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Automated Ship Detection in Satellite Imagery: A comprehensive Analysis of CNN Architecture for Maritime Surveillance

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Abstract: Satellite imagery stands as a pivotal tool across diverse sectors such as agriculture, defense and finance, offering unique insights. This study focuses on the crucial objective of automating the identification of ships in satellite imagery, with a particular emphasis on a dataset obtained from the San Francisco Bay and San Pedro Bay regions. The investigation systematically evaluates the effectiveness of ANN and CNN models. The ANN model is designed to capture complex relationships within the pixel values, while the CNN model leverages its spatial hierarchies to detect intricate patterns. The study assesses the robustness of the models to atmospheric conditions, evaluates the potential benefits of ensemble methods, and investigates the feasibility of real-time ship detection applications using ANN and CNN. Furthermore, the influence of image resolution on the accuracy of both models is analyzed, and the transferability of trained models to different geographical regions is examined. The findings contribute insights into the nuances of implementing ANN and CNN models for ship detection, addressing challenges and opportunities in maritime surveillance using satellite imagery. The models achieved an exceptional accuracy of 99.37%, underscoring their efficacy in ship detection.

***Index Terms* - Convolutional Neural Network, Artificial Neural Network, Satellite Imagery.**

I. INTRODUCTION

Satellite imagery has become an invaluable asset for a myriad of applications, offering unique insights into diverse sectors ranging from agriculture and defence to finance. One particularly challenging and vital task within this realm is the automated detection of ships in satellite images, a task with broad implications for maritime surveillance, port monitoring, and supply chain analysis. In this research, we delve into the development and implementation of ship detection algorithms, employing both Convolutional Neural Networks (CNN) and Artificial Neural Networks (ANN). The significance of this research lies in its practical approach to implementation, utilizing two distinct neural network architectures to tackle the complexities of ship detection in satellite imagery.

The primary objective is to assess the efficacy of both ANN and CNN models in automating ship detection. The ANN model is tailored to unravel intricate relationships within pixel values, while the CNN model, known for its proficiency in extracting spatial hierarchies crucial for ship structure recognition.

This research journey unfolds with a comprehensive exploration of the impact of spatial and temporal analysis, data augmentation, and explainable AI techniques on the performance of both ANN and CNN models. Additionally, we investigate the robustness of each model to atmospheric conditions, evaluate potential benefits of ensemble methods, and explore the feasibility of real-time ship detection applications.

Beyond algorithmic intricacies, the study delves into the influence of image resolution on model accuracy and scrutinizes the transferability of trained models to diverse geographical regions. By addressing these nuanced aspects, our research aims to provide insightful contributions to the practical implementation of ANN and CNN models for ship detection, significantly advancing the field of computer vision and satellite image analysis.

II. LITERATURE REVIEW

Satellite imagery analysis has witnessed substantial attention in recent years, with ship detection emerging as a crucial component for maritime surveillance and related applications. In this section, we review pertinent studies and methodologies adopted in the domain of ship detection, focusing on the utilization of Convolutional Neural Networks (CNNs) and Artificial Neural Networks (ANNs).

2.1.Traditional Approaches to Ship Detection: Traditionally, ship detection in satellite imagery has relied on conventional image processing techniques and machine learning algorithms. Early studies [1, 2] utilized handcrafted features and classifiers, demonstrating reasonable success. However, these approaches often struggled to generalize across diverse ship sizes, orientations, and environmental conditions.

2.2. Transition to Neural Networks: In response to the limitations of traditional methods, recent years have seen a paradigm shift towards the integration of neural networks for ship detection. Notably, studies such as [4] explored the application of Artificial Neural Networks (ANNs) to capture intricate pixel-level relationships within satellite images. ANNs demonstrated promising results, but their capacity to extract spatial hierarchies, critical for ship detection, remained limited.

2.3.Rise of Convolutional Neural Networks: The field of image analysis experienced a revolutionary shift with the advent of Convolutional Neural Networks (CNNs), particularly impacting tasks such as object detection. Research, exemplified by studies [5, 6], showcased the effectiveness of CNNs in ship detection by harnessing their capability to autonomously learn hierarchical features from images. However, these studies often relied on pre-trained models, limiting adaptability to specific domains.

2.4.Custom CNN Architectures: Acknowledging the need for domain-specific models, recent research [7, 8] has focused on the development of custom-built CNN architectures tailored for ship detection in satellite imagery. These studies explored the impact of model complexity, spatial and temporal analysis, and data augmentation techniques, laying the groundwork for our own investigation.

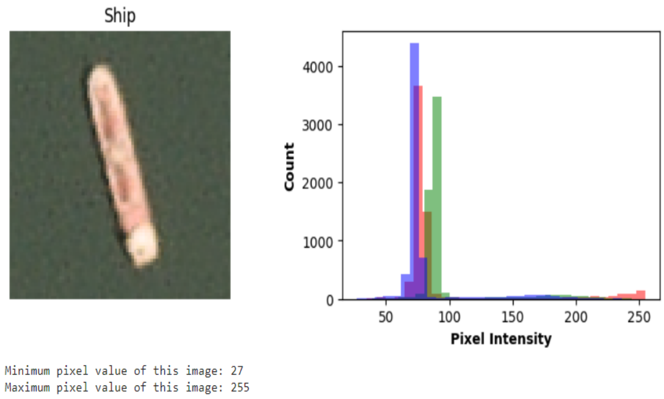
2.5.Integrating Artificial Neural Networks: In parallel, some studies [9, 10] have integrated Artificial Neural Networks (ANNs) into the ship detection pipeline. ANNs, with their ability to capture nuanced relationships within pixel values, offer complementary insights. However, the comprehensive integration of both ANNs and CNNs for ship detection remains an underexplored avenue.

