Multi-Class Ship Classification of Commercial and Naval Vessels using Convolutional Neural Network

A PROJECT REPORT

Submitted by

AKASH VARMA DATLA [RA2111047010131]
AMAN PARASHER [RA2111047010157]

Under the Guidance of

Dr. U.Sakthi

Assistant Professor,
Department of Computational Intelligence

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COLLEGE OF ENGINEERING AND TECHNOLOGY
SRM INSTITUTE OF SCIENCE AND TECHNOLOGY
KATTANKULATHUR- 603 203

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Student Name: **Akash Varma Datla, Aman Parasher**

Registration Number: RA2111047010131, RA2111047010157

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Dr. U.Sakthi	**Dr. R. ANNIE UTHRA**
SUPERVISOR	
ASSISTANT PROFESSOR	**PROFESSOR & HEAD**
DEPARTMENT OF COMPUTATIONAL INTELLIGENCE	DEPARTMENT OF COMPUTATIONAL INTELLIGENCE

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ABSTRACT

This work seeks to classify various ship categories on the high-resolution optical remote sensing dataset known as FGSC-23 using deep learning models. The dataset contains 23 types of ships, but for this study, six categories are selected: Medical Ship, Hovercraft, Submarine, Fishing Boat, Passenger Ship and Liquified Gas Ship. The adopted ship categories were thereafter used to train four deep learning models which included VGG16, EfficientNet, ResNet50v2, and MobileNetv2. The accuracy, precision, and AUC parameters were used to evaluate the models where the best one, ResNet50v2, was set up as accurate. Using these models, it should be possible to achieve a practical deployment aiming at fine-grained classification of ships that will contribute to enhancing maritime surveillance techniques. ResNet50v2 model had the highest precision of 0.9058 and on the other hand MobileNetv2 had the highest AUC of 0.9932. The analysis of the identified models is performed further in this work to illustrate their advantages and shortcomings in adherence to fine-grained ship classification tasks. Based on this research, the practical implications transcend theoretical comparisons of performance metrics, as useful information is provided to improve security applications in the maritime domain, surveillance, and monitoring systems.

Categorization and identification of ships is a very important process in global maritime business because it is used in decision-making processes in fields like security and surveillance, fishing control, search and rescue and conservation of the environment. The models highlighted are namely ResNet50v2 as well as MobileNetv2, proved to be robust in real-time applications such scenarios because of their ability to accurately and proficiently distinguish the differences between the ship types. In addition, this study suggests the luminal possibility of doing further improvement on these models using data enhancement strategies like transfer learning, data augmentation, and hyperparameter optimization which would enable it to perform impressively on any other maritime datasets. Therefore, the outcomes are beneficial for furthering work in automated ship detection and classification and are important toward enhancing the overall effectiveness and safety of navies across the globe.

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ABBREVIATIONS

AI	Artificial Intelligence
FGSC	Fine-Grained Ship Classification
VGG	Visual Geometry Group
ResNet	Residual Neural Network
AUC	Area Under the Curve
CNN	Convolutional Neural Network
ViT	Vision Transformers
SE	Squeeze and Excitation
ADAM	Adaptive Moment Estimation

1 INTRODUCTION

1.1 GENERAL INTRODUCTION

Ship grouping is an important procedure in maritime vigilance systems to sort different kinds of ships with high accuracy. Classification of ships is also important for several reasons such as security, environmental conservation as well as traffic control on water channels. FGSC-23 is a fine-grained dataset in the ship classification field, which includes 23 different ship types and a total of 4052 samples are divided into categories they belong to, which aspect ratio they have and in which direction are dispersed. The dataset has numerous image scenes and fine categorization, which constitutes a complex issue for machine learning since the variations of ship kinds are very close. By focusing on classifying six specific categories of ships from the FGSC-23 dataset: Submarine, Medical Ship, Hovercraft, Fishing Boat, Passenger Ship, Liquified gas ship. Each of these categories was chosen because they were appropriate for both civilian and defense markets. Although the FGSC-23 dataset is commonly used in ship classification research, by focusing on the fine-grained nature of the task in dealing with ships whose intra class variations deviate little from each other. The selected models effectively solve this increased complexity of the problem. It is imperative that differences between classes are well distinguished and hence the objective of the current research is to use enhanced deep learning classification for ship classification. CNN architecture is the most important choice for the tradeoff between performance and computational efficiency.

