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Implementation of The Eco Cycle Classifier Deep Neural Network (Eecdn-Net) Model For Image-Based Waste Classification

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ABSTRACT

Waste management is a global challenge that demands effective solutions, especially in classification and recycling processes. This study presents the development of an Eco Cycle Classifier Deep Neural Network (ECCDN-Net) model based on deep learning for image-based waste classification. The model integrates the DenseNet201 and ResNet18 architectures to improve visual feature extraction and reduce the vanishing gradient problem. The dataset used is *TrashNet,* which contains 2,527 images across six waste categories. Training was conducted over 50 epochs, utilizing data augmentation and class balancing to address the imbalanced data. Results show that ECCDN-Net achieved a validation accuracy of 87.75% and an average F1-score of 0.88. The confusion matrix reveals that the model performs well in recognizing most classes, although it faces difficulty distinguishing categories with high visual similarity, such as plastic and glass. This research demonstrates that ECCDN-Net effectively provides accurate waste classification and could serve as a promising solution for more adaptive and sustainable automatic waste sorting.

Keywords: *Deep Learning*, waste classification, ECCDN-Net, TrashNet, Convolutional Neural Network

1. INTRODUCTION

Along with rapid population growth and urbanization worldwide, increased consumption has led to larger volumes of waste each year. In contrast, existing waste management approaches continue to face various obstacles in the sorting and recycling process [1]. Poor management can lead to environmental pollution, resulting in degraded air, water, and soil quality, and posing various health risks to humans [2]. Therefore, to support the sorting and recycling process, an effective method for sorting and recycling waste is necessary to mitigate these negative environmental impacts.

One promising technological approach is the use of artificial intelligence and intensive learning for the automatic classification of images based on waste. Models based on Convolutional Neural Networks (CNN) have demonstrated superior capabilities in recognizing and classifying various types of waste based on their visual images [3]–[6]. This technology can identify waste categories with high accuracy, thereby replacing the slow and error-prone manual sorting process [4][7][8]. Despite promising results, current CNN-based models face critical challenges such as dependency on large annotated datasets, sensitivity to complex variations in waste appearance, and performance degradation under diverse lighting conditions [9]–[12].

To address these limitations, this study proposes the development of the Eco Cycle Classifier Deep Neural Network (ECCDN-Net) model. This model is designed by combining two proven, reliable, and effective CNN architectures, namely DenseNet201 and ResNet18. Previous research has demonstrated that DenseNet201 excels in terms of parameter efficiency and information flow through its dense connections [13]. At the same time, ResNet18 is effective in addressing the vanishing gradient problem through an efficient and lightweight residual learning mechanism [14][15][12]. Unlike prior works that rely on single architectures or shallow ensembles, ECCDN-Net leverages DenseNet201's dense connectivity for enhanced feature reuse and ResNet18's residual learning to mitigate gradient vanishing, enabling more effective and adaptive feature extraction in complex and varied environments [13]–[17]. The combination of the two allows ECCDN-Net to perform more in-depth and adaptive visual feature extraction, thereby expected to deliver optimal classification performance across various waste categories, including complex-shaped waste and varying lighting conditions [16][17].

This innovative architectural fusion is designed to specifically address real-world complexities in waste imagery, such as irregular shapes and inconsistent illumination, which have been largely underexplored. The proposed model thus represents a meaningful advancement over existing methods by balancing high accuracy, computational efficiency, and robustness.

The implementation of this model is expected to serve as a solution for more efficient and sustainable modern waste management systems. With higher sorting accuracy, recycling effectiveness can be improved, operational costs can be reduced, and the amount of waste ending up in landfills can be significantly reduced [18][19]. In addition, this approach also has the potential to optimize resource utilization and support environmental sustainability programs that are increasingly being launched in various countries [15][19].

