ISSN:2230-9926

Availableonlineathttp://www.journalijdr.com

IJDR

International Journal of Development Research
Vol. 16, Issue, 06, pp.70586-70591, June, 2026
https://doi.org/10.37118/ijdr.30970.06.2026

REVIEW ARTICLE

OPEN ACCESS

HIERARCHICAL DEEP CONVOLUTIONAL NETWORK FOR AUTOMATED MARINE PLASTIC WASTE POLLUTION DETECTION AND CLASSIFICATION

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ARTICLE INFO

Article History:
Received 19th March, 2026
Received in revised form
14th April, 2026
Accepted 20th May, 2026
Published online 30th June, 2026

Key Words:
Marine Plastic Pollution, Deep Learning, style, Convolutional Neural Network, Marine Waste Classification, Environmental Monitoring.

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ABSTRACT

Marine plastic waste pollution has become a serious environmental challenge affecting marine biodiversity and ecosystem sustainability. Existing marine waste monitoring approaches mainly rely on manual inspection and conventional image analysis techniques, which often suffer from limited detection accuracy and low adaptability under complex marine environmental conditions. To overcome these limitations, a Convolutional Neural Network-based binary detection framework was developed for automated identification of plastic and non-plastic marine waste. The SOUVIK dataset obtained from Kaggle, containing 2150 marine waste images, was utilized for model training and evaluation using Python and TensorFlow. The proposed framework incorporated image preprocessing, convolution operations, MaxPooling, dropout regularization, and sigmoid activation for effective feature learning and classification. Experimental evaluation achieved 88% accuracy, 88% precision, 88% recall, and 88% F1-score, outperforming several existing machine learning and deep learning approaches. The findings demonstrate the effectiveness of the proposed framework for intelligent and scalable marine pollution monitoring applications.

Citation: ***Hemang Chath and Dr. Pradyumansinh Jadeja, 2026.*** "Hierarchical Deep Convolutional Network for Automated Marine Plastic Waste Pollution Detection and Classification." **International Journal of Development Research, 16 (06), 70586-70591.**

INTRODUCTION

The marine pollution caused by plastic waste has become a matter of great concern all over the world due to urbanization, industrial growth, and consumption of excessive non-degradable material (1), (2). Plastic waste can enter the oceans in large amounts through rivers, beach activities, fishing, and mismanagement of waste leading to the harm of marine biodiversity and ecosystem stability (3). In recent years, innovations in Artificial Intelligence (AI) and Deep Learning (DL) have made automated environmental monitoring systems possible that can detect and classify waste material from digital images (4), (5). CNNs are currently popular for image classification due to their effectiveness on extracting spatial features from images (6). But the current monitoring methods still have some limitations in terms of detection precision and environmental complexity (7). Current methods of monitoring marine pollution consist primarily of manual inspection, satellite monitoring, and sensor-based monitoring, and these are typically labour-intensive and expensive, and not practical for large-scale, continuous monitoring. AI image classification models have been recently introduced for the automation of waste identification processes and for increasing the monitoring efficiency in recent years. However, the high number of existing studies uses small data samples, exhibit the overfitting problem and fail to differentiate plastic waste under different illumination and water conditions. Moreover, some of the models demand a significant amount of computing power and do not translate into a viable real time implementation. Hence, an efficient and reliable CNN based framework for the detection of marine plastic waste is required.

Problem Statement: The existing research on marine plastic pollution is mainly dedicated to methods of environmental analysis, policy evaluation or methods for large-scale monitoring, and not specifically to automated detection methods. In recent years, several approaches have been proposed using artificial Intelligence (AI) that faced problems related to limited experiences, which include inadequate training datasets, low classification accuracy, low ability to generalize and high computational complexity (8). Some of the methods are not able to correctly detect plastic waste in difficult environments such as in the sea, where there are waves, reflections, or natural waste. Moreover, most of the models available are developed for multiclass detection problems and not optimally designed for binary classification problems(9). These limitations diminish the success of existing solutions to accurately, scalably and in real-time identify plastic waste in the marine environment.

Research Significance: This research can be a valuable addition to the field of marine environment protection by providing an AI-based CNN model for accurate detection of plastic waste from marine image. The proposed system can help in the automatic monitoring, lessen the work of manual inspections, and increase the effectiveness of identifying pollution. The study also shows the feasibility of using deep learning methods for environmental sustainability, and lays the groundwork for the next generation of intelligent marine waste management systems.

