

Waste Classification Using NasNet-Mobile: A Multi-Stage Deep Learning Approach for Environmental Sustainability

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ABSTRACT

Improper waste management remains a significant global challenge, resulting in severe environmental and health impacts. Existing classification systems were designed and studied on large deep learning models, which are computationally expensive and not well-suited for embedded systems. To overcome this challenge, this study introduces a lightweight NasNet Mobile architecture that was trained using a three-stage learning framework. The framework employs transfer learning, fine-tuning, and hyperparameter optimisation to improve the model's performance and generalisation capabilities progressively. To validate the proposed approach, experimental evaluations were conducted on TrashNet and Garbage Classification datasets. The model achieved an accuracy of 91.25% on the TrashNet dataset and 94.85% on the Garbage Classification dataset using the optimal hyperparameter set obtained through the random search technique. These results indicate that the proposed strategy effectively adapts to varying data distributions and outperforms popular Convolutional Neural Network (CNN) architectures, such as VGG-16, ResNet, AlexNet, etc. Therefore, the proposed model provides a reliable foundation for developing scalable and efficient waste classification systems for environmental applications. This study contributes to a practical deep learning approach that improves classification performance while maintaining low resource requirements for sustainable waste management.

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1. INTRODUCTION

In today's rapidly changing world, waste management has emerged as a significant worldwide issue, driven by rapid population growth, accelerating urbanisation, and unsustainable consumption patterns. According to a report from the United Nations Environment Programme (UNEP) [1], the generation of global municipal solid waste (MSW) is expected to reach 2.1 billion tons annually. Even more concerning, only 19% of this waste is currently recycled, while 38% remains uncontrolled as of 2020. If significant action is not taken, the global MSW will increase by 56%, reaching 3.8 billion tons by 2050. In Malaysia, over 39,078 tonnes of MSW are generated each day, most of which are disposed of in landfills [2]. This heavy reliance on landfilling strains available space and poses significant environmental threats, including air and water pollution, soil degradation, and greenhouse gas emissions, which contribute to biodiversity loss in urban areas [3]. These trends highlight the pressing need for innovative and efficient waste management solutions to ensure environmental sustainability.

Among various strategies, recycling is widely regarded as one of the most effective methods for reducing landfill waste and environmental pollution, as it repurposes materials instead of discarding them [4]. However, the effectiveness of the recycling process largely depends on accurate waste classification to

minimise the risk of waste contamination and increase the recyclability of waste [5]. Unfortunately, traditional waste management systems confront significant issues in effectively managing the increasing amount of waste. Manual segregation is often slow, labour-intensive, and prone to errors, as recyclable materials are collected from diverse sources, including industrial sites, commercial establishments, and households [3]. Additionally, the current recycling management in Malaysia remains limited in scope. Existing classification systems are utilised in fully automated intelligent recycling machines that can only collect a limited type of recyclable items (disposable food containers, plastic bottles, and aluminium cans) [6, 7]. Besides that, mobile applications such as KITAREcycle [9] still require users to manually segregate their recyclables using plastic bags, which limits system scalability and user engagement.

To overcome these classification limitations, advancements in artificial intelligence (AI) and computer vision have led to significant improvements in automating waste classification using machine learning and deep learning techniques. The trained classification model can then be implemented to determine the waste categories of everyday consumer or industrial operations using cameras [8], such as smart recycling bins, waste-sorting robots, and mobile applications. CNN is a deep learning approach that is widely utilised for solving the waste classification problem due to their ability to automatically identify relevant features of objects without human supervision [9]. However, many CNN-based waste classifiers are often computationally intensive, making them unsuitable for embedded or real-time applications and they suffer from scalability and accuracy limitations [10]. These challenges highlight the need for a lightweight and memory-efficient CNN framework that can accurately classify multi-type waste.

Therefore, this study aims to investigate the NasNet Mobile-based image classification model for segregating the waste. The NasNet Mobile, one of the lightweight CNN architectures, was explored explicitly for its ability to classify different waste. The NasNet Mobile is selected due to the network hierarchy and parameters has been optimised through neural architecture search (NAS) to deliver the best performance when implemented in the classification system [11]. Although the limitation of the feature depth may result in slightly lower precision, but it utilises only 5.3 million parameters to achieves competitive performance on ImageNet, with 74.0% top-1 and 91.6% top-5 accuracy [12], which is significantly fewer parameters than popular architectures, such as AlexNet (60 million), VGG-16 (138 million), ResNet50 (49 million), DenseNet201 (20 million), Xception (22.9 million), and InceptionV3 (23.9 million). [13-15]

In contrast to previous studies that utilised CNN architecture with higher computational cost for waste classification [16-18], this study presents NasNet Mobile, trained and optimised through a systematic three-stage learning framework. The uniqueness of this study lies in its combination of transfer learning, fine-tuning, and hyperparameter optimisation with a random search technique to achieve the best classification performance using the NasNet Mobile architecture. The contributions of this study are shown below:

1. Deployment of an optimised NasNet Mobile architecture for intelligent waste classification using TrashNet with 6 distinct categories (cardboard, glass, metal, paper, plastic, trash) and Garbage Classification dataset with 12 categories (paper, cardboard, biological, metal, plastic, green-glass, brown-glass, white-glass, clothes, shoes, batteries, and trash), demonstrating the model's versatility and robustness across diverse waste types.
2. Integration of three-stage learning framework encompassing, transfer learning, fine-tuning, and hyperparameter optimisation with random search, strategically designed to optimise model training and significantly enhance the classification performance.
3. This study incorporates comprehensive statistical visualisation, including accuracy and loss curves, confusion matrices, and classification reports to provide deep insights into model behaviour and performance trends, thereby enabling clearer interpretation and validation of the learning outcomes.

This paper is organised into five sections. Section 1 introduces the background and problem statement of this study. Section 2 reviews the performance of different pre-trained model. In Section 3, the details of the architecture of pre-trained models used and the parameters utilised to train the classification model are illustrated. Section 4 explains the results and analysis of the classification models' performance. Finally, Section 5 summarises the conclusion and offers some recommendations.

2. LITERATURE REVIEW

Over the past several years, CNN architectures have gained significant popularity in waste classification tasks due to their ability to automatically learn hierarchical features from raw image data. Unlike traditional rule-based methods, CNNs possess the capability to identify complex dimensional patterns, resulting in them being highly proficient in identifying and classifying diverse waste types of materials. Therefore, the researchers have employed CNN-based models in various innovative waste management systems, including robotic waste bins, mobile applications, web-based platforms and IoT devices.

