AN APPLICATION FOR SHIPS IDENTIFICATION IN SEA USING SMART HYBRID MODELS

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ABSTRACT

In this work, some methods for the classification and recognition of optical images remotely sensed by satellite were analyzed with the aim of verifying their applicability and reliability for uses related to the automatic identification of the presence of ships. The application can have multiple purposes:

- Identify boats with migrants,
- identify co-smugglers' boats,
- Identify vessels in marine protected areas,
- Identify the presence of military ships in a war scenario.ì.

The experimental study was based on the analysis of the most popular data classification methods and on the use of a Keras convolutional network.

INTRODUCTION

The automatic identification of ships and their automatic classification can support a large number of applications in both the civil and military fields. These are wide-ranging tools that use ML and DL techniques on images or parts of images remotely sensed from satellite payloads. These technologies can also be applied to remote sensing images from aerial flights, which normally have better resolution, but the use with satellite images allows much larger areas to be covered and avoids the coverage limits of aerial monitoring. Monitoring marine areas with satellite images is also much cheaper than monitoring by air. However, it should be noted that the use of optical images presents the limitation of their use during the night. Ship detection and classification techniques have great application value in military and civil fields. In the civil sector it constitutes the basis for implementing the supervision of marine resources, monitoring illegal fishing, assistance with maritime rescue, the fight against smuggling, etc.; in the military field, it can be applied to patrolling, protection of interests and rights in territorial maritime regions, and monitoring of ports and important targets especially in case of radio silence that prevents detection and identification by land-based electronic radars. The main contributions of this study concern: (1) an analysis of classification techniques and a comparison of their performances; (2) the experimentation of convolutional network techniques and their performances (3) the use of a large public dataset that can be used as a reliable benchmark on the quality of the methods used, (4) the impact of Sea-Land Segmentation techniques and border ship detection to improve ship identification performance both in the open sea and near the coast. In the context of the study, the term "optical remote sensing images" includes panchromatic remote sensing images (PAN) and multispectral remote sensing images, which mainly contain blue (B), green (G), red (R), near-infrared bands (NIR), infrared remote sensing imagery, i.e. short wavelength infrared (SWIR), medium wavelength infrared (MWIR) and thermal infrared sensors (TIRS). The term "boat" refers to man-made objects that sail on the surface of the sea. During the search, expressions and terms such as "identification of objects", identification of ships or boats", "identification of marine targets", "detection of marine targets", "recognition of vessels", are used without any difference in meaning.

MATERIALS ND METHODS

The dataset consists of image fragments extracted from Planet satellite images collected in the San Francisco Bay area. In the dataset there are 2800 80x80 RGB images labeled with the classification "ship" or "non-ship". The images in the dataset were extracted from PlanetScope full-frame visual scenes, which are orthorectified to a pixel size of 3 meters. The pixel value data for each 80x80 RGB image is stored as a list of 19200 integers within the data list of which the first 6400 entries contain the red domain values, the next 6400 green domain values, and the last 6400 for the blue domain. The images with the boats show different orientations of the same and each image contains only 1 boat whose dimensions can be very variable. The image acquisition conditions are also affected by atmospheric conditions. The "no-ship" class includes 2100 images. A third of these images are a random sampling of different land cover features – water, vegetation, bare earth, buildings, etc. – which do not include any part of a ship. The next third are "partial ships" that contain only a portion of the ship, but not enough to meet the full definition of the "ship" class. The final third are images that have previously been mislabeled by machine learning models, due to bright pixels or anonal features.