To achieve this, four different convolutional neural network (CNN) architectures are used, models including VGG16, EfficientNet, ResNet50v2, and MobileNetv2. VGG16 featured for its simple and classical deep convolutional structure, which is a starting point in the construction of feature extraction. VGG16 is a classic use of small 3x3 convolutional filters that can capture very fine patterns. Since it has many parameters, it is a good comparative model, though. MobileNetV2: In terms of computational cost, one is selected for its efficiency. In MobileNetV2, depth wise separable convolutions are used, drastically reducing the number of parameters and operations while keeping on par accuracy. This is particularly useful in mobile and embedded systems where resources are limited. ResNet50V2: Residual connections are selected for their deep architecture which alleviates vanishing gradient issues. This speeds up the training, especially in deep networks. As ResNet50V2 whose depth is suitable to capture complex features in larger datasets. EfficientNet: Had scalability in mind. Deep, wide, and low resolution together enable a model that is efficient while achieving high accuracy with less parameters.

1.2 MOTIVATION

Accurate ship classification is crucial for maritime operations such as security, traffic control, and environmental protection. The FGSC-23 dataset presents a significant challenge due to the fine-grained nature of the task, where visual differences between ship types are subtle. Traditional methods struggle with such close intra-class variations, emphasizing the need for more advanced deep learning models.

With maritime activities becoming increasingly diverse and complex, there is a growing need for efficient systems that can operate in real-time while maintaining high accuracy. The classification of ships is not only essential for managing civilian maritime traffic but also for defense-related applications, where timely and precise identification of vessels is critical. As the volume of maritime data grows, so does the demand for models that can scale effectively without compromising performance.

This research focuses on enhancing ship classification accuracy and efficiency by using CNN architectures like VGG16, MobileNetV2, ResNet50V2, and EfficientNet. Each model offers unique strengths in feature extraction and computational efficiency, addressing both the complexity of the FGSC-23 dataset and the practical need for real-time, resource-efficient applications in maritime systems. By targeting six specific ship categories relevant to both civilian and defense sectors, this study aims to bridge the gap between high-performance models and practical deployment in maritime surveillance and monitoring.

Ultimately, the motivation behind this study is to provide a solution that balances cutting-edge deep learning techniques with the real-world constraints of computational resources. Through this, we aim to contribute to the development of more reliable and scalable ship classification systems, which can improve the safety and efficiency of maritime operations on a global scale.

2 LITERATURE SURVEY

2.1 SUBTITLE 1: DEEP LEARNING TECHNIQUES FOR SHIP CLASSIFICATION: A COMPREHENSIVE REVIEW

This paper reviews various deep learning techniques utilized for ship classification, focusing on recent advancements and methodologies. The study highlights the growing importance of accurate ship classification in maritime safety, environmental monitoring, and fleet management. With the increasing volume of maritime data, deep learning models, such as Convolutional Neural Networks (CNNs) and their variants, have demonstrated remarkable effectiveness in classifying ships from images. The research emphasizes that models like VGG16, MobileNetV2, and EfficientNet show promising results in terms of precision and accuracy, significantly enhancing the automation of ship classification tasks. However, challenges such as the need for extensive labeled datasets and the computational demands of training these models are discussed, pointing to a need for efficient data augmentation and transfer learning strategies.

2.2 SUBTITLE 2: ENHANCING SHIP CLASSIFICATION WITH PRETRAINED MODELS AND DATA AUGMENTATION

In this study, researchers explore the application of pretrained models and data augmentation techniques in improving ship classification accuracy. The findings reveal that employing models like ResNet50V2 not only accelerates the training process but also enhances the model's ability to generalize to unseen data. Data augmentation strategies, such as rotation, shifting, and zooming, are shown to mitigate overfitting and improve the robustness of the classification system. Despite the advancements, the study identifies potential limitations, including the dependency on the quality of the training data and the challenge of maintaining model performance across various environmental conditions. The integration of these techniques is crucial for developing a reliable ship classification system that operates effectively in diverse maritime scenarios.