The early exploration of CNN in this area was conducted by Ozkaya et al. [19]. They trained various pre-trained models, such as AlexNet, VGG-16, GoogleNet, ResNet, and SqueezeNet, using the TrashNet dataset to classify six waste categories, which are plastic, glass, metal, cardboard, paper and trash. Employing both Softmax and SVM classifiers, it was found that VGG-16 using Softmax obtained an accuracy of 90%, while GoogleNet with SVM achieved 97.86% accuracy. They are the highest accuracy among the different classifiers tested. Following that, a broader investigation by Poudel et al. [20] utilised CNN-based pre-trained models, including InceptionResNetV2, Xception, VGG19, MobileNet, Inception V3, DenseNet201, and ResNet50 to classify seven different waste types. As a result, the DenseNet201 model exhibited the best performance, achieving a training accuracy of 98.65% and a validation accuracy of 95.05%. After that, Sultana et al. [21] suggested integrating a CNN model into the smart trash can robot, so that the robot would be able to identify and grab the trash accurately in outdoor environment, such as along roadsides or in a park. The model was trained using AlexNet on indoor (eg, TrashNet) and outdoor waste datasets, which showcases the versatility of CNNs across diverse environmental contexts.

Subsequently, Liu et al. [8] trained several classification models using different pre-trained models, including 8-layer CNN, AlexNet, VGGNet, and InceptionNet. They then deployed the best-performing model on the Raspberry Pi and an Android application for real-time identification of the waste type. Next, Rijah et al. [22] developed an IoT-based smart waste management device powered by a VGG16-based classification model to categorise plastic, paper, and glass with an accuracy of 84.67%. The confusion matrix indicated that the accuracy for predicting 100 glass, paper, and plastic images in the testing set was 77%, 88%, and 69%, respectively. Besides that, Yong et al. [23] employed MobileNetV2, a lightweight model trained on over 8000 images across four categories (recyclable, kitchen, hazardous, and other wastes) with 245 subcategories. Notably, the MobileNetV2 model achieved impressive accuracy of 82.92%, surpassing a 4-layer CNN model, which achieved only 67.5%.

Most recently, Yi et al. [24] successfully implemented a VGG16-based waste classification model into a web interface. This platform enables users to upload waste images and receive correct disposal guidelines, showcasing the use of CNN in creating public-facing, and user-friendly digital applications. However, most waste classification models rely on popular architectures or high computational cost, such as VGG16, AlexNet, MobileNet, ResNet and Inception. There has been limited exploration of the NasNet-Mobile architecture in waste classification models. This study investigated only NasNet Mobile due to its lightweight architecture and suitability for embedded systems, such as smartphones, microcontrollers and robotic systems. As one of the most effective models within the NasNet family, NasNet-Mobile strikes a balance between classification performance and computational cost, making it a valuable option for real-time waste classification applications [25, 26].

Numerous studies leverage transfer learning, an effective method that utilises pre-trained models to enhance performance on target tasks with limited data [27]. This approach reduces training time and boosts accuracy by enabling the network to reuse the learned features from a huge dataset, such as the ImageNet dataset. Transfer learning has been widely applied to pre-trained models, such as AlexNet, VGGNet, InceptionNet, ResNet, and others in various applications [8, 13, 28, 29]. To further enhance classification performance, researchers often go beyond basic training by applying fine-tuning techniques. This involves unfreezing specific layers in the pre-trained model or in the added layers and retraining them on targeted data, allowing the network to adapt more effectively to the new domain [30]. For example, Babé et al. [31] demonstrated that different fine-tuning strategies could improve the model performance. Alongside fine-tuning, hyperparameter optimisation is another technique used to optimise the performance and generalisation of the model. It can balance the bias and variance by finding the optimal configuration to achieve the best model performance [32]. Multiple studies, including Babé et al. [31] and Salur et al. [33], consistently confirm that hyperparameter optimisation can significantly improve model performance.

Based on the reviewed studies, the model's performance can be improved through fine-tuning and hyperparameter optimisation. Fine-tuning allows for better matching of pre-trained features to specific data, while hyperparameter optimisation explores a broader range of configuration space that can significantly affect model generalisation. However, the previous works that rely on the exhaustive Grid Search technique [34] often suffer from high computational cost due to the repeated training routine. To address this issue, this study introduces the use of the Random Search technique for hyperparameter optimisation offering a more effective method to identify optimal parameter configurations while significantly reducing computational overhead [35].

Therefore, this study proposed a three-stages training framework for waste classification using NasNet-Mobile, involving transfer learning, fine-tuning and hyperparameter optimisation. This approach not only improves model performance for implementation in embedded innovative waste management systems but also provides insight into how different training strategies have an impact on model performance, presenting a practical and efficient solution for sustainable, automated waste classification.

3. METHODOLOGY

This study aims to develop an effective waste classification model using NasNet Mobile. The model is optimised through a three-stage training process comprising transfer learning, fine-tuning and hyperparameter optimisation. The entire training workflow was conducted using Jupyter Notebook on a workstation equipped with an NVIDIA GeForce GTX 1050 Ti GPU. The NasNet Mobile architecture that was pre-trained on the ImageNet dataset, was accessed through the Keras API. The block diagram of the overall training process of the waste classification model is shown in Figure 1.

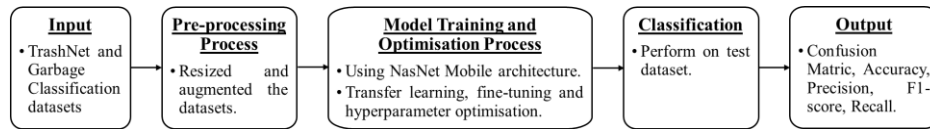


Figure 1. The block diagram of the classification model training process.

3.1. Datasets Preparation

The TrashNet [36] and garbage classification [37] datasets were used to train waste classification models separately. TrashNet includes 6 categories of waste types, whereas the garbage classification dataset includes 12 categories. Figures 2 and 3 show the sample and the number of images from each category in TrashNet and garbage classification datasets respectively.

After that, the datasets were split into training, validation, and testing sets in a ratio of 70%, 15%, and 15%, respectively. All images were resized to 224 x 224 pixels to maintain compatibility with the model input requirements. To strengthen the model and minimise the overfitting, the dataset was pre-processed using data augmentation techniques, such as rotation, shifting, and flipping.

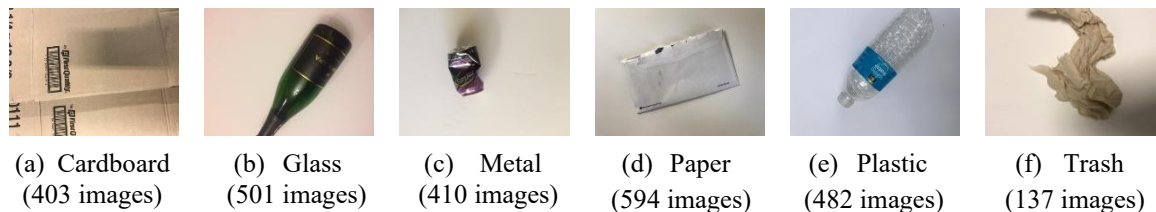


Figure 2. Image samples and the amounts of TrashNet.

