Ship Detection in Navy Using Satellite Images by Deep Learning Approach

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Abstract - Ship identification in satellite images poses significant challenges within the domain of remote sensing. Its importance extends to critical areas such as security, encompassing concerns such as military attacks, accidents, illegal transportation of goods, illegal fishing, territorial violations, and ship hijackings. Additionally, effective traffic management and smuggling prevention heavily rely on accurate ship identification. While synthetic aperture radar (SAR) has historically dominated maritime monitoring, researchers are increasingly exploring optical satellite images as a potential alternative. Previous ship detection techniques have utilized Computer-based image processing vision methods. However, this study proposes a novel approach employing a Convolutional Neural Network (CNN) based method to accurately identify ships in satellite data. The suggested approach entails the utilization and assessment of a custom-designed deep learning model based on CNN architecture. to recognize ships in satellite photos.

Keywords - ship detection, optical images, Convolutional Neural Networks.

1. INTRODUCTION

Ship detection plays an important role in various maritime applications, including maritime security, vessel traffic management, environmental monitoring, and search and rescue operations. Over the years, different technologies have been employed to detect and track ships, and have been used like the Automatic Identification System (AIS) it is a widely adopted solution.

However, AIS has its limitations, which necessitates the necessity for ship detection using satellite images AIS is a radio-based system that utilizes transponders on ships to exchange information about their identity, position, course, and speed. It provides real-time data, enabling efficient vessel tracking and collision avoidance.

AIS is particularly valuable in coastal areas and busy shipping lanes where vessels are equipped with AIS transponders. However, AIS coverage is limited to areas within range of shore-based or satellite-based receivers, leaving vast stretches of open seas and remote regions devoid of AIS information. Moreover, AIS signals can be easily blocked or manipulated, compromising its reliability in certain situations.

In contrast, satellite imagery provides a comprehensive and wide-range of the oceans, allowing for the detection and tracking of ships across large areas. Satellite images offer high-resolution visual Information that can be examined for identification of ships, even in remote or poorly covered regions. By leveraging advanced image processing and computer vision techniques, ship detection using satellite images can provide valuable insights into vessel activities, routes, and behavior of the movement and surveillance of the ships moving in that area and avoid illegal activities.

2. RELATED WORK

The sources related to the field of defense in the ocean using satellite images are remarkable. They cover different methodologies, evaluation techniques, and challenges that serve as a foundation for this research paper on ship detection. This section provides an overview on the work related to Ship detection utilizing a deep learning methodology.

[1] This paper introduces an innovative technique for ship detection, drawing inspiration from human visual perception. The aim is to enhance the accuracy and efficiency of ship detection in complex maritime environments. The method comprises three main stages: local feature extraction, global context analysis, and decision fusion. In the local feature extraction stage, the Scale-Invariant Feature Transform (SIFT) algorithm is applied to detect ship-like key points. These points are then clustered hierarchically to form potential ship candidates. By combining local feature extraction, global context analysis, and decision fusion, the paper presents a fresh approach to ship detection, which demonstrates promising results and potential real-world applications in optical satellite images.

[2] This research paper presents an innovative computational model designed for ship detection in optical satellite images, drawing inspiration from the human visual system's search mechanism. The authors propose a three-stage framework for ship detection. In the first stage, they generate saliency maps using the Itti-Koch model, which captures visual attention mechanisms, highlighting potential regions containing ships. The second stage involves extracting local features using the Scale-Invariant Feature Transform (SIFT) algorithm, which provides distinctive descriptors for ships, facilitating effective localization and differentiation from the background. Lastly, a Support Vector Machine (SVM) classifier is trained to discern ship and non-ship regions based on the extracted SIFT features. The classifier is trained using positive and negative samples, resulting in accurate ship detection. Experimental evaluation using a benchmark dataset demonstrates the model's efficacy, achieving high ship detection accuracy with a minimal false positive rate, even in challenging maritime environments with diverse backgrounds and ship sizes.