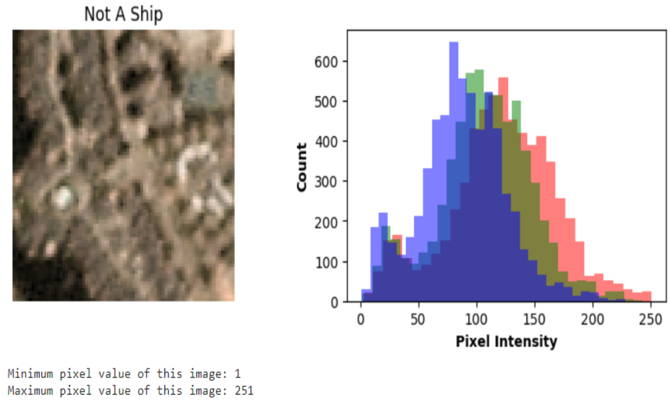
2.6.Gaps and Opportunities: While existing literature provides valuable insights into various aspects of ship detection, there remains a notable gap in the exploration of both ANN and CNN models within a unified framework for satellite imagery analysis. Our research seeks to bridge this gap by developing and evaluating separate ANN and CNN models, unravelling their respective strengths and contributions to ship detection.

III. PROPOSED ARCHITECTURE

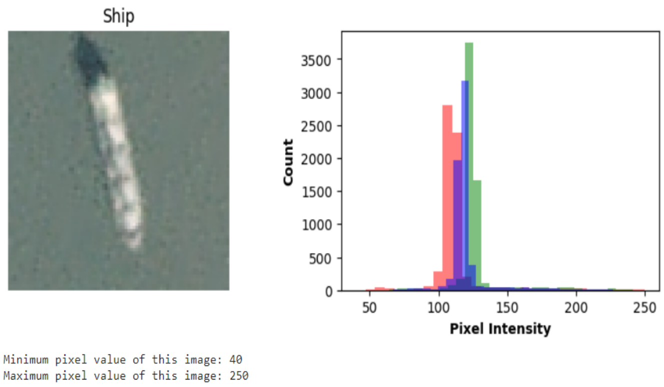
The methodology employed in this research encompasses a systematic approach to understanding and analysing the dataset for ship detection in satellite imagery. Beginning with data collection and pre-processing, we delve into the nuances of the dataset. Data visualization, a crucial exploratory step, provides insights into pixel intensity distributions and guides subsequent decisions. The implementation of Convolutional Neural Networks (CNN) and Artificial Neural Networks (ANN) follows, each tailored to address the complexities of ship detection. Additionally, data augmentation techniques enhance model robustness.

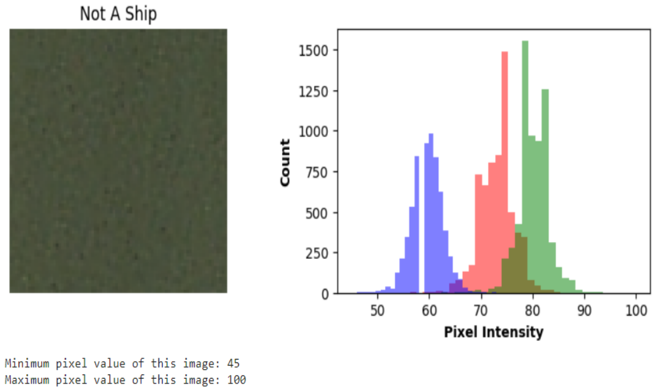
3.1.Data Collection and Data Pre-processing: The dataset utilized in this research is sourced from Planet satellite imagery encompassing the regions of San Francisco Bay and San Pedro Bay in California. It consists of 4000 80x80 RGB images, with each image meticulously categorized as either "ship" or "no-ship." These images were derived from PlanetScope full-frame visual scene products, which have been orthorectified to a 3-meter pixel size. Subsequent to data collection, the raw image data underwent pre-processing, involving reshaping using the `*x.reshape([-1, 3, 80, 80])*` method to meet the input requirements of the models. Comprehensive visualization techniques were employed, including pixel intensity plots, histogram analysis, and channel view visualization, providing insights into the dataset's characteristics.

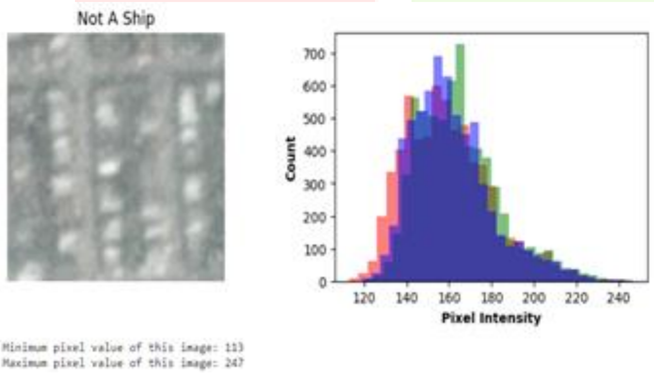




3.2.Data Visualization: Data visualization was instrumental in comprehending the dataset's intricacies. Using a custom Python function and Matplotlib, we visually explored both "Ship" and "Not A Ship" images. The `*plotHistogram*` function showcased pixel intensity distributions for each colour channel, providing insights into image variations. Statistical summaries, including minimum and maximum pixel values, highlighted the diversity within ship images. This comparative analysis guided pre-processing decisions, offering a valuable lens into the dataset's nuances and shaping subsequent steps in our research.