2.3 LIMITATIONS IDENTIFIED FROM LITERATURE SURVEY (RESEARCH GAPS)

The review of recent methods for ship classification highlighted several limitations in existing approaches, particularly in Synthetic Aperture Radar (SAR) image recognition and fine-grained ship classification:

1. **Manual Feature Selection in Traditional Methods**: Earlier methods, such as those using CFAR (Constant False Alarm Rate), rely on manually designed features, which are not only labor-intensive but also struggle with generalization. These methods are particularly vulnerable to challenges like sea clutter and complex maritime environments, limiting their scalability.
2. **Class Imbalance and Dataset Limitations**: Despite advances in deep learning, including the use of CNNs for ship classification, models often suffer from class imbalance, where underrepresented ship classes are inaccurately classified. Studies have shown that class imbalance impacts model performance, especially in SAR datasets where some ship types are rare.
3. **Spatial Information Loss in Deep CNNs**: Conventional CNNs, especially as they deepen, face the challenge of spatial information loss. As features are compressed and reduced through layers, finer details necessary for distinguishing between ships with similar structures may be lost, leading to lower classification accuracy.
4. **Insufficient Handling of High Intra-Class Variation**: Fine-Grained Ship Classification (FGSC) poses unique challenges due to high intra-class variation. Models often struggle to differentiate between ships of similar hull structures but distinct superstructures, which affects classification precision, particularly in military and commercial ship datasets.

2.1 RESEARCH OBJECTIVES

Our project is guided by three core objectives designed to address the critical aspects of ship classification using deep learning models.

1. **Achieving Fine-Grained Classification Accuracy:** The first objective is to improve the fine-grained classification of ships using the FGSC-23 dataset. Focusing on six specific ship categories—Medical Ship, Hovercraft, Submarine, Fishing Boat, Passenger Ship, and Liquified Gas Ship—this study aims to evaluate the performance of four deep learning models: VGG16, EfficientNet, ResNet50v2, and MobileNetv2. By leveraging these models, our goal is to

optimize precision and accuracy, contributing to more effective maritime surveillance and decision-making processes.

2. **Evaluating and Enhancing Model Performance:** The second objective emphasizes the evaluation of model performance based on key metrics such as accuracy, precision, and AUC. The research identifies ResNet50v2 as the most accurate model with a precision of 0.9058 and MobileNetv2 as the model with the highest AUC at 0.9932. Additionally, this objective explores potential enhancements to these models through data augmentation, transfer learning, and hyperparameter optimization to further improve their classification capabilities across various maritime datasets.
3. **Practical Application in Maritime Surveillance:** The third objective is to apply the insights gained from model evaluations to practical maritime surveillance and monitoring systems. This involves identifying how these models can contribute to real-time applications such as ship detection, security, fishing control, and environmental conservation. By refining ship classification techniques, the research aims to support enhanced naval operations and global maritime safety.

3 PROPOSED METHODOLOGIES

This research investigates the application of deep learning modalities for the task of fine-grained ship classification on the FGSC-23 dataset. The approach focuses on six specific ship categories: Submarine, Medical ship, Hovercraft, Fishing boat, Passenger ship, and Liquified gas ship. To achieve accurate classification, four pre-trained convolutional neural networks (CNNs) were utilized: VGG16, EfficientNet, ResNet50v2, and MobileNetv2.

The FGSC-23 dataset comprises high-resolution optical ship images spanning 23 ship categories with 4052 samples. These images are well-suited for fine-grained classification due to the availability of class, aspect ratio, and distribution direction labels. For this study, six categories were selected, covering both civil and naval vessels.