[3] This paper presents a hierarchical approach for ship detection in spaceborne optical images using shape and texture

features. The proposed approach comprises three key stages: initial extraction of ship candidates, verification of ship candidates, and final ship detection. In the first stage, the authors employ morphological operation-based methods to identify potential ship regions based on their distinctive shape characteristics, reducing the search space and enhancing computational efficiency. Moving on to the ship candidate verification stage, a set of shape and texture features are extracted from the identified ship regions. These features encompass elongation, compactness, rectangularity for shape, and Gray-Level Co-occurrence Matrix (GLCM) for texture. The extracted features are then used to train a Support Vector Machine (SVM) classifier capable of distinguishing true ship regions from false positives. In the final ship detection stage, the trained SVM classifier is applied to the remaining potential ship regions, classifying them as either ships or non-ships. Subsequently, the detected ship regions undergo refinement using morphological operations and connected component analysis.

[4] This paper presents a deep learning-based technique for ship detection and classification in optical remote sensing images. The authors propose a two-stage methodology that integrates ship detection and ship classification. In the initial stage, a convolutional neural network (CNN) is trained to identify ships by analyzing image patches. This CNN is trained using a dataset of annotated images to differentiate between regions containing ships and those without. The ship detection stage successfully pinpoints the areas in the image where ships are present. In the subsequent stage, a separate CNN is trained to categorize the detected ship regions into distinct ship types or classes. The classification model is trained using a dataset of labeled ship images representing various classes. This stage enhances the ship detection results by providing detailed information about the specific ship types present in the image. Experimental outcomes demonstrate the efficacy of the proposed approach for ship detection and classification. The deep learning-based technique achieves high accuracy in ship detection and proficiently categorizes ships into different classes.

[5] This paper describes An Experimental Analysis Using Satellite Images" presents an experimental study on the automatic finding of ships using a deep learning approach applied to satellite images. The authors aim to develop an accurate and efficient ship detection system for maritime surveillance and vessel monitoring. The study focuses on the utilizing convolutional neural networks (CNNs) for ship detection. The authors propose a deep learning framework that incorporates pre-processing steps, data augmentation, and CNN-based ship detection models. They evaluate the performance of the models using benchmark datasets and compare the results with traditional ship detection methods. The experimental outcomes demonstrate that the deep learning-based approach outperforms traditional methods, achieving high accuracy in ship detection. The study highlights the potential of deep learning techniques for automatic ship detection, that providing valuable understanding for the development of advanced ship detection systems using satellite imagery.

[6] This paper introduces a method for detecting inshore ships using satellite images utilizing computer vision techniques. The authors address the challenge of detecting ships close to the shore, where they may be partially occluded or exhibit complex visual patterns. The proposed approach involves a multi-stage process. First, a background subtraction technique is applied to remove the static background and retain only the moving objects, potentially including ships. Then, a region proposal network is employed to generate candidate ship regions. The regions are further enhanced using shape and texture analysis to filter out false positives and improve accuracy. Experimental evaluation on a dataset of satellite images demonstrates the efficiency of the proposed method in detecting inshore ships. The approach achieves high detection accuracy even in challenging scenarios with varying ship sizes, occlusions, and complex backgrounds. The paper highlights the potential application in surveillance, vessel traffic management, and maritime security. The detection of inshore ships contributes to improved situational awareness and better understanding of maritime activities in coastal areas that can separate ships that are onshore.

[7] This paper presents a comprehensive approach for detecting ships in satellite images. The authors aim to develop an efficient and accurate system that can automatically identify and locate ships in large-scale optical satellite data. The processing chain described in the paper encompasses several key stages. Initially, image preprocessing techniques are employed to enhance the quality of the satellite imagery, including noise reduction and contrast enhancement. Next, advanced image segmentation methods are utilized to separate ship pixels from the background, enabling focused analysis on ship regions. Following segmentation, the paper focuses on feature extraction. A variety of geometric, textural, and contextual features are computed from the ship regions, capturing important ship characteristics such as size, shape, and texture. These features serve as a descriptive representation of the ships and contribute to subsequent classification. For classification, the authors employ machine learning algorithms such as support vector machines (SVM) or artificial neural networks (ANN). These algorithms are trained on a labeled dataset, enabling them to learn patterns and discriminate between ship and non-ship samples depending on the extracted attributes. The proposed ship detection feature is evaluated using real-world satellite images, demonstrating its effectiveness. The results indicate high accuracy and efficiency in ship detection, showcasing the potential of the processing chain for various applications in maritime surveillance and remote sensing.