2. LITERATURE REVIEW

Various studies have been conducted on the application of deep learning for image-based waste classification to improve the effectiveness of waste management. Research by Hossen et al. [1] demonstrates that the proposed deep learning model, RWC-Net, achieves a remarkably high accuracy rate of 95.01% in classifying six categories of waste. However, challenges related to the imbalance in the amount of waste in the litter category remain an obstacle that affects the results in that category.

Furthermore, a study conducted by Lu and Chen [2] shows that the CNN method is capable of achieving high accuracy in recognizing various waste categories based on visual images. However, it still faces challenges in handling varying lighting conditions. Furthermore, research conducted by Wu et al. [20] has successfully developed a model that combines DenseNet and ResNet to improve classification performance, with results showing an increase in accuracy compared to conventional CNN models, where in this context it generally refers to basic architectures such as LeNet, AlexNet, or VGGNet used as a baseline in waste image classification.

Additionally, research by Pučnik et al. [21] discusses the application of artificial intelligence in automated waste management systems, enabling faster and more efficient waste sorting compared to manual methods. Another study by Kumar Lilhore et al. [3] evaluates the effectiveness of deep learning in supporting automated waste

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sorting processes, finding that CNN-based models can be used in various environmental conditions without significant performance degradation.

In a study conducted by Laksono, Anisa, and Priyandari [22], an artificial intelligence-based waste classification system was developed in combination with sensor technology, enabling more accurate waste detection and sorting. Furthermore, research by Rahmatulloh et al. [23] demonstrated that the application of transfer learning in waste classification can help mitigate dataset limitations by enhancing the model's ability to recognize waste with complex shapes and textures.

A study by Hogan Itam, Chimeme Martin, and Taiwo Horsfall [24] highlighted the importance of data augmentation in improving waste classification accuracy, especially for categories that are underrepresented in the dataset. Meanwhile, research by Fan et al. (2023) [25] investigates the influence of deep learning architectures on computational efficiency in automated waste management systems, finding that the combination of DenseNet and ResNet can achieve optimal performance with lower power consumption.

With numerous studies supporting the effectiveness of deep learning in waste classification, the development of ECCDN-Net is expected to be a better innovation in providing waste management efficiency. Ultimately, this model is not only capable of delivering optimal waste classification accuracy but can also be implemented on a large scale to support more effective and sustainable recycling processes.

3. RESEARCH METHODOLOGY

3.1. MODEL ARCHITECTURAL DESIGN

To enhance the accuracy of waste image classification, various deep learning architectures have been developed to address the challenges of information propagation, gradient stability, and complex variations in visual objects. In this study, we combined two model architectures: DenseNet and ResNet. The advantages of both architectures are implemented in ECCDN-Net, a deep learning model designed explicitly for image-based waste classification. DenseNet in ECCDN-Net supports richer and more representative feature extraction, while ResNet maintains stability in gradient flow. This synergy yields a model that is more adaptable to variations in shape, texture, and lighting conditions, thereby enhancing classification accuracy, resilience to overfitting, and generalization ability on new data [14]. The design of the combined architecture of the two models is illustrated in Figure 1 below.

The input images used are a collection of photos from a publicly available dataset, containing 2,527 images of trash. This dataset is divided into six categories: cardboard, glass, metal, paper, plastic, and waste. Next, these images are processed through a combined architecture, as shown in Figure 1, where the input image, which is 224 × 224 pixels in size with three color channels (RGB), is fed into two main CNN models, namely ResNet-18 and DenseNet-201, in parallel. These two models independently perform deep feature extraction to generate complementary feature vector representations. The extraction results from ResNet18 and DenseNet201 are then combined in a feature fusion layer to form a richer combined feature vector. This vector is further processed by a fully connected layer that maps the features to the target class space. Finally, the softmax output produces classification probabilities for each predefined waste category.