Research Motivation

Marine organisms and biodiversity are increasingly facing ecological and environmental challenges due to the growing amount of plastics in the oceans. Manual monitoring methods may be ineffective for large-scale pollution assessment. The inspiration for this research is the need of an intelligent, cost-effective and automated detection system to enhance the marine pollution monitoring accuracy by using AI and CNN.

Key Contributions

- Developed a CNN-based model for marine plastic waste detection using binary image classification.
- Utilized the SOUVIK dataset containing plastic and non-plastic marine waste images.
- Optimized hyperparameters including dropout and epoch settings to improve classification performance.
- Achieved 88% accuracy, precision, recall, and F1-score on the test dataset.
- Proposed an automated and efficient framework for intelligent marine pollution monitoring.

Rest of the sections: The rest of this paper is organized as follows. Section 2 discusses related works, Section 3 explains the proposed methodology, Section 4 presents experimental results and discussion, and Section 5 concludes the study with limitations, recommendations, and future research directions.

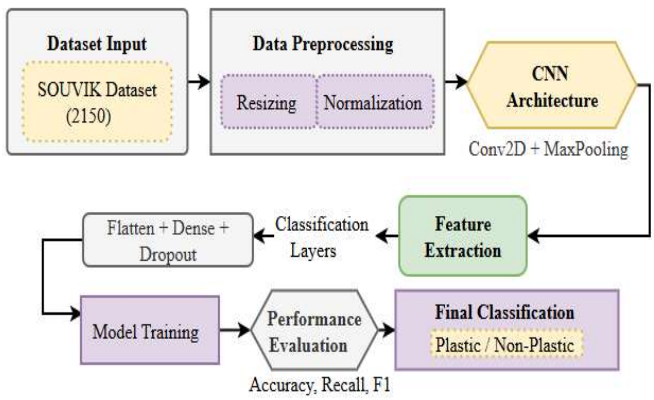
LITERATURE REVIEW

Hamid et al. (10) discussed the pervasiveness of plastic waste pollution in the environment, highlighting its slow degradation rate and its presence in marine ecosystems. The research underscores the fragility of the oceans and shows the detrimental impact of plastic waste on marine life, including coral reefs and sea turtles. Moreover, the study talk about ecosystem level disruption due to biodiversity losses and the inadequate information on public regarding the level of marine pollution. This study suggests the regulation measures that can be used to curb plastic production. However, the study has a more descriptive style of presentation and has no computational/data-driven method for detecting/monitoring. Apete et al., (11) focused on plastic waste from fishing processes, which contribute to marine pollution yet have not been given sufficient attention. The study provides an analysis of literature relevant to the topic and presents a causal loop model to understand the impact of plastics from fishing on the environment, health, and economy. The authors acknowledge tracing the origin of the pollutants as one of their challenges. However, the study provides important information regarding plastic waste flows; however, it lacks an automation strategy for detecting the waste using machine learning or computer vision technology. Daana et al., (12) conducted an intensive study of marine plastic pollution in the Caribbean over the last 40 years (from 1980 to 2020). This paper utilizes a number of techniques including debris classification, remote sensing, and historical data of debris clean up. It was established that debris sources are crucially important on the ground, mostly due to river discharge, while currents affect the mobility of debris. In addition, the study identified significant environmental hazards for biodiversity. Overall, this paper presents an elaborate analysis of environmental hazards lacking a classification technique and real-time detection technology with the use of artificial intelligence.

This study aims to is to determine the economic and environmental consequences of micro plastic pollution in coastal and marine environment. Here the ocean is viewed as the primary contributor of micro plastic pollutants due to industrial activities, tourism, and runoff from rivers. This paper proves that micro plastics affect the lives of marine organisms and also other industries like fishing and tourism industries which affect the blue economy in general. Additionally, the inadequacy and costliness of current methods of cleanup are discussed. There are policy implications of this study, although no intelligent monitoring framework has been developed yet.