[8] This paper introduces ship detection in high-resolution satellites. The authors propose a novel approach that combines an anomaly detector with local shape attributes to achieve accurate and efficient ship detection. The methodology presented in the paper consists of two main components. First, an anomaly detector is applied to identify regions in the image that deviate from the normal background. This detector is trained on a dataset of non-ship regions to learn the characteristics of the background and identify anomalies, which often correspond to ships. The second component focuses on extracting local shape features from the detected anomalies. These features capture the distinctive shape characteristics of ships, such as elongation and compactness. Various shape descriptors, such as circularity or rectangularity, are computed to create a descriptive representation of the

detected anomalies. To classify the detected anomalies as ships or non-ships, a machine learning algorithm, such as a support vector machine (SVM), is employed. The algorithm is trained on a labeled dataset to learn the patterns and distinguish between ship and non-ship instances based on the extracted local shape features. The proposed ship detection method is evaluated using high-resolution optical satellite images, and the results demonstrate its effectiveness in accurately detecting ships while minimizing false detections. The combination of the anomaly identifier and local shape features contributes to improved ship detection performance. In summary, the paper introduces a ship identification method for high-resolution optical images utilizing an anomaly identifier and local shape features. The approach showcases promising results and offers a valuable contribution to the field of remote maritime surveillance and defense.

[9] This paper proposes an approach for precise ship detection utilizing electro-optical satellite images. The authors aim to improve accuracy in ship detection by enhancing the features extracted from the images and incorporating land awareness. The proposed approach involves several steps. Firstly, image preprocessing techniques are employed to enhance the ship features and suppress the background noise. Then, a feature extraction method is utilized to extract discriminative ship features from the preprocessed images. These attributes are subsequently used to train a model using machine learning algorithms. To further enhance the ship detection accuracy, the authors introduce a land awareness component. This component incorporates knowledge about land characteristics, such as coastline information, to refine the ship detection results and reduce false positives. Experimental results provide an effectiveness of the proposed model in accurately detecting ships in electro-optical satellite images. The approach offers potential applications in maritime surveillance, environmental monitoring, and maritime security.

[10] This paper presents a method for detecting ships in high-resolution satellite imagery specifically in inshore areas. The authors propose an approach that approximates harbors by utilizing sea-land segmentation to enhance ship detection accuracy. The method involves several steps. Firstly, a sea-land using a segmentation algorithm is applied to the satellite images to distinguish between water and land regions. This segmentation process helps in identifying potential harbor areas. Next, a set of geometric and texture-based features are extracted from the segmented regions. These features are then utilized to train a machine learning model for ship detection. To further improve the accuracy, the authors introduce an approximation technique that refines the detection results by considering spatial distribution and layout characteristics of the identified harbor areas. Experimental results indicate that the proposed method effectively detects ships in inshore regions with high accuracy. The approach has potential applications in maritime surveillance, port management, and coastal security.

[11] This paper published in the journal Remote Sens presents an approach for ship detection in multispectral satellite images, particularly in complex environmental conditions. The authors address the challenge of accurately detecting ships when various attributes such as cloud cover, sun glint, and sea clutter affect the image quality. The proposed approach involves multiple steps. Initially, image preprocessing techniques are applied to enhance the ship features and mitigate the impact of environmental conditions. Then, a set of spectral and spatial features are exported from the preprocessed images. These features capture the unique characteristics of ships, enabling differentiation from the background. To further improve ship detection accuracy, a machine learning algorithm is used to train a ship classifier using the extracted features. The classifier is capable of distinguishing ships from other object noise in the multispectral satellite images. Experimental outcomes demonstrate effectiveness of the proposed approach in ship detection under complex environmental conditions. The approach has potential applications in maritime surveillance, maritime traffic monitoring, and emergency response operations.

