Detection Of Ships in Satellite Imagery Using Deep Learning Techniques

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***Abstract*—In the commercial/military realm, ship detection hasa variety of applications, and offshore security is an increasingly important need for countries around the world. For many private and public institutions, it is essential to comprehend marine activities on water bodies and at sea. Illegal, Unregulated, and unreported fishing and human trafficking must be prevented or deterred by the monitoring and regulation of activities like fishing, cargo transportation, passenger travel, and recreational traffic and it aids in preventing illegal activity. The numerous disruptions and sounds in these kinds of photos make ship detection one of the most difficult tasks. Because ships come in a variety of shapes and sizes, it might be challenging to identify a pattern or any regularity in these pictures. When there are merely ships of different types in the ocean, it is comparatively simpler in a homogenous environment. The issue, however, becomes tenfold in heterogeneous environments, which include additional components like beaches, harbors, vessels, rocks, islands, etc. The advantage of Synthetic Aperture Radar (SAR) in remote sensing is that it offers continuous coverage during all weather conditions.**

***Index Terms*—Ship Detection, Satellite Imagery, Deep Learning**

I. INTRODUCTION

In remote sensing image classification, machine learning has proven to be an essential research field. Data for picture classification are composed of numerous sample s that are each represented by numerous datasets. High levels of accuracy in classification and training performance are therefore extremely difficult to achieve. Machine learning approaches have been widely utilized to create precise classification models. To boost the detection accuracy, a number of strategies have been put forth in this area. Even other hybrid methods are put forth; however, they are incompatible with extreme weather since they could result in erroneous detection.

Despite not being perfect in all circumstances, these cutting-edge techniques were reliable to a point. This is the rationale behind considering deep learning. In order to achieve high levels of accuracy, CNN models can be trained using thousands of instances, including all possible worst-case scenarios. The main objective is to detect objects, and in this case, a ship is the object. The CNN neural network performs excellently in this regard. A deep learning model represents data at different levels of abstraction by incorporating multiple layers of processing. Through the combination of convolutional neural net- works (CNN) and powerful graphical processing units (GPUs), it has been able to achieve astounding success in the object classification and detection. Image classification is crucial (Wen et al., 2015) in satellite imagery interpretation. Moreover, in numerous fields, including land management, urban planning, environmental research and monitoring, and the early detection of natural disasters. There are a number of applications for satellite images of ships with high resolution, including maritime monitoring, illegal fishing, secure and efficient transport in harbors, military purposes, and many more.

Ship Detection is the basic need in maritime security; It maybe used to look for lost ships, commercial and also military ships. Though Automated Identification Systems exists in Ships, they can be manually disabled to avoid identification. Therefore, there is a need to develop and automated shipdetection system which can perform its task in real time andis also controlled only by the authorized personnel.

II. RELATED WORKS

Various papers describe the techniques and methods suggesting the implementation ways as discussed here.

An algorithm for detecting ships using three-channel RGB SAR images based on YOLO-V4 was presented by the authorsin [1]. Using SAR image data and feature extraction through network, they propose a multi-channel fusion SAR processing method. Based on YOLO-V4, the researchers built an end-to- end CNN where each grid detects objects belonging to its grid. The new NSLP image processing method and YOLO-V4-lightlightweight model were adopted in order to enhance the results,which resulted in reduced false identifications and accurateseparation of ships from similar embankments.

The authors in [2] presented a paper discussing Deep Learning for detection of ships and their classification. This paper aims to detect and classify ships. They presented a novel method for automatically categorizing ships and small Unidentified Floating Objects (UFOs) based on optical aerial data collected in the visible spectrum (CNN). They enhanced image by a distinct method for the backdrop and the ground toreduce visual noise and improve contrast and got the desired results. They applied ship detection masks to see if the ship located in the frame or not, and used four classes of boats, and detected them all. They applied various CNN Networks, such as ResNet 50, ResNet v2, VGG-16, and VGG-19, to classify ships. Their comparison was based on factors like accuracy, F1- score, validation and loss. They concluded that ResNet v2 has the minimum loss value, highest validation accuracy, and highest F1 score. This network's superiority over the competition has been established.

