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MARINE DEBRIS IMAGE CLASSIFICATION IN COASTAL WATERS USING DEEP LEARNING WITH CNN ARCHITECTURE

Darmansah[1*], Fortia Magfira[2], Sarah Astiti[3], Novri Adhiatma[1]

Universitas Putera Batam, Batam, Indonesia[1]
https://www.upbatam.ac.id[1]
darmansah071@gmail.com*, ad.novri@gmail.com

Universitas Maritim Raja Ali Haji, Tanjung Pinang, Indonesia[2]
https://umrah.ac.id[2]
fortiamagfira@umrah.ac.id

Universitas Telkom Kampus Purwokerto, Purwokerto, Indonesia[3]
https://purwokerto.telkomuniversity.ac.id[3]
sarahas@telkomuniversity.ac.id

(*) Corresponding Author
(Responsible for the Quality of Paper Content)

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Abstract— *This study investigates the capability of a convolutional neural network (CNN) to classify marine debris into five material-based categories: plastic, cans, glass, wood, and organic material, using a locally collected dataset from Batam waters. It evaluates classification accuracy, class-level performance, model errors, and visual features affecting classification. The dataset comprises 1,250 images collected at several locations in Batam using a Canon EOS R100 camera and processed through resizing, normalization, and data augmentation. The CNN was trained using the Adam optimizer with a learning rate of 0.001 and evaluated using accuracy, precision, recall, F1-score, and a confusion matrix. The model achieved 92% accuracy, with macro-averaged precision, recall, and F1-score of 0.92. Plastic achieved the highest performance (F1-score: 0.96), while wood and organic material recorded the lowest (0.88). Classification errors were concentrated in categories with similar visual textures and colors, particularly wood and organic material. These findings demonstrate the influence of class-specific visual characteristics on CNN classification performance and highlight the importance of analyzing class-level errors. This study provides a baseline for developing more robust marine debris classification models for Indonesian coastal environments. However, real-time implementation, drone-based image acquisition, edge inference, and operational latency remain beyond its scope.*

Keywords: *Batam waters, Convolutional Neural Network, deep learning, image classification, marine debris.*

INTRODUCTION

In the past twenty years, marine debris pollution has become one of the world's most pressing environmental problems [1], [2], [3], [4]. According to a report by the United Nations Environment Programme (UNEP), approximately 11 million tons of plastic waste enters the oceans every year. Plastic accounts for at least 85% of all marine debris [5]. This number is expected to nearly triple by 2040 without significant intervention [6]. Most of this waste originates from human activities in coastal areas, industry, maritime transportation, and poorly managed domestic waste [7]. These activities damage marine ecosystems, kill biota, destroy coastal habitats, and pose a threat to human health through the marine food chain [8].

With more than 17,000 islands and a coastline of 108,000 km, Indonesia, the world's largest archipelagic country, faces many problems

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in managing marine debris [9]. According to the 2023 Marine and Coastal Resources Statistics published by the Central Statistics Agency (BPS), increased economic activity in coastal areas, population growth and urbanization, and increased utilization of coastal areas increase the risk of waste entering aquatic ecosystems. Research by the National Research and Innovation Agency shows that marine waste management in Indonesia still requires a more representative and data-based monitoring system to support the achievement of the national target of reducing plastic waste in the sea [10]. Increasing marine pollution in various regions of Indonesia, including Batam City, is caused by increased economic activity, coastal population density, and poor waste management systems [11], [12].

Batam is located near international shipping routes and has many industrial, trade, international port and maritime transportation activities [13], [14], making it one of the national strategic areas vulnerable to marine debris. Waste in Batam waters originates not only from local activities but also from ocean currents carried from other areas around the Strait of Malacca and the South China Sea [15]. As a result, the amount of floating and coastal waste has increased, directly impacting marine ecosystems, the fishing industry, tourism, and the environmental health of coastal communities [16].

Currently, the main problem in marine debris management is the manual identification and monitoring process. Conventional methods are time-consuming, expensive to operate, and heavily reliant on human observation, which is prone to error and subjectivity. Due to limited human resources and the difficulty of performing real-time operations, manual methods are inefficient at scale. Furthermore, object identification is further complicated by changes in lighting, waves, water reflections, and turbidity in the marine environment [17]. In digital image-based environmental monitoring, advances in AI, particularly deep learning, have opened up new opportunities [18]. Convolutional Neural Networks (CNNs) are a very popular image processing technique [19]. A CNN is an artificial neural network structure designed to automatically recognize visual patterns through a process of deep feature extraction [20]. The advantage of CNNs over traditional classification methods lies in their ability to automatically learn object characteristics without the need for manual feature extraction [21].

In recent years, CNNs have demonstrated outstanding performance in various industries, including object detection, medical image classification, security systems, autonomous vehicles, and environmental monitoring [22]. CNNs are capable of classifying images with accuracy above 90%, especially for datasets with complex visual patterns [23]. CNNs' capabilities make them one of the best methods for digital image-based marine debris classification [24].