3. METHODOLOGY

This paper proposes an experiment using ship images extracted from a satellite images dataset acquired from the Kaggle platform [12]. These images capture the Earth's surface, featuring roads, farmland, buildings, and other objects. The satellite images from PlanetScope depict the
San Pedro Bay and San Francisco Bay regions in California. The dataset comprises 4k RGB images with an 80x80 pixel resolution, categorized into two classes: "ship" and "non-ship." Various image preprocessing techniques were subsequently applied to improve the image quality. Afterward, the Convolutional Neural Network (CNN) model was trained using the sample images. The figure below illustrates the proposed ship detection model.

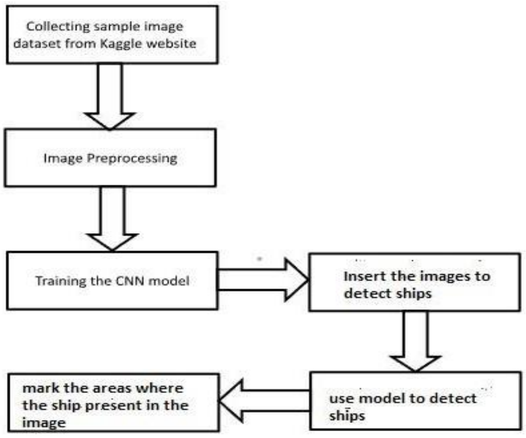

Fig 1. Proposed Model for ship detection

A. Dataset

The dataset comprises RGB images with a resolution of 768 × 768 pixels, containing encoded pixels representing ship locations in satellite photos. These encoded pixels were converted into binary masks, with "1" indicating the presence of a ship and "0" denoting the absence of a ship. When a mask with a value of "1" is present, it is transformed into a bounding box by calculating the four corner coordinates of the mask. To optimize computational resources, all images were resized to 256 × 256 pixels. Due to the original data having inverted axes, the x and y coordinates were also flipped accordingly.

B. Image Preprocessing and Model Architecture

Image preprocessing is a crucial step in ship detection using optical images with Convolutional Neural Networks

(CNNs). Proper preprocessing helps enhance the quality of data and improves the efficiency of the CNN model. Below are some typical image preprocessing steps for ship identification using CNNs:

- Image Resizing: Resizing the images to a standard size is often necessary to ensure uniformity in the input data for the CNN model. This step reduces computational complexity and memory requirements during training and inference.
- Image Normalization: Normalizing the pixel values of the images helps bring them to a consistent range, usually between 0 and 1 or -1 to 1. This step makes the training process more stable and efficient.
- Data Augmentation: Data augmentation technique is used to artificially increase the magnitude of the training dataset by creating modified versions of the original images. Common augmentations include rotation, flipping, scaling, and translation. Data augmentation improves the model's generalization and robustness to variations in ship orientations and backgrounds.
- Image Cropping: If the images contain large areas without relevant information, cropping the images to focus on the regions of interest (ships) can reduce computation and improve the model's performance.
- Noise Reduction: Applying noise reduction techniques, such as Gaussian blurring or median filtering, can help remove unwanted noise and artifacts from the images, leading to better feature extraction by the CNN.
- Color Space Conversion: Converting the images to different color spaces (e.g., RGB, HSV, LAB) might be beneficial, depending on the specific characteristics of the dataset and the application.
- Mask Generation: For pixel-level ship segmentation tasks, generating masks that highlight ships in the images is essential for training the CNN to learn the ship's shape and location accurately.
- Mean Subtraction: Subtracting the mean pixel value of the complete dataset from each image can further assist in normalization and mitigate illumination variations.

It's necessary to note that the choice of preprocessing steps may vary depending on specific dataset and the properties of the images. Proper experimentation and tuning of these steps are essential to achieve optimal results with CNN-based ship identification models.

