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SHIP TRACKING & DETECTION IN SAR IMAGES USING DEEP LEARNING MODEL

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Abstract- Synthetic aperture radar (SAR) is a notion that the creator of this project describes for detecting ships from satellite-taken sea photos. Using the Faster R-CNN (Region Based Convolution Neural Networks) Algorithm, ships may be located in SAR photos. The VGG ImageNet Network's ship photos will be used to train the RCNN algorithm, which will then extract features from the images based on the images' height, width, and colour channel. Convolution neural network (RCNN) filter train pictures features map from several layers. The train vector will be kept with every object detection from the picture with a value of 1, and all background features will be marked as 0. Every time a new SAR test image is uploaded, the RCNN algorithm will use the train vector to find objects with ships. The project's goal is to create a deep learning algorithm that uses SAR images as an input and processes it in segments. The application will show the same image in the console window when the procedure is finished, with marks if any objects that are ships are discovered; otherwise, the same image will be shown without any alterations. By conducting various experiments on our proposed system by collecting some sample ship images from KAGGLE website, we can train the application and then test the application on sample ship images. Here I used Google Collab as platform to execute the proposed application on some sample SAR images and find out the efficiency of our proposed application.

Index Terms:

Region Based Convolution Neural Network, ImageNet, Synthetic Aperture Radar(SAR),KAGGLE.

1. INTRODUCTION

For marine security, which includes, among other things, traffic surveillance, protection against illicit fishing, oil discharge management, and sea pollution monitoring, ship detection from remote sensing imagery is an essential application. Typically, an Automated Identification System (AIS) is used for this, which wirelessly broadcasts the location, identity, and destination of the ship to adjacent receivers on other ships and land-based systems using VHF radio frequencies. AIS are highly good at keeping track of ships that are legally required to have a VHF transponder installed, but they are ineffective at finding those that are not and those who have disconnected their transponder.

What method do you use to find these hostile ships? Here, satellite images can be useful. Radio waves are used in Synthetic Aperture Radar (SAR) photography to capture images of the Earth's surface. To construct a prospective deep learning application that aids in our education and allows us to experience the highs and lows of deep learning and its allies. In order to create a fantastic deep learning solution that might benefit communities and businesses, we want to acknowledge the technical complexity of deep learning. The SAR imageries will be automatically fed into a deep learning computer, which will then process them via several segments and output the pictures with marks if any ships are found, or the same image without any alterations if no ships are found.