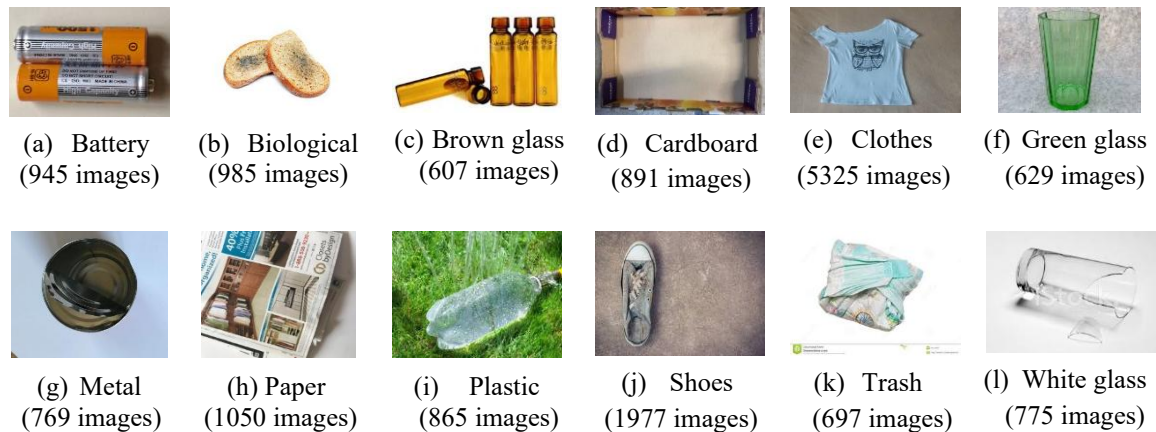


Figure 3. Image samples and the amounts of the Garbage Classification dataset.

3.2. Model Architecture

This study utilised the NasNet Mobile architecture [12, 38] as a pre-trained model for transfer learning. The NasNet model was constructed using reinforcement learning, which helps to identify an ideal architecture for improved performance. It is different from the designed pre-trained model, such as AlexNet, VGG-16 or ResNet, NasNet learns its own optimal building blocks through the neural architecture search (NAS) process conducted on the CIFAR-10 dataset.

During this process, the controller recurrent neural network (RNN) was trained to sample numerous potential architectures from the search space that includes different layer types, hyperparameters, activation

functions, and skip connections. The validation accuracy that evaluated of each sampled architecture is used as a reward signal to update the agent via reinforcement learning. The process is illustrated in Figure 4. After identifying the optimal convolutional cells, they are arranged multiple times to build a scalable CNN that accommodates different dataset sizes and computational limitations.

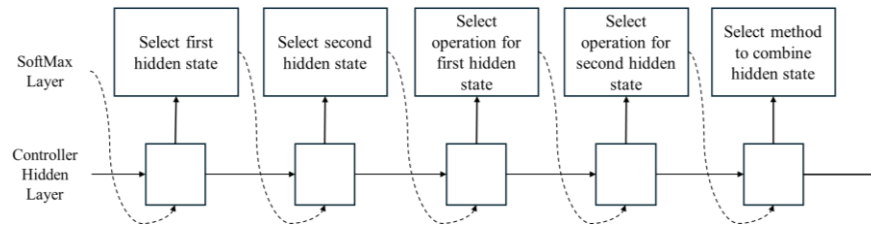
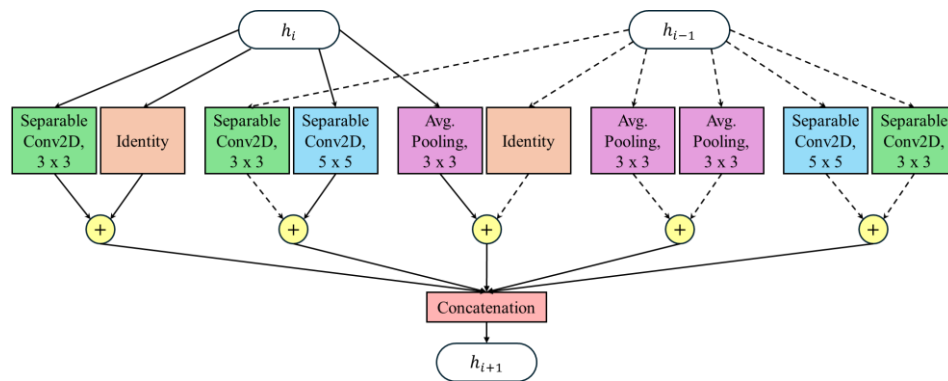
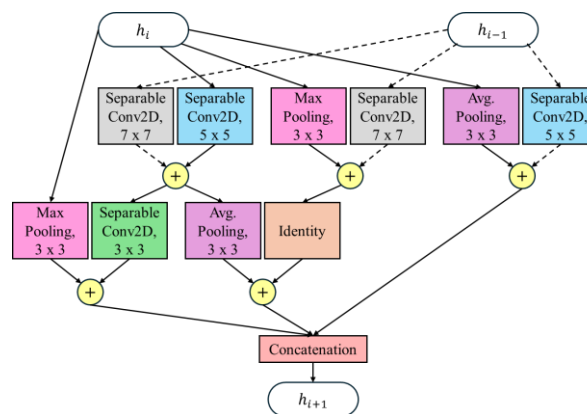


Figure 4. The construction process of a convolutional cell using an RNN controller

There are 2 convolution cells that were generated, which are Normal Cell (return the same dimension feature map) and Reduction Cell (return the feature map with reduction by a factor of two). Their architectures were depicted in Figure 5, where h_i and h_{i-1} are initial hidden states and h_{i+1} is the final output. The complete NasNet architecture as shown in Figure 6 is built by hierarchically stacking the cells, in accordance with the configuration provided in the Keras implementation of the pre-trained model. This hierarchical stacking pattern enables architecture to scale the different image sizes efficiently. It was implemented with two different input sizes: 224 x 224 and 331 x 331, resulting in NasNet-Mobile and NasNet-Large respectively. Since the parameter of NasNet Mobile (5.3 million) is lower than that of NasNet Large (89 million) [26], the NasNet Mobile is more reliable and suitable for this study.



(a) Normal cell



(b) Reduction cell

Figure 5. The architecture of cells.

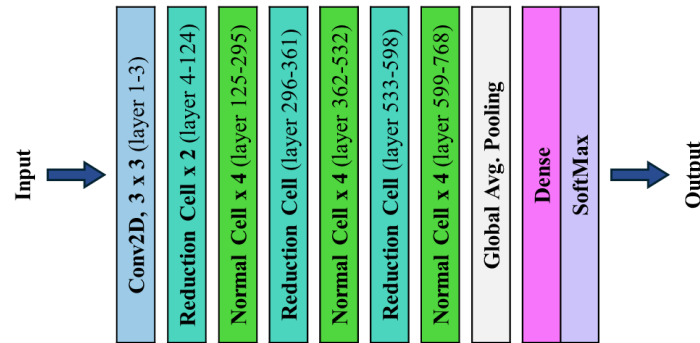


Figure 6. The basic architecture of NasNet Mobile.

