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Deep Learning for Ship Detection Using Satellite Images

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ABSTRACT: The detection of marine and onshore river ships has been investigated using both detection and ranging (SAR) and optical satellite imaging. Traditional ship recognition techniques, which are commonly used on SAR photos, may have a high false alarm rate and be influenced by the sea level model, particularly in streams and offshore locations. Traditional detection techniques based on optical images do not work well on small and growing ships. This study employs neural architectures to provide a rapid geographic deep convolution network (R-CNN) technique for detecting ships in high-resolution satellite data. To begin, we select GaoFen-2 optical satellite photos with a horizontal resolution of m and partition the large image region using an R-R-CNN. The area has been divided into discrete fields of interest (ROI) that may or may not contain ships. Following that, the ROI images are subjected to ship recognition techniques based on a geographical area deep neural network (R-CNN). In a proposed method to achieve more accurate results of comparatively tiny and collecting ships (RPN), we use an effective option approach to detect, Faster-RCNN, and keep improving the architecture of its previous convolutional (CNN), VGG16, while using delivery is available feature representations and having to perform ROI consolidation on a larger previous layer.Finally, we compare the element (fe model (DPM), two other widely used target recognition architectures, the bolt action fully convolutional analyzer, the previous VGG16-based Faster-RCNN, and our enhanced Faster-RCNN to the active shape model, one of the most influential classic ship detection techniques. Experiments show that our improved Faster-RCNN method outperforms the competition.

1.INTRODUCTION

There are numerous applications for ship detection on remote sensing photos in defense and civil security. inshore surface, inland waterway surface Boat ID involving satellite pictures can give continuous area data for route the board and marine pursuit and salvage, guaranteeing the viability and security of action adrift and on inland streams, for example, sea transportation supplies. It additionally assists with administering and fabricate huge beach front zones and harbors, which assists with keeping up with the climate and ocean wellbeing, as well as seaward regions and inland waterways. The majority of current research [1–11] is based on SAR pictures taken with synthetic aperture radar. Regardless, creating and tackling a legitimate measurable model for a muddled ocean region is troublesome.

Utilizing an optical satellite image-based target detection method is an additional option in light of the aforementioned issues. Over the past few generations, optical satellite images have provided a wealth of structure, outline color, and texture information. Additionally, vessel recognition using 2D image detection techniques in Landsat images has already been extensively studied [14–16]. The customary techniques for delivery acknowledgment depend on division calculation [17], and expects that the ocean level be in extraordinary condition; However, there is insufficient detection accuracy. Many different researchers started using physical facilities on custom elements like the classification algorithm (SVM), Xgboost, decision trees, and so on [18,19]. These custom elements are based on characteristics that were hand-engineered, like the svm classifier (SVM), logistic regression, decision trees, and so on. Convolutional brain organization (DCNN) can separate semantic level picture includes that are powerful to picture commotion and morphological changes and relative places of targets [36-39]. It is possible to detect ships of a variety of sizes, shapes, and colors using the DCNN-based methods, which are superior to conventional target detection techniques. However, due to its use in optical remote sensing images, the majority of studies combine a CNN with SAR images that lack color. Besides, it is as yet a test to recognize little endlessly transports that are thickly near one another.

An improved R-CNN method for ship detection on optical remote sensing images is presented in this study to address the aforementioned issue, particularly with regard to the classification of fleet clusters and small warships. A large number of remote sensing images with a spatial resolution greater than 1 m are now available thanks to advancements in remote sensing techniques. Examples of such images include Quick Bird, GeoEye, WorldView, GaoFen-2 (GF2), GaoFen-4, and others. These submeter-range spatial data photos can be used to identify small ships and distinguish them from groups. We focus on GF2 optical images, which were taken from China's first spatial and spectral satellites and have a resolution of one millimeter [40]. The photos in GF2 are of high quality and feature a lot of color.