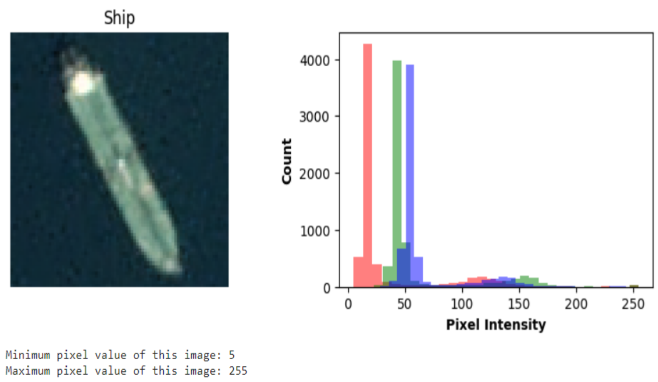


Fig1. Pixel intensity vs Count Visualization for Ship and Not a ship Classes

3.3.Channel View Visualization: Channel view visualizations were conducted to explore the distribution of pixel values in individual colour channels (Red, Green, and Blue). This detailed analysis provided insights into how colour information is distributed across images, particularly for "Not A Ship" (label 0) and "Ship" (label 1) categories. By examining the spatial distribution of pixel intensities in each channel, these visualizations aided in identifying unique features associated with different labels. The nuanced exploration of colour dimensions contributes significantly to the interpretability of the dataset, guiding subsequent modelling decisions for more accurate ship detection.

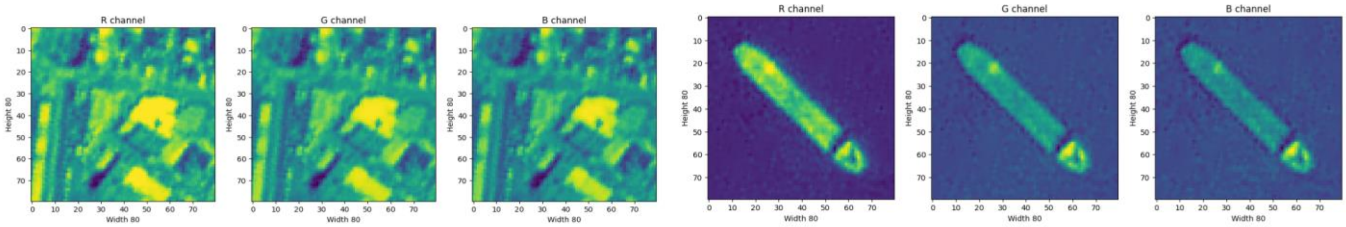


Fig2. Channel view Visualization: Pixel value distribution into individual colour channel

3.4.Artificial Neural Network (ANN) Model Implementation: The initial phase of model development focused on an Artificial Neural Network (ANN). A custom ANN model was constructed using the Keras framework. The model architecture comprised Flatten and Dense layers, each utilizing ReLU activation, and a final Dense layer employing sigmoid activation for binary classification. Training the ANN spanned 100 epochs, monitored for accuracy, and incorporated early stopping to mitigate overfitting.

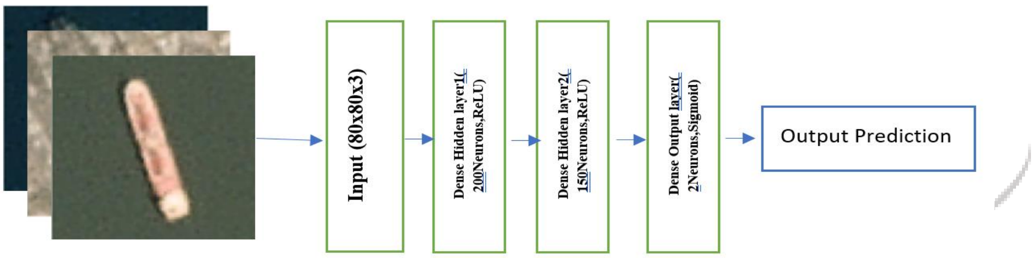


Fig4: ANN Model Architecture

3.5.Convolutional Neural Network Implementation: Subsequently, a Convolutional Neural Network was developed. The CNN model integrated Conv2D, MaxPool2D, Dropout layers, and fully connected layers with ReLU activation. The model was configured with categorical cross-entropy loss, utilized the Adam optimizer, and employed a softmax activation function for the final layer. Training spanned 100 epochs with early stopping for optimal convergence.