In recent years, deep learning has been widely used for marine debris detection and classification. TrashCan is one of the important datasets that provides material annotation and instance segmentation for 7,212 underwater images, with approaches such as Faster R-CNN and Mask R-CNN [25]. Another study by Fulton et al. used 5,720 images from JAMSTEC and compared several architectures, including YOLOv2, Faster R-CNN, Tiny-YOLO, and SSD for underwater debris detection [26]. Meanwhile, the SeaClear dataset provides 8,610 shallow water images from various locations and cameras and was evaluated using Faster R-CNN and YOLOv6 the study showed that domain shift between locations and cameras can affect the model's generalization ability [27]. Several studies also show that dataset quality has a greater impact on model performance than just the choice of CNN architecture [26], [27], [28], [29]. Degraded image quality, small object size, limited number of datasets, and inability to generalize the model across conditions are the main problems in underwater object detection. [25].

Previous research, however, still has several significant limitations. First, most studies used generic datasets, which are not representative of marine conditions in Indonesia, especially in tropical waters like Batam. Compared to international datasets, tropical waters have varying levels of turbidity, lighting, and object variety. Second, most studies have not comprehensively addressed the influence of marine environmental conditions on classification model performance. Consequently, they fail to capture the complexity of debris objects in open water areas. Most previous research has stopped at the laboratory experiment stage, without producing intelligent systems that can be directly used for ocean monitoring. This suggests that further research is needed to develop ocean monitoring systems capable of operating automatically and in real time. Therefore, research is needed that not only produces classification models with high accuracy, but also has the ability to adapt to complex marine environmental conditions.

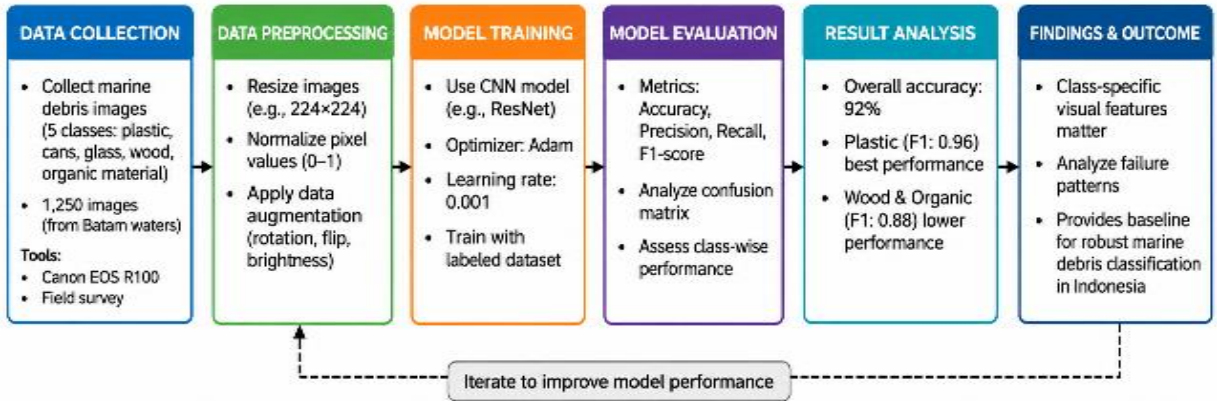
Based on these issues, this study investigates CNN-based marine debris image classification using a locally collected dataset from Batam waters. Images were collected from Nongsa, Sekupang, and Barelang Bridge during January–April using a Canon

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EOS R100 camera with a native resolution of 3984 × 2240 pixels. The dataset contains 1,250 images categorized into five classes: plastic, cans, glass, wood, and organic materials. Each image was labeled according to its waste category through an annotation process conducted by the researchers and field experts. The class distribution is reported to describe the balance of the dataset, while the labeling procedure is further evaluated for annotation consistency. Before model training, the images underwent preprocessing and data augmentation to improve the quality and robustness of the classification model. This study contributes an empirical evaluation of CNN-based marine debris classification under local coastal conditions and provides class-level performance analysis to identify categories that are more difficult to distinguish. The findings are intended to provide a baseline for future development of AI-based marine debris monitoring in Indonesian coastal waters.

MATERIALS AND METHODS

Conceptually, this research is based on the relationship between dataset quality, preprocessing, CNN architecture design, and model training parameters on image classification performance. In the context of Deep Learning, model quality is strongly influenced by the system's ability to learn visual feature representations of objects. Therefore, this research places the data collection and processing stages as the main foundation for improving classification model performance. The research stages can be seen in Figure below.