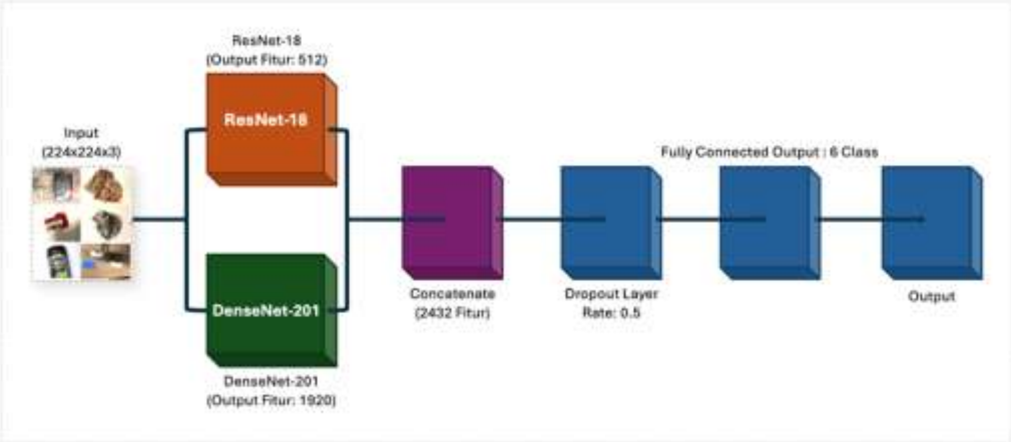

FIGURE 1. A combination of two models, namely DenseNet and ResNet, was used, implemented in ECCDN-Net.

As explained earlier, this study employs two models: DenseNet and ResNet. The DenseNet architecture utilizes the concept of dense connections, where each layer receives input from all previous layers and passes its output to all subsequent layers [13]. This approach enables more efficient information and gradient flow, reduces the loss of essential features, and reduces the number of parameters without compromising accuracy [22]. The architecture of DenseNet is illustrated in Figure 2 below.

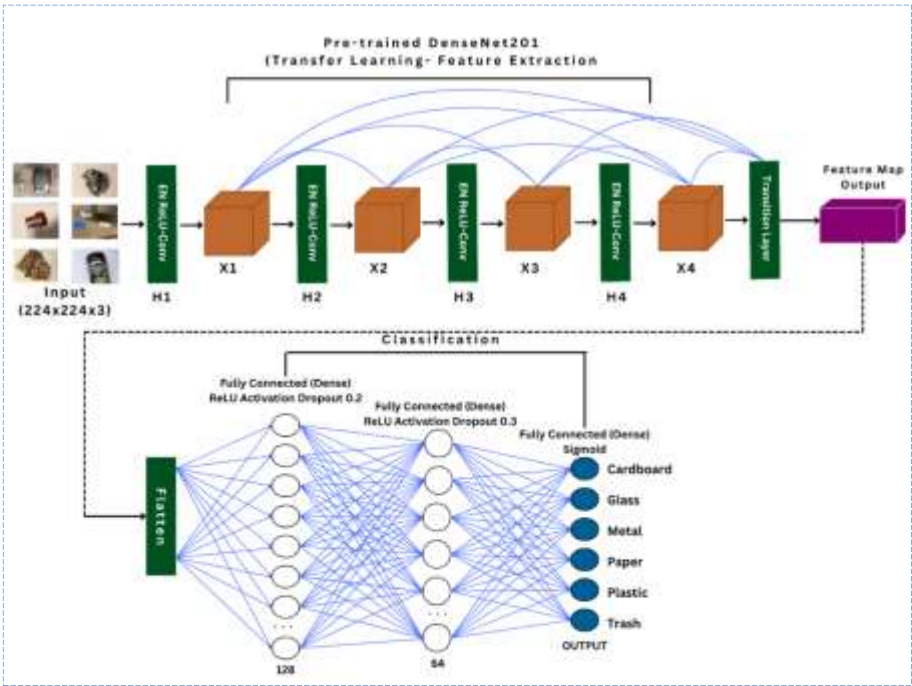

FIGURE 2. DenseNet Architecture

Although there are many connections in Figure 2, DenseNet is more efficient in terms of parameter usage compared to other CNN architecture models. This is because each layer only needs to learn new feature maps and does not need to relearn feature maps that have already been discovered in previous layers. The second model that forms the basis of the combined model is the ResNet model, shown in Figure 3.1

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below. The architecture of the ResNet model shown in Figure 2 uses a residual learning mechanism through shortcut connections between layers to overcome the vanishing gradient problem that commonly occurs in deep neural networks [12][17]. This residual structure helps retain relevant information and speeds up convergence during the training process.