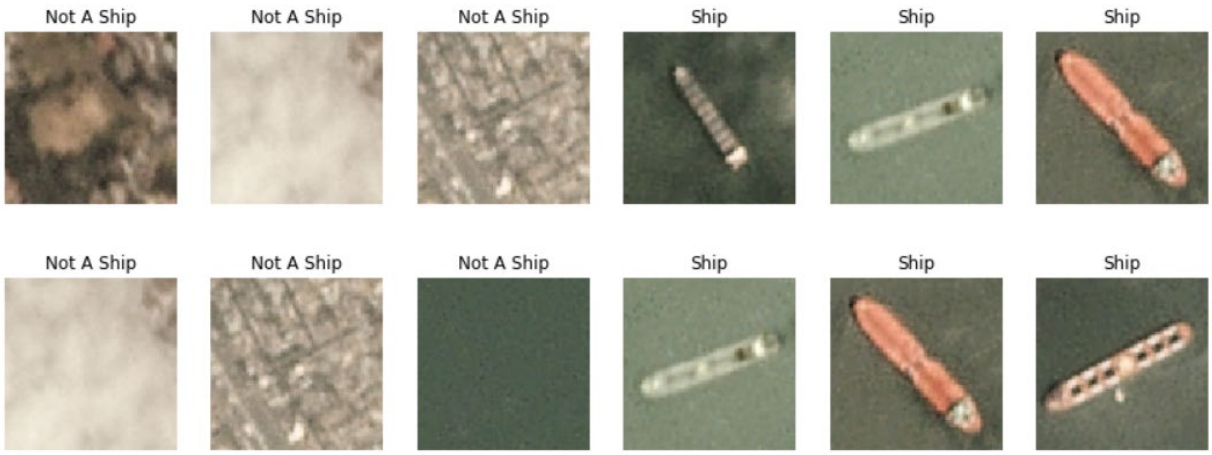


Figure 1 – Image dataset classification in “not a ship” and “ship”

The CNN technology is applied in ship detection and classification of remote sensing image tasks increasingly since it demonstrates its powerful feature representation abilities in 2015.[38] For a better understanding, the term “CNN structure design based method” used in this paper refers to a method that focuses on designing and improving the CNN architecture for ship detection and classification; on the other hand, the term “feature design based method” refers to a method that focuses on designing feature descriptions for ships or backgrounds. Consequently, it provides statistical data on the number of publications, CNN structure design based methods, and feature design based methods in years respectively according to the literature collection mentioned above. The feature design based methods dominant the early ship detection and classification research. However, ship detection and classification based on CNN structure design attract majority research attention in recent years as the development of CNN technology.

RESULTS AND DSCUSSION

The application ibrida has the following schema logico:

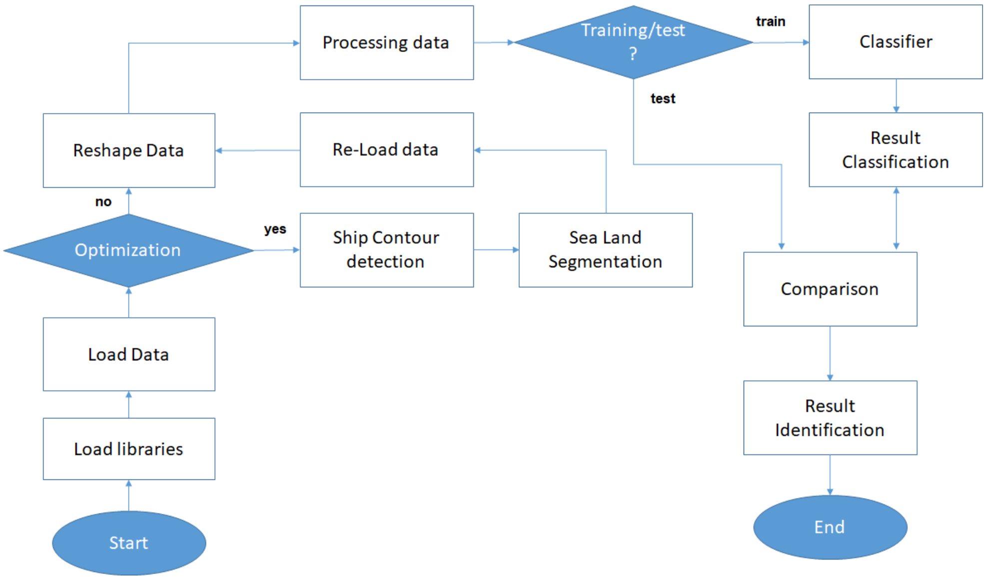


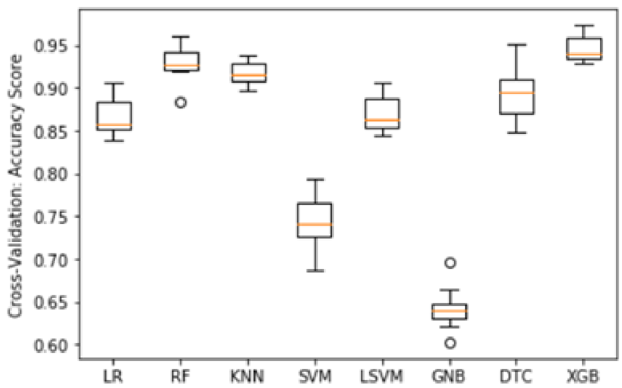
Figure 2 – Logical scheme of the application of identification of boats from remote sensing optical images from satellite

As can be seen from the figure, the application of hybrid methods is optional.

Evaluation of popular classifier

We have compared a series of classifiers among the most used ones, obtaining as a result that the XGB Classifier provides greater accuracy when applied to the dataset considered. For all the classifiers we adopted a split parameter equal to 20. With the use of different classifiers for the recognition of ships at sea, we obtained the results shown in the following table:

Table 1 –Comparison Accuracy of Classification Algorithms

Classification Algorithms	Algorithm Cmparison Accuracy
LR: 0.866071 (0.019965) RF: 0.928125 (0.019505) KNN: 0.916518 (0.014265) SVM: 0.745536 (0.031441) LSVM: 0.870089 (0.020208) GNB: 0.642411 (0.024078) DTC: 0.892411 (0.028125) XGB: 0.946875 (0.016397)	

Where

- LR = LogisticRegression
- RF = RandomForestClassifier

- `KNN = KNeighborsClassifier`
- `SVM = Support Vector Machine SVC`
- `LSVM = LinearSVC`
- `GNB = GaussianNB`
- `DTC = DecisionTreeClassifier`
- `XGB = XGBClassifier`

The accuracy achieved with XGBoost Classifier was 0.946875. In the recognition there are some false rejections for images in which boats are present. The recognition accuracy of images in which there are no boats is higher

Evaluate Convolutional Network

Abbimao also evaluated the performance of a keras-based convolutional network adopting 20 epochs. Evaluation of Convolutional Network was based on Keras CNN Infrastructure. We adopted a training with epochs = 14 obtaining an accuracy of identification of 0.938 The data relating to the accuracy of identification of boats at sea is obtained from the metrics "precision, recall and F1_score" adopted:

	precision	recall	f1-score	support
No Ship	0.99	0.93	0.96	430
Ship	0.80	0.97	0.88	130
avg / total	0.95	0.94	0.94	560

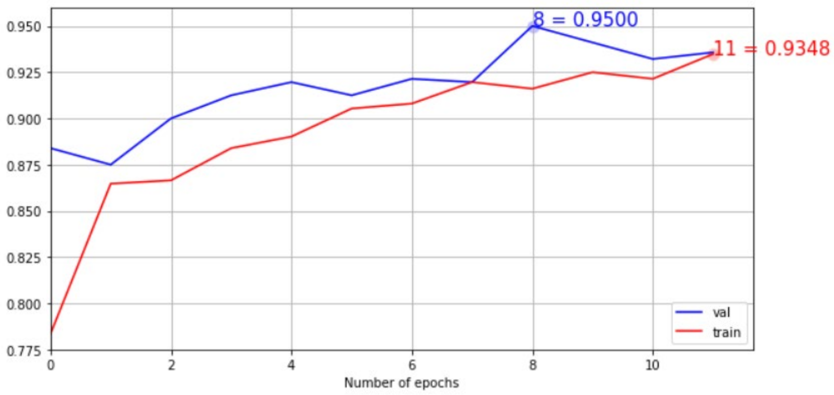


Figure 3 – Number of Epochs

To increase the recognition accuracy we decided to adopt two algorithms for Sea-land segmentation based on the histogram of sea regions to approximate the intensity distribution of sea pixels and then determine the segmentation threshold of the sea area and Contour detection [47] as shown in the following figures