To distinguish small ships from clusters and detect them, additional relevant information is required. Theoretically, images with a greater degree of definition, such as Quick Bird and GeoEye, ought to yield better results when it comes to detection. In our review, nonetheless, GF2 is more savvy.

To overcome the aforementioned issue, particularly with regard to the recognition of small warships and ship groups, we present an updated R-CNN method for vessel classification on optical satellite images in this study. Numerous remote sensing images with granularities exceeding 1 m are now accessible thanks to advancements in multispectral sensors. Examples of such images include Quick Bird, GeoEye, WorldView, GaoFen-2 (GF2), GaoFen-4, and others.

These submeter sensitivity satellite images can be used to distinguish small ships from clusters. The GF2 optical images, which were taken from Korea's first spatial and spectral satellite and have a resolution of one millimeter [40], are the primary focus of this article. The high resolution of the GF2 images provides a wealth of color, texture, and other features that are essential for identifying small ships and distinguishing ships across clusters. Theoretically, images with a greater degree of definition, such as those from GeoEye and Speedy Bird, should yield better results when detected. In our review, in spite of the fact that, GF2 is more financially savvy

2.LITERATURE SURVEY

2.1. Sensor platform used for ship recognition

According to Kanjir et al. [10], the most commonly used sensors in marine surveillance applications are optical, infrared, and radar sensors. Radar is a common technology that has been used in ship monitoring and detection since the 1990s. The satellite-based sensor is also popular for ship detection, which necessitates remote sensing, continuous monitoring, and frequent data collection..

2.2. Object detection approach

The deep learning-based classification algorithm is a growing area of research interest. Lin et al., in [11], have developed a method for object detection in remote sensing images that is rotationally invariant. Their invariant highlights have conveyed great exactness in the location of complicated objects in remote detecting pictures. Huang and others 12] have introduced their arbitrary backwoods strategy, where the preparation speed is quicker contrasted with the regular methodology yet keeping up with a similar precision execution. An original strategy in light of meager portrayal and Hough casting a ballot (SR-Hough) was presented by Yokoya and Iwasaki [13]. In the remote sensing images, this method focuses on finding instances of a particular object or a class of objects. Prasad et al.'s [14] have presented a study that examines various challenges in maritime surveillance, such as occlusion, orientation and scale variations, a large number of object classes, and weather variations.

Yu et al. also presented a machine learning strategy [15] to use a context-driven Bayesian saliency model to identify dim and small objects in an FLIR image. However, explicit object feature definition is required for these conventional machine learning methods. The conventional approach has been fundamentally altered by learning-based features thanks to recent advancements in computer vision and deep learning. Krizhevsky et al., the winner of the ImageNet Large Scale Visual Recognition Challenges (ILSVRC), [16] has promoted the utilization of profound Convolutional Brain Organization (CNN) for picture acknowledgment, location and especially for characterization. Since then, a great deal of research has been done on CNNs, with the activation function, optimization technique, network architecture, and regularization mechanism all getting better [17]. Tang et al. [18] have used SPOT-5 dataset images to detect and classify ships using a combination of a compressed-domain framework, a deep neural network, and extreme machine learning. Zhang et al. [19] also propose the sequential convolutional neural network (S-CNN) method, which combines CNN with the saliency detection method, with the same objective in mind. They discovered that their approach performs better than the R-CNN. [20] provides a succinct overview of the most recent saliency object detection technique. Liu and co. [21] have also used Google Earth images to classify ships and found that the CNN method performed better than support vector machines and standard neural networks. In contrast, the work in [22] utilized the same strategy with a focus on the navy application. They highlighted the significance of spatial relationship in enhancing accuracy by introducing a brand-new method known as spatially related detection with convolutional neural network (SPARCNN).