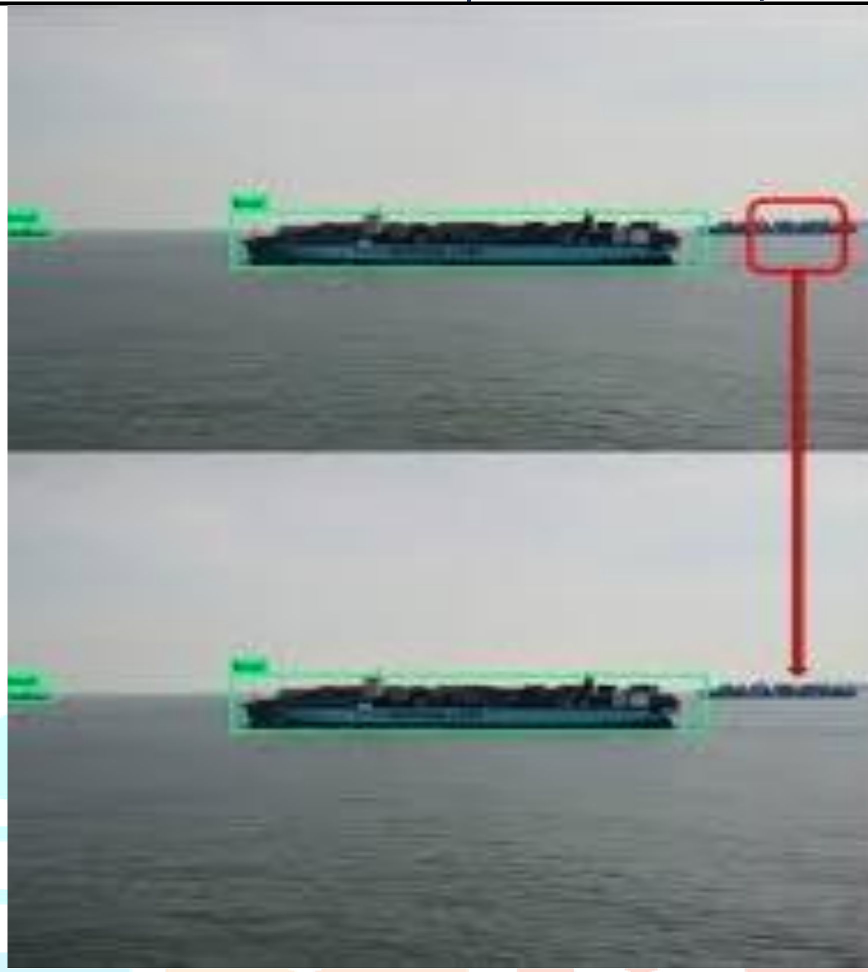


Figure.1 Represents the Ship Detection from SAR images

From the above figure 1[8], we can clearly find out that ship is detected from SAR images which are captured on deep marines which are very complex task for normal person to identify and recognize with our eye.This captured image is now applied using CNN model to identify the real characteristic of that ship and find out the features which are required to identify whether it is a ship or not.

2. LITERATURESURVEY

This section will mostly focus on the background research that has been done to demonstrate the effectiveness of our suggested Method. The most crucial stage of the software development process is the literature review. This stage is extremely important for the creation of any programme or application since it affects a number of variables, including time, cost, effort, the number of lines of code, and the strength of the firm. Once each of these many requirements has been met, we must choose the operating system and programming language that will be utilised to create the application. As soon as the programmers begin creating the application, they will first determine whether pre-defined innovations have been made using the identical notion before attempting to reinvent the work.

MOTIVATION

Two well known authors, Timo Balz and Bahaa Mohamdi,et.al, proposed a paper “Using convolutional neural network (CNN) approach for ship detection in Sentinel-1 SAR imagery “and outlined Compliance with port laws and standards is ensured by precise marine ship surveillance and monitoring. This objective has proven challenging to meet in applications including marine traffic control, ship search and rescue, territorial legislation, and fisheries management due to the increasing volume of waterborne activity. Ship detection is challenging, especially in challenging weather such at night or on overcast days. High-resolution data from synthetic aperture radar (SAR) can get beyond these restrictions. When compared to conventional image-based object recognition approaches, using machine-learning algorithms to identify ships in a SAR-based picture can improve identification detection outcomes. This exploratory study presents an investigation of efficient ship detection and ship count in a Sentinel-1 SAR picture dataset from 2015 to 2018 [1].

Two well known authors, Ghazanfar Latif and Mohammed Zikria,et.al, proposed a paper "Maritime Ship Detection using Convolutional Neural Networks from Satellite Images". In the current environment, when international trade and commerce are at their peak, the need of effective monitoring and management of maritime traffic for the purpose of ensuring the safety and security of the ships cannot be overstated. Serious marine challenges such ship hijackings, illegal fishing, and encroachments on sea borders, the illicit trade in sea freight, accidents, and military assaults are of interest to many different parties. This necessitates the development of an automated, precise, quick, and reliable marine monitoring system that can prevent or lessen the impact of such problems. In this study, a CNN-based deep learning model that can recognize ships from satellite photos is proposed, put into practice, and evaluated. Two models, CNN Model 1 and CNN Model 2, are trained using various architectures [2].

