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CONVOLUTION NEURAL NETWORK (CNN) BASED OBJECT DETECTION IN OCEANOGRAPHIC IMAGERY

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ABSTRACT— The oceanography plays the vital role in the monitoring of the large scale areas from the satellite imagery sources. The ship vessel, debris, planes, crashed planes and boats detection, recognition and localization becomes very important for the surveillance of the multiple objects in the wider area like oceans. The satellite imagery collected from the satellite sources makes very larger volumes of data, which makes it very difficult for live monitoring by humans. Hence the requirement of automated surveillance mechanisms becomes higher for the segmentation, localization, detection and recognition of the objects in the ocean images. The proposed model has been designed by using the neural networks with the color and texture based features for the detection and analysis of the objects in the oceanographic imagery. The results have proved the proposed model's robustness with only 8 negative cases out of 86 total cases, which makes the accuracy of the detection up to 90.32% overall.
KEYWORDS—Ship detection, vessel detection, object recognition, geo-tagging.

INTRODUCTION

When an aeroplanes or ships are reported missing across the oceans, it becomes very tough task to spot and localize the area containing the debris or other traces of the lost object. The oceans have covered the 71% area of the total earth, and it becomes a very difficult task to analyze the oceanic areas manually. The computerized image processing models specifically designed for the analysis of the oceanic imagery can be considered as the best approaches. The several methods have been already proposed and implemented for the similar applications. The existing models have been found inefficient while evaluated on the basis of system accuracy, elapsed time or object detection problems. This shows the lack in the technology of spotting the objects and marking the debris from the satellite images. The remote senogrpahy techniques are always efficient in making the detection of such objects quite efficient. In this paper, the colour and texture based technique has been proposed along with the neural network classification for the object detection and classification. The proposed object classification method will incorporate the supervised classification paradigm for the knowledge discovery based object detection in the oceanic imagery. The Histogram of Gradients (HoG) along with scale invariant feature transform (SIFT) has been utilized for the colour and texture based analysis respectively. The neural network classifier is expected to increase the robustness and accuracy of the proposed classification system.

LITERATURE REVIEW

Yasen Zhang et.al. (2014) has presented a new technique to detect inshore ships using shape and context information. In this paper, the energy based function has been utilized to produce the robust and flexible contour like structure for the segmentation of the objects in the given image, which further undergoes the deep learning for the recognition of the useful objects to extract the useful information. Thomas H et. al. (2012) has worked towards the N-hard problem for the detection of debris in the ocean images. This model is made capable of detection of the low profile and smaller sizes debris items in oceanographic imagery. Shivani Agarwal et. al. (2013) has studied the possibility of the multispectral analysis for the geographic and biodiversity for the estimation of the various dense and sparse green areas in the city of Bangalore, India. Nagendra, Harini et. al (2008) has worked on the estimation and assessment of the biodiversity among the developed area (i.e. urban and semi-urban areas), which has been aimed to the monitoring of the green belt area. Peter Hofmann et. al(2004) – presents that Remote sensing from airborne and space borne platforms provides valuable data for mapping, environmental monitoring, disaster management and civil and military intelligence.

EXPERIMETNAL DESIGN

The hybrid deep neural network has been utilized for the purpose of classification of the vehicles in the primary categories of light and heavy vessels in the oceanic images collected from the satellite sources. The hybrid deep neural network has been used with the multiple layers with the enabled convolution behavior in the coiling formation for the learning of the training data into the sequential order. The random weights are initialized and calculated on the basis of the number of the input hidden layers. The overall algorithm has been defined in the following steps:

Algorithm 2: Hybrid deep neural network (HDNN)

- n Initiate the activation function for the neural networks denoted by ‡ phi
- n Define the derivative of the activation function {phi} ‡ phid
- n Begin the Forward Propagation network
  - ® Define the Input data in the form of input nodes (i) over the given input (x).
    - ÿ Run the iteration for each input object or node (i)
    - ÿ Return the output vector $result_i$ which equals x_i stands for calculated cost.
  - ® Compute the Hidden layer processing over the given nodes j
    - ÿ Run the iteration for each given object j
    - ÿ $result_j$ = $Â_i$ phi(w_{ji}◊$result_i$)
  - ® Define the output layers of the neurons k
    - ÿ Run the iteration for each given neuron k
    - ÿ $result_k$ = $Â_k$ phi(w_{kj}◊$result_j$)