3.1 PREPROCESSING AND DATA AUGMENTATION

To ensure the models generalize well and to prevent overfitting, the dataset was divided into training, validation, and test sets. Preprocessing included resizing all images to a uniform size of 224x224 pixels, followed by normalization. Simple data augmentation techniques such as rotation, flipping, and scaling were applied to the training set to enhance generalization. These steps aimed to improve model robustness while working with high-resolution ship images.

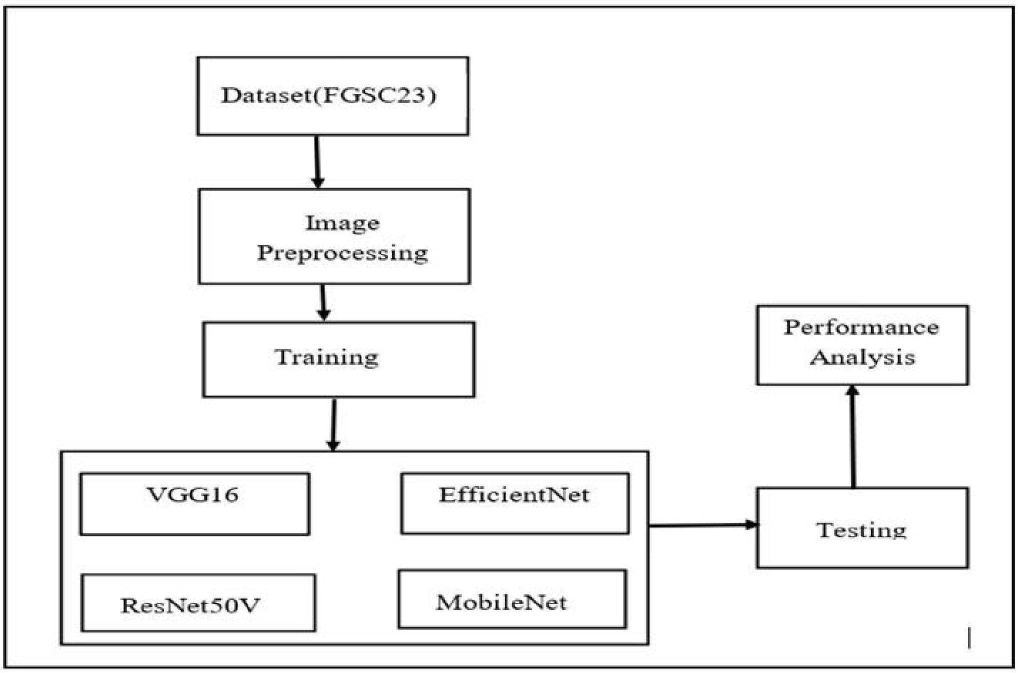

Fig 3.1.1 Process Flow Diagram of Ship Classification

3.2 MODEL ARCHITECTURES

Four deep learning models were employed to classify the ships from the FGSC-23 dataset. Each model brought unique capabilities to the classification task:

1. **VGG16**: This convolutional neural network (CNN) has 16 layers. Despite its simplicity, VGG16 is known for effective feature extraction. It uses convolutional and pooling layers for feature extraction, followed by fully connected layers for classification.
2. **EfficientNet**: EfficientNet optimizes both performance and computational resources by scaling in three dimensions—depth, width, and image resolution. It provides high accuracy with minimal computational overhead, making it ideal for large datasets like FGSC-23.
3. **ResNet50v2**: ResNet50v2, with its 50 layers, incorporates identity mapping to address the vanishing gradient problem, facilitating deeper training. The model's architecture enables it to capture hierarchical features and classify complex ship categories effectively.
4. **MobileNetv2**: MobileNetv2 employs depth-wise separable convolutions to significantly reduce the computational load without compromising accuracy. This makes it particularly suitable for real-time applications on mobile and embedded devices.