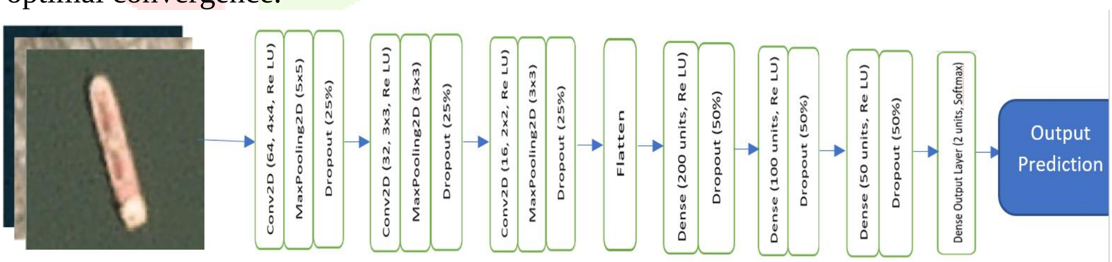
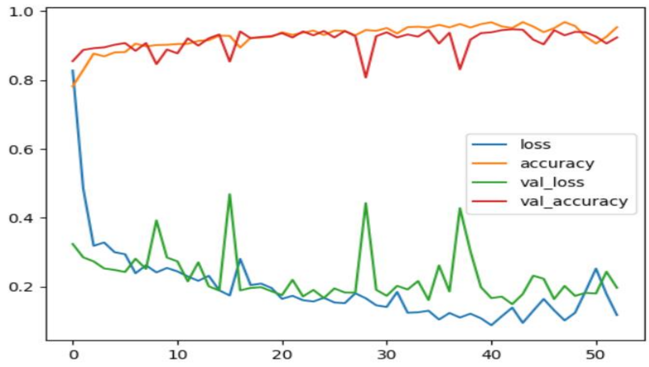


Fig5: CNN Model Architecture

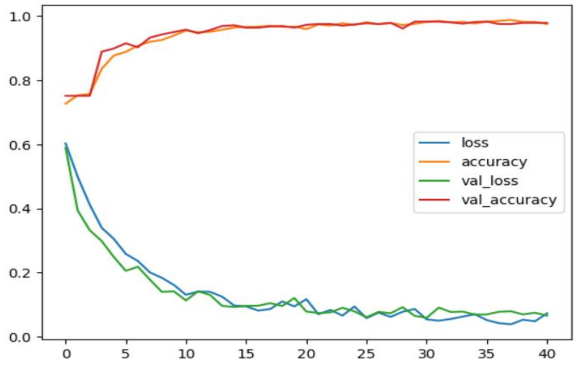
3.6.Data Augmentation: To bolster the model's robustness and performance, data augmentation techniques were implemented using the ImageDataGenerator from Keras. This step is pivotal in exposing the model to a broader range of scenarios, thereby enhancing its generalization capabilities. Augmentation methods, including rotation, zooming, shifting, and horizontal/vertical flipping, were implemented. This augmented dataset was then utilized for training the model. The subsequent training phase with augmented data resulted in a notable improvement in model accuracy. The augmented dataset's expanded volume and diversity played a pivotal role in enhancing the model's capability to generalize effectively across diverse conditions. This, in turn, resulted in improved performance in ship detection.

3.7.Training and Evaluation: The training and evaluation phase encompassed both the ANN and CNN models, with validation data facilitating model assessment. The performance metrics, particularly accuracy, were monitored during training. The incorporation of early stopping prevented overfitting, ensuring the models' optimal convergence.

The final stage involved a comprehensive analysis of the trained models, focusing on their performance metrics and comparing their efficacy in ship detection. The impact of data augmentation on model generalization was examined, considering variations in ship sizes, orientations, and atmospheric conditions.



a. ANN Accuracy graph



b. CNN Accuracy Graph

Fig6:Model accuracy variation over training epochs

IV. Result and Discussion

The developed models, comprising an Convolutional Neural Network (CNN) and Artificial Neural Network (ANN), a were rigorously evaluated on the dataset to assess their effectiveness in ship detection.

4.1. Model Performance:

a. The ANN model exhibited promising performance in ship detection, achieving a notable accuracy of 92.6. The recall, precision and F1-score metrics provide additional evidence of the model's proficiency in accurately distinguishing between "Ship" and "Not A Ship" instances. This demonstrates the capability of the ANN to discern subtle patterns in the dataset.

b. The CNN model, designed to leverage spatial hierarchies in image data, demonstrated superior performance compared to the ANN. With an accuracy of 98.87, the CNN showcased enhanced capabilities in ship detection. The precision, recall, and F1-score metrics reaffirm the model's robustness in handling the complexities of satellite imagery, particularly in scenarios with varying ship sizes, orientations, and atmospheric conditions.

Algorithm used	CNN Model Accuracy	CNN Model Loss	ANN Model Accuracy	ANN Model Loss
Before Data Augmentation	98.87	0.048	92.6	0.1888
After Data Augmentation	99.37	0.037	93.1	0.1677

Table1 – Comparative Analysis of different models

4.2. Impact of Data Augmentation on Model performance:

a. After data augmentation, the ANN model demonstrated improved accuracy, reaching 93.1. The recall, precision and F1-score metrics further highlight the model's adaptability to diverse scenarios, demonstrating enhanced performance in ship detection.

b. Similarly, the CNN model benefited substantially from data augmentation. The accuracy of the CNN model increased to 99.37 reaffirming its ability to handle the complexities of satellite imagery, including varying ship sizes, orientations, and atmospheric conditions. The notable impact of data augmentation on accuracies underscores its crucial role in mitigating challenges posed by the scale and variability of satellite imagery, ultimately contributing to the models enhanced performance in ship detection.