Source: (Research Results, 2026)

Figure 1. Research Framework

Dataset Collection

The first stage in the research framework was the collection of marine debris image datasets in Batam waters. The use of local datasets was crucial for this study because most previous studies used public or international datasets, which do not always adequately represent the characteristics of Indonesia's tropical marine environment. The research dataset was collected directly in several locations in Batam waters, namely Nongsa, Sekupang, Tanjung Pinggir and Barelang Bridge, during the period of January - April using a Canon EOS R100 camera with a native resolution of 3984 × 2240 pixels. Due to the influence of ocean lighting, water surface reflectance, turbidity levels, and the variety of unstructured debris shapes, the visual complexity of Batam waters is significantly higher than image classification in a controlled environment. Data was collected by categorizing waste into five main categories: plastic, cans, glass, wood, and organic. These categories were chosen based on the types of waste most commonly found along Batam's coast and waters, as plastic is difficult to decompose and easily moves in the marine environment. Therefore, this research focuses not only on creating a classification model but also on supporting a visual data-based marine pollution monitoring system.

Data Preprocessing

This study applies several preprocessing techniques such as image resizing, normalization, data augmentation, and dataset partitioning. In the Image Resizing stage, image dimensions are required because the dataset is obtained from multiple sources with varying resolutions. The first stage is standardizing the image size (image resizing) to 224x224 pixels. This method is used to standardize the input dimensions to meet the requirements of the CNN architecture. While this can cause geometric distortions in elongated or irregularly shaped objects, this effect is minimized

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through data augmentation, allowing the model to consistently learn the visual characteristics of each trash category. Using letterboxing or aspect ratio-preserving resizing techniques, this limitation can be addressed in future research. Resizing process using equation below:

$$I'(x,y) = I\left(\frac{x^w}{w'}, \frac{y^H}{H'}\right) \quad (1)$$

Description:
$I'(x,y)$ = resized image
$I(x,y)$ = original image
W, H = original image size
$W'\ H'$ = target image size

The 224 x 224 size was chosen because it matches the input standards of various contemporary CNN architectures, such as VGG16 and ResNet, and helps the process of developing more complex models. To improve the stability of the pixel value range, data normalization is performed in the next step. RGB image pixel values typically range between 0 and 255, and too high values can cause unstable model training and slow optimizer convergence. The following is the equation used in normalization, such as equation below:

$$X_{norm} = \frac{X}{255} \quad (2)$$

Description:
X = original pixel value
X_{norm} = normalized pixel values.

After the image reduction process is complete, the entire image is normalized by dividing the pixel values from 0 to 255 into 0–1. By standardizing the scale of the input data, normalization aims to make the CNN learning process more stable, accelerate convergence, and reduce the risk of gradient instability during training. Furthermore, this study uses data augmentation methods to synthetically increase the variation of training data without the need to collect additional data directly. Augmentation techniques used include: rotation, image flipping, zoom and lighting adjustments. Conceptually, the goal of augmentation is to generate a broader distribution of data so that the model doesn't just learn the orientation of specific objects. This is crucial because marine debris is irregularly positioned due to ocean currents and waves. To ensure that model evaluation was performed using previously unseen data while maintaining a representative distribution of each debris category, the dataset was divided into training and testing sets using an 80:20 stratified split. Stratification was performed based on the five debris classes to preserve approximately the same class proportions in both the training and testing sets. This procedure helps reduce potential bias caused by differences in class distribution between the two subsets. The equation used for dividing the dataset is like equation below:

$$D = D_{train} + D_{test} \quad (3)$$

Description:
D = states the total number of datasets.
D_{train} = data used to train the CNN model.
D_{test} = data used to test model performance after the training process is complete.

CNN Model Design

This study used a Convolutional Neural Network (CNN) model to classify marine debris into five categories: plastic, cans, glass, wood, and organic materials. The CNN architecture consisted of four convolutional layers stacked in a stepwise fashion, with the number of filters increasing from 32, 64, 128, to 256. Increasing the number of filters allowed the network to learn increasingly complex visual features from marine debris images. For each convolutional layer, a 3 × 3 kernel and ReLU activation function are used. Next, after each convolutional layer, a 2 × 2 Max Pooling is applied to reduce the spatial dimension of the feature map while retaining the most dominant feature information. To reduce the risk of overfitting, after the feature extraction stage, a Dropout of 0.50 is used. The feature map is then flattened with Flatten and passed to a fully connected layer of 128 units with ReLU activation function. Five units with Softmax activation function represent the five categories of marine debris in the output layer. The model was trained using the Adam optimizer with a training ratio of 0.001 and a categorical cross-entropy loss function. Training used a batch size of 32 with up to 50 epochs. Before being fed into the model, all input images were standardized to a size of 224 × 224 × 3.