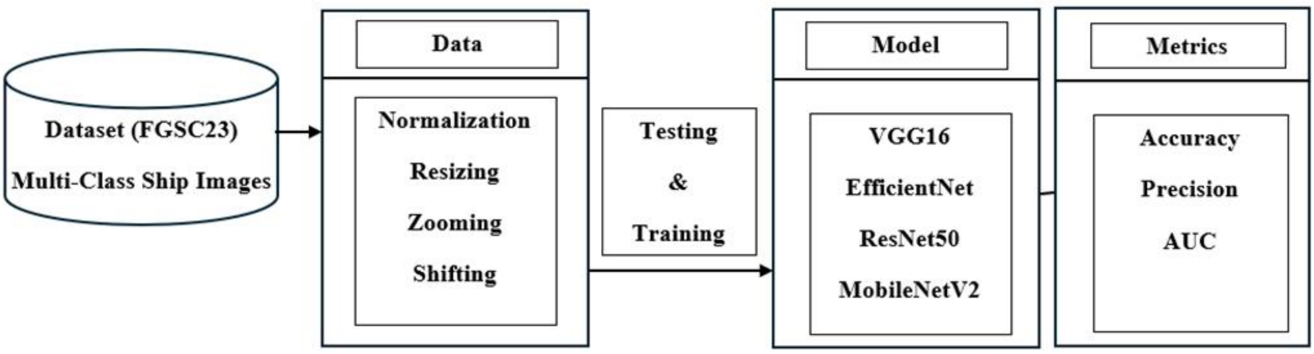

Fig 3.2.1 Architecture Diagram of Ship Classification

In brief, the workflow of ship classification using deep learning, which is illustrated in Fig. 3.2.1, consists of data preprocessing, model training, model testing, and model performance testing to select an optimum deep learning model for the chosen problem.

3.3 TRANSFER LEARNING AND TRAINING

All four models were pre-trained on the ImageNet dataset and then fine-tuned on the FGSC-23 dataset. Transfer learning allowed the models to leverage pre-learned features, reducing the amount of data required to achieve high performance.

Each model was trained using the Adam optimizer and categorical cross-entropy loss function. The training was limited to 50 epochs with early stopping to prevent overfitting. The models were trained with careful monitoring to ensure they did not overfit, and training was halted when the validation loss plateaued.

3.4 EVALUATION METRICS

The models were evaluated using key metrics: accuracy, precision, and Area Under the Curve (AUC). These metrics provided a comprehensive view of each model's performance on the fine-grained classification task.

1. **Accuracy**: Accuracy measures the overall performance of the model by calculating the percentage of correctly classified instances. It is defined as:

$$\text{Accuracy} = \frac{\text{True Positives} + \text{True Negatives}}{\text{Total Samples}}$$

2. **Precision**: Precision assesses the model's ability to avoid false positives by measuring the proportion of true positives among the predicted positives. It is defined as:

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}}$$

3. **Area Under the Curve (AUC)**: AUC evaluates the model's ability to distinguish between classes. It provides a balanced measure between True Positives (TP) and False Positives (FP) across various thresholds:

$$\text{AUC} = \int_0^1 \text{True Positive Rate}\, d(\text{False Positive Rate})$$

In terms of performance, EfficientNet and MobileNetv2 outperformed the other models due to their lightweight architectures and efficient computation strategies. MobileNetv2, with its depth-wise separable convolutions, required fewer trainable weights and operations, allowing for high efficiency. EfficientNet's compound scaling method also optimized the model for both performance and computational efficiency.

ResNet50v2 demonstrated strong performance, leveraging its skip connections to handle deeper models and capture complex patterns. However, VGG16, despite its depth, struggled with overfitting due to its large number of parameters and high computational demands, resulting in comparatively lower accuracy.

4 RESULTS AND DISCUSSIONS

This project evaluated the performance of four deep learning models—MobileNetV2, ResNet50V2, VGG16, and EfficientNet—for ship classification, using accuracy, precision, and AUC as key metrics. ResNet50V2 achieved the highest accuracy at 87.9%, closely followed by MobileNetV2 and EfficientNet, both with 87.5%, demonstrating these models' strong feature extraction capabilities. In contrast, VGG16 lagged with an accuracy of 43.7%, likely due to its simpler architecture, which limits its ability to distinguish fine-grained differences among ship types.