The ResNet architecture incorporates a residual learning approach, utilizing shortcut connections between layers to address the vanishing gradient problem commonly encountered in deep neural networks [12][17]. These residual connections preserve essential information and accelerate the training process. In theory, deeper networks should outperform or at least match the performance of shallower ones. However, in practice, increasing depth without ResNet can lead to reduced accuracy due to gradient-related issues. ResNet overcomes this limitation by enabling the successful training of deep models without a performance drop, resulting in improved accuracy across a wide range of computer vision applications.

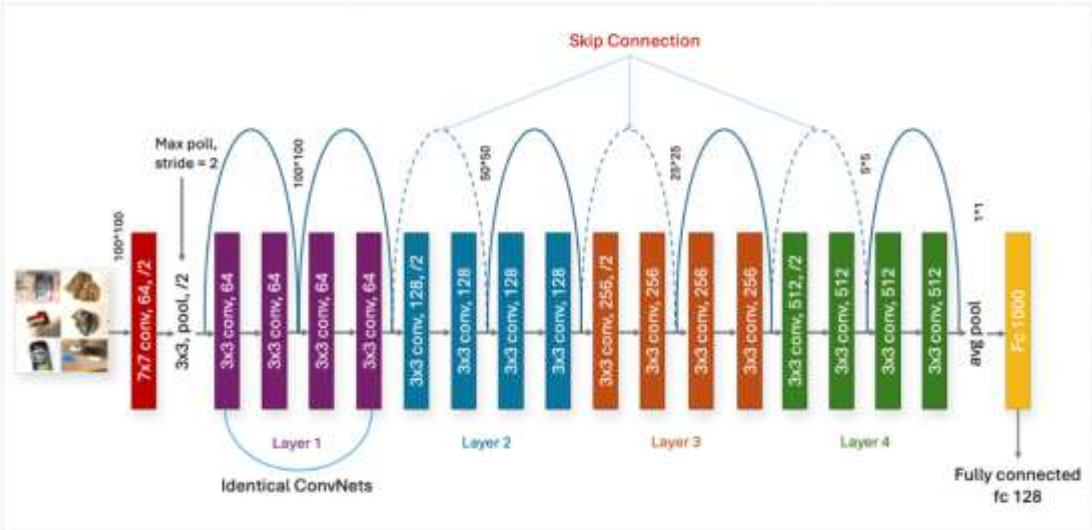

FIGURE 3. ResNet Architecture

3.2 METHODOLOGY

This study employs a comprehensive and systematic framework that begins with the initial step of data collection, ensuring the acquisition of relevant and high-quality data needed for the subsequent stages. Following this, the process continues through several critical phases, including exploratory data analysis, data pre-processing to enhance data quality and suitability for modeling, and the design and initialization of the model. The workflow then advances to the training and validation phase, during which the model learns from the data and its performance is rigorously tested. Finally, the study concludes with a thorough model evaluation to assess the effectiveness and accuracy of the developed system. The entire general workflow of this study is clearly illustrated in the framework diagram presented in Figure 4 below.