Training Model

After the preprocessing stage was completed, the CNN model was trained using 80% of the training data with a batch size of 32, 50 epochs, and the Adam optimizer with a learning rate of 0.001. The backpropagation algorithm was used to update the network weights during training to minimize the loss function. This study used the categorical crossentropy loss function because it is suitable for

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classification problems of various classes, including five types of marine debris. The following is the formula used at this stage, which can be seen in the equation below:

$$L = -\frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{c} y_{ij} \log\ (y_i) \quad (4)$$

Description:
L = It is the loss value
N = number of samples in one training process (batch);
C = number of classes
y_i = It is the actual label
log (y_i) = The logarithmic function is used to penalize incorrect predictions.

With N as the number of samples in a batch. Since the output layer uses the softmax activation function, the predicted probabilities for the five classes are given by the following equation:

$$\sum_{c=1}^{5} y_{i,c} = 1 \quad (5)$$

The Adam algorithm uses this loss value to update the network weights through backpropagation. In this study, the model was trained using a learning rate of 0.001, a batch size of 32, and a maximum of 50 epochs. The training process aims to minimize the categorical cross-entropy value so that the predicted class probabilities are closer to the actual labels.

Testing Model

Using a stratified partitioning based on five categories of marine debris, the dataset was divided into 80% training data and 20% testing data. Before training, the testing data was isolated. Afterward, it was not used for weight updates, parameter optimization, or model selection. Any data-dependent training and preprocessing processes used only the training data. After the model was trained, the testing data, previously unseen by the model, was used once to make predictions and evaluate model performance using precision, accuracy, recall, F1 score, and confusion matrix. This was done to avoid missing data and provide an estimate of model performance on data not used during training.

Model evaluation

To comprehensively evaluate the performance of the CNN model, several metrics were used: precision, accuracy, recall, F1 score, and confusion matrix. The precision score is used to measure the overall classification accuracy, while the precision, recall, and F1 scores are calculated using macroaverages, so that each class has equal weight during the evaluation process regardless of the number of samples used. This method was chosen because the goal was to evaluate model performance evenly across all marine debris categories. Additionally, misclassification patterns within each class were analyzed using a confusion matrix. This analysis identified which debris categories were frequently confused with other categories, providing insight into the model's strengths and limitations in distinguishing the visual characteristics of each type of marine debris.

RESULTS AND DISCUSSION

This study uses deep learning methods with a convolutional neural network (CNN) architecture to develop an image classification system for marine debris in Batam waters. The system aims to automatically identify various types of marine debris based on the visual characteristics of the objects found in digital images. The following are the results and discussion of this study:

Marine Debris Image Classification Results

In the testing phase, the Convolutional Neural Network (CNN) model was tested using marine debris images from Batam waters to determine how well the CNN could identify the visual characteristics of each object. Five types of marine debris were tested: plastic, cans, glass, wood, and organic matter. The CNN Model Prediction Results can be seen in the image below:

Test Image	Actual Label	Predicted Label	Probability
	Plastic	Plastic	0.97
	Can	Can	0.93
	Glass	Glass	0.94
	Wood	Wood	0.89
	Organic	Organic	0.88

Source: (Research Results, 2026)
Figure 2. Classification Results

The prediction results shown in the figure represent the model's confidence level for individual test images, not an aggregate performance metric for each waste class. In the example images shown, the model produces prediction probabilities of 0.97 for plastic, 0.94 for glass, 0.93 for cans, 0.89 for wood, and 0.88 for

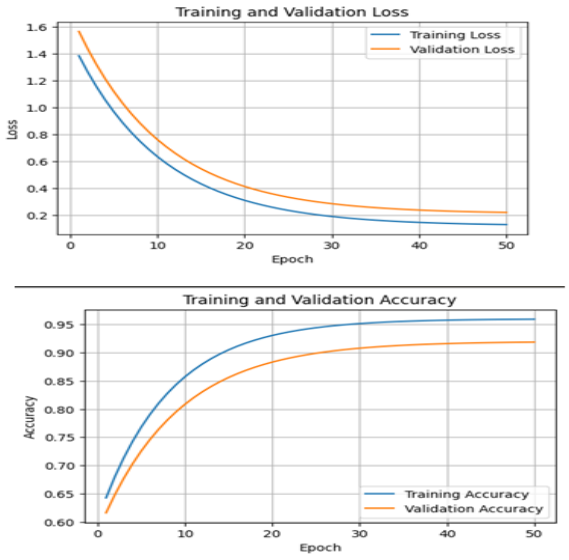
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organic materials. These values are obtained from the output of the Softmax layer, which generates probability distributions for the five classes in each image. The class with the highest probability value is designated as the model's prediction result. Therefore, these probability values only indicate the model's confidence level in its prediction for a particular image and cannot be interpreted as accuracy, precision, recall, or F1-score values at the class level. Overall and class-level model performance was evaluated using a classification report and a confusion matrix. Based on the classification report, the model achieved a macro-average precision of 0.92, a macro-average recall of 0.92, and a macro-average F1-score of 0.92, with an overall accuracy of 92%. Unlike individual prediction probabilities, these metrics are calculated based on the entire test data and are therefore more appropriate for assessing model performance. The confusion matrix was then used to show the distribution of correct and incorrect predictions for each of the five marine debris classes.