Precision results showed a similar trend, with ResNet50V2 and MobileNetV2 leading at 90.5% and 90.3%, respectively, while EfficientNet scored 87.1%. VGG16 again underperformed with a precision of 50%, indicating frequent misclassification. In terms of AUC, MobileNetV2 achieved the highest score at 99.3%, followed closely by EfficientNet at 99.2%, and ResNet50V2 at 98.5%, confirming their reliability in distinguishing between classes. VGG16's AUC of 80.5% further reflected its limitations in capturing complex patterns within the data.

Overall, ResNet50V2, MobileNetV2, and EfficientNet demonstrated effective and balanced performance across all metrics, highlighting the advantage of modern architectures with optimizations like residual connections and compound scaling. VGG16's lower scores across all metrics underscore the importance of architectural complexity for accurate, fine-grained classification.

Model	**Accuracy (%)**	**Precision (%)**	**AUC**
MobileNetv2	**87.5**	**90.3**	**99.3**
ResNet50v2	**87.9**	**90.5**	**98.5**
VGG16	**43.7**	**50.0**	**80.5**
EfficientNet	**87.5**	**87.1**	**99.2**

Table 4.1: Performance Analysis

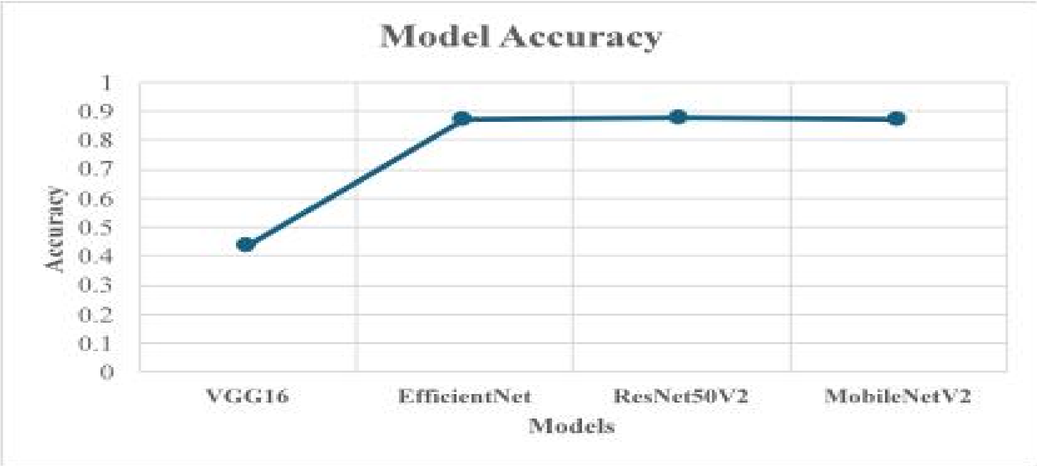

Fig 4.1: Accuracy Comparisons of Different Models

In fig 4.1, the accuracy of ResNet50v2 was excellent and achieved an impressive 87.98% for most ship categories. On the other hand, VGG16 showed extremely low accuracy of 43.75 % (i.e significantly lower accuracy as it has more difficulties differentiating closely related ship classes).

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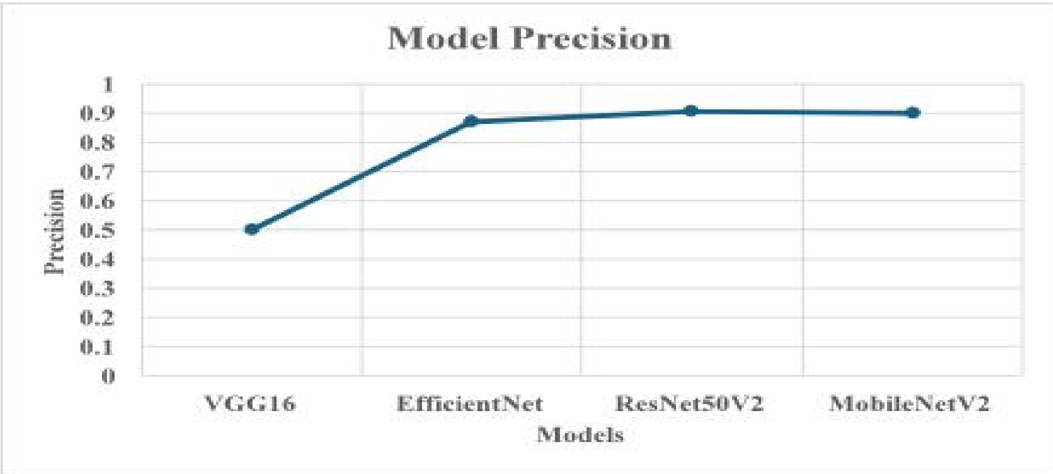