The model architecture for ship identification using optical imagery with a Convolutional Neural Network (CNN) typically consists of several layers designed to extract and learn meaningful features from the input images. Below is a common CNN architecture used for ship detection:

- Input Layer: The primary layer in the CNN is the input layer, which receives the preprocessed images as input. The dimension of the input images is often standardized to a specific dimension to ensure consistency.
- Convolutional Layers: Convolutional layers are the core building blocks of a CNN. They consist of a batch of learnable filters (also called kernels) that slide over the input image, performing convolutions to detect various features. Each filter is responsible for capturing specific patterns, edges, or textures from the input image. Multiple convolutional layers are stacked to learn increasingly complex and hierarchical features.
- Activation Function: Following each convolutional layer, an activation function, such as ReLU (Rectified Linear Unit), is applied element-wise to introduce non-linearity to the model. This allows the CNN to learn more complex relationships between the input data and the output.
- Pooling Layers: Pooling layers, typically MaxPooling, are used to downsample the spatial aspects of the feature maps while retaining important information. MaxPooling selects the maximum value from a specific region of the feature map, reducing the computational load and aiding in translation invariance.
- Fully Connected Layers: After several convolutional and pooling layers, the feature maps are flattened into a 1D vector. This vector is fed into one or more fully connected layers. These layers are similar to normal neural network layers, and they learn high-level representations by amalgamating the characteristics extracted from the preceding layers.
- Output Layer: The output layer depends on the specific task. For ship detection, it is typically a binary classifier that predicts if a ship is present or absent in the input image.
- Loss Function: The model is trained using a suitable loss function, such as binary cross-entropy, which compares the predicted probabilities and the ground truth labels.
- Optimizer: The model uses an optimization algorithm, such as Adam or stochastic gradient descent (SGD), to update the model's weights during training and minimize the loss function.
- Training and Evaluation: The CNN is trained on a labeled dataset containing images with corresponding ship presence/absence labels. After training, the model is evaluated on a separate test dataset to assess its performance in ship detection.

It is essential to emphasize that the exact architecture and the quantity of layers employed might differ based on the task's intricacy, the computational resources at hand, and the dataset's size.

C. Model Training

The dataset is split into training and testing subsets. The training subset is utilized to update the model's weights, while the validation subset is utilized to monitor the model's performance during training and avoid overfitting. CNN model is trained using the training dataset. The model is fed with batches of images, updating the weights after each batch to minimize the loss. The training process is typically done for multiple epochs, where each epoch represents one pass through the entire training dataset. After each epoch, the model's performance is evaluated on the validation dataset. Monitoring the validation performance helps identify when the model starts to overfit, allowing for early stopping or adjusting hyperparameters.

D. Model Testing

A separate dataset known as test dataset is prepared to cross verify the accuracy of trained model, which contains images that the model has never seen during training. There are some common evaluation methods to determine the accuracy of the model, they are as follows:

- Accuracy: The accuracy metric represents the correct predictions made by the model over the total number of test samples. It is the most straightforward evaluation metric and provides an overall view of the performance of the model.

A = (n) / (N)

Where A represents Accuracy, n and N signifies the number of correct predictions and the total amount of test samples respectively.

- Confusion Matrix: A confusion matrix is a table that shows the amount of correct and incorrect predictions detected in the model for each class (ship detection). It provides more detailed information about the model's performance and helps identify which ships are frequently misidentified.
- ROC Curve: The Receiver Operating Characteristic (ROC) is a graphical representation of the model's performance at various classification thresholds. It plots the true positive rate (TPR or recall) against the false positive rate (FPR) as the threshold for classifying a sample is varied.
- Precision: Precision is the ratio of true positive predictions to the total amount of positive predictions made by the model. It measures how many predicted positive samples were actually positive.

Precision = (True Positives) / (True Positives + False Positives)

E. Ship Detection

Once this model is trained and validated, it can be deployed in real-time applications. In such applications, the ship module captures images from the device, preprocesses the images, and passes them through the trained model to highlight the ships in that area.

F. User Interface

The User Interface (UI) module focuses on providing an interactive platform for users to experience. The UI module is responsible for providing a user friendly interface and also provides good command over the system.

Features of User Interface module include:

- Python Flask: Python Flask is a web framework that helps you build web applications and websites utilizing the Python language. It provides a set of tools and libraries to handle tasks like handling web requests, routing URLs, and generating HTML pages. With Flask, we can create interactive and dynamic web pages that respond to user actions and input. It allows you to connect the backend (server-side) Python code with the frontend (client-side) HTML, CSS, and JavaScript code.
- Device storage: The interface allows the user to choose a file in the form of an image and the model will detect the ships and mark it.
- Ship Detection: The image processed utilizing a pre-trained deep learning model to observe the image and detect the ship in the image. The model analyzes each pixel to identify and mark the ships in an image.