Model Training and Validation Results

The model training process was conducted over several epochs to assess the model's ability to learn marine debris image patterns. The training and validation results are shown in the following graph.



Source: (Research Results, 2026)

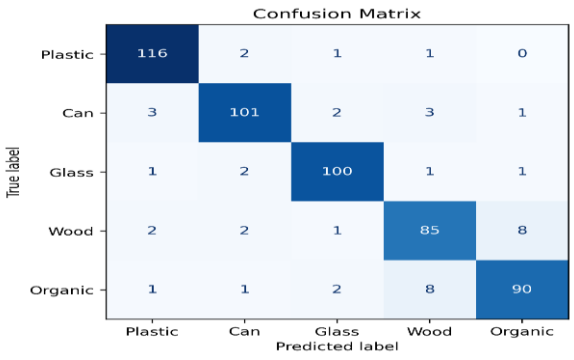
Figure 3. Training and Validation Results

The CNN model training process was carried out for 50 epochs with a batch size of 32 and a learning rate of 0.001. During the training process, model performance was monitored based on accuracy and loss values on the training and validation data. The training and validation results are shown in Figure 3. At the 50th epoch, the model achieved a training accuracy of 96.0% and a validation accuracy of 92.0%. The loss values at the end of training were 0.12 for the training data and 0.21 for the validation data, respectively. The difference between training and validation accuracy of approximately 4 percentage points indicates a moderate generalization gap. The higher validation loss compared to the training loss also indicates overfitting, although validation accuracy remained relatively stable in the final epochs. The curve in Figure 3 shows the progression of the learning process over 50 epochs.

The horizontal axis shows the number of epochs, while the vertical axis shows the accuracy and categorical cross-entropy loss. The loss values on the training and validation data gradually decreased, while the accuracy increased and then tended to stabilize in the final epochs. This pattern indicates that the model had reached a relatively stable learning state before the end of the training process. These training and validation results are distinct from the test results. Evaluation on the test data is performed after the training process is complete and is used to measure the model's generalization ability to data not used in the model parameter update.

Evaluation Results Using Confusion Matrix

To determine the level of classification success for each waste category, model performance evaluation was carried out using a confusion matrix. The following is an figure of the model evaluation:



Source: (Research Results, 2026)

Figure 4. Confusion Matrix Results

Based on the confusion matrix in Figure 4, model performance was analyzed separately for each marine debris category. In the Plastic class, the model correctly classified 116 out of 120 images, while the remaining 4 images were misclassified to other classes. In the Can class, 101 out of 110 images

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were correctly classified. For the Glass class, the model correctly classified 100 out of 105 images. Meanwhile, in the Wood and Organic classes, 85 out of 98 and 90 out of 102 images were correctly classified, respectively. Thus, the correct prediction rates per class were 96.67% for Plastic, 91.82% for Can, 95.24% for Glass, 86.73% for Wood, and 88.24% for Organic, respectively. The results show that the Plastic and Glass classes have a relatively higher proportion of correct predictions, while Wood and Organic show higher error rates. A confusion matrix was used to identify error patterns between classes, particularly the possibility of a trade-off between Wood and Organic.

This analysis provides more detailed information than simply using the overall accuracy value. To support the reliability of the results, the evaluation also needs to include a measure of statistical uncertainty. In a hold-out split-based evaluation, a 95% confidence interval can be calculated for the proportion of correct predictions in each class. In further research or in revised experiments using stratified k-fold cross-validation, model performance will be reported as the mean ± standard deviation, along with 95% confidence intervals for accuracy, precision, recall, and F1-score.

Classification Report Results

The model evaluation results were also analyzed using a classification report to obtain more detailed information about the performance of each class. The results can be seen in the table below:

Table 1. Classification Report Results

Class	Precision	Recall	F1-Score	Support
Plastic	0.97	0.96	0.96	120
Can	0.93	0.92	0.92	110
Glass	0.94	0.95	0.94	105
Wood	0.88	0.87	0.88	98
Organic	0.89	0.88	0.88	102
Accuracy			0.92	535
Macro Average	0.92	0.92	0.92	535
Weighted Average	0.92	0.92	0.92	535

Source: (Research Results, 2026)

Macro-average and weighted-average are used to provide two perspectives on model performance. Macro-average assigns equal weight to each class, making it more suitable for assessing performance balance between categories, while weighted-average considers the number of samples (support) for each class, thus representing performance based on the actual data distribution. In this study, the number of samples between classes ranged from 98 to 120 images, so class imbalance was relatively limited. The similarity of the macro-average and weighted-average values of 0.92 indicates that class distribution does not significantly impact the aggregate metrics. However, these two values still need to be interpreted in conjunction with the per-class metrics and confusion matrix, as the aggregate average cannot indicate the most misclassified classes.

