Ship Detection Approach Using Machine Learning Algorithms

Abdirahman Osman Hashi[1](✉), Ibrahim Hassan Hussein[1], Octavio Ernesto Romo Rodriguez[2], Abdullahi Ahmed Abdirahman[1], and Mohamed Abdirahman Elmi[1]

[1] Faculty of Computing, SIMAD University, Mogadishu, Somalia
Wadani12727@gmail.com, {aaayare,m.abdirahman}@simad.edu.so
[2] Department of Computer Science, Faculty of Informatics, Istanbul Teknik Üniversitesi, 34469 Maslak, İstanbul, Turkey

Abstract. The control of territorial waters is critical, since water occupies more than 70% of earth surface. Due to that fact, maritime security and safety is essential, in order to reduce illegal operations including piracy, illegal fishing and transportation of illicit goods. With the rapid development of artificial intelligence, ship detection research has increased as well. Several researchers have addressed this issue by proposing a variety of solutions such as VGG and Dense Net. Nevertheless, these proposed solutions have not provided enough accuracy in term of ship detection. Therefore, the primary objective of this work is to propose a robust model that can detect ships by applying artificial intelligence and machine learning models, those are Random Forest, Decision Tree, Naive Bayes and CNN. The result achieved in this experiment will tackle the forementioned problems and conduct research on how ships could be detected. Based on the result, Random Forest outperforms other models in terms of accuracy, scoring 97.20% for RGB and 98.90% for HSV, in comparison with Decision Tree and Naive Bayes those are scored 96.82% for RGB and 97.18% for HSV and 92.43 for RGB and 96.30% for HSV respectively. Meanwhile, CNN scored 90.45% for RGB and 98.45% for HSV. Overall, Random Forest is the best model so far, achieving a good result in terms of RGB and HSV 97.20% and 98.90% respectively. The significance of the proposed method for the field of artificial intelligence is to introduce a novel method to detect Ships.

Keywords: Deep learning · Naive Bayes · Random forest · Artificial intelligence · Convolutional neural network

1 Introduction

The precise and concurrent identification of moving ships has become an important part of marine video surveillance, resulting in increased traffic safety and security. With the fast advancement of artificial intelligence, intelligent methods to improve ship identification outcomes in marine applications are becoming possible. The visual picture quality is often reduced in real-world imaging settings owing to poor weather conditions, such

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as rain, haze, and low light, among others. The apparent degradation has the potential to jeopardize the safety and security of maritime traffic. Furthermore, since it enables for accurate and real-time identification of moving ships, high-quality images has become an essential component in maritime video surveillance. As a result, a great deal of effort has gone into improving low-visibility enhancement and ship recognition in a variety of imaging scenarios [1].

As a consequence of many international cooperation efforts, the frequency of cases of maritime piracy has recently reduced. The Ministry of Defense proposed 3,200 million JPY for anti-piracy operations off the coast of Somalia in Japan's FY2017 national budget. A important marine route between Japan and Europe must pass through this area through the Suez Canal. The Japanese Maritime Self-Defense Force has sent a fleet to protect Japanese ships [2]. This works well, but it would have been much better if Somalis had been able to identify ships using ship detection models.

Machine learning has opened new opportunities for better picture categorization and detection in recent years. It has started Machine learning methods to learn picture characteristics automatically and discover possible object characters and distribution rules across the object that are not defined by human cognition [3]. Three criteria should be fulfilled by a competent ship detecting technique. The first is robustness; the detecting technique should be resistant to changes in light, clouds, and waves. The second need is generality; the detection technique must be capable of detecting both in-shore and offshore ships. Last but not least, computational efficiency: the detecting technique should be computationally efficient. This is particularly important when working with large-scale remote sensing pictures [4]. Recent years, numerous researchers such as [5, 6] and [7] have proposed different solutions for ship detection. However, these proposed solutions were not provided enough accuracy in term of ship detection. Hence, the primary key objective of this paper is to intend by proposing robust model that can detect ships in the sea by applying four machine learning models, those are CNN, Random forest, Decision Tree and Naive Bayes.

This paper is organized with five sections. The upcoming section discusses the related work of ship detection methods that other researchers have proposed before. Section three explains the proposed methodology for ship detection that uses four machine learning algorithms. The next section illustrates the experiment result and dataset description that is applied for the proposed model. And the final section presents the conclusion and future work recommendations.