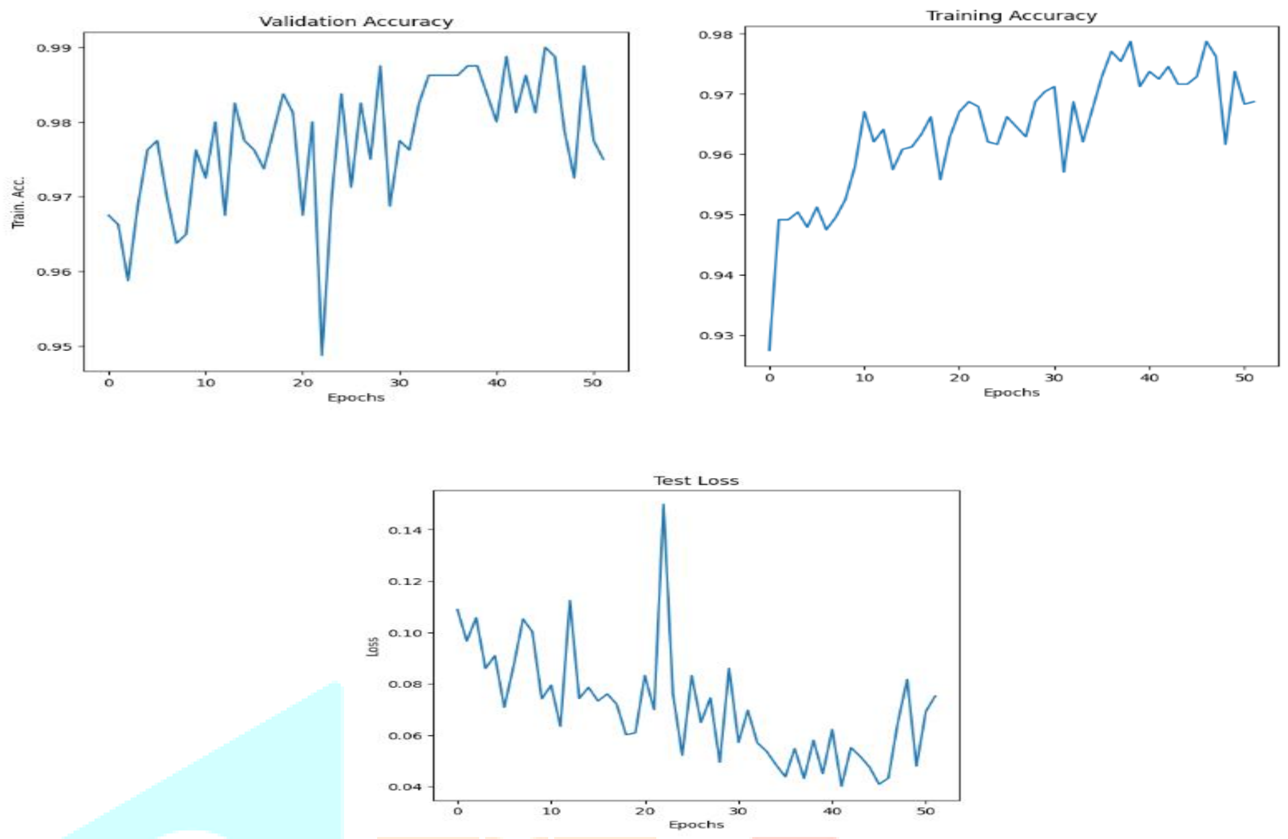


Fig7: Training and Evaluation Plots

4.3. Channel view Analysis: The channel view visualizations provided valuable insights into the dataset's features. By examining the distribution of pixel values in individual color channels, the models benefited from enhanced interpretability. The distinctive patterns identified in the channel views played a pivotal role in refining the models' understanding of ship characteristics, contributing to their successful differentiation between ship and non-ship instances.

4.4. Error: While the overall performance of both models is commendable, it is essential to examine cases where predictions deviate from ground truth labels. Understanding the nature of errors can shed light on specific challenges faced by the models. Whether misclassifying ships or failing to identify them, an in-depth examination of these instances informs future model refinement and highlights areas for improvement.