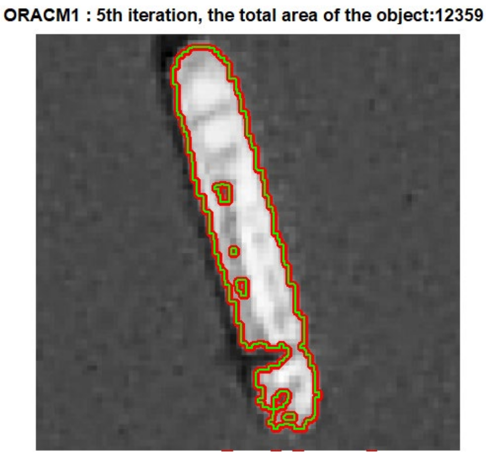


Figure 4 – Contour detection

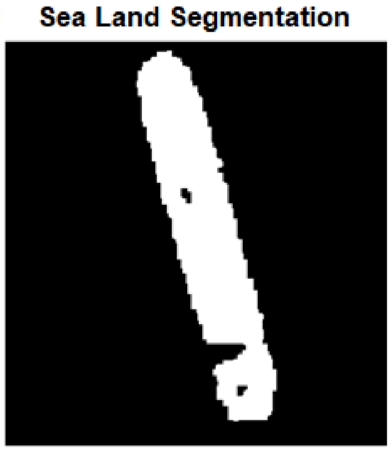


Figure 5 – Segmentation of sea water

The combined application of the sea-land segmentation and contour detection algorithms to the entire dataset significantly influenced the identification performance of boats in the open sea, even if the identification capacity increased as per the following table

Table 2 – Comparison before and after sea land segmentation and contour detection

Models	Before Optimization	After Optimization
XGBoost	0.946875	0.986863
Keras	*0.938343*	0,972235

The training and testing algorithms operate on images that have undergone sea land segmentation, while for each image in which a boat has not been detected, a check is made to understand whether it was possible to obtain a boat-shaped outline for that boat. If a boat profile is present then it is assumed that there is still a boat in the image. The presence of an outline both strengthens the identification of boats where they are not detected but also reduces detection errors of boats not supported by the presence of an outline. The residual identification errors depend on:

a. limits of the segmentation and contour detection algorithms in the vicinity of coastal areas or
b. bad atmospheric conditions.

CONCLUSIONS AND FUTURE WORKS

We have seen that the application of the XGBosst algorithm is found to be superior to the application of classifier algorithms and the CNN-KERAS algorithm. Furthermore, we experimented with the application of two algorithms, sea land segmentation and c. The combined application of the sea-land segmentation algorithm and the contour detection algorithm with which we managed to obtain superior identification accuracy both with XGBoost and with CNN-KERAS. The entire data set significantly influenced the performance of identifying boats in the open sea. To reduce the computational burden, these algorithms were adopted only on the reduced set of images for which there was no boat identification. This is in order to be sure that we have not made a false rejection which in this context would be more serious than a false acceptance. Starting from the 94% accuracy obtained with the XGBoost and CNN-KERAS classifier. Obviously these two methods slowed down the performance of the training and testing and identification phases, but they allowed the identification accuracy to be significantly improved. The method used is very effective with vessels in the open sea, but its performance deteriorates in the identification of vessels close to the coast. This degradation of performance near the coast does not affect the application purposes underlying the experimentation which are to identify migrant boats (but also smugglers) especially as they move towards the coasts of sovereign countries without an official request to the destination country. The method appears quite robust even with low resolution satellite images. Images of data set used are provided by different satellite and in different weather conditions so we have and different resolution. The intensity of pixels and therefore the quality of the starting images affects the quality of the images after the reshape and therefore the identification of the boats and contours

For future work it will be possible to operate on two levels:

1) Quality and resolution of the satellite images of the source images which also affects the reshape result.
2) Preprocessing algorithms to improve color quality and vessel contours.
3) Cloud Filtering Optical remote sensing imaging is inevitably affected by weather conditions such as cloudy and foggy, which introduces interference within ship detection and classification and arouses false alarms. Therefore, it is crucial to suppress the influence of clouds and fog on optical remote sensing images when performing ship detection and classification tasks. There are three common methods in cloud filtering: (A) cloud mask threshold based on the Gaussian distribution model; (B) threshold segmentation based on band ratio; (C) cloud filter based on Fourier transform.

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