2 Background and Related Work

Due to the increasing need for applications in the scope of maritime security and safety, marine monitoring research has increased recently. With the objective of maritime border control, fight against piracy, observing ocean pollution, and related missions, several organizations and government agencies must guarantee the safety of ships and the overall security of maritime operations. The oceans and seas occupy about 71% of the earth's surface, as a result of that, water transportation has played a significant role in global economies throughout history [8]. However, the sea is fraught with threats ranging from piracy to the potential of mishaps. Furthermore, numerous illegal operations, including illegal fishing and the transportation of illicit goods might take place, especially in the Indian Ocean. There are resources such as satellites that can be used to keep track of these enormous seas. However, sophisticated image processing techniques are required for the identification and the following categorization of ships and maritime transportation-vehicles traversing the seas using satellite images. In conjunction with monitoring the seas for the intention of ships guard, prevention of illegal fishing and illicit goods transportation, countries must also control their shores and nearby waterbodies in search of military threats, including enemy ships and submarines from a defensive standpoint [7].

Through history; Airbus, previously known as the European-Aeronautic-Defense Space-Company, has offered a wide range of maritime surveillance services with effective solutions and intense monitoring of marine areas with fine fidelity [8]. Airbus supplied researchers with data in order for them to create an automatized prediction model that could track the activity of ships, correctly identify every ship in all the satellite pictures given, therefore preventing illegal maritime operations [9]. Given the increment of maritime traffic, there is a greater chance of illicit operations occurring in the water, such as piracy and illegal goods transportation. Airbus had the aim to develop a comprehensive maritime surveillance system to constantly check ship traffic and prevent criminal operations including piracy, illegal fishing, and the transport of illicit goods. Furthermore, a system like that would safeguard the maritime environment, since it would help prevent accidents that could result in pollution [5].

On account of the benefits that automated surveillance of the seas or oceans areas could result in, ship location is an imperative application when we talk about area of computer vision or in specific an image processing field. The benefits of creating a model that can locate and examine ships in an autonomous way range from stopping piracy, illegal fishing, illicit transportation of goods. As a result of recent technological advancements, the interest in Neural-Network research for detecting and classificating specific items in pictures has increased. Ship detection is one of these applications that may provide significant benefits to the parties involved but yet not implemented in Somalia which is currently dealing with the forementioned problems [3].

On the other hand, to predict the object's minimal circumscribed rectangle and minimize the redundant detection area, a method based on rotation anchor approach was developed [10]. For identifying ships, the experiment's dataset relies on remote sensing photos from Google Earth. The RDFPN performed better in ship identification in complicated pictures, particularly in identifying densely packed ships, according to the findings. The authors used K-Nearest Neighbors, Random Forest, Naive Bayes in another approach for ship identification using satellite imagery [11]. Deep Learning techniques were also put to the test, with researchers using pre-trained network designs as a comparison network. When the Deep Learning technique was compared to conventional methods, the Random-Forest model had the highest accuracy in the category of classical methods, scoring 93% of accuracy in detection. In contrast, the methods in the category of Deep Learning obtained 94% of accuracy in detection [12].

Since last decade most researchers were always working on ways to enhance current algorithms, which is something that typically happens as the quantity of datasets grows. Between the input and output layers of a typical deep learning classifier, there are many layers of CNN that allow for sophisticated non-linear information processing [13]. Chua et al. [14] compared three traditional machine learning algorithms: histogram of oriented gradient (HOG), exemplar-SVM, and latent-SVM [15] to determine their particular benefits, and discovered that exemplar SVM is excellent for specificity measurement. Chen et al. [15] proposed a detection technique that uses a fully convolutional neural network (FCNN) segmentation method and then identifies the item using bounding box regressions, with the class labelled by a CNN classifier.

3 Proposed Methodology

It is well know that the research methodology presents the sequence of the follows and the structure overview of the proposed model, this proposed model consists of four models: CNN, Random forest, Decision Tree and Naive Bayes. As already mention we are trying to find which algorithms can give us the best accuracy of ship detection and we are dealing with images that airbus ship detection provides. It is also a notable to mention that we used Yolovov3 as it is one of the most advanced of object detection.

