Comparison of AlexNet Algorithm with DenseNet Algorithm for Aquatic Debris Detection on Ocean Surfaces

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Keywords: Novel AlexNet Algorithm, Convolutional Neural Network, Deep Learning, DenseNet Algorithm, Marine Debris, Ocean Surfaces, Research.

Abstract: This research aims to spot aquatic debris on ocean surfaces using the novel Alexnet algorithm, comparing its performance against the DenseNet algorithm. Materials and Methods: To enhance the detection of aquatic debris, two algorithms such as Novel AlexNet and DenseNet are compared with iteration done for each group as 20 are implemented on the data set with a G-Power of 80% and confidence level of 95% using the clinical software. The dataset used for this research consists of 324 JPG images of marine debris and 724 JPG images of the ocean with varying degrees of clarity, including images with noise. Results: With an accuracy of 93.77%, the Novel AlexNet algorithm identifies and measures objects with more accuracy than the DenseNet algorithm, with 92.91%. It shows that there is no statistical significance difference between the Novel Alexnet Algorithm and DenseNet Algorithm with $p=0.530$ (Independent Sample T-test $p<0.05$). Conclusion: The detection of aquatic debris using the Novel AlexNet algorithm provides superior performance compared to the DenseNet algorithm, as concluded from the obtained results.

1 INTRODUCTION

The escalating volume of waste in the Earth's oceans has emerged as a pressing environmental issue, posing risks to ecosystems, wildlife, and human well-being. Debris finds its way into the oceans through rivers, sewage outlets, and wind transport. Furthermore, maritime vessels contribute to the ocean's waste accumulation, resulting in the formation of garbage patches (Politikos, 2021). Ocean currents and winds occasionally transport marine debris great distances from its origin in the ocean. Within the sea, specific regions known as garbage patches emerge as locations where marine debris gathers due to prevailing currents. Machine learning, a recent field in Computer Science, encompasses a range of data analysis methods (Chen, 2022). A portion of these methods relies on established statistical approaches like logistic regression and principal component analysis, while several others do not. Deep learning gained momentum in object recognition and detection through the introduction of AlexNet (Huang, 2021). A group of scientists employed deep learning in their investigation of image-based water recognition, and over time, the methodology advanced in complexity (Y. Wang, 2022) (James et al., 2017). The application of deep learning techniques and their applications can increase the efficiency of the process by automating the removal of marine garbage, discovering its distribution, and improving debris identification.

Most statistical techniques aim to identify the optimal probabilistic model describing observed data within a related model class. Similarly, in machine learning, the focus is on finding models that best suit the data, solving optimization problems. Unlike before, these machine learning models aren't confined to probabilistic models. (Marin et al., 2021), (G. Ramkuamr et al., 2021). These regions are visible to the naked eye and consist predominantly of microplastics.

2 LITERATURE SURVEY

In the last 4 years, there have been 81 articles in IEEE Explorer and 2250 articles in Google Scholar. Many publications that focus on various applications were produced. There are a few thorough studies on the identification of deep-sea debris, however, the

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majority of marine debris detection exclusively concentrates on the sea surface and coast (Vethaak, 2022). Although certain detection networks have started to be deployed to find trash in the ocean, the results have not been adequate(Wolf et al. 2021). In the prior research titled "A Deep Feature-Based Strategy for Categorizing Marine Debris," the suggestion is put forth to employ the DenseNet Algorithm for recognizing and categorizing marine debris. The study assesses how a neural network classifier, trained using deep CNN feature extractors, performs when the feature extractor is held constant versus when it's adapted in the given task (Huang 2021) (Sivakumar et al 2022). Annotations at the image level, indicating the existence or absence of target objects, prove adequate for Weakly Supervised Learning (Y. Wang 2022). Weakly Supervised Learning merely necessitates image-level annotations that specify whether the target objects are present in an image or not. In this study, the AlexNet algorithm is employed as the backbone network for object classification. The limitation of this study involves the replacement of the final two fully connected layers with two convolutional layers and a Global Average Pooling layer. In contrast, the current paper employs a configuration of five convolutional layers and eight interconnected layers (Wu, 2020).

The research gap was identified using the present technique with poor accuracy. The existing method has shortcomings, such as the significant amount of information required for accurate forecasting. While using less data for testing and training, the recommended solution, the Novel AlexNet algorithm, delivers improved accuracy. The present research tests the detection of aquatic debris on ocean surfaces using the Novel Alexnet algorithm and the DenseNet algorithm.

3 PROPOSED METHODOLOGY

Image Processing Lab is utilized to conduct the research in the Department of Computer Science and Engineering, Saveetha School of Engineering, Saveetha Institute of Medical and Technical Sciences, Chennai. The study involved selecting two groups and comparing their processes to derive results (Freitas, Silva, and Silva, 2021). G power value is obtained as 80% where alpha value is 0.05 and 0.2 is beta value with a 95% confidence interval. A sample is determined to 20 for each group (https://clincalc.com/stats/samplesize.aspx).