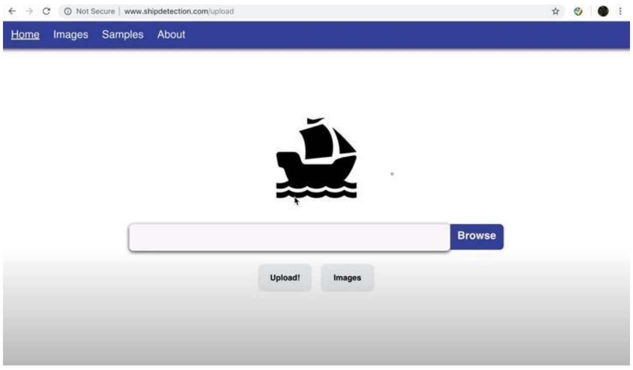

Fig 2. User Interface

4. EXPERIMENTAL RESULTS AND PERFORMANCE EVALUATION

Results of ship detection using optical images can be quite diverse and impactful. Here are some key outcomes and benefits that such a system can offer:

- Maritime Surveillance and Security: Ship detection systems play an important role in enhancing maritime surveillance and security. By accurately identifying ships in real-time from optical satellite or aerial imagery, authorities can monitor vessel movements, detect potential security threats, and respond swiftly to illegal activities, smuggling, or piracy.
- Environmental Monitoring and Compliance: Ship detection systems aid in environmental monitoring and compliance by identifying vessels that may be involved in illegal fishing or oil spills. Monitoring ship traffic patterns can help enforce environmental regulations and protect marine ecosystems.
- Search and Rescue Operations: In cases of emergencies or accidents at sea, ship detection systems can assist in search and rescue operations by quickly locating vessels in distress. This timely information can lead to more effective and efficient rescue missions, potentially saving lives.
- Economic Analysis and Trade Monitoring: Ship detection systems can provide valuable data for economic analysis and trade monitoring. By tracking shipping activities and identifying trends in ship traffic, authorities and businesses can make informed decisions regarding international trade and economic planning.
- Illegal Immigration and Human Trafficking: In coastal regions prone to illegal immigration and human trafficking, ship detection systems can aid in identifying suspicious vessels and potentially prevent illicit activities.
- Research and Scientific Studies: Researchers and scientists can use ship detection systems to study maritime traffic patterns, migration routes of marine species, and oceanic phenomena. The data collected from such systems can contribute to valuable scientific research and environmental studies.
- Cost-Effective Surveillance: Compared to traditional methods such as manned aerial patrols or ships, ship detection using optical images with automated systems can be more cost-effective and provide broader coverage over large geographical areas.
- Disaster Response and Relief Efforts: During natural disasters such as hurricanes or tsunamis, ship detection systems can assist in monitoring the movement of relief vessels and coordinating disaster response efforts more effectively.

In conclusion, ship detection by optical images holds significant potential for a range of applications, from enhancing maritime security to supporting environmental conservation and scientific research. The accurate and timely information provided by such systems can lead to more informed decision-making and better management of maritime resources.

To evaluate the effectiveness of the proposed system comprehensive tests were conducted. The efficiency of the system was assessed with the help of various metrics.

- Accuracy: The accuracy is typically measured as the percentage of correctly classified facial expressions out of the total number of expressions in the dataset or during real-time testing. For example, if the model correctly identifies 97 out of 100 images with ships, the accuracy would be 97%.

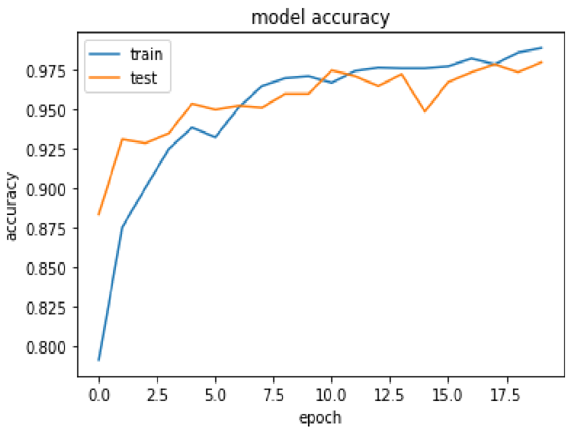

Fig 3. Accuracy of the Model

- Confusion Matrix: A confusion matrix is a table that shows the number of correct and incorrect predictions made by the model for each class (ship detection). It provides more detailed information about the model's performance and helps identify which facial expressions are frequently misclassified.