The activation function in general is definitive for the structuring of the output node that is computed from an input or set of input nodes. The activation function either enables or disables the overall behaviour of the classification algorithm. In the neural network (which is considered as the biological inspired classifier), the activation function defines the percentage of the action potential firing for the input neural nodes or cells. In the simplified definition, the activation function primarily decides whether the neural require to the fire the output or not, which is controlled by the binary bits to define the enabled or disabled behaviour. The activation function is defined in the following algorithm:

Algorithm 3: Activation Function

- ® Being the activation function
- ® Activate the Layers (**input** and **output**)
- ® Run the iteration for each object i and neurons k
  - o calculate $result_i$
- ® Run the iteration for each hidden neuron j
  - o calculate $result_j$
- ® Run the iteration for each hidden neuron k
  - o calculate $result_k$ o **result** = {$result_k$}

RESULT ANALYSIS

Precision

The parameter of the precision is one the parameters to measure the accuracy of the system, which is entirely based upon the percentage of the total matches founds from the input data according the user requirement. The higher precision value signifies the robustness of the proposed model applied over the image data. The manual classification has been performed to measure the statistical type I and type II errors, which defines the overall results in the various categories or selection or rejection. The precision is also termed as the sensitivity and given by the following equation:

P = Alpha / (Alpha + Lambda) * 100

Where P is the precision, Alpha here stands for the true positive and beta stands for false negative.

PARAMETER	VALUE	95% CI
Precision	94.08 %	75.29 % to 100.00 %

Table 1: Evaluation of the proposed model using precision

Recall

Recall gives the overall probability of the test among the matching samples out of the total selected and rejected cases. The false rejection cases significantly reduces the overall accuracy of the system, hence the impact of the false rejection cases is studied with the parameter of recall.

Recall = Alpha / (Alpha + Gamma) * 100

PARAMETER	VALUE	95% CI
Recall	93.10 %	75.29 % to 100.00 %

Table 2: Recall based evaluation of the Proposed model

Positive Predictive Value

Positive predictive values are influenced by the prevalence of correct results in the population that is being tested. If we test in a high prevalence setting, it is more likely that persons who test positive truly have matching probability than if the test is performed in a population with low prevalence.

Positive Predictive Value = A/(A+B) × 100

PARAMETER	VALUE	95% CI
Positive Predictive Value	93.50 %	75.29 % to 100.00 %

Table 3: Positive predictive value calculated from the simulation results Accuracy

The overall accuracy of the system is measure by dividing the correct number of the detection samples (True positive and true negative) by the total number of the test cases. The accuracy clears the overall performance of the system unlike the specific cases defined by the precision or recall. The following table defines the accuracy of the system:

Accuracy = (Total correct results/ Total test cases) *100

PARAMETER	VALUE	95% CI
Accuracy	93.41%	75% to 100 %

Table 4: Accuracy based evaluation of the proposed model.

CONCLUSION

	Predicted (NO)	Predicted (YES)	
Actual (NO)	TN = 6	FP = 8	14
Actual (YES)	FN = 1	TP = 78	79
	7	86	84

The 84 results have been recorded as correct out of the total number of 93 test cases. Out of the 79 positive cases (as per pre-defined), 78 cases have been found producing the correct results and 1 produced the wrong results, whereas out of 14 negative cases (as per pre-defined), 8 are incorrect and 6 are correct. The proposed model has predicted total 7 negative cases, out of which 6 are correct and produces the 85.71% accuracy in this class, whereas has produced nearly 91% accuracy in the positive cases with 78 correct results out of total 86 cases. The proposed has been recorded with 84 correct and matching cases overall out of the total 93 cases, which makes nearly 90.32% accuracy overall.

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