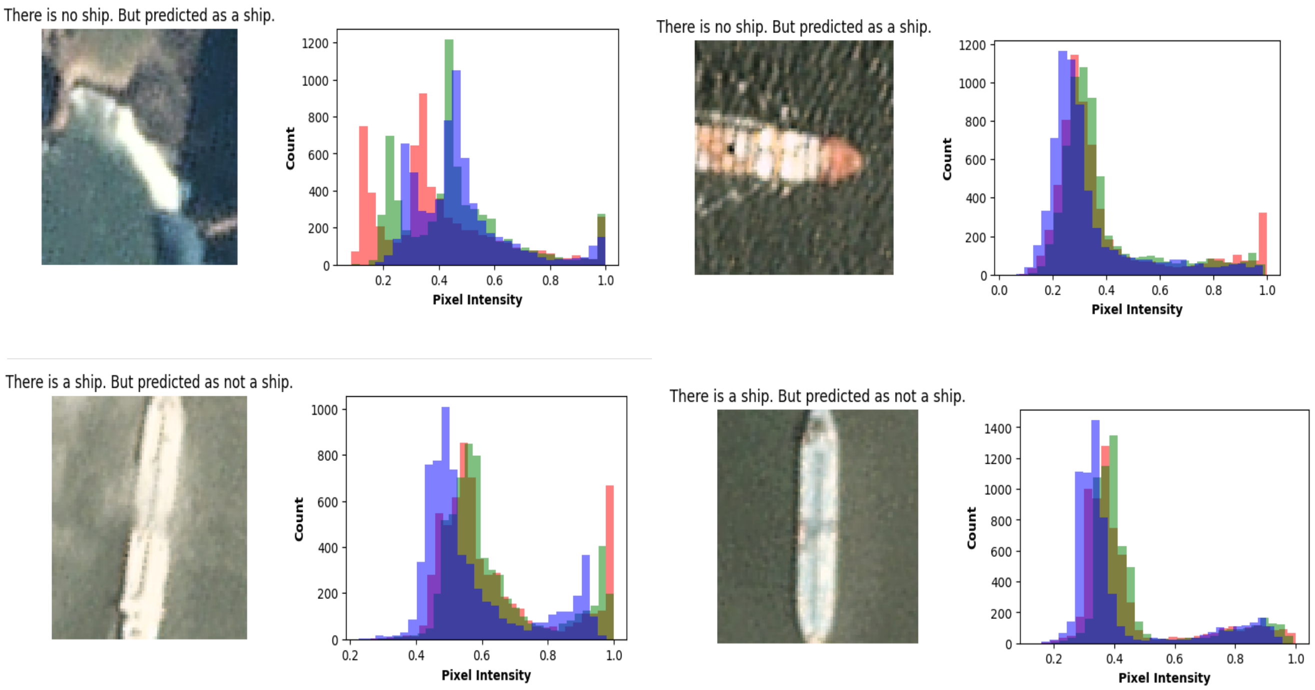
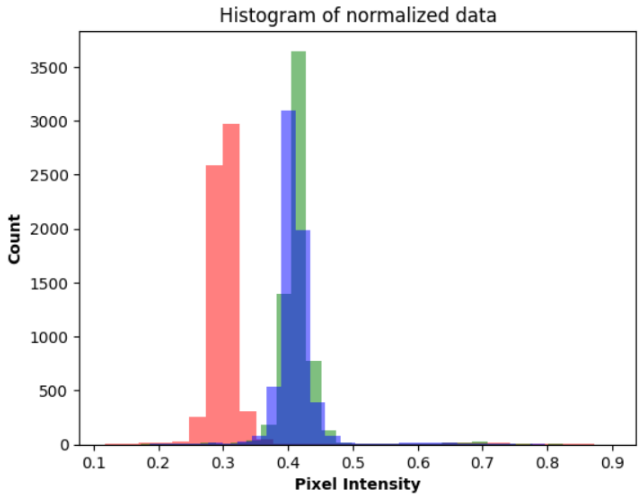


Fig8: Error prediction

A comparative analysis with existing studies in ship detection using satellite imagery highlights the competitive performance of the proposed models. The achieved results, coupled with the interpretability gained from channel view analyses, position this research as a significant contribution to the field of automated ship detection in satellite imagery.



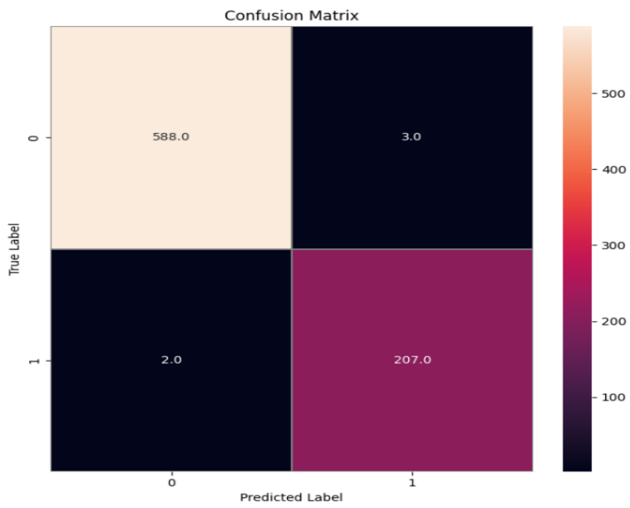


Fig9: (a) Histogram of normalized data (b) Confusion matrix heatmap

V. DATASET

Comprising 4000 80x80 RGB images labelled as "ship" or "no-ship," this dataset is extracted from Planet satellite imagery covering the San Francisco Bay and San Pedro Bay areas. The images, sourced from PlanetScope full-frame visual scene products, serve the purpose of automating ship detection in satellite imagery.

- Image Format: The dataset is distributed as shipsnet.zip, containing PNG images labelled in the format {label} _ {scene id} _ {longitude} _ {latitude}.png.
- Data Representation: The pixel values for each 80x80 RGB image are organized as lists containing 19200 integers, with 6400 entries per color channel. Images are arranged in row-major order.
- Class Labels: Binary labels ("ship": 1, "no-ship": 0) distinguish between images with and without ships. The "ship" class includes 1000 images capturing various ship sizes, orientations, and atmospheric conditions.
- Geospatial Information: Image filenames include longitude and latitude coordinates, enhancing the dataset with geospatial context.
- JSON Format: The dataset is also distributed as shipsnet.json, containing data, labels, scene_ids, and location lists.