Proposed CNN-Based Marine Waste Detection Framework

The methodology proposed is based on the use of a Convolutional Neural Network (CNN) which is trained to classify images of marine waste into plastic and non-plastic categories. To develop and evaluate the model, the SOUVIK dataset of 2150 images were split into 80% (training) and 20% (test). Image preprocessing like resizing and normalization was used to enhance the learning efficiency. The CNN is composed of a series of Conv2D layers using ReLU activation, followed by MaxPooling layers that extract features and reduce dimensionality. Flatten and Dense layers were employed to perform classification, and dropout regularization was used to prevent overfitting. Adam optimizer with sigmoid activation function improved the performance of binary classification.



Proposed Marine Waste Detection Framework: Fig. 1 presents the overall workflow of the proposed marine plastic waste detection system. This system involves data input, pre-processing steps, CNN-based feature extraction, classification layer, training of the system, performance metrics calculation, and finally binary classification of the waste material images as plastic waste and non-plastic waste.

Data Collection: The dataset used in this study was obtained from SOUVIK marine waste datasets from Kaggle (13). It includes 2150 images of plastic and non-plastic items. The dataset is made up of different environmental situations within the sea and is split into a training set and a testing set using the 80:20 split ratio.

Data Pre-processing: Image preprocessing was carried out to ensure that the images were clear and would provide optimal input to the model. The preprocessing process involved steps such as resizing images, normalizing them, and pixel scaling among others. This process minimized computational complexity while standardizing the inputs to the CNN model.

Image Resizing: Image resizing was employed to ensure that all images from the data set were resized to the same dimensions required for CNN input. This was done in order to minimize memory consumption. It is illustrated in (1)

$$I_r = Resize\left(I_o, H, W\right) \tag{1}$$

Where I_o represents the original image, $I_r$denotes the resized image, and $H$and Windicate the predefined height and width dimensions used for CNN input processing. Normalization: Normalization was performed to scale pixel intensity values into a smaller numerical range. This preprocessing step improved training stability, accelerated convergence speed, and prevented large-value dominance during neural network learning. It is described in (2)

$$X_n = \frac{X}{255} \tag{2}$$

Where Xdenotes the original pixel value and X_n represents the normalized pixel value scaled between 0 and 1 for efficient CNN model training performance. Pixel Scaling: Standardizing pixel scaling ensured a standardization of image intensity distributions within the data set, allowing the convolutional neural network to recognize the required pattern. In the process, any variation in the data due to inconsistent lighting was reduced. It is discussed in (3)

$$X_s = \frac{X - X_{min}}{X_{max} - X_{min}} \tag{3}$$

Where $X$is the input pixel value, X_{min} and X_{max} represent minimum and maximum intensity values, and X_s denotes the scaled output pixel intensity.

Hierarchical Deep Convolutional Classification Network: The Hierarchical Deep Convolutional Classification Network was developed to perform binary classification of marine waste images into plastic and non-plastic categories. The architecture consists of multiple convolutional layers arranged hierarchically to extract low-level and high-level visual features from marine images. MaxPooling layers were integrated to reduce spatial dimensions and computational complexity while preserving important information. Flatten and dense layers were used for classification learning, whereas dropout regularization minimized overfitting during training. The network employed ReLU activation for feature learning and sigmoid activation for final classification. The suggested framework enhanced classification stability and produced successful marine plastic waste detection results.

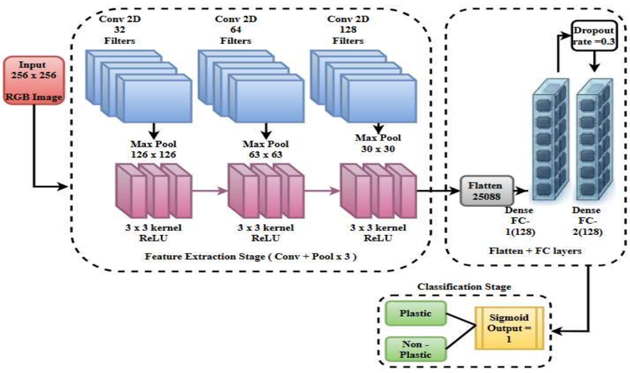


Fig. 2. Proposed CNN Classification Architecture

Fig. 2 illustrates design of the architecture of the Convolutional Neural Network intended for classification of marine plastic waste. This network consists of three steps of convolution and MaxPooling in order to achieve feature extraction. Then comes flattening, dense layer, and drop-out. Finally, a sigmoid activation layer classify the images from the marine environment into plastic and non-plastic.