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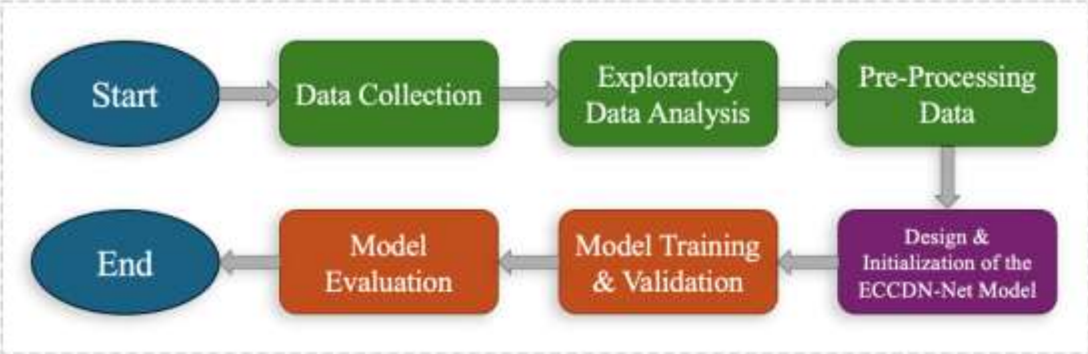

FIGURE 4. The research framework begins with the data collection process and ends with model evaluation.

3.2.1. DATASET AND DATA PREPROCESSING

The dataset used is TrashNet, a publicly available image dataset comprising 2,527 images of trash. This dataset is divided into six categories: cardboard, glass, metal, paper, plastic, and waste. Exploratory data analysis (EDA) revealed an imbalance in the number of images between classes, with the paper category having the most images (594) and trash having the fewest (137). To address this, class weighting techniques were applied during the training process to impose a greater penalty on classification errors in minority classes. Data preprocessing was performed to standardize and enrich the dataset. All images were resized to 224 × 224 pixels. On the training data, data augmentation techniques such as random resizing, Cropping, random rotation (±15 degrees), and horizontal flipping were applied to increase data variation and model robustness. The validation data is not subjected to augmentation to ensure objective evaluation. Next, all images are normalized using the mean and standard deviation values from the ImageNet dataset. The dataset is then divided into 80% for training data (2,021 images) and 20% for validation data (506 images). Examples of the images used in the dataset are shown in Figure 5 below.

FIGURE 5. Examples of dataset images per category

3.2.2. MODEL ARCHITECTURE AND TRAINING

The model implemented in this study is the Eco Cycle Classifier Deep Neural Network (ECCDN-Net), an ensemble architecture that combines two CNN models, namely ResNet18 and DenseNet201, as feature extractors. The features extracted from both models are concatenated to form a combined feature vector of dimension 2432 (512 + 1920). This vector is then passed to the final classification block, which consists of a Dropout layer (0.5) and a Fully Connected Layer to generate class predictions. The transfer learning approach is employed by freezing the pre-trained weights of ResNet-18 and DenseNet-201, so that only the parameters in the final

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classification block are trained. The model training process was conducted over 50 epochs using the Cross Entropy loss function with class weighting and the Adam optimizer. The ReduceLROnPlateau scheduler was used to adjust the learning rate adaptively. To prevent overfitting, an early stopping strategy was applied by monitoring the validation loss. The model with the best validation performance was saved for the final evaluation stage.

3.2.3. MODEL EVALUATION

The performance of the ECCDN-Net model was evaluated using validation data that the model had never seen during training. The evaluation metrics used to measure model performance included accuracy, precision, recall, and F1-score for each class. Additionally, a confusion matrix was used to analyze the distribution of classification errors in greater detail.

4. RESEARCH RESULTS

This section presents the results of the training and evaluation process of the developed Eco Cycle Classifier Deep Neural Network (ECCDN-Net) model. The analysis includes model performance during 50 training epochs, evaluation of performance metrics per class, and error analysis through a confusion matrix.

4.1. MODEL TRAINING AND VALIDATION PERFORMANCE

The ECCDN-Net model's training and validation process was conducted for 50 epochs to ensure optimal convergence. The results of each epoch, including train loss, train accuracy, validation loss, and validation accuracy, were documented in detail, as shown in Table 1 below.