The authors in [3] proposed a new classification technique called Transfer Learning-Convolutional Neural Net- work (TC-CNN). Through transfer learning, they classified remotely sensed images using different CNN architectures. Pre-processing and compression of the satellite data have been performed. In their experimental analysis, the proposed TL-CNN resulted in an increase in classification accuracy of 99.99%, when compared to the existing algorithms such as CNN, which is 99.91% accurate, SAE, which is 93.98% accurate, and DBN, which is 95.91% accurate.

In [4], the authors discussed the use of Transfer Learning with ResNet for detecting smart ships. Deep learning was chosen due to its ability to be automatic or at least semi-automatic, which is one of the contemporary methods. This paper's main objective was to detect ships with high accuracy. They used Fastai library for simplification of training neural networks in a fast and accurate manner. They concluded that the proposed strategy outperforms a wide range of cutting-edge approaches which are based on experimental analysis. This result was achieved by using a pre-trained model with a transfer learning strategy

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The authors in [5] discussed Deep Learning for Detecting and Identifying Vessels from Spaceborne Optical Imagery. They achieved 0.795 F1-scores using a RetinaNet based vessel detection model on a multiscale dataset. RetinaNet was used to develop the model. For determining whether two images represent the same vessel, they implemented a Twin neural network. Twin neural networks ranked candidate vessels efficiently from an autonomous test set with top one accuracy of 38.7% and top ten accuracy of 76.5%. Approximately 2500 vessels were used to train a twin neural network.

Machine learning methods for detection of ships using satellite imagery has been presented by the authors in [6]. In data preprocessing, HOG feature extraction was used to improve the results of several machine learning methods on binary classification tasks. Furthermore, they implemented convolutional neural networks (CNNs) with 99% accuracy. After 32 epochs, their CNN model outperformed the other models with an accuracy of 99%

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The authors in [7] have suggested a DenseNet architecture to find and categorize ships in harbor regions. For classification, CNN has been employed for classification. The ideal setting has been reached after a number of adjustments. The optimization hyperparameters for optimizer selection, batch size, and learning rate has all been adjusted. According to experimental findings, the Adam optimizer has over 99.75% success rate and 0.0001 learning rate when applied. DenseNet can accurately categorize ships with above 90% precision. In order to improve the accuracy of ship detection in SAR imagery, the authors in [8] developed an anchor box optimization technique. The R-CNN and its adaptable anchor sets performed better with Residual Networks as a backbone. Using both anchor parameters, they observed a significant improvement in the process of ship detection of over 4.29% in the mean Average Precision.

The authors in [9] presented four object detection pipelines based on a new dataset that has incredibly small objects in images, including faster RCNNs, YOLOs, SSDs, and SIM-RDWNs. These pipelines include fast region-based CNN, quicker single-shot detectors, and faster SSDs. Using 2213 objects for training, they calculated the anchors by fine- tuning the parameters. These four methods were examined using their special dataset. Models meet real-time requirements on satellite images with small, closely spaced objects, and perform well on unidentified satellite images.

An optical remote sensing technique based on CNN was presented by the authors in [10] for detecting inshore ships. Two stages were primarily involved in the proposed method: the selection of regions based on ship heads and the localization of ships based on a multitasking network that performed bounding-box classification and regression. As part of this approach, they created candidate locations by using a classification network while searching the world for ship heads. For precise pinpointing of ships, bounding-box regression process is used to improve the bounding boxes of target ships and the classifier is used to eliminate incorrect detections. Optical satellite pictures show that the suggested technique is effective at detecting inland ships.

III. METHODOLOGY

The algorithm used for this purpose is ResNet50. Residual network, most commonly known as ResNet, is a special type of neural network. It stacks architectural structures called Residual blocks, one over the other to form a network. A technique called skip connections, connects activation layers to further layers by skipping some layers in between to form a residual block. This network has evolved to solve the vanishing gradient problem. ResNet50 is a pre-trained 50-layer deep learning model trained on ImageNet, to aid in image classification. It can classify objects into 1000 categories.

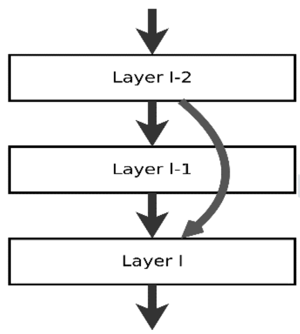


Fig. Canonical form of a residual neural network A layer l-1 is skipped over activation from l-2.