A well known author, Vishal Gupta,et.al, proposed a paper "Ship Detection from highly cluttered images using CNN". One area of computer vision that is now being studied is the classification and detection of vessels from crowded pictures. The coastline region is complicated, which makes it harder to tell various vessels apart. The environment and the visual characteristics of the boats make categorization a challenge. The visual aspect ratio is quite low and is typical of most vessel types. We offer the robust approach for the classification of ships developed from Support Vector Machine, bag of features, and Convolutional Neural Networks because the conventional CNNs methods are sluggish and not very accurate (CNNs). In order to eliminate the incorrect candidates, Support Vector Machine, a supervised transfer learning approach, is first presented. Due of the ships' extreme unpredictability, a variety of characteristics are used to manage the varied characteristics of several vessel classifications. In order to correctly categories the ships from the database, CNNs framework is finally employed for the deep feature extraction. The suggested technique is trained using a data set of more than 2700 photos and 16 distinct ship classifications. The approach improves classification accuracy and trains and evaluates the findings in terms of the confusion matrix. With an accuracy of 91.04 percent, the suggested Convolutional Neural Networks (CNNs) model exceeds the other earlier techniques [3].

A well known author, Hasheer Tanvir,et.al, proposed a paper "Using convolutional neural network (CNN) approach for ship detection in Sentinel-1 SAR imagery". In this author discussed about the Compliance with port laws and standards is ensured by precise marine ship surveillance and monitoring. This objective has proven challenging to meet in applications including marine traffic control, ship search and rescue, territorial legislation, and fisheries management due to the increasing volume of waterborne activity. Ship detection is challenging, especially in challenging weather such at night or on overcast days. High-resolution data from synthetic aperture radar (SAR) can get beyond these restrictions. When compared to conventional image-based object recognition approaches, using machine-learning algorithms to identify ships in a SAR-based picture can improve identification detection outcomes. This exploratory research presents an investigation of efficient ship recognition and ship count in a crowded sea using Sentinel-1 SAR photos from 2015 to 2018. [4].

A well known author, Hua Zong,et.al, proposed a paper "A Novel CNN-based Method for Accurate Ship Detection in HR Optical Remote Sensing Images via Rotated Bounding Box ". In this author discussed about difficult to recognize ships with sufficient accuracy in optical remote sensing photographs. Even the most cutting-edge convolutional neural network (CNN) based techniques are unable to provide outcomes that are highly good. Some latest techniques perform the detection using the rotating bounding box in order to more precisely find the ships in a variety of orientations. However, it makes detection much more challenging since the computer now needs to precisely forecast a second variable—ship orientation. By addressing certain common shortcomings of existing CNN-based ship identification systems, a novel CNN-based approach is suggested in this study. The quality of overall prediction is limited by the fact that existing approaches must predict all unknown variables in one regression procedure and predefine multi-oriented anchors in order to create rotating area recommendations [5].

3. EXISTING SYSTEM AND ITS LIMITATIONS

In order to recognise ships, all prior algorithms needed manually segmented sea photographs from the hands. If the segmentation was inaccurate or blur was captured in test images, ships would either not be spotted at all or would be detected incorrectly. Author remained unanswerable in order to get over this problem. There is no reliable CNN algorithm that can find the ships and identify them based on extracted attributes.

Limitations of the Existing System:

1. The deep learning property was not the focus of the current system.
2. Numerous applications of machine learning use images as their primary prediction input.
3. For image-based applications in basic machine learning, we employ the Computer Vision package, however it's not always correct.
4. The ships over sea Synthetic aperture radar were unable to be identified by the current Ml algorithms (SAR).
5. Because of this, it is extremely difficult for end users to follow the ships across great distances.

4. PROPOSEDWORK AND ITS ADVANTAGES

We attempt to create a CNN model for image analysis in the suggested system. Using the Faster R-CNN (Region Based Convolution Neural Networks) Algorithm, ships may be located in SAR photos. The VGG ImageNet Network's ship photos will be used to train the RCNN algorithm, which will then extract features from the images based on the images' height, width, and colour channel. Convolution neural network (RCNN) filter train pictures features map from several layers. The train vector will be kept with every object detection from the picture with a value of 1, and all background features will be marked as 0. The RCNN algorithm will use the train vector on the SAR test picture whenever a fresh SAR test image is uploaded in order to recognise objects with ships' properties.