3.PROPOSED SYSTEM

- In maritime surveillance, automatic ship detection of synthetic aperture radar (SAR) images is commonly utilized. SAR images have the ability to detect in all weather conditions and at all times of day. As a result, a variety of object detection algorithms have been presented, spanning from classical to deep learning techniques.
- Seagoing boats are susceptible to current ship detecting technologies. In order to address these issues, this project proposes a unique multi-scale ship detection approach in SAR images based on a Multi-scale Faster R-CNN network.
- To begin, the SAR pictures are decomposed into a pyramid structure and the features are extracted using a multi-scale network. Then, utilizing the feature map for each layer, the region proposal network (RPN) is used to generate suggestions that include ship targets Finally, to acquire the final detection performance, these recommendations are fed into the classification network.

3.1 IMPLEMENTATION

Data Collection and Preprocessing:

Collect a dataset of high-resolution optical remotely sensed images that contain ships.

Annotate the images to create a labeled dataset, where ships are marked or segmented.

Split the dataset into training and testing sets.

Preprocess the images, which may include resizing, normalization, and augmentation techniques to increase the size and diversity of the training set.

Building the CNN:

Design the architecture of the Convolutional Neural Network (CNN) for ship extraction.

Choose an appropriate deep learning framework (e.g., TensorFlow, PyTorch) to implement the CNN.

Define the layers of the CNN, including convolutional layers, pooling layers, and fully connected layers.

Train the CNN on the labeled training dataset using backpropagation and gradient descent.

Post CNN Processing:

Extract the ship-related features from the output of the CNN.

Apply post-processing techniques to refine the extracted ship regions and improve the accuracy. This may involve filtering, thresholding, morphological operations, or other image processing techniques.

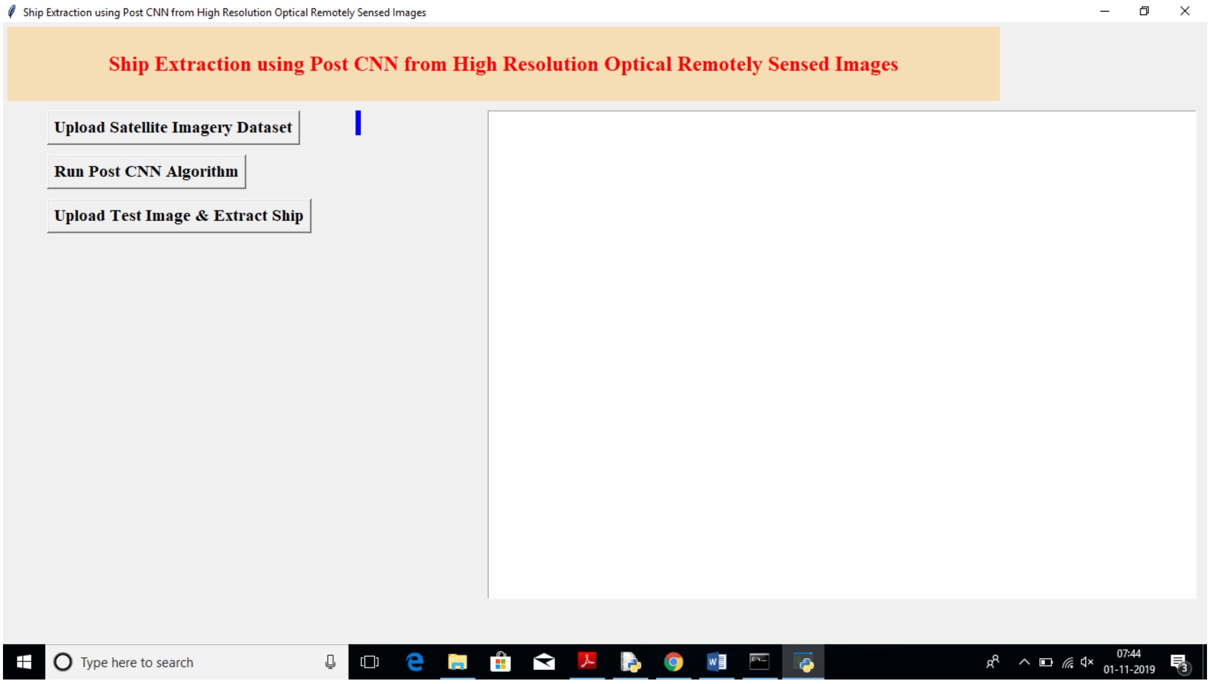
Evaluation and Validation:

Evaluate the performance of the ship extraction model using the labeled testing dataset.
Measure metrics such as accuracy, precision, recall, and F1 score to assess the model's performance.
Iterate and fine-tune the model architecture or hyperparameters if necessary.