  Following are the components of the confusion matrix:
  - True Positive (TP): The number of samples that belong to a particular class and are correctly predicted as that class by the model.
  - False Positive (FP): The number of samples that do not belong to a particular class, but are incorrectly predicted as that class by the model.
  - True Negative (TN): The number of samples that do not belong to a particular class and are correctly predicted as not belonging to that class by the model.
  - False Negative (FN): The number of samples that belong to a particular class, but are incorrectly predicted as not belonging to that class by the model.

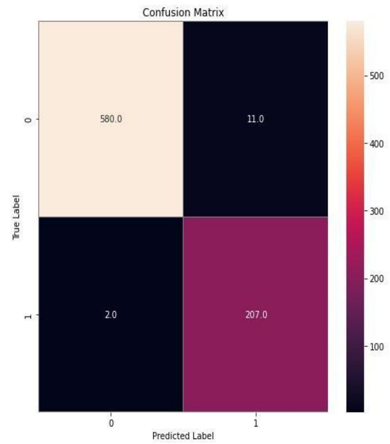

Fig 4. Representation of Confusion Matrix

- Precision: Precision is calculated as the fraction of true positive predictions (correctly predicted positive samples) to the total amount of positive predictions made by the model (true positive plus false positive). It represents how well the model avoids false positives and correctly identifies positive samples for a particular class. Mathematically, precision is defined as:

  Precision = True Positives / (True Positives + False Positives)

  A high precision score indicates that the model is making fewer false positive predictions, and the positive predictions made by the model for a specific class are likely to be accurate.

5. FINDINGS AND IMPLICATIONS OF THE RESEARCH

The research helped in finding more advanced and interactive ways to detect ships. The key findings and their implications are mentioned:

- Accuracy and Performance: The research demonstrates the effectiveness of the ship detection model in accurately identifying the ships in the given image. The trained convolutional neural network (CNN) model achieves a high accuracy, indicating its capability to recognize ships.
- Improved Maritime Security: Accurate ship detection using optical images has significant implications for enhancing maritime security and surveillance. It enables authorities to detect and track vessels in real-time, aiding in the detection of suspicious activities and potential security threats.
- Enhanced Environmental Monitoring: Ship detection's precision in optical images contributes to better environmental monitoring, helping to detect illegal fishing, oil spills, and other marine pollution incidents. This information can be crucial for enforcing environmental regulations and protecting marine ecosystems.
- Search and Rescue Efficiency: The capability to quickly and accurately detect ships in distress can have a profound impact on search and rescue operations, leading to a more efficient and effective response during emergencies at sea.
- Improved Port Management: Ship detection systems can optimize port management by providing insights into vessel traffic patterns and congestion. This data can aid in

scheduling dockings and managing port operations more efficiently.

- Cost-Effective Surveillance: Utilizing optical images for ship detection can offer a cost-effective alternative to traditional manned patrols, allowing for broader surveillance coverage over large maritime areas.

It is essential for these findings and implications are subject to ongoing research and advancements in ship detection technology. Researchers continue to explore new methods and techniques to further improve the accuracy, efficiency, and applications of ship detection using optical images.

6. CONCLUSION AND FUTURE WORK

The conclusion of the ship detection system has successfully demonstrated the potential of combining image recognition and ship detection. The system utilizes a trained convolutional neural network (CNN) model to accurately recognize and detect ships and mark them in the image. By analyzing the shape, size of the ship the CNN model can detect the ship.

The system shows promising results and has practical applications in enhancing maritime surveillance in identifying ships that has been invisible to AIS with the potential to shape the future of surveillance in domain of defense. However, further research and development are needed to refine the system, address any limitations, and explore its wider applications in different contexts.