Model Prediction Results

To directly assess the model's capabilities, testing was conducted on several marine debris images using the trained CNN model. The following is an image of the model testing:



Source: (Research Results, 2026)

Figure 5. Model Prediction Results

The prediction results show that the CNN model can use the visual characteristics learned during training to correctly classify most marine debris images. The model produces predictions with high confidence in images with clearly visible objects and good contrast against the background. In contrast, in test images with more complex visual conditions, such as low lighting, reflections on the water surface, high turbidity, and occlusion, the model still shows some classification errors. These conditions are particularly evident in wood and organic materials, which are more difficult to distinguish from other types due to their similar textures and color shifts. According to the prediction analysis, images of plastic, cans, and glass tend to be more easily recognized due to their shape, texture, and color contrasting more strongly with their surroundings. Images of wood and organic objects, on the other hand, experience prediction errors when the objects are covered in seawater or have uneven lighting.

Discussion

The results showed that the CNN model achieved 92% accuracy with a macro-average precision, recall, and F1-score of 0.92 each. However, per-class analysis revealed differences in

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performance. Plastic had the highest F1-score (0.96), while Wood and Organic had the lowest (0.88). This pattern is consistent with the confusion matrix, which showed more errors in the Wood and Organic classes. The error is likely related to the similarity in texture, color, and surface pattern between Wood and Organic. Lighting conditions, water reflections, turbidity, and occlusion can also reduce the available visual information, making it more difficult to distinguish features between the two classes. However, these factors should be considered as possible contributors because their effects have not been tested in a controlled manner. To confirm the superiority of the model, empirical comparisons are needed using the same dataset with architectures such as VGG16, ResNet, and MobileNet, as well as traditional methods such as SVM or KNN. Comparisons should use the same preprocessing, data splitting, and evaluation metrics. Results can be reported based on accuracy, macro-F1, number of parameters, and training time. In this study, such direct comparisons have not been conducted, so the model's superiority over other methods cannot be empirically claimed.

CONCLUSION

This study shows that the CNN model is able to classify five categories of marine debris, namely Plastic, Can, Glass, Wood, and Organic, with an accuracy of 92% and macro-average precision, recall, and F1-score of 0.92. The evaluation results show that the model provides the best performance in the Plastic and Glass classes, while the Wood and Organic classes have relatively lower performance, which is likely related to the similarity of visual characteristics such as texture and color. While these results demonstrate the potential of CNN for marine debris classification, this study still has several limitations. The data used was only 1,250 images, and data collection was conducted at a specific location in Batam waters. Therefore, it is unclear whether the model can be applied to different environmental conditions in specific areas. Furthermore, this study has not conducted external validation using datasets from various locations or sources. Furthermore, this study has not tested the system in real-time conditions, such as latency testing and implementation on drone-based acquisition systems or edge devices. Therefore, the results of this study should be viewed as initial evidence of CNN classification capabilities on marine debris datasets from Batam waters, not as proof that the system is ready for operational implementation. Further research requires the use of larger and more diverse datasets, stratified k-fold validation and cross-validation, and external validation, as well as real-time testing and evaluation under various environmental conditions.

DECLARATION OF AI USE

The authors declare that generative artificial intelligence (AI) tools were used in the preparation of this manuscript. ChatGPT and Quillbot were used to assist with English language editing and grammar correction. The authors reviewed and revised all AI-assisted content and take full responsibility for the accuracy, originality, and final content of the manuscript.

AUTHOR CONTRIBUTIONS

The following is the role of each author in this article:

Author	Contribution Roles
Darmansah	Conceptualization, research design, methodology development, project administration, writing and editing of manuscripts.
Fortia Magfira	Investigation, Data Curation, Validation.
Sarah Astiti	Software development, implementation of the Convolutional Neural Network (CNN) architecture, model training, validation, and performance evaluation.
Novri Adhiatma	Data analysis, result interpretation and visualization.

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CONFLICT OF INTEREST STATEMENT

The authors declare that there are no conflicts of interest related to the research, writing, or publication of this article.

REFERENCE

[1] M. E. Purba, A. Z. Situmorang, G. L. Br Ginting, M. W. P. Lubis, and F. M. Sinaga, "Klasifikasi Sampah Organik dan Anorganik Menggunakan Algoritma CNN," *J. Sifo Mikroskil*, vol. 26, no. 1, pp. 37–54, 2025, doi:

10.55601/jsm.v26i1.1510.

[2] E. Rafsanjani Fajrin, A. Damar, and Taryono, "Marine Debris Pollution and Its Impact on the Mangrove Ecosystem (Case Study: Karimunjawa Island and Kemujan Island, Indonesia)," *J. Pengelolaan Sumberd. Alam dan Lingkung.*, vol. 14, no. 3, pp. 516–524, 2024, doi: 10.29244/jpsl.14.3.516.