The System design mainly consists of:

A. Data Acquisition
B. Data Pre-processing
C. Defining the Classifier Model
D. Splitting the Data
E. Training and Optimization of the Model
F. Analysis of Results

A. Data Acquisition

Collecting a large dataset of images that contain both ships and non-ships. This dataset will be used to train the ResNet algorithm. The dataset we have used in this project is available publicly on the internet. The data from the dataset is used to train the model, validate and to test and evaluate the final performance of the model.
The dataset MASATI-V2 dataset has been collected from a US based Military database [10]. The dataset consists of about 7000 images across 7 classes.

B. Data Pre-processing

The goal of pre-processing is an improvement of image data that reduces unwanted distortions and enhances some image feature important for further image processing.
Data pre-processing is a stage where the acquired data is brought into the form of input as per our model requirements. It includes image resizing, noise removal etc. The images of dataset have been resized to 224 * 224 pixels. Transfer learning is a technique in machine learning and deep learning where a pre-trained model developed for one task is reused as the starting point for a new but related task. Instead of training a new model from scratch, transfer learning allows us to leverage the pre-trained model's knowledge, which can lead to faster training and better performance on the new task, especially when the new dataset is small or similar to the original dataset.

Class	# samples	Description
Ship	1,027	Sea with a ship (no coast)
Detail	1,789	Ship details
Coast & ship	1,037	Coast with ships
Multi	304	Multiple ships (with and without coast)
Sea	1,022	Sea (no ships)
Coast	1,132	Coast (no ships)
Land	1,078	Land (no sea)

Fig. Distribution of the classes in the MASATI Dataset.

C. Defining the Classifier Model

The most commonly used algorithm for an image classifier is a deep learning model (CNN architecture). Two CNN models have been developed; one a pre-defined CNN architecture (hereafter referred to as model 1) and another, a transfer learning model with the ResNet50 architecture as input layer (hereafter referred to as model 1).
For the ResNet model two hidden layers are used, the first with 16 nodes and ReLU activation layer and the second with 2 nodes and softmax activation function, and a flatten layer to reshape the output of the second layer into a 1D array. The output layer uses softmax activation function and the loss function is binary cross-entropy. While finetuning the ResNet model, only three layers named 'res5c_branch2b', 'res5c_branch2c', 'activation_97' are set to be trainable.

D. Splitting the Data

The dataset has been split on the train and test data in the ratio 0.75:0.25. Further, the train data has been split into train and validation data in the ratio 0.80:0.20. Further, to increase the amount of data for training, data augmentation has been used. Data augmentation is a process where in new data can be generated from the existing data by making some small changes to it. We have augmented data using the transformations with rotation-angle, zoom-range, width and height shift range and shear-range etc.

E. Training and Optimization of the Model

The models have been trained for 5 epochs each and the results are compared. Initially, the weights of the ResNet50 layer have been freezed and trained. Next, as a step towards finetuning, the residual layers and activation layers have been trained and another model has been developed. This finetuned model is hereafter referred to as Model 3.

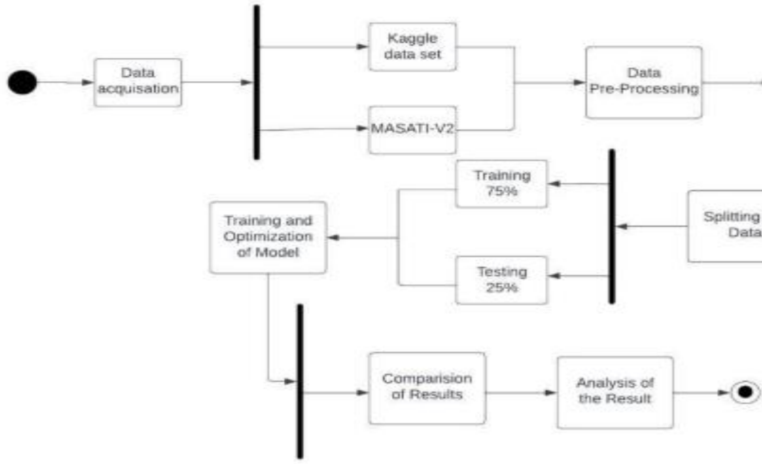
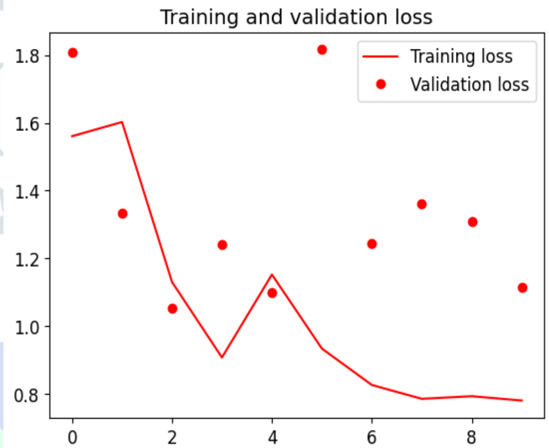