Utilizing the MATLAB software, the proposed work was designed and implemented, with the dataset for the code implementation being provided by Kaggle. This dataset comprises 724 jpg file format images of clear ocean and 324 jpg file format images of aquatic debris, allowing for the analysis of both clear ocean and debris records (Y. Wang, 2022). The Windows 11 OS served as an experimental environment for deep learning. A minimum of 4 GB of RAM was used in the hardware setup, which included an Intel Core i3 CPU. 64-bit system sort was employed. Utilizing MatLab code, Code is implemented. To execute an output process for accuracy during code execution, the image set is processed behind this code.

3.1 AlexNet Algorithm

Novel AlexNet Algorithm is used as a sample preparation of group 1. Eight layers comprise the Novel AlexNet algorithm, including three interconnected and five convolutional layers. Convolutional filters and ReLU, a nonlinear activation function, are both included in every layer(Kang et al., 2022). Rectified Linear Units (ReLU) are used by Novel AlexNet to help models learn and solve issues more quickly, as well as address difficulties with disappearing gradients. The first convolutional network used to improve GPU performance is called Novel AlexNet (Alom et al., 2021). The results of Novel AlexNet show that a large-scale, deep convolutional neural network can break records on a highly challenging dataset with just supervised learning. A new phase of research was inaugurated by CNN's Novel AlexNet, the company's inventor. The implementation of Novel AlexNet is rather straightforward given the abundance of deep learning frameworks available (Wu, 2021).

3.2 Procedure of Novel AlexNet Algorithm

Input - Dataset records
1. Apply pre-processing techniques to the object images to eliminate any background noise.
2. Use the threshold algorithm to convert the pre-processed image to a binary image.
3. Identification of the parts of the binary images must be carried out.
4. Segment the individual object from the image.
5. Extract the major axis, minor axis, and area geometric features of each individual object.
6. Evaluate the quality by analyzing the average feature values extracted from the sample.
7. Classify the sample according to its type and grade, based on the analysis performed.

3.3 DenseNet Algorithm

In the context of preparing samples for group 2, the DenseNet algorithm is employed. DenseNet operates by combining the output of the preceding layer with that of the following layer, while ResNet employs an additive approach (+) to merge the previous layer (identity) with the subsequent layer (Kikaki et al., 2022). The main purpose behind developing DenseNet was to address the reduced accuracy caused by the vanishing gradient problem in deep neural networks. To put it simply, the information vanishes along the way due to the extensive path between the input and output layers (G. Wang et al., 2021). Through the utilization of the composite function operation, the output from the initial layer is used as input for the subsequent one. This composite procedure involves components like convolution layers, pooling layers, batch normalization, and non-linear activation (Li and Wang, 2022). The network has L(L+1)/2 direct connections as a result of this linkage. L is the number of architectural layers. There are many variations of the DenseNet, including DenseNet-121, DenseNet-160, and DenseNet-201. The numerical values represent the neural network's layer count.

3.4 Procedure for DenseNet Algorithm

Input - Training Set

1. Load the pre-trained DenseNet model and create a new model by adding a global average pooling layer and a fully connected layer with sigmoid activation for binary classification.
2. Compile the new model using an optimizer, loss function, and evaluation metrics.
3. Augment the training data using the ImageDataGenerator function to reduce overfitting.
4. Train the new model using the fit_generator method and evaluate it on the validation set using the evaluate_generator method.
5. Fine-tune the DenseNet model by unfreezing some of its layers and retraining on the augmented data with a smaller learning rate. Use the trained model to predict the presence of aquatic debris in ocean surface images.

Statistical Analysis

To perform statistical analysis of Novel AlexNet and GoogleNetDenseNet, SPSS software was employed. The dependent variables consisted of image characteristics such as objects, distance, frequency, modulation, pixel distribution, while the independent variables included frame rate and resolution. The statistical software used for analysis was IBM SPSS version 26. For both algorithms, datasets were generated using a sample size of 10. Testing variables for accuracy and loss were employed, and grouping was performed using Group ID.

4 RESULTS

The effectiveness of the Novel AlexNet algorithm in predicting aquatic debris in ocean surfaces was compared to that of the ResNet-50 algorithm and the accuracies are found to be 93.77% and 92.91% respectively.

Novel AlexNet and DenseNet's mean and accuracy results are shown in Table 1. Novel AlexNet's mean value is better than DenseNet's, which has a standard deviation of 1.63330 and 1.41324, respectively.

The results of Novel AlexNet and DenseNet's independent sample T-test are displayed in Table 2. It demonstrates no statistically significant difference between the Novel Alexnet Algorithm and the DenseNet Algorithm with a value of p=0.530 (Independent Sample T-test p0.05).

Figure 1 illustrates the mean accuracy and loss compared with Novel AlexNet and DenseNet. The Novel AlexNet and ResNet T-test results are displayed as a bar graph. It displays the Novel AlexNet and DenseNet accuracy and loss numbers. The accuracy numbers looked like bars.