[3] M. F. D. Syamsuddin, A. P. A. Nevandra, D. Yona, A. Yamindago, S. H. J. Sari, and A. T. Yanuar, "Beach Cleanliness and Marine Debris Characteristics for Sustainable Coastal Tourism in Prigi Bay, Indonesia," *Ilmu Kelaut. Indones. J. Mar. Sci.*, vol. 30, no. 3, pp. 329–344, 2025, doi: 10.14710/ik.ijms.30.3.329-344.

[4] A. Amir, F. Lestari, K. Ismail, and A. Dhamar Syakti, "Strategies for Preventing Fishing Vessel Debris Pollution in Tarempa's Coastal Fishing Port, Kepulauan Riau," *J. Perikan. dan Kelaut.*, vol. 29, no. 2, pp. 283–290, 2024, doi: 10.31258/jpk.29.2.283-290.

[5] M. L. A. Kaandorp, D. Lobelle, and C. Kehl, "Global mass of buoyant marine plastics dominated by large long-lived debris," *Nat. Geosci.*, vol. 16, no. August, 2023, doi: 10.1038/s41561-023-01216-0.

[6] W. Ali, P. Doyen, and R. Amara, "Marine plastic pollution and bioplastic alternatives: a review," *Environ. Chem. Lett.*, 2026, doi: 10.1007/s10311-026-01906-2.

[7] P. L. Haji, N. T. Barat, A. I. Nafsi, and L. L. Sitohang, "Jurnal Kesehatan Lingkungan Indonesia Analisis Eksploratif Sampah Laut di Wilayah Pesisir Studi Kasus," *JKLI*, vol. 25, no. 1, pp. 1–11, 2026, doi: 10.14710/jkli.75202.

[8] Chairun Annisa Aryanti, Fatmawati, Fitriah Amir, Haeruddin, and Maria Yosephine Simbolon, "Literature Review: Identifikasi Mikroplastik Terhadap Lingkungan Laut Dan Biota Laut," *J. Ris. Kelaut. Trop. (Journal Trop. Mar. Res.*, vol. 7, no. 1, pp. 16–26, 2025, doi: 10.30649/jrkt.v7i1.111.

[9] D. N. Putri and I. M. A. Arsana, "Kajian Terhadap Aspek Geospasial Kabupaten/Kota yang Bercirikan Kepulauan di Indonesia," *Geoid*, vol. 18, no. 2, p. 253, 2023, doi: 10.12962/j24423998.v18i2.12955.

[10] E. B. Fatwa, S. Hariyadi, and Taryono, "Strategi Keberlanjutan Pengelolaan Pencemaran Sampah Plastik Di Pesisir Kota Dumai Riau Melalui Pendekatan Analisis Mactor Sustainability Strategy of Plastic Pollution Management in the Coastal Area of Dumai City Riau Through Mactor Analysis Approach," *J. Kebijak. Perikan. Indones.*, vol. 16, no. 2, pp. 95–108, 2024, doi: 10.15578/jkpi.16.2.2024.85-98.

[11] Y. Adicita *et al.*, "Kajian Pengelolaan Sampah Perkotaan pada Pulau Kecil Padat Penduduk di Pulau Lengkang, Kota Batam," *J. Wil. dan Lingkung.*, vol. 10, no. 3, pp. 226–235, 2022, doi: 10.14710/jwl.10.3.226-235.

[12] M. Veronica and G. Prajati, "Journal of Green Engineering for Sustainability Solid Waste Management Evaluation Existing Condition of Waste Generated Based on Population and Population Density in Batam City," *J. Green Eng. Sustain.*, vol. 2, no. 1, pp. 16–21, 2024, doi: 10.63643/jges.v2i1.244.

[13] K. Handoko, N. Adhiatma, and P. Simanjuntak, "Perbandingan K-Means dan DBSCAN dalam Analisis Pola Pergerakan Kapal Menggunakan Data Automatic Identification System (AIS)," *Josh*, vol. 7, no. 3, pp. 727–734, 2026, doi: 10.47065/josh.v7i3.9363.

[14] S. Astiti and A. W. Aranski, "Prediction of Potential Fishing Zones Using K- Means Clustering and Random Forest in Batam Waters," *JUITA J. Inf.*, vol. 14, no. 1, pp. 221–230, 2026, doi: 10.30595/juita.v14i1.29679.

[15] S. Prasetyaningsih and S. A. Salsabilla, "Efektivitas Penerapan Video" Mengubah Sampah Plastik Menjadi Energi Berkelanjutan" di Kota Batam," *J. Integr.*, vol. 14, no. 1, pp. 47–51, 2022, doi: 10.30871/ji.v14i1.3969.

