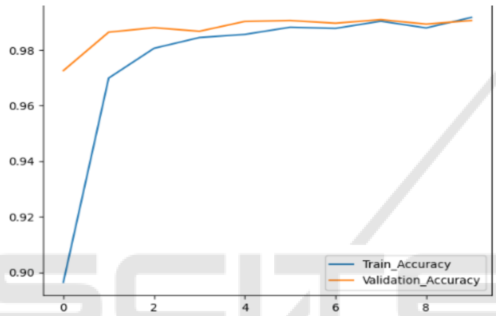


Figure 4: Training and Validation Accuracy.

The training loss ratio and validation loss ratio of the proposed scheme known as ILCNN are depicted in the figure that can be seen below, which is referred to as Figure 5.

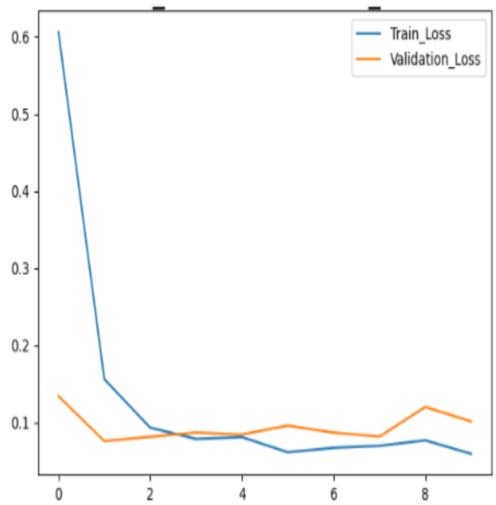


Figure 5: Training and Validation Loss.

The web page for administrator authentication, the website for picture uploading, and the page for result prediction are all depicted in the following images: Figure 6, Figure 7, and Figure 8. These representations demonstrate the output of the suggested method.

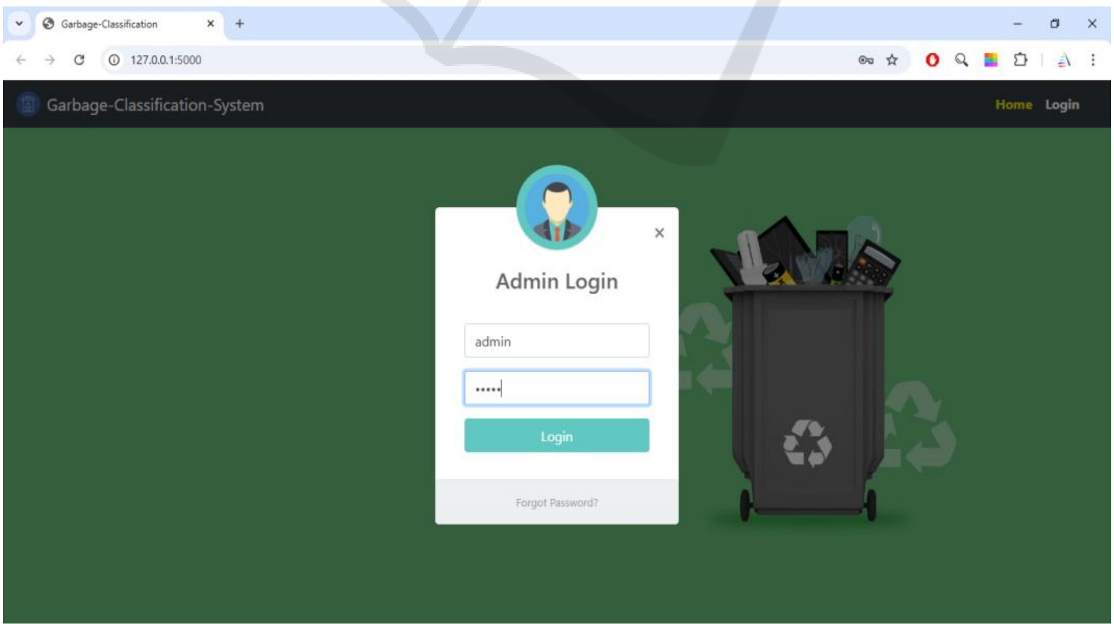


Figure 6: Administrator Authentication.

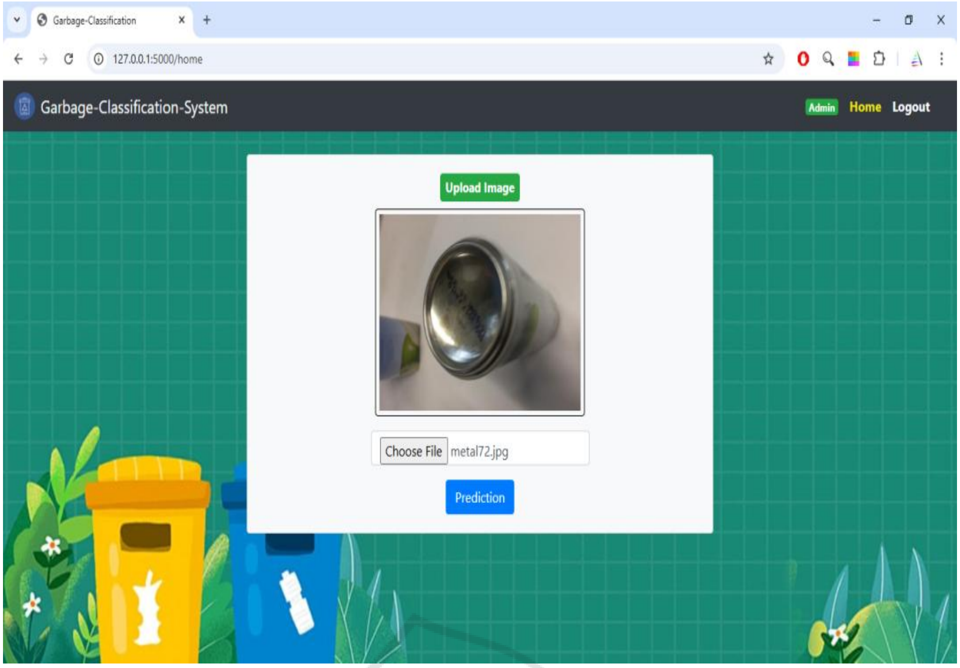


Figure 7: Image Uploading Port.