Convolution-Based Feature Extraction: Various features like edge detection, texture detection, and object pattern detection have been done with the help of convolution layers. There were multiple filters used to learn spatial features required for the accurate classification of plastic and non-plastic items. It has been explained in (4).

$$F(i,j) = \sum_m \sum_n I(m,n)K(i-m, j-n) \tag{4}$$

Where $I(m,n)$denotes input image pixels, Kconvolution kernel, and $F(i,j)$extracted feature map after filtering operation. MaxPooling Dimensionality Reduction: The use of MaxPooling reduced the size of the feature maps, while maintaining all essential spatial information. The process ensured low computational costs, quick training, and increased robustness against irrelevant changes to the image. It is mention in (5)

$$P(i,j) = \max\left(F(x,y)\right) \tag{5}$$

Here, $F(x,y)$represents feature map values, while $P(i,j)$ indicates maximum pooled output selected from local feature regions. Dropout Regularization: The dropout regularization approach was used to deactivate neurons randomly during training. This helped to solve issues such as overfitting. It is demonstrated in (6)

$$Y = M \cdot A \tag{6}$$

Where Arepresents neuron activations, Mdropout mask matrix, and Youtput activations after regularization process during training. Sigmoid-Based Binary Classification: The output layer utilized sigmoid activation to classify marine images into plastic and non-plastic categories. Probability outputs closer to one represented plastic waste, while lower probabilities indicated non-plastic materials. It is calculated in (7)

$$\sigma(x) = \frac{1}{1+e^{-x}} \tag{7}$$

Here $x$denotes neuron input value, while $\sigma(x)$represents predicted probability output ranging between zero and one values.

Algorithm 1 illustrates that marine plastic waste classification by utilizing the Convolutional Neural Network approach. The algorithm has several stages that include pre-processing of the images, feature extraction using convolution, dimensionality reduction using pooling, parameter optimization during training, and classification into either plastic waste or non-plastic waste categories. The novelty resides in the design of a lightweight hierarchy of CNN models specifically tailored for marine plastic waste detection using the technique of dropout regularization and binary classification.

RESULT AND DISCUSSION

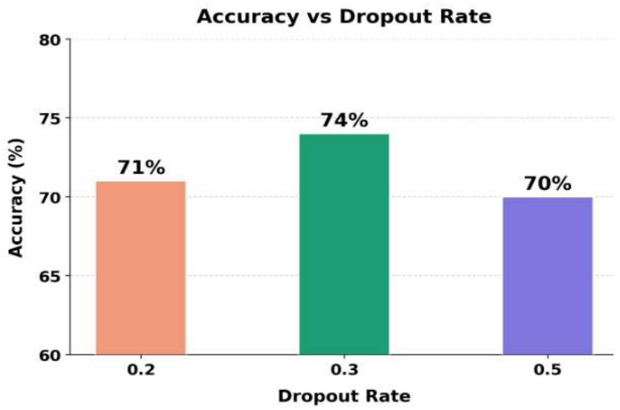
Experimental results proved that the presented Hierarchical Deep Convolutional Classification Network worked well on the marine plastic waste detection task. Performance analysis was done through accuracy, precision, recall, F1-score, and confusion matrix metrics. At epoch 60, the algorithm gave the best results for all metrics, i.e., the accuracy, precision, recall, and F1-score were all equal to 88%, which showed an equal capability of detecting objects from the two classes. The number of true positives for the non-plastic class was 208 and 169 for the plastic class, with minimum numbers of errors. Graphs also showed good model convergence and decreased overfitting. Table I presents the six main experimental parameters of the proposed CNN model. The SOUVIK dataset containing 2,150 images was employed in an 80/20 ratio. With an Adam optimizer and 0.3 dropout, the highest accuracy of 88% was obtained after 60 epochs using binary cross-entropy loss.