Fig 4.2: Precision Comparisons of Different Models

In fig 4.2,With a precision of 90.58%, it turns out that ResNet50v2 was quite reliable at predicting from ship categories. On the other hand, VGG16 precision was 50.0%, showing a high rate of misclassifications.

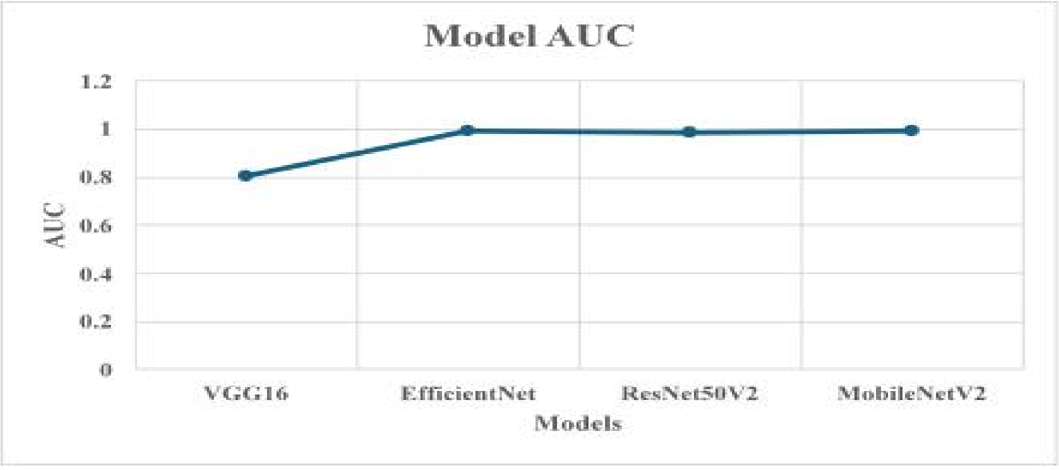

Fig 4.3: AUC Comparisons of Different Models

AUC Comparisons the AUC overall score gives the amount by which the model can correctly separate between positive and negative classes at different thresholds. This is shown in Fig. 4.3 where the accuracy of MobileNetv2 with the maximum AUC score of 99.32% portrays a good discriminating ability between the six ship categories. EfficientNet was right behind at a 99.25% AUC, and a very good performance by ResNet50v2 at 98.51%. VGG16 shortly with an AUC of 80.50%.

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5 CONCLUSION AND FUTURE ENHANCEMENT

5.1 CONCLUSION

This study focuses on the classification of six ship categories from the FGSC-23 dataset using four deep learning models: VGG16, ResNet50v2, EfficientNet, and MobileNetv2 are on the list. The FGSC-23 dataset, famous for its in-depth classification and wealth of scenes, provided an ideal platform for assessing these model performances. Among the choices, ResNet50v2 excelled by reaching an accuracy score of 87.98%, a precision rate of 90.58%, along with a high AUC score of 98.51%, which serves as potential evidence of its applicability for classifying the positive and negative categories with much certainty. MobileNetv2 saw 90.32% precision along with an AUC of 99.32%, both indicators which were approximately equal to EfficientNet's strong performance-to-size ratio measured at 99.25% AUC.