[16] D. A. Rifanti, I. G. Hendrawan, and I. B. Mandhara Brasika, "Pergerakan Sampah Laut Yang Berasal Dari Sungai Di Perairan Selat Badung Dengan Pemodelan Numerik," *J. Mar. Res. Technol.*, vol. 5, no. 2, p. 114, 2022, doi: 10.24843/jmrt.2022.v05.i02.p10.

[17] W. Gong, J. Tian, and J. Liu, "Underwater Object Classification Method Based on Depthwise Separable Convolution Feature Fusion in Sonar Images," *Appl. Sci.*, vol. 12, no. 7, 2022, doi: 10.3390/app12073268.

[18] S. Zhu, W. Luo, and S. Duan, "Enhancement of Underwater Images by CNN-Based Color Balance and Dehazing," *Electron.*, vol. 11, no. 16, 2022, doi: 10.3390/electronics11162537.

[19] R. Holiyanti, S. Wati, I. Fahmi, and C. Rozikin, "Pendeteksi Sampah Metal untuk Daur Ulang Menggunakan Metode Convolutional Neural Network," *J. Tek. Inform. dan Sist. Inf.*, vol. 8, no. 1, pp. 261–274, 2022, doi: 10.28932/jutisi.v8i1.4492.

[20] Y. Puspitasari, J. J. Siang, A. G. Prabawati, U. Kristen, and D. Wacana, "Comparison Of

Accredited Rank 2 (SINTA 2) based on Decree No. 225/E/KPT/2022 issued by Direktorat Jenderal Pendidikan Tinggi, Riset, dan Teknologi, Kementerian Pendidikan, Kebudayaan, Riset, dan Teknologi Republik Indonesia, dated December 7, 2022. Published by LPPM Universitas Nusa Mandiri.

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Convolutional Neural Network Architectures Efficientnet-B4 And Mobilenetv2 In Cataract Disease Detection," *JITK*, vol. 11, no. 4, pp. 1020–1027, 2026, doi: 10.33480/jitk.v11i4.7502.

[21] P. N. Andono and E. H. Rachmawanto, "Deteksi Karakter Hiragana Menggunakan Metode Convolutional Neural Network," *JANAPATI*, vol. 11, pp. 183–192, 2022, doi: 10.23887/janapati.v11i3.50144.

[22] O. Nurdiawan *et al.*, "Optimizing Vgg-16 Convolutional Neural Network For Pap Smear Image Classification In Cervical Cancer Detection," *JITK*, vol. 11, no. 3, pp. 821–828, 2026, doi: 10.33480/jitk.v11i3.7131.

[23] R. Pujiati and N. Rochmawati, "Identifikasi Citra Daun Tanaman Herbal Menggunakan Metode Convolutional Neural Network (CNN)," *J. Informatics Comput. Sci.*, vol. 3, no. 03, pp. 351–357, 2022, doi: 10.26740/jinacs.v3n03.p351-357.

[24] M. Muslihati, S. Sahibu, and I. Taufik, "Implementasi Algoritma Convolutional Neural Network untuk Klasifikasi Jenis Sampah Organik dan Non Organik," *MALCOM Indones. J. Mach. Learn. Comput. Sci.*, vol. 4, no. 3, pp. 840–852, 2024, doi: 10.57152/malcom.v4i3.1346.

[25] M. Jian, N. Yang, C. Tao, H. Zhi, and H. Luo, "Underwater object detection and datasets: a survey," *Intell. Mar. Technol. Syst.*, vol. 2, no. 1, 2024, doi: 10.1007/s44295-024-00023-6.

[26] A. A. A. Fernandes, M. Koehler, N. Konstantinou, P. Pankin, N. W. Paton, and R. Sakellariou, "Data Preparation: A Technological Perspective and Review," *SN Comput. Sci.*, vol. 4, no. 4, pp. 1–20, 2023, doi: 10.1007/s42979-023-01828-8.

[27] L. Tuggener, J. Schmidhuber, and T. Stadelmann, "Is it enough to optimize CNN architectures on ImageNet?," *Front. Comput. Sci.*, vol. 4, 2022, doi: 10.3389/fcomp.2022.1041703.

[28] F. Chen and J. Y. Tsou, "Assessing the effects of convolutional neural network architectural factors on model performance for remote sensing image classification: An in-depth investigation," *Int. J. Appl. Earth Obs. Geoinf.*, vol. 112, no. April, p. 102865, 2022, doi: 10.1016/j.jag.2022.102865.

[29] A. Hussain, K. Ullah, M. Afaq, M. Munsif, A. Hussain, and S. W. Baik, "Quality over quantity: a data-centric survey of annotation errors in object detection datasets," *Artif. Intell. Rev.*, vol. 59, no. 3, 2026, doi: 10.1007/s10462-026-11502-z.

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