3.3. Training Process

The waste classification model was developed through three progressive stages, which are transfer learning, fine-tuning and hyperparameter optimisation. Initially, transfer learning was employed to train the model using pre-trained weights from the NasNet Mobile model. During this process, all layers of the base model were frozen, meaning their weights were preserved from the original ImageNet training. The top classification layer of NasNet Mobile was removed. Later, a custom classification head was attached to the NasNet Mobile backbone. This head consisted of a global average pooling layer, followed by a dense layer with 256 neurons and a ReLU activation function, a dropout layer with a rate of 0.4, a dense layer with 128 neurons and ReLU activation function, a dropout layer with a rate of 0.2, and lastly a dense output layer with six neurons and a Softmax activation function for classifying of six classes as seen in Figure 6. It was modified to optimise the model's performance by reducing its computational complexity [39, 40] and improving robustness against input noise and variability [41]. The compile model was trained on the TrashNet and garbage classification datasets using batch sizes of 8 and 128, respectively, over 100 epochs with the Adam optimizer set to a learning rate of 0.0001. To prevent overfitting and reduce training time, the early stopping callback was applied during the training process, allowing the training process to be automatically terminated if the loss did not increase for 10 consecutive epochs. This enabled the model to adapt to the new task for the classification of different types of waste. This transfer learning stage established a foundational performance baseline for further improvements.

After that, fine-tuning was conducted using a lower learning rate of 0.00005 to further enhance the model's performance. Various configurations were explored by unfreezing different layer levels of the NasNet Mobile architecture (Figure 4). Through experimentation, it was found that unfreezing and fine-tuning a specific range of layers from 635 to 724, corresponding to the second and third normal cells within the final normal cell block (layer 599-768), yielded better classification results than only tuning the fourth normal cell of the last normal cell block. By unfreezing these layers, the model was able to update more relevant task features on the datasets while preserving the integrity of earlier learned representations. The remaining layers of the network remained frozen.

Finally, hyperparameter optimisation was conducted using a random search strategy to further improve classification performance further. This approach involves randomly sampling combinations of hyperparameters (optimisers, learning rates, batch sizes and epochs) from the defined search space, as shown in Figure 7. Due to the hardware limitations, only five random search iterations were performed, and the best-performing configuration was selected based on the result.

At each stage, the model's performance was evaluated using the training and validation accuracy and loss graphs for every epoch, the test set confusion matrix, and the test set performance evaluation metrics, including accuracy, precision, recall, and F1-score. The results of precision, recall and F1-score were calculated using the formula given in Table 2 by extracting values from the binary confusion matrix, shown in Figure 8. The binary confusion matrix is divided into 4 parts, including True Positive (TP), False Negative (FN), False Positive (FP) and True Negative (TN). Then, the resulting model from this three-stages training process was compared against other well-known CNN architectures to evaluate its performance and effectiveness in waste classification tasks.

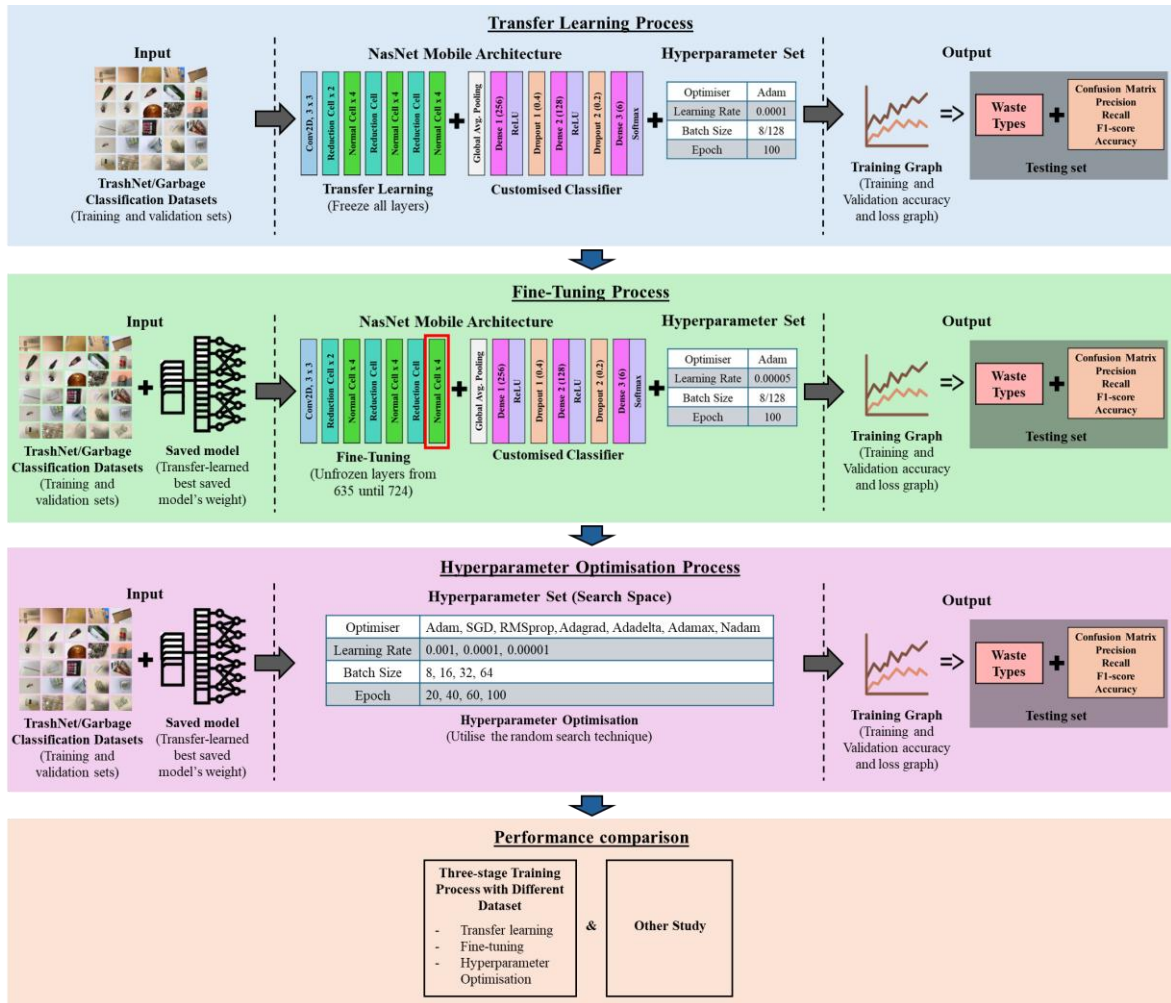


Figure 7. The model improvement process from transfer learning to hyperparameter optimisation.