ResNet50v2 has surpassed all networks repeatedly in both accuracy and precision, thus emerging as the favored option for maritime object classification, which requires accurate typology. The success of VGG16 in image categorization tasks was not sufficient for the fine-grained classification challenge, resulting in an accuracy of 43.75% and 50.00% precision. Across the FGSC-23 dataset, findings show that ResNet50v2 is the leading model for ship classification, making it usable for real maritime applications in security, traffic management, and environmental monitoring. Investigations going forward might examine ensemble learning methods that fuse several models for better classification, along with expanding the analysis to represent all 23 vessel types in the FGSC-23 dataset, improving both preprocessing and data augmentation to improve performance and generalization.

In the Future, the flexibility of the model can be increased by integrating supplementary ship classes from the complete FGSC-23 dataset or alternative resources.

5.2 FUTURE ENHANCEMENTS

This project holds several promising avenues for future improvement. By implementing these enhancements, we can increase model accuracy, reduce computational load, and broaden the applicability of the ship classification system to real-world scenarios.

1. Hyperparameter Optimization is an essential step to ensure that our model performs at its best. Currently, fixed values for hyperparameters like learning rate, batch size, and dropout rates are used, but these may not be optimal. In the future, we can explore advanced hyperparameter tuning techniques, such as Grid Search or Random Search. Tools like Optuna and Keras Tuner can automate this search, identifying the ideal combination of hyperparameters more efficiently than manual adjustments. This optimization could lead to improved model accuracy and potentially reduce training time by minimizing the need for trial and error.
2. Another valuable enhancement would be to experiment with Additional Pretrained Models beyond those already employed. While we currently use VGG16, MobileNetV2, EfficientNet, and ResNet50V2, other architectures like InceptionNet or DenseNet could offer unique advantages. For instance, DenseNet's connectivity pattern helps retain spatial information, which may be beneficial for distinguishing fine details in ship images. Additionally, Vision Transformers (ViT), known for excelling in vision tasks by capturing long-range dependencies, could further improve classification accuracy by focusing on critical features in different parts of the image.
3. Integrating Attention Mechanisms could also improve the model’s ability to identify critical features. Techniques like Self-Attention or Squeeze-and-Excitation (SE) blocks allow the model to focus more on important areas within the image, such as specific structures or markings unique to each ship type. This could enhance classification performance, especially for classes that share similar shapes but have distinct details.
4. While basic data augmentation has already been applied, Advanced Data Augmentation Techniques could further increase model robustness. Introducing sophisticated transformations such as cutout, random erasing, or mixup can simulate more diverse conditions in the training data. These techniques would make the model less susceptible to minor variations in image orientation, lighting, or background, which could occur in real-world maritime environments.

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[15] **H. Fu, Y. Li, Y. Wang and P. Li,** "Maritime Ship Targets Recognition with Deep Learning," *2018 37th Chinese Control Conference (CCC)*, Wuhan, China, 2018

7 APPENDIX

7.1 A - CONFERENCE PRESENTATION

This project has been accepted for presentation at SmartCom-2025-Pune, India and publication in Springer LNNS series subject to fulfilment of Guidelines by Springer.

7.2 B - PUBLICATION DETAIL

Sakthi U <sakthiu@srmist.edu.in> Tue, Oct 15, 5:58 PM
to AMAN, me

---------- Forwarded message ---------
From: **SMARTCOM 2025** <smartcom2025@easychair.org>
Date: Tue, Oct 15, 2024 at 11:01 AM
Subject: SMARTCOM 2025 notification for paper 43
To: U Sakthi <sakthiu@srmist.edu.in>

Dear U Sakthi

Paper ID : 43

Title : Multi-Class Ship Classification of Commercial and Naval Vessels using Convolutional Neural Network

Greetings to you .. !!

Congratulations! On behalf of the Program Committee of SmartCom - 2025 - Pune, India, I am happy to inform you that your paper mentioned above has been ACCEPTED for oral presentation in SmartCom - 2025 and publication in Springer LNNS series subject to fulfilment of Guidelines by Springer. An accepted paper will be published in the Springer proceedings (LNNS) only if the final version is accompanied by the payment information (i.e transaction reference number) subject to a quality check as per Springer Guidelines.

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7.3 C - PLAGIARISM REPORT

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