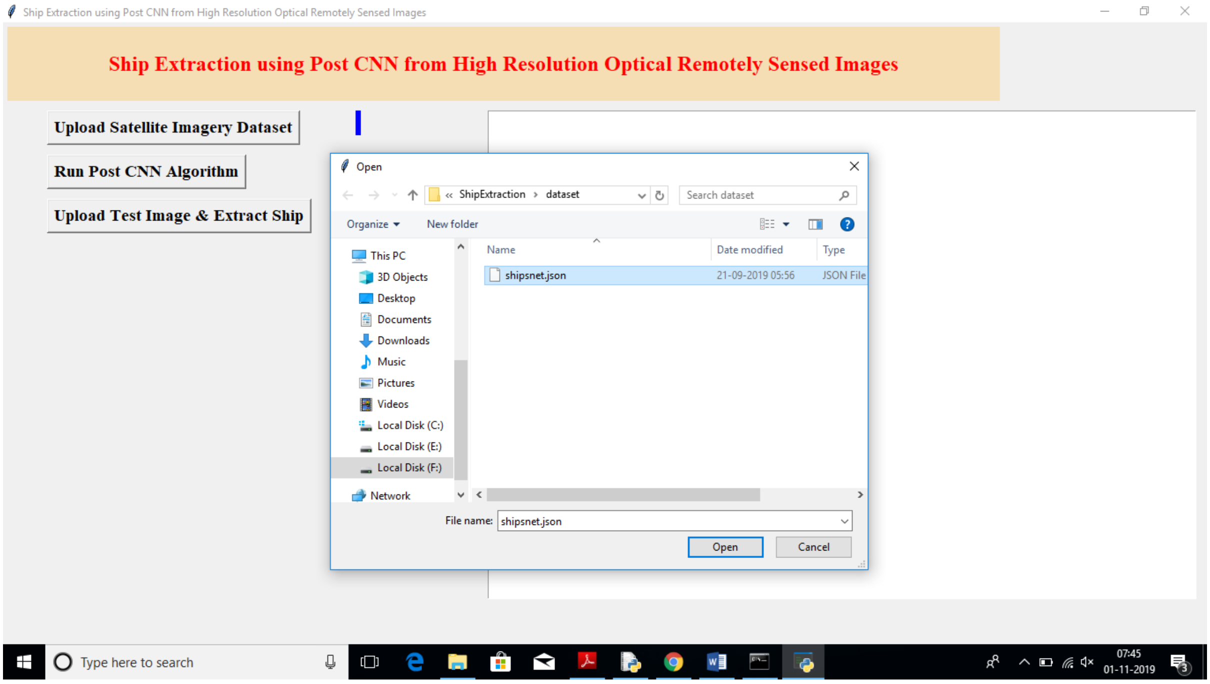
Deployment and Inference:

Once the model achieves satisfactory performance, deploy it in a production environment or integrate it into an application.
Provide input images to the deployed model for ship extraction.
Process the extracted ship regions further if required for downstream tasks or visualization.

