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(Research Article)

Classification of vessel types using the visual geometry group based convolutional neural network

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Abstract

This study explores the application of Convolutional Neural Networks (CNNs) for the classification of vessel types within Nigerian pilotage districts, focusing on the Visual Geometry Group (VGG) architecture. The research methodology encompasses data collection, preprocessing, model selection, training, and evaluation, resulting in a robust dataset of 15,760 images representing 394 different vessel types. The VGG model achieved a validation accuracy of 94%, alongside a precision of 92%, recall of 90%, and an F1-score of 91%. These metrics indicate strong classification capabilities, yet also reveal potential overfitting, as evidenced by a plateau in validation accuracy after 50 epochs. The confusion matrix highlights the model's challenges in accurately classifying certain vessel types, suggesting a need for further refinement. Overall, this work contributes to the growing body of knowledge in maritime Artificial Intelligence (AI) applications, with implications for improved operational efficiency and safety in port management.

Keywords: Convolutional Neural Networks (CNN); Visual Geometry Group (VGG); Pilotage Districts; Artificial Intelligence (AI); Port Management

1. Introduction

Pilotage districts are designated areas in a country's territorial waters where pilots guide vessels in and out of ports. In Nigeria, these districts have unique characteristics and vessel traffic patterns. Correct vessel type identification is essential for port authorities to allocate resources effectively, manage berthing, and comply with regulatory and security protocols. Traditional methods rely on manual processes, which can be error-prone and inefficient in high-traffic ports or with large datasets [1].

Recent advancements in artificial intelligence (AI) and machine learning, especially convolutional neural networks (CNNs), have improved vessel classification accuracy and efficiency. CNNs, a type of deep learning model, are effective for image recognition and classification, making them ideal for maritime traffic monitoring applications [2]. Models such as Visual Geometry Group (VGG), Residual Networks (ResNet), and AlexNet have been widely used for their feature extraction capabilities, enabling accurate classification of vessels from visual data, including images and video footage [3], [4]. For example, Wang et al. achieved significant improvements in vessel classification by integrating CNNs with transformer architectures, achieving up to 91.9% accuracy in ship type identification [5].

Applying VGG-based CNNs in Nigerian pilotage districts could enhance vessel classification, leading to more efficient resource allocation, improved safety, and streamlined port operations. This automation reduces human error and speeds up processing, especially useful in high-traffic maritime areas. Studies have shown that integrating attention mechanisms with CNN architectures can further refine classification, reaching precision rates above 95% [6]. Such

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advancements are crucial in a maritime nation like Nigeria, where port operations are integral to economic growth and national security [1].

This study aims to apply VGG based CNN model to vessel classification within Nigeria's pilotage districts, analyzing performance and operational benefits.

Convolutional Neural Networks (CNNs) are a specialized form of deep learning architecture that has greatly advanced computer vision and image recognition applications. Designed to replicate the structure of the human visual cortex, CNNs are highly effective at processing and analyzing visual data, making them suitable for tasks such as object detection and image classification [1], [2].

A typical CNN is composed of multiple convolutional layers that learn hierarchical features from input data, with each layer capturing increasingly complex representations. Pooling layers often follow these convolutional layers, which down-sample the feature maps, reducing spatial dimensions and enhancing translation invariance [3], [4]. Finally, fully connected layers combine the extracted features from previous layers to perform classification or regression tasks [5].

The VGG (Visual Geometry Group) architecture, developed by researchers at the University of Oxford in 2014, is known for its simplicity and depth, consisting of small 3x3 convolutional filters. This design enables the network to capture complex features while maintaining computational efficiency. Although VGG is computationally intensive, it has shown excellent performance in image classification tasks on challenging datasets like ImageNet, achieving high accuracy at the cost of increased memory requirements [7]. Despite these limitations, VGG remains widely used due to its robustness and accuracy in a variety of computer vision tasks [8].

In maritime and other applications, vessel classification is crucial for optimizing port operations, ensuring safety, and adhering to environmental regulations. Implementing CNNs, particularly architectures like VGG, can automate vessel classification, increasing accuracy and efficiency compared to manual methods [9]. However, challenges such as varying environmental conditions, poor lighting, and partially obscured vessels still hinder CNN-based classification systems in maritime environments. Addressing these issues requires large, diverse datasets and advanced techniques to handle complex maritime conditions [10], [11] as presented in this paper.

2. Methodology

The methodology employed in this research aims to develop an accurate and efficient vessel classification system for Nigerian pilotage districts by leveraging convolutional neural networks (CNNs). The proposed approach comprises several key stages: data collection, preprocessing, model selection, training, and evaluation. Additionally, confusion matrix was generated to visualize misclassifications for each model, helping to identify specific challenges encountered by the CNN architecture and providing insights for future improvements. The dataset characteristics is given in Table 1

Table 1 Dataset Characteristics

Characteristics	Value
Number of Images	15,760
Number of Vessel types	394

The data collection involved gathering a diverse, representative dataset of vessel images from various sources, including port authorities, maritime agencies, online repositories, and crowdsourcing. The collected dataset underwent preprocessing steps essential for optimizing performance and generalization capabilities. These steps, which included image resizing, normalization, and data augmentation, were crucial for standardizing the input data, enhancing image quality, and increasing dataset diversity and robustness.