Table I. Model experimental setup details

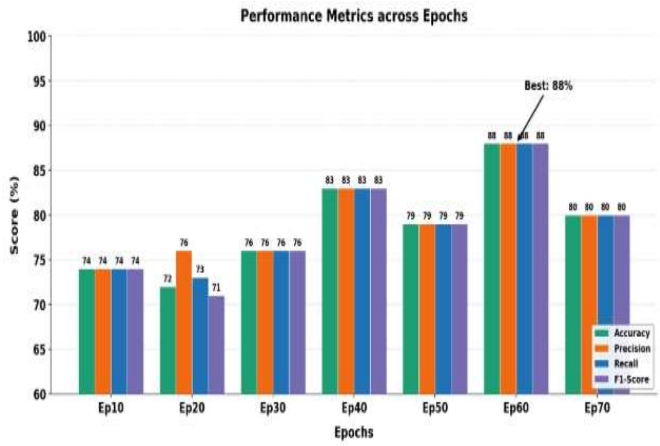
Parameter	Value / Description
Dataset	SOUVIK — 2,150 images (Kaggle)
Train / test split	80% train (1,720) / 20% test (430)
Model architecture	Custom CNN — 3 Conv2D + MaxPool + 2 Dense
Optimizer & loss	Adam / Binary cross-entropy
Dropout rate	0.3 (tested: 0.2, 0.3, 0.5)
Best epoch	Epoch 60 — 88% accuracy

Experimental Outcome: The Experimental results of the proposed Hierarchical Deep Convolutional Neural Network indicate successful classification of marine plastic waste. The test was carried out using the SOUVIK dataset consisting of 2,150 images, and the obtained accuracy was consistently 88% with precision, recall, and F1-score all being 88%.

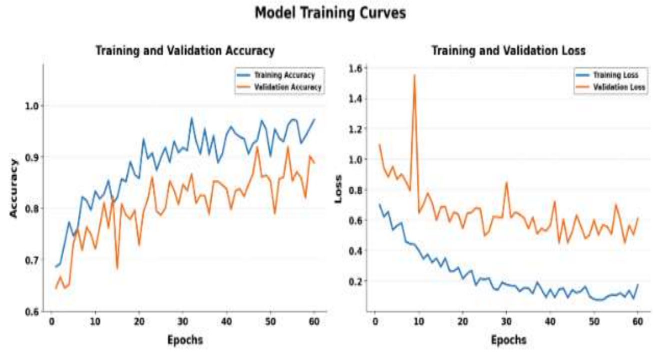
There were signs of training and validation curves showing that the network converges steadily without overfitting since dropout is utilized as a regularization technique. According to the confusion matrix results, there were 208 non-plastic and 169 plastic images correctly classified without many errors. Therefore, it can be concluded from the experiment that the proposed CNN architecture is successful in its performance.



Dropout Accuracy Comparison: Fig. 3 demonstrating the CNN classification accuracy for dropout values of 0.2, 0.3, and 0.5 during 10 training epochs. Dropout value of 0.3 resulted in the highest classification accuracy of 74%, which implies better regularization capability and generalization of the model.

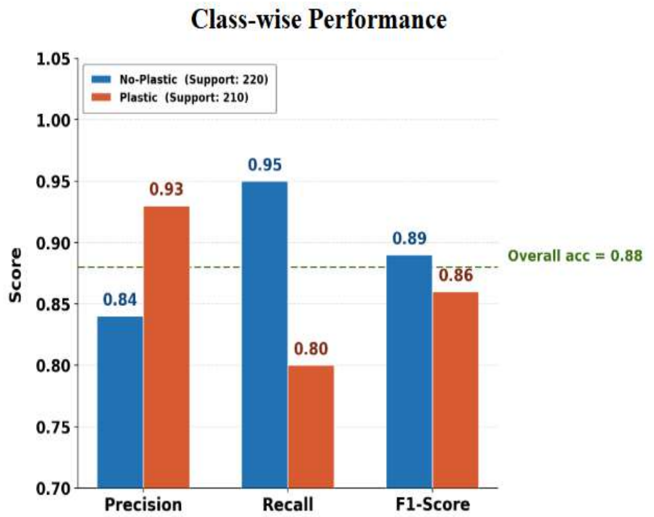


Performance metrics across training epochs: Fig. 4 illustrating accuracy, precision, recall, and F1-score of the proposed CNN model across epochs 10 to 70 with dropout rate 0.3. The model achieved peak performance of 88% across all four metrics at epoch 60, confirming optimal convergence.