		Predicted Classes	
		Positive	Negative
Actual Classes	Positive	True Positive (TP)	False Negative (FN)
	Negative	False Positive (FP)	True Negative (TN)

Declaration of the parts:

- TP = Accurate identification of the positive category.
- FN = Failure identification of the negative category.
- FP = Incorrect identification of the positive category.
- TN = Correct identification of the negative category.

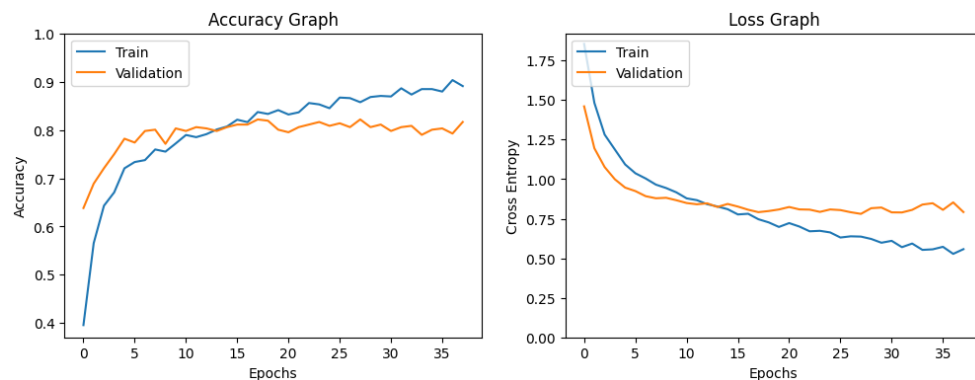
Figure 8. An example of a binary confusion matrix.

Table 1. The function and formula of performance evaluation metrics.

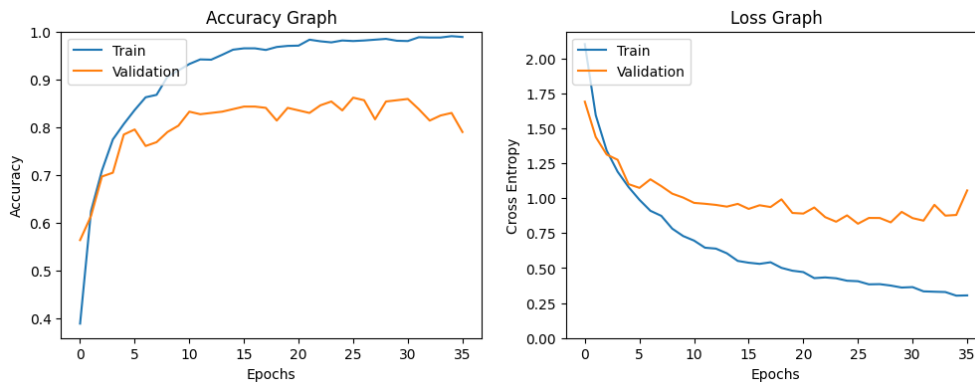
Evaluation Metric	Function	Formula
Precision	Concentrate on the accuracy of positive predictions.	$Precision = \frac{TP}{TP + FP}$
Recall	Evaluate how well the classification model identifies all positive instances.	$Recall = \frac{TP}{TP + FN}$
F1-score	Balance precision and recall.	$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall}$
Accuracy	Determine the total of items that have been classified correctly.	$Accuracy = \frac{TN + TP}{TN + FP + TP + FN}$

4. RESULT AND DISCUSSION

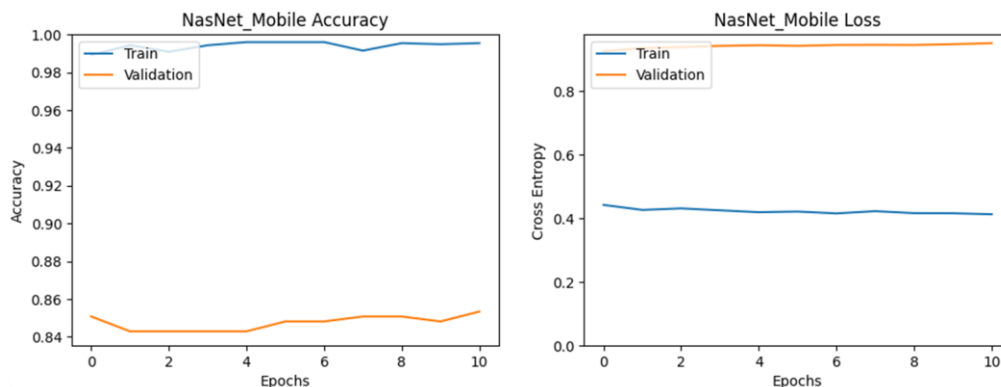
The classification model was trained using the NasNet Mobile architecture through transfer learning, fine-tuning and hyperparameter optimisation. The results of the training process using the TrashNet dataset, including the accuracy and loss graph, as well as the confusion matrix for each stage, are illustrated in Figures 9 and 10, respectively. Based on Figure 9, the accuracy increased steadily (87% training and 80% validation accuracy) during the transfer learning stage. The model performance further improved to 94% training accuracy and 84% validation accuracy in the fine-tuning stage, despite minor signs of overfitting. After hyperparameter optimisation, the model achieved its best stability and generalisation with an optimal hyperparameter configuration that consisted of a batch size of 64, 40 epochs, the Nadam optimiser, and a learning rate of 0.00001, reaching 99% training and 86% validation accuracy with minimal loss divergence. Moreover, confusion analysis indicated consistent improvements across all waste categories. These outcomes confirm that fine-tuning and optimised hyperparameters substantially improved the model's classification performance.



(a) Transfer learning.



(b) Fine-tuning.



(c) Hyperparameter optimisation.

Figure 9. The accuracy and loss graph of the training process using the TrashNet dataset at different stages.