Hence, to do the pre-processing, the images in this research are first subjected to a block section. Following this phase, the color and texture characteristics are retrieved from the picture blocks to be utilized as training data. A hybrid feature vector is created by combining these characteristics. Then, using the previously extracted feature vectors, the Naive Bayes, Decision Tree, and Random Forest classifiers are trained, this method has been done other researchers too. The categorization of ship blocks and non-ship blocks on the blocks of test images was done as the last step after the classifiers had been trained. There are three main steps that have done before applying the models. Here are the steps:

1. Block division
2. Feature Extraction
3. Color Feature

For the block division, in comparison to pixel-based detection, the block-based method offers more meaningful and comprehensive detection. It offers more homogenous information based on the image's color and texture richness, as well as the ability to create vectors quickly. This research used 64×64 pixel blocks throughout the preprocessing stage, but there are other researchers that have applied 16×16 and 32×32 pixel blocks. The second step is to apply a binary mask in order to label images if they are from a ship or not.

As it is important to choose the appropriate features in order to achieve the right classification, it is also important to do a feature selection based on the image blocks by creating a feature vector from the extracted features in the data. Similar to that, the color feature is also important as it gives information about the visual perception of pixels. This proposed method considers two different color spaces: HSV (Hue-Saturation-Value) and RGB (Red-GreenBlue) (Fig. 1).

From this figure, we can see that after the pre-processing stage, there are numerous steps to follow before applying the model, such as block division, feature extraction, and color features that will play an important role in extracting the appropriated images. After that, we trained CNN, Random forest, Decision Tree and Naive bayes.

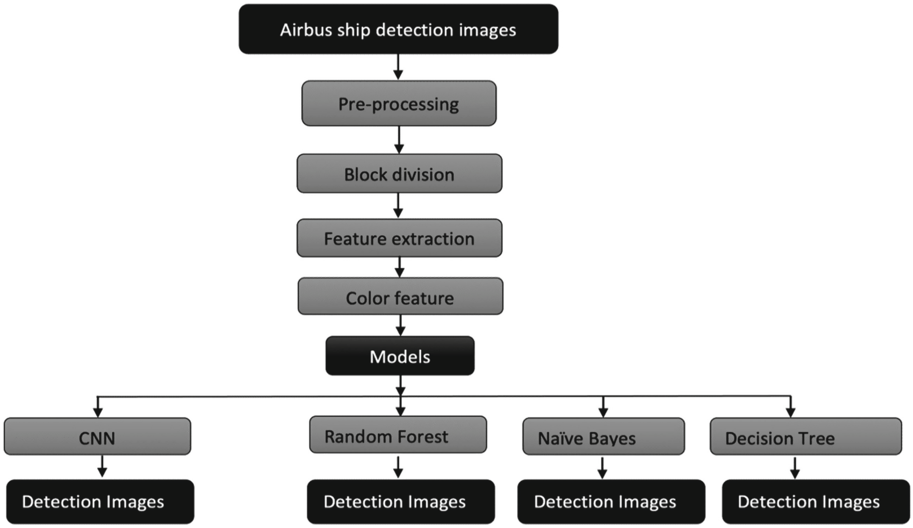

Fig. 1. Proposed methodology

It is well know that Convolutional Neural Networks (CNN) have achieved significant success in the perception and detection of the image as it consists of one or more layers and these layers are the input layer, sub-sampling, and fully connected layer. The upcoming figure demonstrates how CNN is applied to image detection by applying the sub-sampling layer followed by the convolution layer, and then again by doing sub-sampling later and finally producing a fully connected MLP (Fig. 2).