Fig. High Level Design

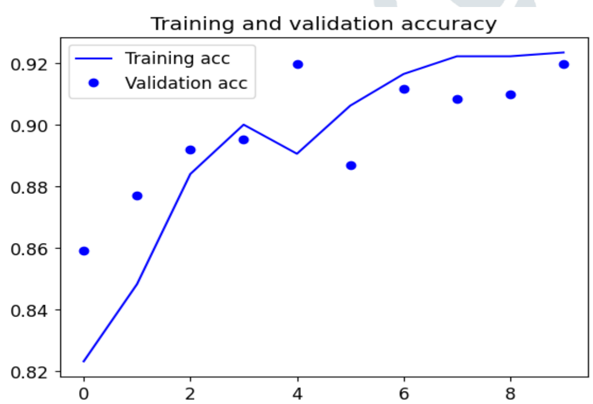
F. Analysis of Results

The results obtained from all the 3 models have to be obtained and compared using different performance metrics like accuracy and loss graphs, ROC curve, Confusion matrix etc.

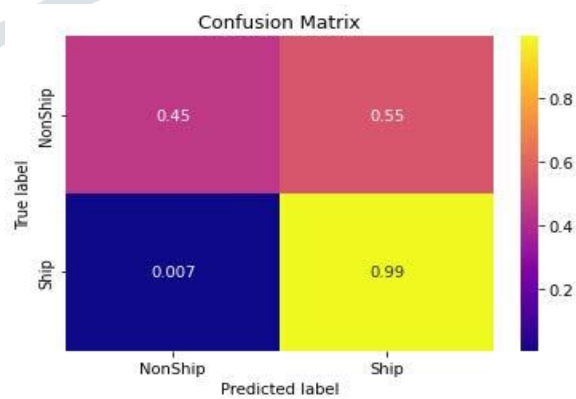


IV. EXPERIMENTAL ANALYSIS AND RESULTS

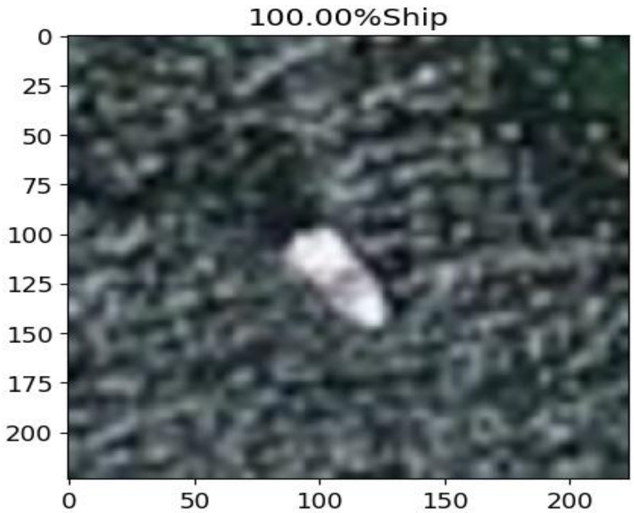
Multiple Performance metrics were calculated for all the 3 models for the dataset. The accuracy and loss graphs were plotted while training each model. The proposed system for Ship Detection, using ResNet50 detects the ships and various classes of the ships images.

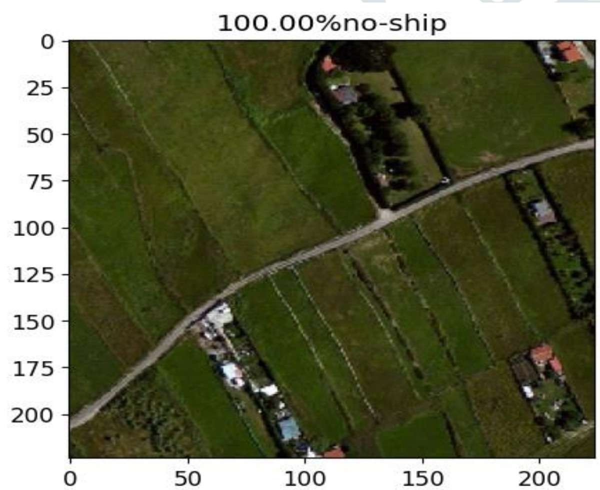


A confusion matrix is a n*n (2*2 in this case) which compares the actual labels of the images to the labels of the images predicted by our model



V.OUTPUTS





Ship detection plays a vital role in the maritime security. Hence, a classifier model is developed to classify a given input image as "ship" and "no-ship".