Advantages of the proposed system:

1. The data that machine learning uses is vast. Additionally, it is helpful for little bits of data. On the other hand, deep learning is effective when the volume of data grows quickly.
2. A framework built on CNN is effective at identifying ships in SAR photos.
3. The squeeze and excitation approach is utilised to improve the performance of detection. Only the top Kvalues will be maintained with 1 after RCNN extracts features from train pictures, Excitation vector ranks the important object recognition features, and then only those features. The remaining values are set to 0.
4. Then, using the squeeze approach, the redundant sub-feature maps are suppressed. In plain English, excitation will recognise the top K characteristics, accept them, and squeeze approach will eliminate all unnecessary features. Squeeze and Excitation will be applied, and RCNN will have train model with important relevant features. When we give new test image then that model apply on test image to detect ships.

5. THE PROPOSED ARCHITECTURE

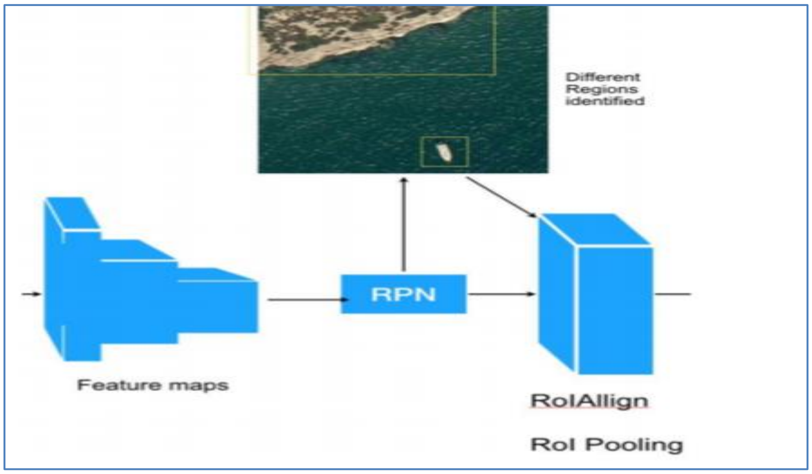


Figure.2 Represents the Proposed Architecture Diagram

From the above fig 2, we can clearly identify the proposed system has the following components such as :

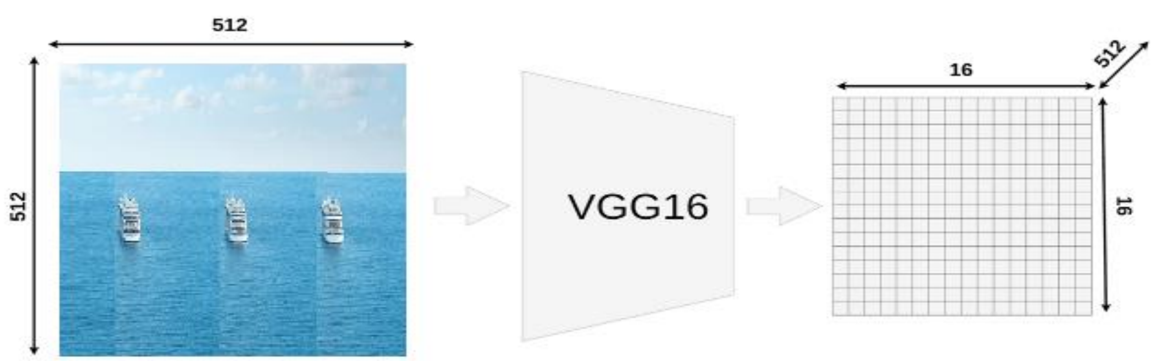
1) Feature Maps
2) RPN
3) RoI Allign
4) RoI Pooling

Initially we will try to gather SAR images which are captured on large marines and now the images are trained for identifying the ships which are present in that image. For doing that we try to categorize the application with following modules like feature maps, RPN, RoI Allign, RoI Pooling.