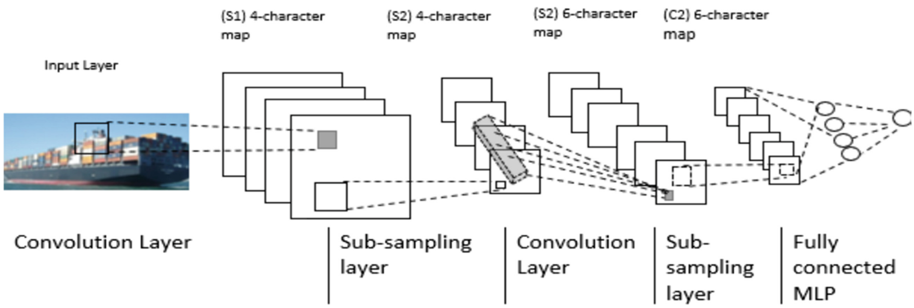

Fig. 2. CNN to Fully connected MLP

On the other hand, the second model we trained is the Random Forest, which is one of the most popular machine learning models. RF is a decision tree-based community learning algorithm that solves supervised learning tasks such as classification. It has a low noise tolerance and does not oversleep. It has much better performance categorization outcomes than the NB and DT approaches. It integrates several decision trees by generating stronger models in order to get a more accurate and stable estimate. During the training phase, the method uses a random data sample to build a model of several decision trees based on various data subsets. The unpredictability of the random forest model is a benefit, since it makes it more resilient than a single decision tree and eliminates the issue of conventional data being too compatible and comparable.

It is also applied to the Decision Tree (DT) algorithm, which is the second technique that delivers the most effective outcomes among machine learning algorithms. It may be used for regression and classification. A knot, branch, and leaf make up a decision tree. The root is at the top, the branch is the route from the root to the other nodes, and the leaf is the final outcome of these branches. This algorithm asks a series of questions to the data to be trained, and the outcomes are determined based on the responses. The information gain and information gain rate methods are computed while constructing a decision tree, depending on the criteria or attribute value of the branch in the tree.

The last model we applied is the Naive Bayes (NB) algorithm, which is a machine learning method that is regulated. It's a straightforward probability model for multiple classifications based on the premise of feature independence. NB implies that each feature contributes to the possibilities given to a class in its own right.

4 Results and Discussion

4.1 Dataset

The Kaggle platform [16] was used to generate a dataset of ship pictures from satellite photos for this study. The satellite pictures show the earth's surface, including farmland, buildings, roads, and other features. PlanetScope complete views of the San Francisco Bay and San Pedro Bay regions of California were used to create these pictures. It contains 4000 RGB pictures with a resolution of 80 $\times$ 80 pixels for two issue classes: “ship” and “non-ship.”

Table 1. Total number of samples

Class	Numbers of imges in each sample
Ships	1000
Non-Ships	3000

The pictures for the ship class must show the whole look of a single ship. It comes in a variety of sizes and orientations, as well as some ambient sounds. A non-ship class is made up of one or more of the following three elements: 1) random samples of various land cover characteristics such as buildings, water, vegetation, bare soil, and so on; 2) a partial picture of a ship; and 3) noises produced by bright pixels or strong linear features (Table 1).

4.2 Results

Following the steps that are mentioned after preprocessing in the methodology, we have obtained a hybrid vector by extracting color from each image's contents based on the block size. After that, the results were evaluated based on the block sizes while keeping in mind the successful classification. As we are dealing with each block size, we created different vectors that have different sizes based on block size and then apply the color space. As mentioned before, in this study it used 64 × 64 block sizes, and after we divided them into 64 × 64 block sizes, we found 40752 images.

By using Yolovov3 as mentioned in the methodology, we have created the bounding box and bounding area to make it more clear by feeding it into our models, so that the classification will be more accurate. Here is the picture that demonstrates the division of each picture into bounding boxes and bounding areas (Fig. 3).

	ImageId	Ship	Boundingbox	BoundingboxArea
0	000194a2d.jpg	1	[0.625, 0.38671875, 0.026041666666666668, 0.02...	440.0
1	000194a2d.jpg	1	[0.0983072916666667, 0.496744791666667, 0.01...	153.0
2	000194a2d.jpg	1	[0.3665364583333333, 0.23372395833333334, 0.01...	517.0
3	000194a2d.jpg	1	[0.09765625, 0.5032552083333334, 0.00130208333...	6.0
4	000194a2d.jpg	1	[0.4557291666666667, 0.244140625, 0.0247395833...	722.0

Fig. 3. Image bounding box

We can see from this figure that each image has a bounding box and a bounding box area, which is a vector based on the block size for each image. Hence, it is easy to fit the model or to apply it with a blanched bounding box. Before applying any model, here is the dataset images which we meant to detect the ships from inside the images.