TABLE 1.
Training results using the ECCDN-Net model with 50 epochs

Epoch	Train Loss	Train Accuracy	Validation Loss	Validation Accuracy
1	1.7775	2.519	1.6043	4.506
2	1.5257	4.419	1.4068	6.166
3	1.3361	5.651	1.2456	6.858
4	1.1954	6.264	1.1297	7.233
5	1.0829	6.823	1.0436	7.411
…	…	…	…	…
46	3.718	8.812	4.609	8.735
47	3.837	8.832	4.525	8.735
48	3.714	8.916	4.517	8.775
49	3.770	8.822	4.564	8.755
50	3.681	8.827	4.532	8.755

Based on this data, a consistent upward trend in performance is evident. The accuracy of the training data (train accuracy) shows a progressive increase, starting from 25.19% in the first epoch and reaching 88.27% in the 50th epoch. This indicates that the model has effectively learned the relevant features from the training data. In line with this, the validation accuracy also shows a significant upward trend, rising from 45.06% to stabilize above 85% after the 30th epoch, demonstrating the model's ability to generalize on previously unseen data. The increase in accuracy and decrease in loss can be visualized in Figure 6.

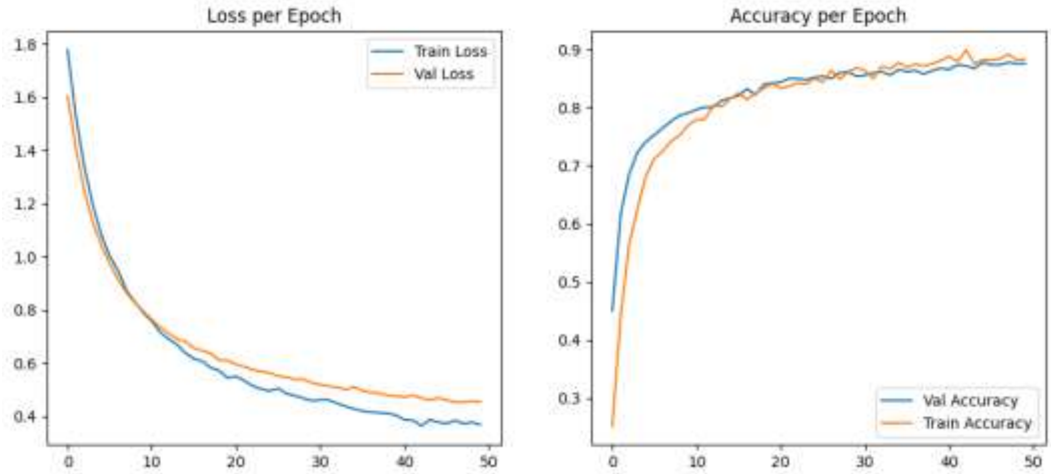

FIGURE 6. Visualization of the ECCDN-Net model training results.

The visualization of the training process, as shown in Figure 4.1, reinforces these findings. The loss curves for the training and validation data show a convergent decrease, where the train loss decreases from 1.7775 to 0.3681 and the validation loss decreases from 1.6043 to 0.4532. The steadily increasing accuracy curve, with no significant gap between the training and validation curves, indicates that there is no significant overfitting. Overall, these results demonstrate that the ECCDN-Net model performs well and consistently in image-based waste classification tasks.

4.2. CLASSIFICATION PERFORMANCE EVALUATION PER CLASS

For a more in-depth analysis, model performance was evaluated using a classification report on validation data. This report, presented in Table 2, details the precision, recall, and F1-score metrics for each waste category.

TABLE 2.
Model Performance Evaluation Results

Class	Precision	Recall	F1-Score	Support
Cardboard	0.99	0.92	0.95	77
Glass	0.86	0.88	0.87	105
Metal	0.85	0.87	0.86	86
Paper	0.88	0.92	0.90	116
Plastic	0.89	0.82	0.85	89
Trash	0.69	0.76	0.72	33

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Accuracy			0.88	506
Macro Avg.	0.86	0.86	0.86	506
Weighted Avg.	0.88	0.88	0.88	506