Once the SAR image is loaded, now we try to identify the main features present on that image and from those features we try to categorize the Region Proposal Network(RPN).This RPN is one which contains some object which is having some dimensions. Now we can apply RoI pooling. Convolutional neural networks are frequently used for object detection tasks, and one common operation employed in these tasks is region of interest pooling, or RoI pooling. Detecting several autos and pedestrians in a single shot, for instance its purpose is to perform max pooling on inputs of non-uniform sizes to obtain fixed-size feature maps (e.g. 7×7).

1) FEATURE MAPS EXTRATION

The fast R-CNN network is distinct from the regular R-CNN network. It only allows for the extraction of one convolutional feature, VGG16 in our case.



VGG16 feature extraction output size

Our model converts a 512x512x3 (width, height, and RGB) input picture into a 16x16x512 feature map using VGG16. Various input sizes are possible (often lower; the default input size for VGG16 in Keras is 224x224).If you examine the output matrix, you'll see that its width and height are exactly 32 times (512/32 = 16) smaller than the original picture. This is significant since it requires scaling down all RoIs.

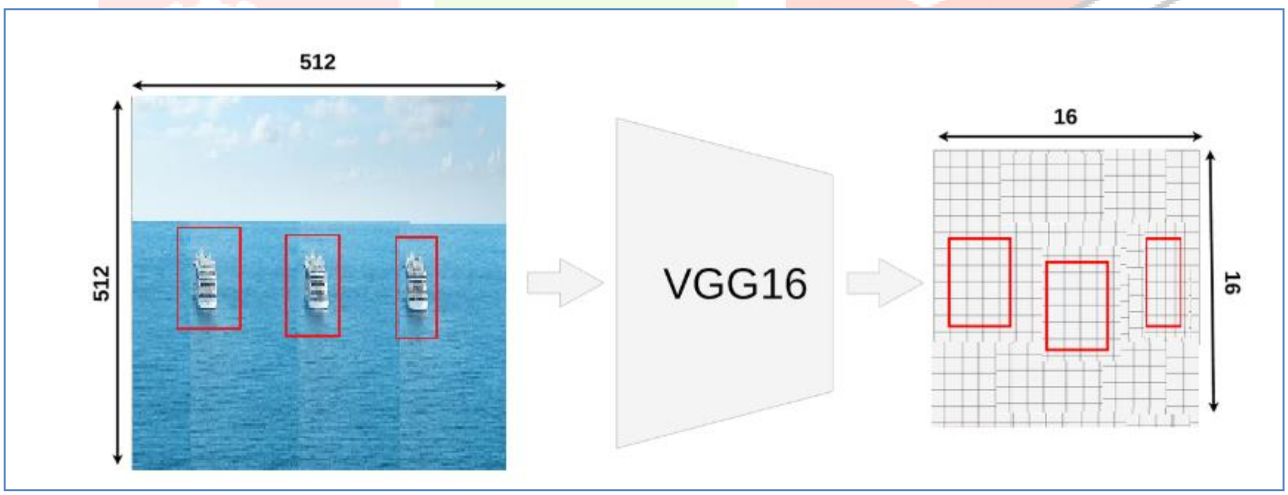
2) SAMPLE ROIS IDENTIFICATION

Here we have 3 different RoIs. In the actual Fast R-CNN you might have thousands of them but printing all of them would make image unreadable.

Always keep in mind that RoI is NOT a bounding box. Although it may appear to be one, it is only a suggestion for further consideration. Many believe this since the majority of articles and blog posts create suggestions instead of real products.