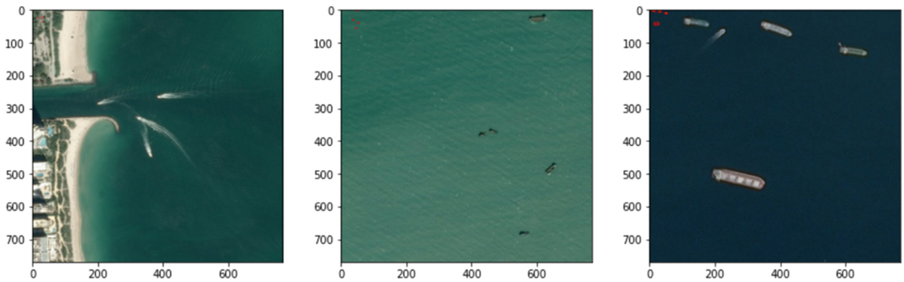

Fig. 4. Image of undetected images

From Fig. 4, we can see that there are certain ships in each image. However, after applying the models, we detected the ships in each image. Here is the detected result after applying the models.

Figure 5 illustrates how each image is block sized and then detected the ship by putting a red rectangle box which clearly shows that the model has performed and segmented the image accurately. Although there are other images where there is no ship in the image, the trained model returned without block sizing it and putting the rectangle boundary box around it.

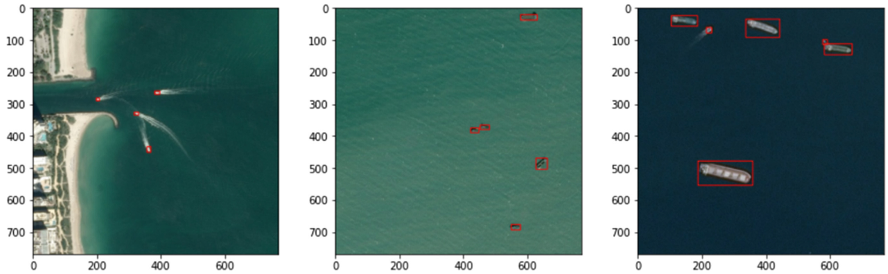

Fig. 5. Detected ship results

In terms of classification performance of the Random Forest, Decision Tree, and Naive Bayes, we applied only based on the forementioned color features that are RGB and HSV. Here is the accuracy of the classification performance (Table 2).

Table 2. Accuracy of the classification performance

Color space	Models			
Color features	Random forest	Decision tree	Naive Bayes	CNN
RGB	97.20	96.82	92.43	90.45
HSV	98.90	97.18	96.30	98.45

It can be seen from this table that Random Forest has achieved the highest accuracy compared to the decision tree, Naive Bayes, and CNN, yet the decision tree has also outperformed compared with Naive Bayes. However, the decision tree has also achieved a good accuracy performance, close enough to the Random Forest and better than CNN and Naive Bayes. Though our benchmark author [12] has also implemented these models, nevertheless, our implemented Random Forest has overall outperformed compared even with other author [12] results. However, the decision tree accuracy of the other author has scored 98.75, which is close enough to the Random Forest but still lower accuracy than the HSV that we obtained for this model. It is also worth noting that other researchers' Naive Bayes outperformed our implemented model, scoring 95.03, 98.72, RGB, and HSV, respectively. However, our model's Naive Bayes has achieved 92.43, 96.30 RGB and HSV respectively.

Due to the complexity and number of convolutional layers, our CNN model has achieved slightly lower performance compared with other Random Forests. CNN has achieved 98.45 compared to Random Forest, which has scored 98.90 in the HSV. Overall, Random Forest is the best model so far that has achieved a good result in terms of RGB and HSV, 97.20 and 98.90 respectively.

5 Conclusions

This work addresses the issue of detecting ships using artificial intelligence. We proposed a more accurate ship detection approach using four machine learning models. Those are Random Forest, Decision Tree, Naive Bayes, and CNN. Before applying the model, it was observed that doing block size and color highlighting played an essential role for feature extraction. Based on the results, Random Forest outperformed other models in terms of accuracy, as it scored 97.20% for RGB and 98.90% for HSV. Although other models have also performed well, their accuracy was slightly lower than the Random Forest technique.

For future work, it is important to classify the detected ships into categories based on the ship's operation. This will require the implementation of more complex features such as classifying objects according to their shapes and sizes.

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