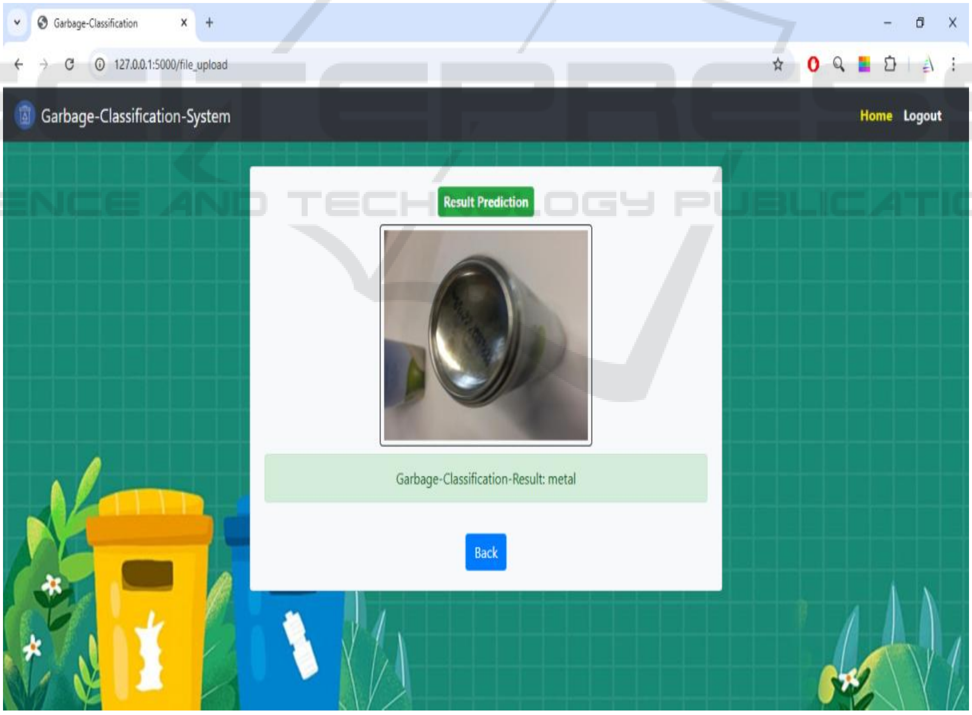


Figure 8: Result Prediction.

The prediction accuracy of the proposed scheme, which is referred to as ILCNN, is depicted in the following figure, which is referred to as Figure 9. In order to evaluate the prediction accuracy of the suggested scheme, it is cross-validated with the traditional deep learning model known as CNN. A descriptive representation of the same may be found in the table that follows, which is referred to as Table-1.

Table 1: Analysis of Prediction Accuracy Between Ilcnn and Cnn.

Iterations	CNN (%)	ILCNN (%)
25	93.64	98.71
50	92.15	98.63
75	93.76	97.49
100	92.55	97.82
125	93.09	98.19
150	92.61	98.74
175	92.61	98.05
200	92.51	98.26
225	92.47	97.93
250	91.69	98.19

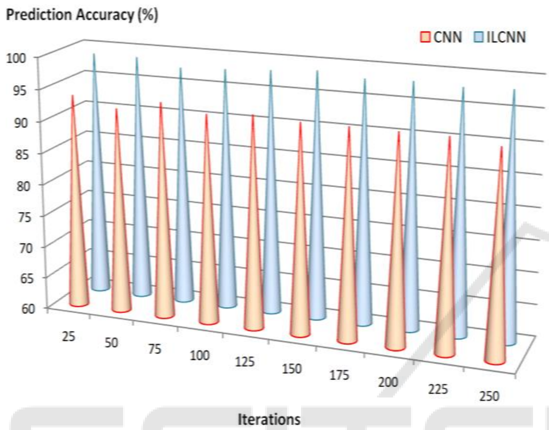


Figure 9: Prediction Accuracy Evaluation.

5 CONCLUSIONS AND FUTURE SCOPE

The garbage detection and classification model is built on top of an enhanced attention mechanism, activation function, and classification layer mechanism on the ILCNN. A recognition accuracy of 96.55% is achieved by the enhanced model on the self-constructed garbage dataset. Based on the findings, the suggested system may automate the categorization work, which in turn reduces operating expenses and human error, greatly improving the efficiency of waste management procedures. By substituting global average pooling for the fully connected layer, the suggested garbage recognition model ILCNN demonstrates how to decrease the model's parameter count while simultaneously improving the recognition result. To increase the model's identification performance, the Mish activation function allows for more precise feature extraction from the target and better use of the retrieved visual data.

Going forward, we intend to train the model using a wider variety of garbage image data in order to better prepare it for real-world application settings. Eventually, garbage detection and classification with little power consumption and great accuracy, serving as a benchmark for researchers and engineers in the upcoming years. The system's practical use in waste management might be further enhanced by enabling real-time waste categorization in varied situations through its implementation on edge devices.

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