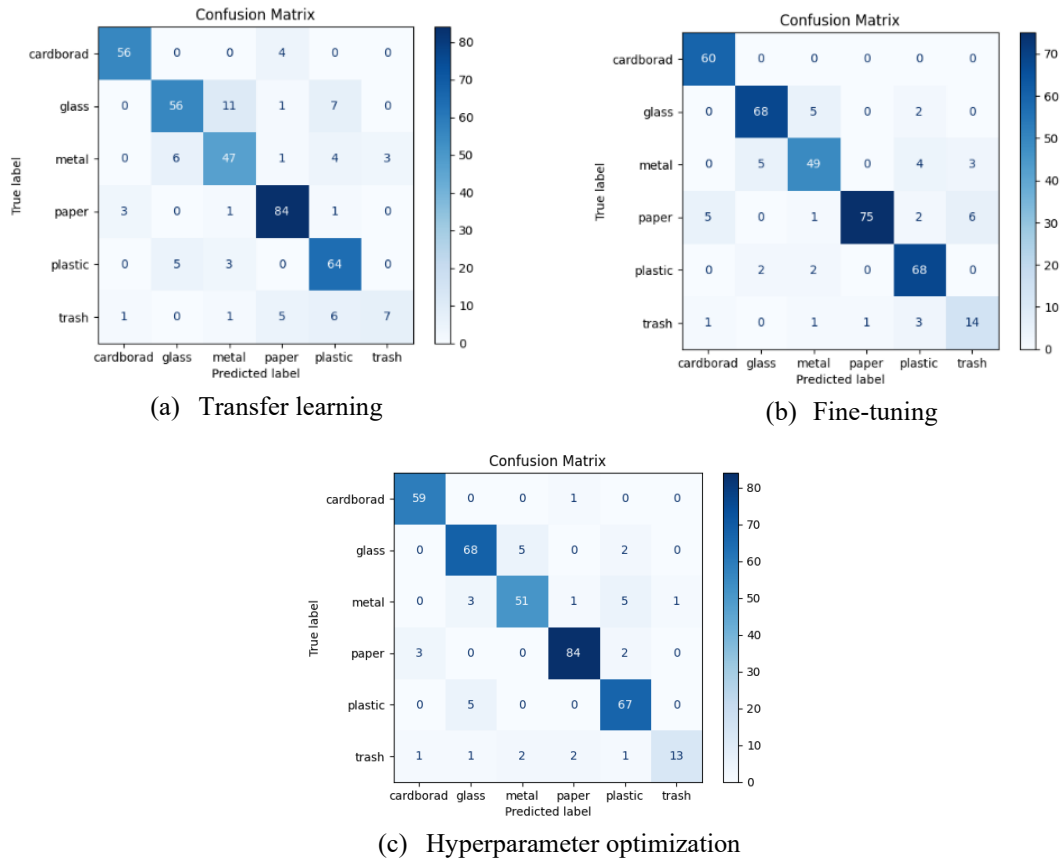
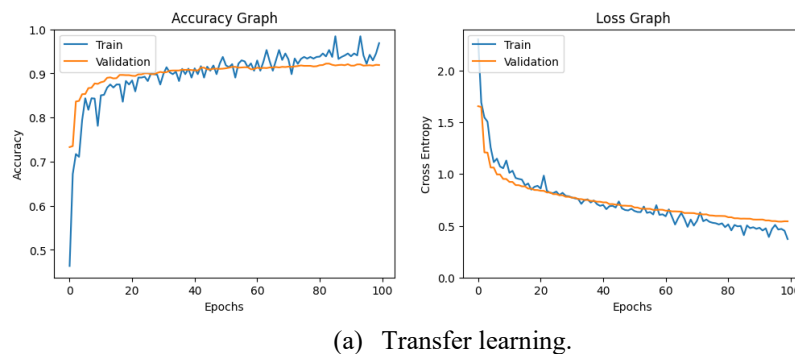
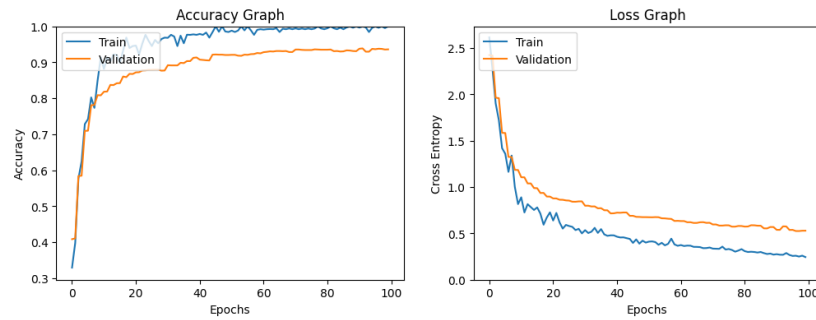


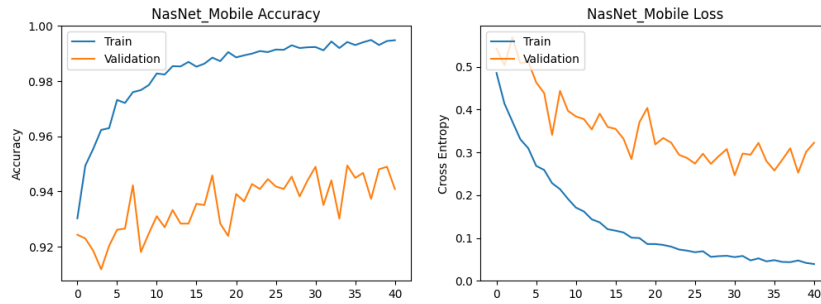
Figure 10. The confusion matrix results of each stage using the TrashNet dataset.

To verify the effectiveness of the proposed approach beyond the TrashNet dataset, an additional dataset with more waste categories, namely the garbage classification dataset (12 categories) was introduced for benchmarking. This comprehensive evaluation presented a comparative perspective on the performance of the NasNet-Mobile model, employing a three-stage training process across various data distributions and varying levels of category complexity. As shown in Figure 11 below, the model showed a similar trend of performance improvement across all training stages. During transfer learning, the accuracy gradually increased, reaching a level comparable to that of both training and validation, which converged around 90% to 93%, accompanied by a corresponding reduction in loss. Fine-tuning further boosted performance, resulting in training accuracy that approached 100% and validation accuracy of approximately 94%, along with more stable training and validation losses, indicating effective adaptation to the new data distribution. Following hyperparameter optimisation, the NasNet Mobile model achieved stability with an optimal hyperparameter configuration that consisted of a batch size of 8, 100 epochs, the Nadam optimiser, and a learning rate of 0.0001, attaining approximately 99% training and 94% validation accuracy with minimal loss divergence. The confusion matrices in Figure 12 below support these findings, revealing fewer misclassifications and enhanced consistency across all waste categories. The consistent improvement pattern across both datasets demonstrates that the fine-tuning strategy and optimised hyperparameters significantly contribute to model scalability and robustness in multi-class waste classification tasks.



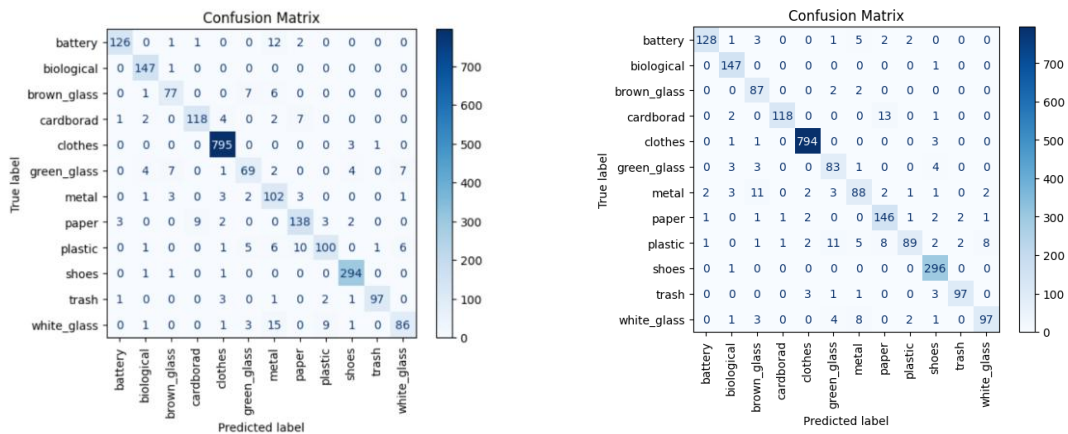


(b) Fine-tuning.