The VGG architecture (as shown in Figure 1), developed by the University of Oxford, is notable for its simplicity and depth. It uses a series of convolutional layers followed by max-pooling layers and fully connected layers. The VGG architecture introduced smaller 3x3 convolutional filters, which are stacked to achieve a larger receptive field, allowing the network to capture complex features while maintaining a manageable parameter count. This research specifically implements the VGG-16 variant, which consists of 16 convolutional layers and three fully connected layers. These layers are organized into five blocks, each containing two to four convolutional layers followed by a max-pooling layer. The final block is followed by three fully connected layers, with the last layer being a softmax layer for classification.

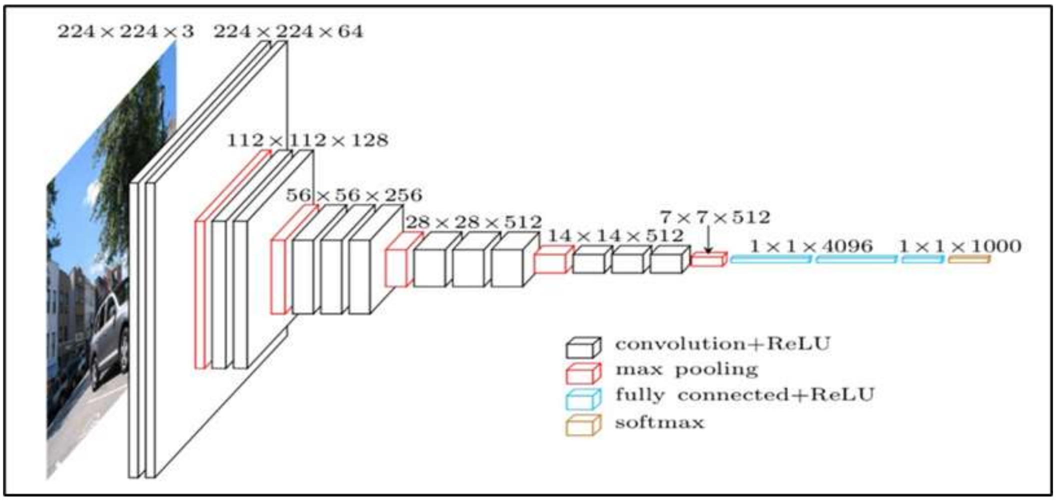

Figure 1 VGG Architecture

The training process was conducted using advanced deep learning frameworks and libraries, such as PyTorch and Sklearn. These frameworks provide efficient implementations of CNN architectures, optimizers, loss functions, and utilities for data handling and model training. Key steps in the training process included data loading and preparation, model initialization, selection of loss function and optimizer, hyperparameter tuning, training loop, checkpointing, and early stopping. The training process was monitored using metrics like training and validation loss, accuracy, and other performance indicators specific to vessel classification. These metrics were tracked throughout training, enabling real-time analysis and monitoring.

In CNN training for vessel classification, selecting appropriate loss functions and optimization algorithms is crucial for achieving optimal performance and convergence. To evaluate the performance of the trained CNN models, suitable metrics were employed, providing quantitative measures of the models' classification accuracy, strengths, weaknesses, and areas for improvement. The evaluation metrics used in this research included accuracy, precision, recall (sensitivity), F1-score, and confusion matrix.

3. Results and Discussion

The training and validation accuracy for VGG based on aforementioned methodology is given in Figure 2.