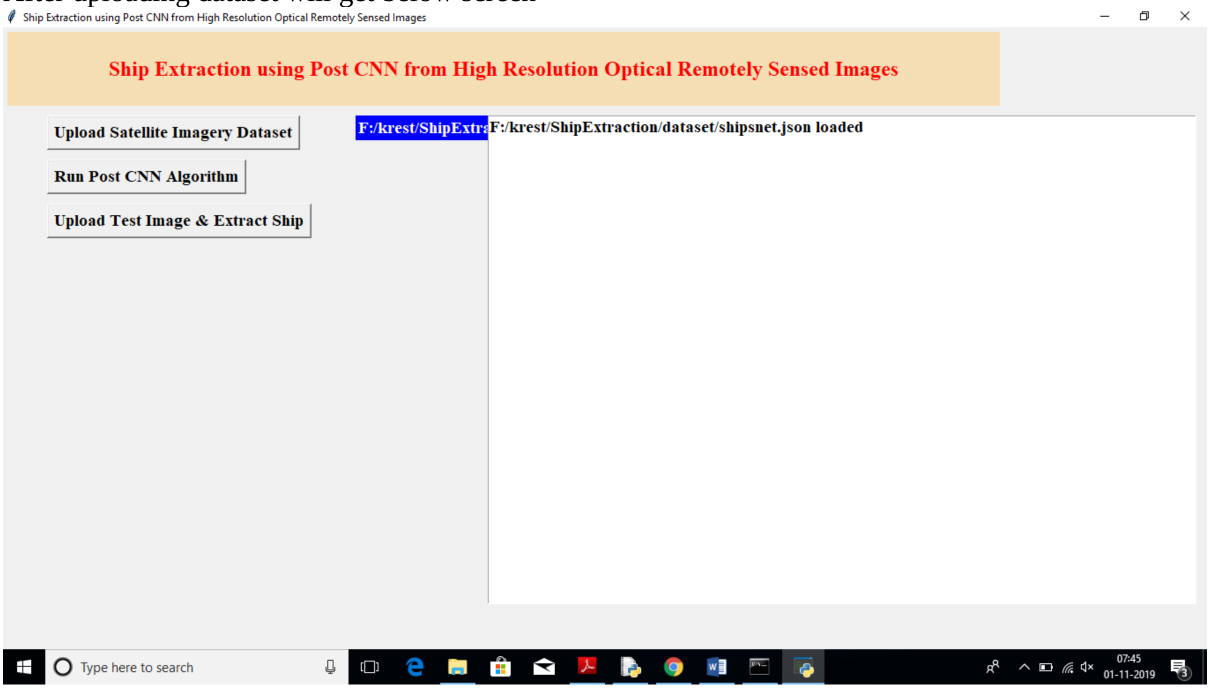
4.RESULTS AND DISCUSSION



In above screen click on ‘Upload Satellite Imagery Dataset’ button to upload ship image dataset



After uploading dataset will get below screen



After uploading dataset click on ‘Run Post CNN Algorithm’ button to generate CNN model on uploaded images dataset