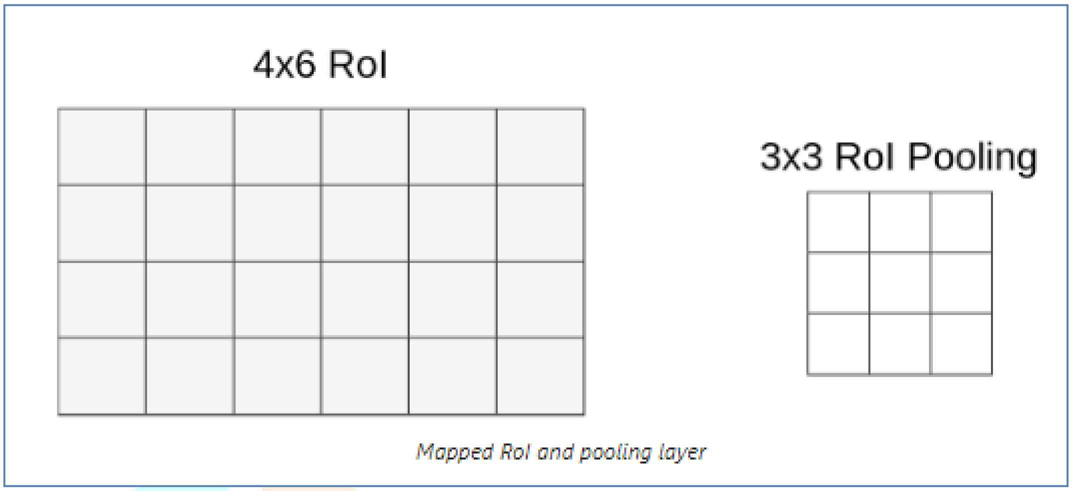
3) EXTRACTING ROIS FROM FEATURE MAPS

Now we can extract the RoIs from feature maps and all these are identified in this way



4) RoI POOLING

Now we may apply pooling to it after our RoI has been mapped onto a feature map. Once more, we will select the RoI Pooling layer's size purely out of convenience; nevertheless, keep in mind that this size may vary.



Mapped RoI and pooling layer

This time, the only issue to consider is size rather than coordinates. Fortunately (or perhaps merely because to the pooling layer's handy size), 6 can be divided by 3 to provide 2, but when you divide 4 by 3, you get 1.33.

6. IMPLEMENTATION MODULES

Implementation is a stage where theoretical design is converted into programmatically manner. Here we will try to divide the application into number of modules and then try to do coding for those modules. The application is mainly divided into 4 modules. They are as follows:

1. Load Dataset Module
2. Pre-Processing Module
3. Train the Faster R-CNN model
4. Upload Test image and Detect the Ship

1. LOAD DATASET MODULE

In this module we try to load the dataset collected from kaggle.com website which contains several images collected from satellite over sea.There were a small percentage of images in both the Train and Test set that had slight overlap of object segments when ships were directly next to each other. Any segments overlaps were removed by setting them to background (i.e., non-ship) encoding. Therefore, some images have a ground truth may be an aligned bounding box with some pixels removed from an edge of the segment. These small adjustments will have a minimal impact on scoring, since the scoring evaluates over increasing overlap thresholds.

https://www.kaggle.com/c/airbus-ship-detection/data

Here we load the sample data from the google drive that is the json formatted file having a .json file extension name

2) PRE-PROCESSING MODULE

Here in this module we try to pre-process the images by adjusting the height, size and width properties and try to separate the images into test and train. Here for test purpose we try to collect both ship related images and normal images and then try to train the system.

3) TRAIN THE FASTER R-CNN MODEL

In this module, we try to use some pre-trained models like VGG16 and RESNET 50 and then apply those models using 'VGGImageNet.h5py' file. Once these models are trained on sample images then it will undergo internal processing and finally try to figure out the images which are having ship and which are not generated any ship.