Table 1: Group Statistics between Novel AlexNet algorithm and DenseNet algorithm.

	Group	N	Mean	Std. Deviation	Std. Error Mean
Accuracy	AlexNet	20	93.7730	1.63330	0.36522
	DenseNet	20	92.9125	1.41324	0.31601
Loss	AlexNet	20	4.2160	1.65847	0.37085
	DenseNet	20	7.8355	1.47372	0.32953

Table 2: Independent Sample T-Test. It shows that there is no statistical significance difference between the Novel Alexnet Algorithm and DenseNet Algorithm with p=0.530 (Independent Sample T-test p<0.05).

		Leven's Test of Equality of Variances		T-test for Equality of Means					95% Confidence Interval of the Difference	
		F	Sig	t	df	Sig (2-tailed)	Mean Difference	Std Error difference	Lower	Upper
Accuracy	Equal Variance assumed	3.347	0.075	0.634	38	.530	.30600	.48296	-671	1.283
	Equal Variance not assumed			0.634	37.231	.530	.30600	.48296	-672	1.2843
Loss	Equal Variance assumed	3.814	0.058	-1.971	38	.055	-.97800	.49610	-1.982	.2631
	Equal Variance, not assumed			-1.971	37.482	.056	-.97800	.49610	-1.98277	.2677

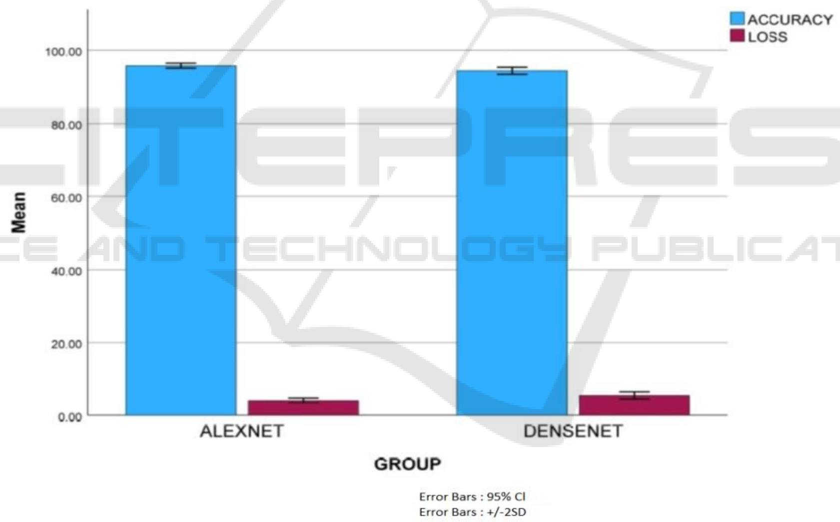

Figure 1: Comparison of Novel AlexNet and DenseNet in terms of mean accuracy and loss. The mean accuracy of Novel AlexNet is better than DenseNet. X-axis: Novel AlexNet VS DenseNet, Y-axis: Mean accuracy: Error bar with +/- 2SD.

5 DISCUSSION

The study's findings revealed that the significance value obtained is 0.011 (p<0.05), indicating a statistical significant difference between the two groups. Moreover, based on the accuracy analysis, the Novel AlexNet algorithm was found to perform better than DenseNet. Specifically, the Novel AlexNet classifier achieved an accuracy of 93.77%, whereas the GoogleNetDenseNet classifier had an accuracy of 92.40%.

The research work (Marin et al., 2021) examined multiple approaches for extending the connection of a CNN in the time domain to determine the image and enhance the feature of debris. It achieves an accuracy of 91 % using DenseNet in the research. Classification of deep learning CNN is said to be a type of artificial neural network that detects and recognizes objects using the previously saved image data set (Freitas, Silva, and Silva, 2021). The main goal of pattern recognition is to accurately classify an input pattern as one of the several output classes. The two main steps of this approach are feature selection and classification (Politikos, 2021). Since the classifier won't be able to distinguish between badly chosen features, feature selection is essential to the entire process (Kikaki et al., 2022). This research application can be used in classifying the Debris on Ocean surfaces and shores. A few other applications include with the help of this approach the amount of garbage that is mixed with water bodies is determined and also used to classify the debris in the ocean (Vethaak, 2022).

The factors affecting the study include the collection of datasets from various sources. Another factor that affects the study is the time required to classify the data for both classification and detection. The limitation of this study, the debris present below the surface cannot be determined due to the lack of light below the surface. The future scope of this study includes the way to introduce hybrid algorithms to improve accuracy. The future scope of this study is that the system should be expanded to include a larger number of objects with lesser time consumption in training the data set.

6 CONCLUSION

The Aquatic Debris Recognition Data set was used to improve the performance of image classification. The study employed the Novel AlexNet algorithm and DenseNet for this purpose. The mean accuracy of the Novel AlexNet algorithm was found to be 93.77%, whereas that of DenseNet was 92.91%. It can be inferred that the Novel AlexNet algorithm yields higher accuracy than the DenseNet algorithm.

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