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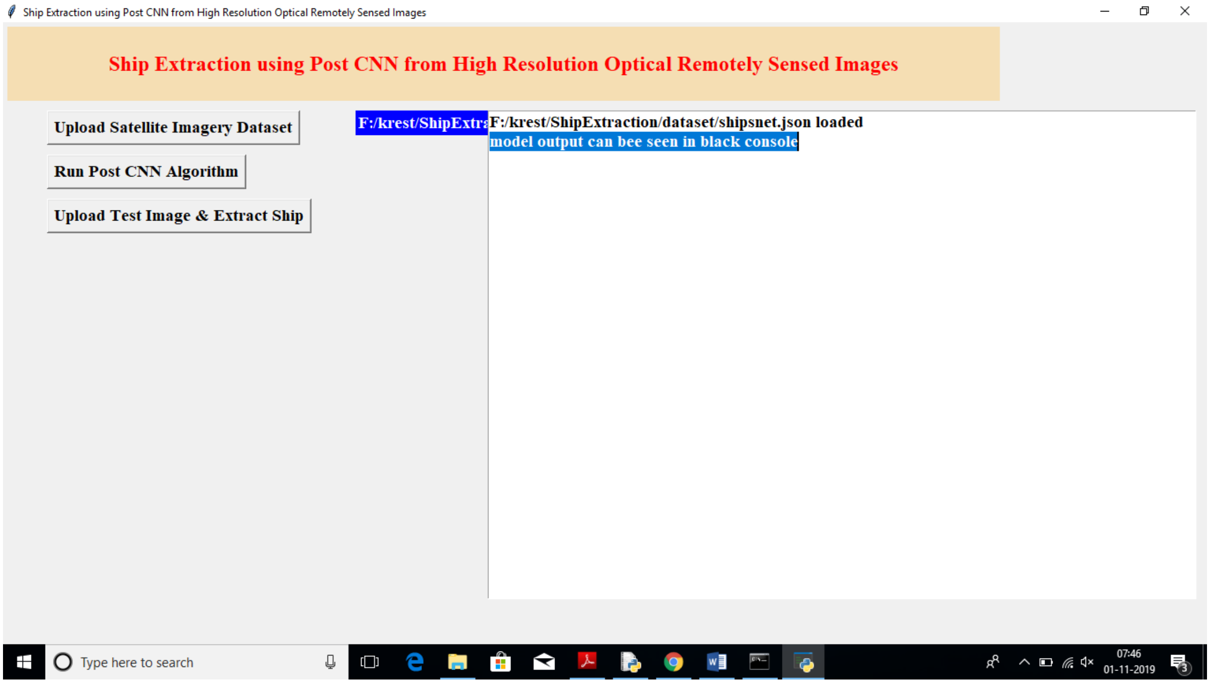