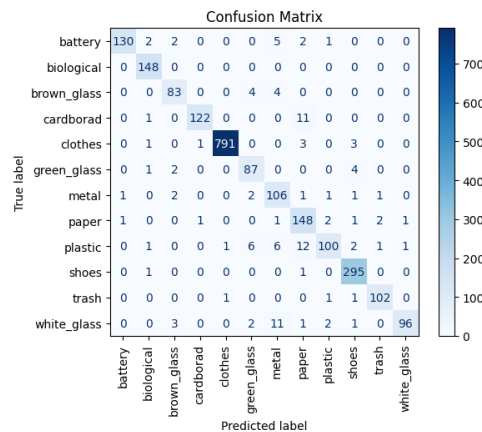
(c) Hyperparameter optimisation.

Figure 11. The accuracy and loss graph of the training process using Garbage Classification dataset at different stages.



(a) Transfer learning.

(b) Fine-tuning.



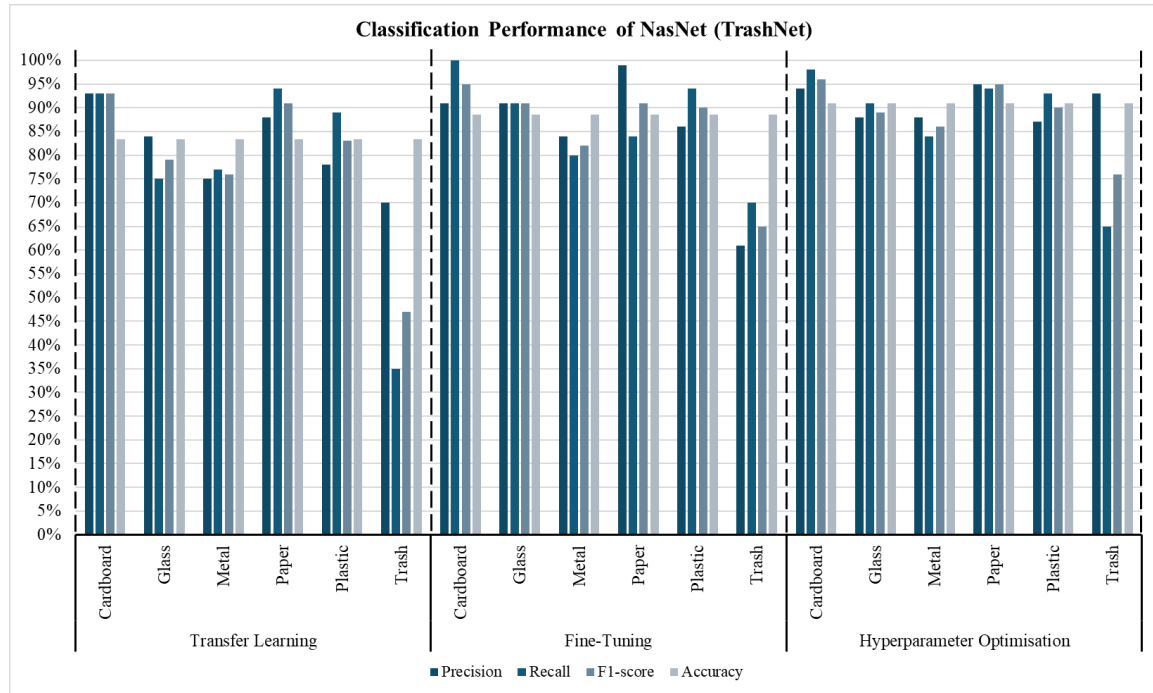
(c) Hyperparameter optimization.

Figure 12. The confusion matrix results of each stage using Garbage Classification dataset.

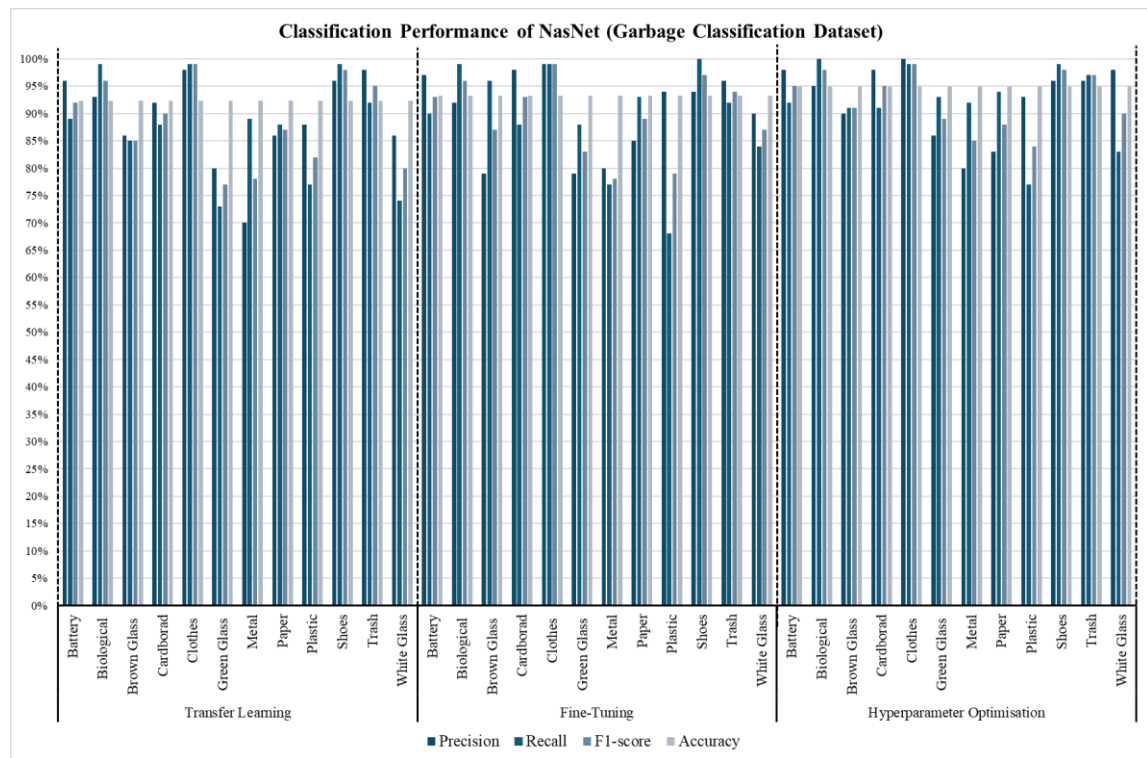
Additionally, the performance evaluation metrics (precision, recall, F1-score and accuracy) for each stage of both datasets are computed using the data from corresponding confusion matrices and shown in Table 2. In addition, these metrics are illustrated in the histogram, as shown in Figure 13 below.