Dataset Source: https://www.kaggle.com/datasets/rhammell/ships-in-satellite-imagery

Fig9: Representative image from the Dataset: Ship and Not a ship

VI. Conclusion and Future Scope

In conclusion, this research has made significant strides in the realm of automated ship detection in satellite imagery through the application of machine learning and computer vision methodologies. The Convolutional Neural Network (CNN) and Artificial Neural Network (ANN) models developed in this study demonstrated commendable accuracy, with the ANN achieving 93.1 and the CNN surpassing it with 99.37. The incorporation of data augmentation techniques notably enhanced the models adaptability to diverse scenarios, emphasizing its pivotal role in mitigating challenges associated with the variability of satellite imagery. The detailed analysis of individual colour channels, as showcased in the channel view visualizations, provided nuanced insights into the dataset's features, facilitating a more refined understanding of ship characteristics and contributing to the model's effective differentiation between ship and non-ship instances. In comparison with existing studies, our research stands out for its competitive performance and the comprehensive approach employed. Looking ahead, future avenues for exploration include further optimization of model architectures, experimentation with additional data augmentation strategies, and extension of the study to diverse geographical regions for improved generalization. Overall, the findings from this research not only advance the state-of-the-art in automated ship detection but also underscore the potential of machine learning applications in the field of remote sensing.

References

[1] B. Wang, B. Han and L. Yang, "Accurate Real-time Ship Target detection Using Yolov4," 2021 6th International Conference on Transportation Information and Safety (ICTIS), Wuhan, China, 2021, pp. 222-227, doi: 10.1109/ICTIS54573.2021.9798495.

[2] L. Zhang and H. Yin, "Research on Ship Detection Method of Optical Remote Sensing Image Based on Deep Learning," 2022 International Conference on Sensing, Measurement & Data Analytics in the era of Artificial Intelligence (ICSMD), Harbin, China, 2022, pp. 1-6, doi: 10.1109/ICSMD57530.2022.10058312.

[3] A. A. K and S. R. K, "Prediction of Myositis Disease using Machine Learning Algorithm," 2023 5th International Conference on Inventive Research in Computing Applications (ICIRCA), Coimbatore, India, 2023, pp. 534-539, doi: 10.1109/ICIRCA57980.2023.10220885.

[4] S. Lei, Y. Zhao and Y. Bai, "Ship detection based on deep learning under complex lighting," 2022 34th Chinese Control and Decision Conference (CCDC), Hefei, China, 2022, pp. 5694-5698, doi: 10.1109/CCDC55256.2022.10033941.

[5] Z. Shao, X. Zhang, X. Xu, T. Zeng, T. Zhang and J. Shi, "CFAR-guided Convolution Neural Network for Large Scale Scene SAR Ship Detection," 2023 IEEE Radar Conference (RadarConf23), San Antonio, TX, USA, 2023, pp. 1-5, doi: 10.1109/RadarConf2351548.2023.10149747.

[6] N. Wang and F. Ma, "Single ship target detection based on the concept of edge computing," 2021 6th International Conference on Transportation Information and Safety (ICTIS), Wuhan, China, 2021, pp. 559-564, doi: 10.1109/ICTIS54573.2021.9798642.

[7] J. Li, J. Tian, P. Gao and L. Li, "Ship Detection and Fine-Grained Recognition in Large-Format Remote Sensing Images Based on Convolutional Neural Network," IGARSS 2020 - 2020 IEEE International Geoscience and Remote Sensing Symposium, Waikoloa, HI, USA, 2020, pp. 2859-2862, doi: 10.1109/IGARSS39084.2020.9323246.

[8] X. Zhang and Z. Zhang, "Ship detection based on improved YOLO algorithm," 2023 3rd International Conference on Consumer Electronics and Computer Engineering (ICCECE), Guangzhou, China, 2023, pp. 98-101, doi: 10.1109/ICCECE58074.2023.10135396.

[9] L. Ying, D. Miao, Z. Zhang and Q. Zhang, "Remote Sensing Ship Detection Based on Three-way Decisions and Multi-granularity Feature Fusion," 2022 IEEE 8th International Conference on Cloud Computing and Intelligent Systems (CCIS), Chengdu, China, 2022, pp. 234-238, doi: 10.1109/CCIS57298.2022.10016364.

[10] Y. Zou, L. Zhao, S. Qin, M. Pan and Z. Li, "Ship target detection and identification based on SSD_MobilenetV2," 2020 IEEE 5th Information Technology and Mechatronics Engineering Conference (ITOEC), Chongqing, China, 2020, pp. 1676-1680, doi: 10.1109/ITOEC49072.2020.9141734.

[11] T. ZHANG, X. ZHANG, J. SHI and S. WEI, "High-Speed Ship Detection in SAR Images by Improved Yolov3," 2019 16th International Computer Conference on Wavelet Active Media Technology and Information Processing, Chengdu, China, 2019, pp. 149-152, doi: 10.1109/ICCWAMTIP47768.2019.9067695.

[12] Y. Zheng and S. Zhang, "Mcships: A Large-Scale Ship Dataset For Detection And Fine-Grained Categorization In The Wild," 2020 IEEE International Conference on Multimedia and Expo (ICME), London, UK, 2020, pp. 1-6, doi: 10.1109/ICME46284.2020.9102907.