From the above experimental results, it is conclusive that the model 3 (model in which the pre-trained ResNet50 was finetuned) is giving the best results, i.e., 82.6% and 93 % accuracy in both the datasets respectively. As a scope of future work, there are 2 things:

- Create a dataset which is more suitable for the Indian coastline from the Indian satellite data.
- Dive into multi-class classification of the identified ships.

V. CONCLUSION

In this paper, we have discussed numerous techniques for detecting ships in the images obtained from sensors and to detect enemy ships, monitor fishing activity, goods transportation and any other illegal activities. It is evident from many researches that Deep learning is an ideal approach to detect ships in real time. We can utilize deep learning approaches like SVM, VGG, GoogleNet, Resnet, Inception Resnet etc. to detect ships with accuracy and minimumloss. With the help of this survey and study, it is obvioustthat we can detects ships from images by employing various datasets that contains ship features and attributes and super- vised and unsupervised machine learning approaches. Dataset raw images can be enhanced for more accurate results. To improve prediction outcomes, model review, dataset analysis, and feature extraction are also crucial.

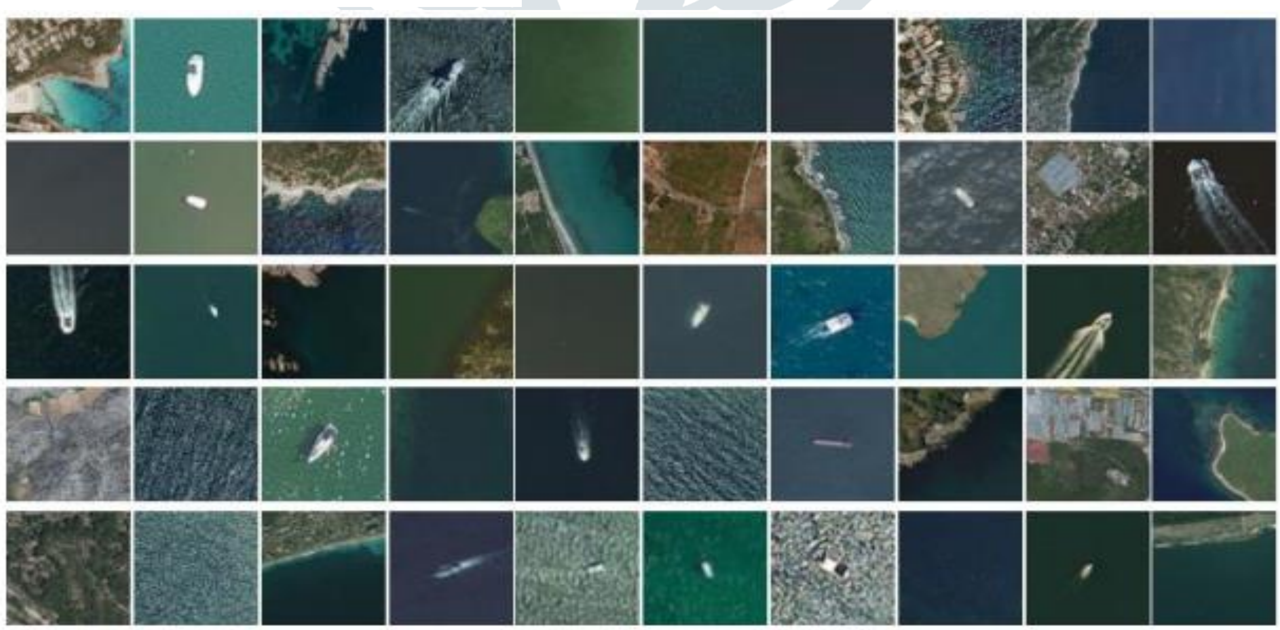


Fig: Some images of MASATI dataset.

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