Table 2. The performance evaluation report of each stage for both datasets.

Dataset	Stages	Waste Types	Precision	Recall	F1-score	Accuracy
TrashNet [26]	Transfer Learning	Cardboard	93%	93%	93%	83.29%
		Glass	84%	75%	79%	
		Metal	75%	77%	76%	
		Paper	88%	94%	91%	
		Plastic	78%	89%	83%	
		Trash	70%	35%	47%	
	Fine-Tuning	Cardboard	91%	100%	95%	88.59%
		Glass	91%	91%	91%	
		Metal	84%	80%	82%	
		Paper	99%	84%	91%	
		Plastic	86%	94%	90%	
		Trash	61%	70%	65%	
	Hyperparameter Optimisation	Cardboard	94%	98%	96%	91.25%
		Glass	88%	91%	89%	
		Metal	88%	84%	86%	
		Paper	95%	94%	95%	
		Plastic	87%	93%	90%	
		Trash	93%	65%	76%	
Garbage Classification [38]	Transfer Learning	Battery	96%	89%	92%	92.31%
		Biological	93%	99%	96%	
		Brown Glass	86%	85%	85%	
		Cardborad	92%	88%	90%	
		Clothes	98%	99%	99%	
		Green Glass	80%	73%	77%	
		Metal	70%	89%	78%	
		Paper	86%	88%	87%	
		Plastic	88%	77%	82%	
		Shoes	96%	99%	98%	
		Trash	98%	92%	95%	
		White Glass	86%	74%	80%	
	Fine-Tuning	Battery	97%	90%	93%	93.21%
		Biological	92%	99%	96%	
		Brown Glass	79%	96%	87%	
		Cardborad	98%	88%	93%	
		Clothes	99%	99%	99%	
		Green Glass	79%	88%	83%	
		Metal	80%	77%	78%	
		Paper	85%	93%	89%	
		Plastic	94%	68%	79%	
		Shoes	94%	100%	97%	
		Trash	96%	92%	94%	
		White Glass	90%	84%	87%	
	Hyperparameter Optimisation	Battery	98%	92%	95%	94.85%
		Biological	95%	100%	98%	
		Brown Glass	90%	91%	91%	
		Cardborad	98%	91%	95%	
		Clothes	100%	99%	99%	
		Green Glass	86%	93%	89%	
		Metal	80%	92%	85%	
		Paper	83%	94%	88%	
		Plastic	93%	77%	84%	
		Shoes	96%	99%	98%	
		Trash	96%	97%	97%	
		White Glass	98%	83%	90%	



(a) TrashNet dataset.



(b) Garbage classification dataset.

Figure 13. The histogram of performance evaluation metrics.

The proposed three-stage training on NasNet Mobile demonstrated consistent improvements in classification performance across both the TrashNet and Garbage Classification datasets. During transfer learning, the pre-trained NasNet-Mobile effectively adapted its learned features, archieving 83.29% and 92.31% of accuracy, respectively. Then, fine-tuning further refined specific feature extraction layers, allowing the model to learn particular characteristics, which increased the accuracy to 88.59% (TrashNet) and 93.21% (Garbage Classification). After hyperparameter optimisation, the model achieved its best stability and generalisation with the optimal hyperparameters, reaching 91% (TrashNet) and 94.85% (Garbage

Classification) accuracy. These progressive improvements can be attributed to controlled unfreezing of layers, regularisation, and adaptive learning rates. Confusion matrices also validated these enhancements, indicating misclassification and improved precision, recall, and F1-scores across all classes. Therefore, NasNet Mobile demonstrated strong scalability and adaptability, as it maintained high classification consistency when evaluated on a larger and more diverse dataset. Besides that, the optimised NasNet Mobile achieved superior performance and outperformed the other popular CNN model from the previous study, as shown in Table 3, which typically reported accuracies between 67% and 90%. This indicated the potential of NasNet-Mobile as a lightweight alternative model and a highly accurate solution for waste classification tasks, particularly in resource-constrained environments, such as IoT systems or embedded classification systems.

Table 3. The accuracy comparison with other studies.

References	Waste Types	Pre-trained Model	Accuracy
Liu et al. [8]	Metal, Plastic, Paper and Glass	VGG-16	84.60%
		VGG-19	71.20%
		AlexNet	56.60%
Kolla et al. [16]	TrashNet	ResNet50	81.00%
Xhang et al. [17]	NWNU Trash	DenseNet169	82.80%
Gywali et al. [18]	Plastic, Paper, Metal, and Glass	ResNet18	87.8%
		AlexNet	87.14%
		GoogleNet	88.10%
Ozkaya et al. [19]	TrashNet	ResNet	89.38%
		VGG-16	90.00%
		SqueezeNet	80.43%
Rijah et al. [22]	Plastic, Paper, Glass	VGG-16	84.67%
Yong et al. [23]	Recyclable, Kitchen, Hazardous, and other wastes	MobileNetV2	82.92%
		Proposed CNN with 4 layers	67.50%
Proposed method	TrashNet	NasNet-Mobile	91.25%
	Garbage classification dataset		94.85%

5. CONCLUSION

This study successfully established an efficient deep learning methodology for classifying different types of waste using the lightweight and powerful NasNet-Mobile architecture. By adopting a structured three-stage training process comprising transfer learning, fine-tuning and hyperparameter optimisation, the model achieved significant performance improvements across both TrashNet and the Garbage Classification datasets. It attained 91.25% accuracy on TrashNet and 94.85% accuracy on the Garbage Classification dataset, each obtained using specific optimal hyperparameter settings through the random search technique. These results demonstrated that the proposed strategy effectively improves feature adaptation, generalisation capabilities, and convergent stability, outperforming several benchmark CNN models reported in the literature. Furthermore, the scalability and lightweight of the NasNet Mobile, attribute to its cell-based architecture make it suitable for real-time or embedded applications in the intelligent waste management systems.

For future work, the dataset could be further enhanced to address the class images imbalance issue that may affect the model's generalisation, as categories with fewer samples contribute less to gradient update during training. To address this issue, a balanced dataset can be constructed using data-level methods, such as Generative Adversarial Networks (GANs) and Variational Autoencoders (VAEs) [42]. Additionally, future work could also explore on integration of advanced optimisation techniques, such as Particle Swarm Optimisation (PSO) and Cuckoo Search Algorithm (CSA) [43-45], to enable a broader exploration of global search space and further improve the classification performance. Furthermore, the combination of NasNet-Mobile with other algorithms, such as Vision Transformer [46], Bagging, and Random Forest [47], could be investigated to enhance classification robustness and accuracy while maintaining computational efficiency.

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