Future research directions will prioritize integrating location features into the object detection/classification system to precisely ascertain the ship's position and integrate it with AIS (Automatic Identification System). Furthermore, additional experiments should be conducted to evaluate various sensors, like SARs (Synthetic Aperture Radars), under challenging conditions where visible spectrum imagery is unavailable, such as during nighttime, cloudy weather, or foggy conditions. Moreover, exploring multi-modal scenarios by integrating different sensors and leveraging saliency estimation methods not only for ship classification but also for determining the precise positions of identified ships and other objects like yachts, boats, and aircraft will be a key focus. The incorporation and utilization of available HPC (High-Performance Computing) resources will also be a significant aspect of future work.

REFERENCES

[1] Yang, Q. Xu, F. Gao and L. Hu, "Ship detection from optical satellite images based on visual search mechanism," 2015 IEEE International Geoscience and Remote Sensing Symposium (IGARSS), Milan, Italy, 2015, pp. 3679-3682, doi: 10.1109/IGARSS.2015.7326621.

[2] F. Bi, B. Zhu, L. Gao and M. Bian, "A Visual Search Inspired Computational Model for Ship Detection in Optical Satellite Images," in IEEE Geoscience and Remote Sensing Letters, vol. 9, no. 4, pp. 749-753, July 2012, doi: 10.1109/LGRS.2011.2180695.

[3] C. Zhu, H. Zhou, R. Wang and J. Guo, "A Novel Hierarchical Method of Ship Detection from Spaceborne Optical Image Based on Shape and Texture Features," in IEEE Transactions on Geoscience and Remote Sensing, vol. 48, no. 9, pp. 3446-3456, Sept. 2010, doi: 10.1109/TGRS.2010.2046330.

[4] Ying Liu, Hong-Yuan Cui, Zheng Kuang and Guo-Qing Li"Ship Detection and Classification on Optical Remote Sensing Images Using Deep Learning" ITM Web Conf. **Volume** 12, 2017 The 4th Annual International Conference on Information Technology and Applications (ITA 2017)

[5] **Krishna Patel**, **Chintan Bhatt**,* and **Pier Luigi Mazzeo** "Deep Learning-Based Automatic Detection of Ships: An Experimental Study Using Satellite Images" Received: 28 April 2022 / Revised: 6 June 2022 / Accepted: 23 June 2022 / Published: 28 June 2022

[6] A. H. Özcan and C. Ünsalan, "Detecting inshore ships in satellite images," 2015 23nd Signal Processing and Communications Applications Conference (SIU), Malatya, Turkey, 2015, pp. 1220-1223, doi: 10.1109/SIU.2015.7130057.

[7] Corbane, Christina & Najman, Laurent & Pecoul, Emilien. (2010). A complete processing chain for ship detection using optical satellite imagery. International Journal of Remote Sensing - INT J REMOTE SENS. 31.10.1080/01431161.2010.512310.

[8] Z. Shi, X. Yu, Z. Jiang and B. Li, "Ship Detection in High-Resolution Optical Imagery Based on Anomaly Detector and Local Shape Feature," in IEEE Transactions on Geoscience and Remote Sensing, vol. 52, no. 8, pp. 4511-4523, Aug. 2014, doi: 10.1109/TGRS.2013.2282355.

[9] Lee, S.-H.; Park, H.-G.; Kwon, K.-H.; Kim, B.-H.; Kim, M.Y.; Jeong, S.-H. Accurate Ship Detection Using Electro-Optical Image-Based Satellite on Enhanced Feature and Land Awareness. Sensors **2022**, 22, 9491. https://doi.org/10.3390/s22239491

[10] Beşbınar, Beril & Alatan, A (2015). Inshore ship detection in high-resolution satellite images: approximation of harbors using sea-land segmentation. 96432D. 10.1117/12.2194928.

[11] Xie, Xiaoyang & Li, Bo & Wei, Xingxing. (2020). Ship Detection in Multispectral Satellite Images Under Complex Environment. Remote Sensing. 12.792.10.3390/rs12050792.

[12] https://www.kaggle.com/datasets/msambare/fer2013