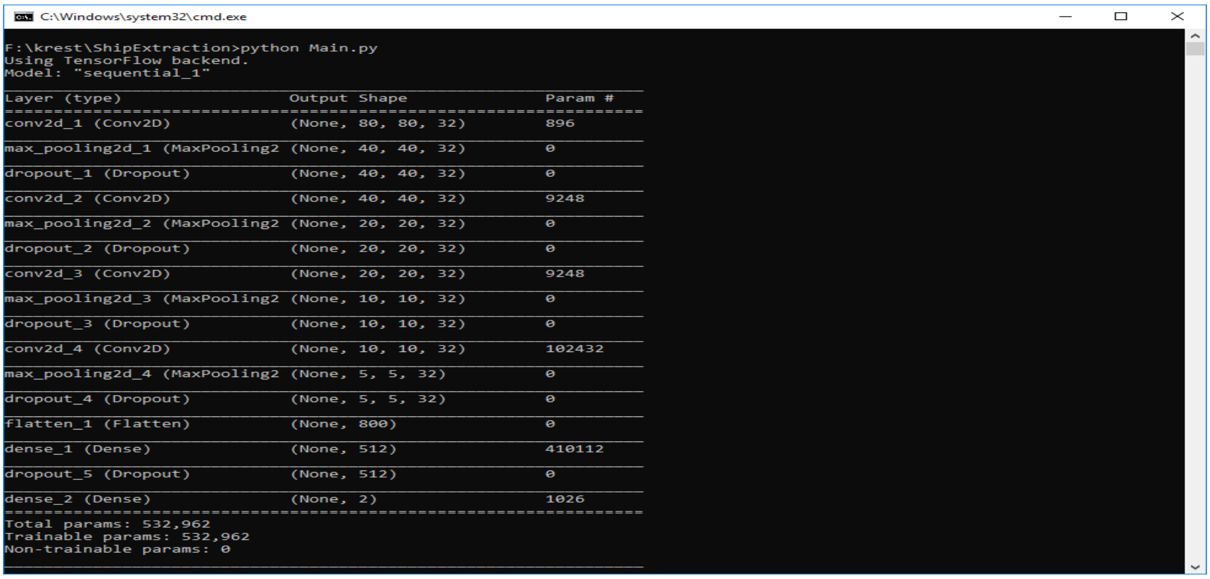
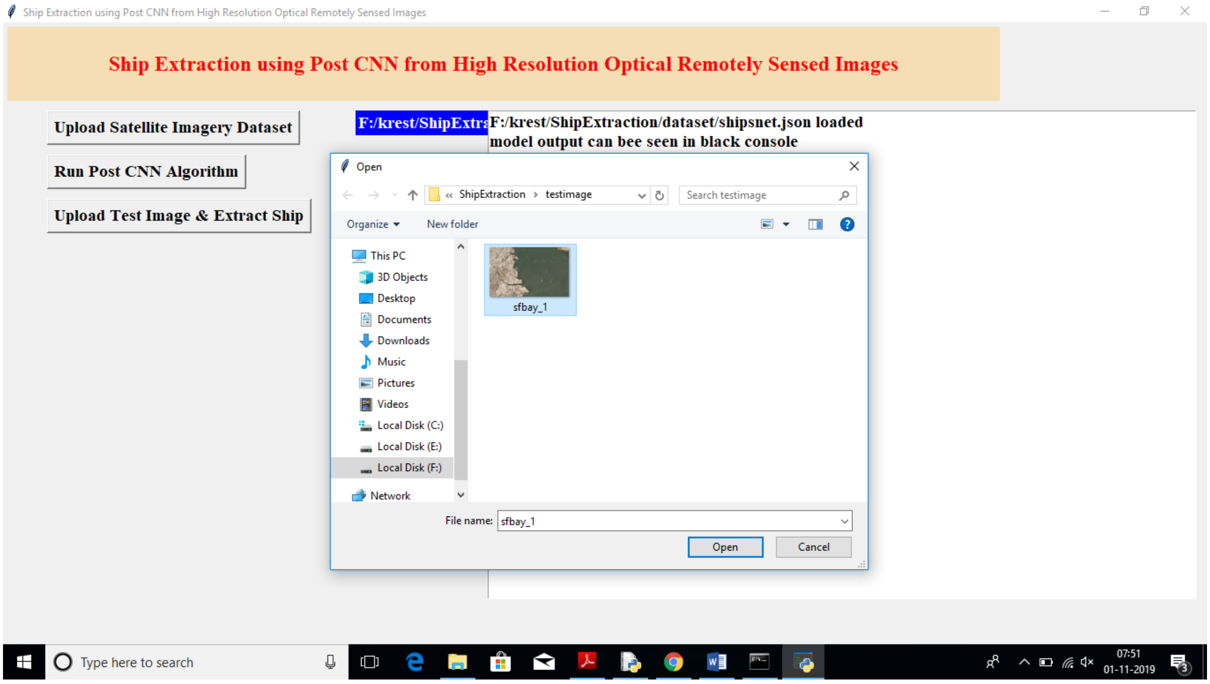