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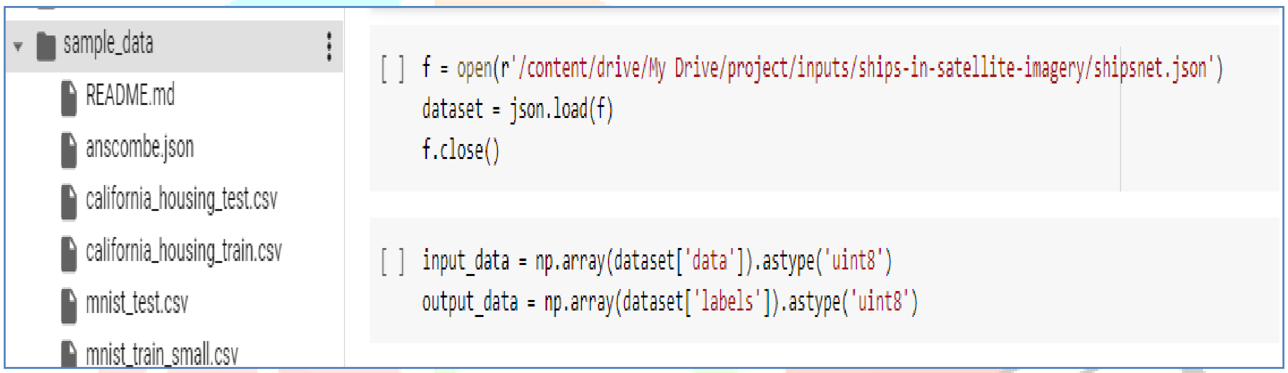
4) UPLOAD TEST IMAGE AND DETECT THE SHIP

In this module we will upload test image and then application extract features from this test image and then apply pre-trained CNN models like RESNET 50 and VGG 16 model to train model on that test image to detect ships

7. EXPERIMENTAL REPORTS

Here we designed the application in python programming and the following are the some of the sample screens.

LOAD THE DATASET



From the above window we can clearly see that dataset is downloaded from kaggle and it is converted as .Json file and now we can load that file as input.

DATA PRE-PROCESSING

From the above window we can clearly identify the data is pre-processed and now we can able to design our proposed Model.

DESIGN THE MODEL

+ Code + Text RAM Disk

```
[ ] # network design
    model = Sequential()

    model.add(Conv2D(32, (3, 3), padding='same', input_shape=(80, 80, 3), activation='relu'))
    model.add(MaxPooling2D(pool_size=(2, 2))) #40x40
    model.add(Dropout(0.25))

    model.add(Conv2D(32, (3, 3), padding='same', activation='relu'))
    model.add(MaxPooling2D(pool_size=(2, 2))) #20x20
    model.add(Dropout(0.25))

    model.add(Conv2D(32, (3, 3), padding='same', activation='relu'))
    model.add(MaxPooling2D(pool_size=(2, 2))) #10x10
    model.add(Dropout(0.25))

    model.add(Conv2D(32, (10, 10), padding='same', activation='relu'))
    model.add(MaxPooling2D(pool_size=(2, 2))) #5x5
    model.add(Dropout(0.25))

    model.add(Flatten())
    model.add(Dense(512, activation='relu'))
    model.add(Dropout(0.5))

    model.add(Dense(2, activation='softmax'))
```

From the above window we can clearly identify model is developed.

TRAINING THE MODEL WITH OPTIMIZATION

Here we try to train the model and then try to optimize the model. Once model is trained now we can able to test the input.

+ Code + Text RAM Disk

```
[ ] # optimization setup
    sgd = SGD(lr=0.01, momentum=0.9, nesterov=True)
    model.compile(
        loss='categorical_crossentropy',
        optimizer=sgd,
        metrics=['accuracy'])

    # training
    model.fit(
        X_train,
        y_train,
        batch_size=32,
        epochs=230,
        validation_split=0.5,
        shuffle=True,
        verbose=2)
```

SHIP IS DETECTED FROM SAMPLE IMAGE

From the above image we can clearly see that our proposed model efficiently identified the ship from SAR images which is collected from large marine.

8. CONCLUSION

In this work, we came to the final conclusion that the RCNN filter can successfully train pictures' feature maps from various convolutional neural network layers. The train vector will be kept with every object detection from the picture with a value of 1, and all background features will be marked as 0. The RCNN algorithm will use the train vector on the SAR test picture whenever a fresh SAR test image is uploaded in order to recognise objects with ships' properties.

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