The table above shows that the ECCDN-Net model achieved an overall accuracy of 88%. The model performed very well on several primary classes. For example, the cardboard class achieved an F1-score of 0.95, paper 0.90, and glass 0.87, indicating that the model was able to identify these categories with high accuracy and consistency. However, some challenges were found in certain classes. The plastic class shows a high precision value (0.89) but a lower recall (0.82), indicating that while the optimistic predictions are accurate, the model fails to identify some plastic samples correctly. The greatest challenge was observed in the trash class, which is a minority class in the dataset. This class recorded the lowest F1-score of 0.72, with a precision of 0.69 and a recall of 0.76. This indicates that the model still struggles to distinguish the trash category from other types of waste.

4.3. ERROR ANALYSIS WITH CONFUSION MATRIX

The classification error analysis is further explored through the confusion matrix visualized in Figure 7 below.

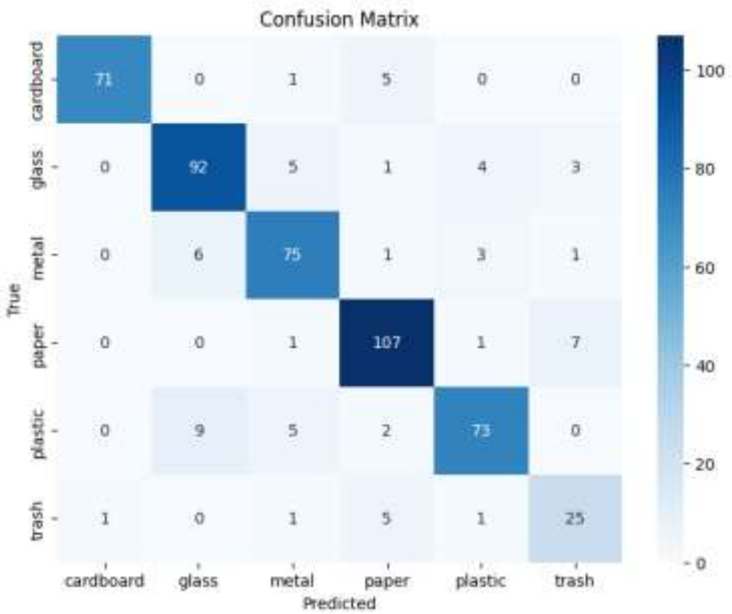

FIGURE 7. Confusion matrix model data validation.

From Figure 4.2, it is evident that predictions on the main diagonal (correct predictions) are overwhelmingly dominant for most classes. The paper class achieves the best performance, correctly classifying 107 out of 116 samples. The cardboard class is also highly accurate, with 71 out of 77 samples correctly identified. However, the confusion matrix also highlights areas of model confusion. The most notable classification errors occur in the plastic class, where nine samples are incorrectly classified as glass and five as metal. This is likely due to visual similarities between these materials, such as transparency or surface gloss. Additionally, the trash class, which had only 33 validation samples, incorrectly classified five samples as paper and 1 sample as cardboard. These errors align with the classification report results, confirming that the model's performance tends to decline in classes with fewer samples and visual similarities to other courses.

5. CONCLUSION

Based on the research results, it can be concluded that the developed ECCDN-Net model achieves optimal accuracy and efficiency in image-based waste classification using a deep learning approach. This model successfully demonstrated a significant improvement in training and validation accuracy during the training process, indicating its ability to recognize various types of waste in diverse conditions. The research objective of developing a high-accuracy classification model was achieved through the application of a combined architecture of DenseNet201 and ResNet18. This combination successfully optimized the process of extracting visual features from various waste categories. The results show that the model generalizes well on the validation data, although it still faces challenges in classes with limited sample sizes, such as the trash category.

Additionally, the ECCDN-Net model demonstrated robustness in handling variations in lighting conditions and complex waste shapes. This aligns with developing a model that can be implemented in real-world waste management to support a more efficient and sustainable recycling process. With an accuracy of 88%, this model demonstrates strong potential for application in automated waste management systems across various environments, ranging from household to industrial scales.

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