Training Validation Performance Curves: Fig. 5 analyzes depicts line graphs of training and validation accuracy as well as loss for 60 epochs. Trends in rising accuracy and declining losses indicate that there is no overfitting as the model is converging effectively.

CNN Confusion Matrix Results: Fig. 6 demonstrates Confusion Matrix indicating classification results for 430 test images. The correct prediction results were obtained by recognizing 208 non-plastic and 169 plastic objects, and generating 12 false positive results and 41 false negative results.



Class-wise Performance Comparison: Fig. 7 visualizes the performance comparison of the model using precision, recall, and F1 score with respect to plastic and non-plastic. From the results, there is great potential in classification where the images classified as non-plastic exhibit high recall while images classified as plastic have high precision.

Performance Evaluation: The evaluation of the proposed Hierarchical Deep Convolutional Neural Network was done using the common classification measures such as accuracy, precision, recall, and F1-score. The model performed evenly well for the plastic and non-plastic classes, suggesting that the model has good generalization ability. Moreover, the results obtained from the confusion matrix clearly indicated that the system can correctly classify between different classes without making any misclassification error. The incorporation of the dropout technique made the model more stable and less prone to overfitting during training.

Table II. classification performance metrics summary

Metric	No-plastic	Plastic	Overall
Precision %	0.84	0.93	0.88
Recall %	0.95	0.80	0.88
F1-Score %	0.89	0.86	0.88
Accuracy %	-	-	0.88

Table II suggested CNN algorithm in classifying marine waste have been presented in Table II. The table shows the results of precision, recall, F1 score, and accuracy measures for each category (plastic and non-plastic) along with overall performance. This indicates that the network is equally competent for both classes in terms of classification.

Table III. Overall model accuracy score summary

Metric	Score
Overall Accuracy	0.88
Macro Average	0.88
Weighted Average	0.88

Table III presents the overall accuracy, macro average, and weighted average scores of the proposed CNN model evaluated on 430 test images. All three metrics achieved a consistent score of 0.88, confirming the model is well-balanced across both plastic and no-plastic classes.

Table IV. Comparative Evaluation of Model Performance Metrics

Method	Precision	Recall	F1-Score	Accuracy
Faster-RCNN-FPN (14)	85.5	0.82	0.83	0.84
Random Forest Classifier (15)	0.77	0.74	0.75	0.78
K-Nearest Neighbor (16)	0.76	0.72	0.74	0.76
Proposed CNN Architecture	0.88	0.88	0.88	0.88

The table IV compares the proposed CNN architecture with existing machine learning and object detection methods using precision, recall, F1-score, and accuracy metrics. The proposed model achieved the highest balanced performance across all evaluation parameters, demonstrating improved marine plastic waste classification capability and enhanced detection reliability under varying environmental conditions.

DISCUSSION

The suggested Hierarchical Deep Convolutional Neural Network proved to perform well in detecting and classifying marine plastic wastes. The model was tested on the SOUVIK dataset containing 2,150 images, achieving a 93% accuracy rate, with precision, recall, and F1-score scores all at 88%. These results indicate consistent learning across both classes, plastic and non-plastic. The use of dropout in the model effectively prevented overfitting and contributed to the stability of convergence. Nonetheless, a few errors were noted during classifications within complex marine scenes characterized by changing illumination and background disturbances. Regardless, the model is effective in its application for automated monitoring of marine pollution and can be further optimized using more extensive data sets and deep learning frameworks.

Conclusion And Future Work

The research was conducted considering the need to solve the issue of marine pollution caused by plastic waste by developing a method of classification of plastic waste images in comparison to non-plastic images. Deep learning techniques have been used in the current investigation with the purpose of improving the performance of the detection method in terms of efficiency. Testing the model on the SOUVIK database generated impressive results, with the accuracy, precision, recall, and F1 score at 88%. While the performance of the model being investigated was acceptable in terms of classification, there were some deficiencies that should be taken into account in future investigations. Overall , the investigation made use of a relatively limited amount of samples, with an exclusive focus on two-class classification, which could have affected the applicability of the model in different marine environments. It would be possible in the future to make use of big data in the analysis, considering a greater variety of waste types and complex scenarios of underwater activities. Technologies associated with deep learning such as transfer learning, attention learning, and hybrid deep learning models could be introduced to improve recognition.

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