In above screen in selected text we can see model details are printed at black command prompt. So see black console to CNN model details

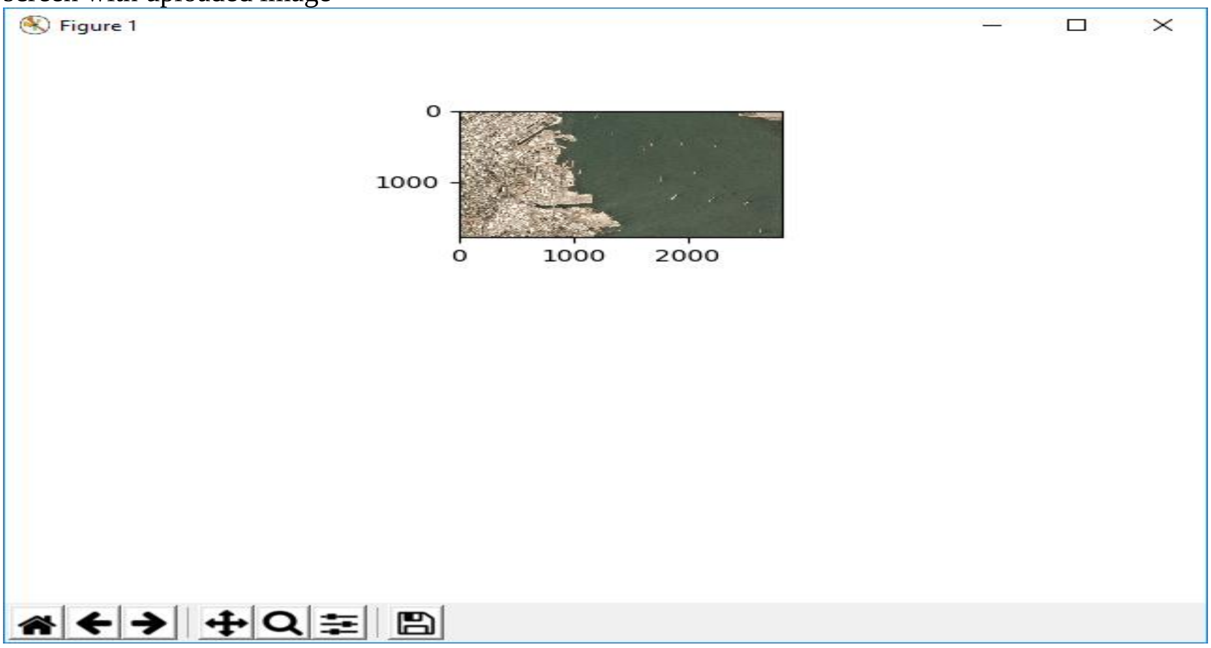


In above screen we can see CNN model is generated with images and for each image CNN generated multiple models with various sizes, in above screen we can see first CNN model generated on 80X80 image size then 40X40 then 20X20 etc. due to generating multiple models capability CNN can perform ship detection or extraction with high accuracy.

Now click on 'Upload Test Image & Extract Ship' button to upload test image and to extract ship



In above screen I am uploading image with sea and ships, now click on open button to view below screen with uploaded image



In above screen we can see uploaded image, now close this image screen and main screen to allow CNN to start ship extraction. Please close above image screen and main window and then see output from black console

5.CONCLUSION

Ship extraction from high-resolution optical remotely sensed images using a Post Convolutional Neural Network (CNN) is a complex process that involves data collection, preprocessing, model building, post-processing, evaluation, and deployment. By following these steps, it is possible to develop a ship extraction model that can accurately detect and extract ships from the images.

The success of the ship extraction model heavily relies on the quality and diversity of the labeled dataset used for training. Collecting a representative dataset and carefully annotating ship regions is crucial to ensure the model learns to accurately identify ships in various scenarios.
The CNN architecture plays a vital role in learning the ship-related features from the images. Designing an effective architecture with appropriate convolutional, pooling, and fully connected layers is essential. Training the CNN using backpropagation and gradient descent helps optimize the model's parameters to improve its ship detection capabilities.
After the CNN processing, post-processing techniques are applied to refine the extracted ship regions. This step helps enhance the accuracy of the model by filtering out false positives, applying thresholding, and utilizing morphological operations or other image processing techniques.
Evaluation and validation of the ship extraction model are critical to assess its performance. Metrics such as accuracy, precision, recall, and F1 score can provide insights into the model's effectiveness and its ability to correctly detect ships in the testing dataset. Iterative refinement and fine-tuning of the model may be necessary to improve its performance.
Once the model demonstrates satisfactory results, it can be deployed in a production environment or integrated into an application for ship extraction tasks. Input images can be processed using the deployed model, and the extracted ship regions can be further utilized for downstream tasks or visualizations.
In conclusion, ship extraction from high-resolution optical remotely sensed images using a Post CNN approach offers great potential for applications such as maritime surveillance, vessel traffic monitoring, and environmental studies. By following the implementation steps outlined above and continuously improving the model, accurate ship detection and extraction can be achieved, contributing to various domains that rely on the analysis of remotely sensed imagery

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