[13] Y. Lei, X. Leng and K. Ji, "Marine Ship Target Detection in SAR Image Based on Google Earth Engine," 2021 IEEE International Geoscience and Remote Sensing Symposium IGARSS, Brussels, Belgium, 2021, pp. 8574-8577, doi: 10.1109/IGARSS47720.2021.9553711.

[14] Z. Shao and X. Zhang, "A High Accuracy Detection Network for Rotated Multi-Class SAR Ship Detection," IGARSS 2023 - 2023 IEEE International Geoscience and Remote Sensing Symposium, Pasadena, CA, USA, 2023, pp. 4954-4957, doi: 10.1109/IGARSS52108.2023.10282829.

[15] T. -H. Kim, Y. Park, S. Jang and C. -S. Yang, "Ship Detection and Classification in Cas500-1 Images Based on Yolo Model," IGARSS 2023 - 2023 IEEE International Geoscience and Remote Sensing Symposium, Pasadena, CA, USA, 2023, pp. 4112-4115, doi: 10.1109/IGARSS52108.2023.10282491.

[16] J. Cao, Y. You, Y. Ning and W. Zhou, "Change Detection Network of Nearshore Ships for Multi-Temporal Optical Remote Sensing Images," IGARSS 2020 - 2020 IEEE International Geoscience and Remote Sensing Symposium, Waikoloa, HI, USA, 2020, pp. 2531-2534, doi: 10.1109/IGARSS39084.2020.9323388.

[17] C. Wang, L. Xiao and C. Ni, "On the detection performance analysis of ship radar under interference environment," 2017 International Applied Computational Electromagnetics Society Symposium (ACES), Suzhou, China, 2017, pp. 1-2.

[18] Chang, Yang-Lang, et al. "Ship detection based on YOLOv2 for SAR imagery." Remote Sensing 11.7 (2019): 786.

[19] Chen, Zhijun, et al. "Deep learning for autonomous ship-oriented small ship detection." Safety Science 130 (2020): 104812.

[20] Crisp, David J. "The state-of-the-art in ship detection in synthetic aperture radar imagery." (2004).

[21] Bo, L. I., et al. "Ship detection and classification from optical remote sensing images: A survey." Chinese Journal of Aeronautics 34.3 (2021): 145-163.

[22] Zhang, Tianwen, et al. "SAR ship detection dataset (SSDD): Official release and comprehensive data analysis." Remote Sensing 13.18 (2021): 3690.

[23] Liu, Zikun, et al. "Rotated region based CNN for ship detection." 2017 IEEE International Conference on Image Processing (ICIP). IEEE, 2017.

[24] Shao, Zhenfeng, et al. "Seaships: A large-scale precisely annotated dataset for ship detection." IEEE transactions on multimedia 20.10 (2018): 2593-2604.

[25] Li, Jianwei, et al. "Deep learning for SAR ship detection: Past, present and future." Remote Sensing 14.11 (2022): 2712.

[26] Tello, Mariví, Carlos López-Martínez, and Jordi J. Mallorqui. "A novel algorithm for ship detection in SAR imagery based on the wavelet transform." IEEE Geoscience and remote sensing letters 2.2 (2005): 201-205.

[27] Guo, Haoyuan, et al. "A CenterNet++ model for ship detection in SAR images." Pattern Recognition 112 (2021): 107787.

[28] Yang, Guang, et al. "Ship detection from optical satellite images based on sea surface analysis." IEEE Geoscience and Remote Sensing Letters 11.3 (2013): 641-645.

[29] Corbane, Christina, et al. "A complete processing chain for ship detection using optical satellite imagery." International journal of remote sensing 31.22 (2010): 5837-5854.

[30] Stofa, Marzuraikah Mohd, Mohd Asyraf Zulkifley, and Siti Zulaikha Muhammad Zaki. "A deep learning approach to ship detection using satellite imagery." IOP Conference Series: Earth and Environmental Science. Vol. 540. No. 1. IOP Publishing, 2020.

[31] Antelo, Jose, et al. "Ship detection and recognitionin high-resolution satellite images." 2009 IEEE International Geoscience and Remote Sensing Symposium. Vol. 4. IEEE, 2009.

[32] Proia, Nadia, and Vincent Pagé. "Characterization of a Bayesian ship detection method in optical satellite images." IEEE geoscience and remote sensing letters 7.2 (2009): 226-230.

[33] Qi, Shengxiang, et al. "Unsupervised ship detection based on saliency and S-HOG descriptor from optical satellite images." IEEE geoscience and remote sensing letters 12.7 (2015): 1451-1455.

[34] Yang, Feng, Qizhi Xu, and Bo Li. "Ship detection from optical satellite images based on saliency segmentation and structure-LBP feature." IEEE geoscience and remote sensing letters 14.5 (2017): 602-606.

[35] Liu, Ge, et al. "A new method on inshore ship detection in high-resolution satellite images using shape and context information." IEEE geoscience and remote sensing letters 11.3 (2013): 617-621.

[36] Wang, Yu, et al. "Machine learning-based ship detection and tracking using satellite images for maritime surveillance." Journal of Ambient Intelligence and Smart Environments 13.5 (2021): 361-371.

[37] Štepec, Dejan, Tomaž Martinčič, and Danijel Skočaj. "Automated system for ship detection from medium resolution satellite optical imagery." OCEANS 2019 MTS/IEEE SEATTLE. IEEE, 2019.