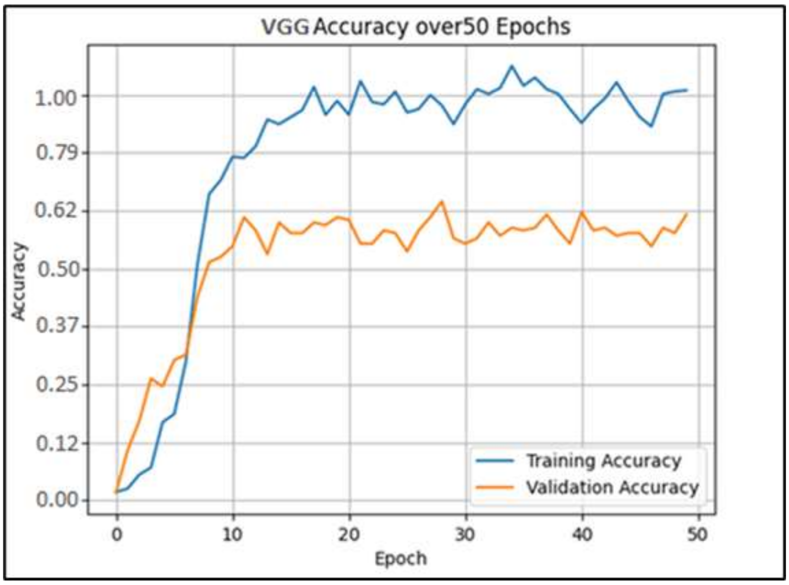

Figure 2 Training and Validation Accuracy Curves for VGG

As illustrated in Figure 2, the VGG model demonstrated a consistent reduction in both training and validation loss over the course of training, indicating that the model was effectively learning from the data. Simultaneously, accuracy on both the training and validation sets showed a steady upward trend, reflecting the model's improving performance. By the end of training, the VGG model achieved a high validation accuracy of 94%, signifying strong generalization to unseen data.

To gain deeper insights into the model's classification capabilities and potential areas for improvement, a confusion matrix was created, focusing on specific vessel types. This matrix, shown in Figure 3, provides a visual representation of correct classifications and misclassifications among selected vessel categories, helping to identify which types the model handled well and which may require further refinement.

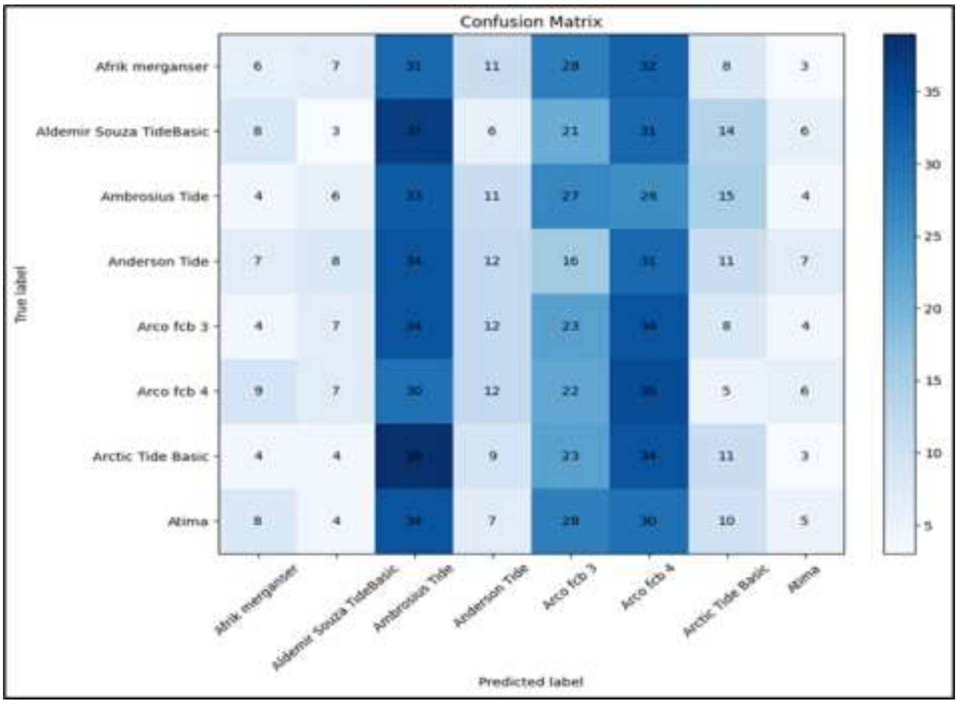

Figure 3 Confusion Matrix for VGG

The confusion matrix serves as a valuable tool for evaluating the model's performance in classifying various vessel types and highlights the specific types of misclassifications that occurred. By analyzing the matrix, it becomes evident that the VGG model has difficulty accurately classifying certain classes of vessels. This insight is crucial for understanding the model's limitations and identifying potential areas for improvement in the classification process.

The detailed performance metrics for the VGG model, which quantify its effectiveness across different vessel categories, are presented in Table 2. These metrics include precision, recall, and F1-score, offering a comprehensive view of how well the model performs in distinguishing between the various types of vessels..

Table 2 Performance Metrics for VGG

Metric	Value (%)
Accuracy	94
Precision	92
Recall	90
F1-Score	91

The performance metrics presented in Table 2 highlight the effectiveness of the VGG model in vessel classification tasks. Achieving an accuracy of 94% indicates that the model correctly identified the vast majority of vessel types in the dataset, reflecting a strong capability in distinguishing between various classes. Precision at 92% and recall at 90%

further emphasize the model's reliability, suggesting that it not only identifies a high proportion of true positives but also maintains a low rate of false positives. The F1-score of 91% balances precision and recall, offering a holistic view of the model's classification performance.

However, these metrics also imply areas for potential enhancement. The plateau in validation accuracy at 92% after 50 epochs, while training accuracy continues to increase, signals a risk of overfitting, where the model may be memorizing the training data rather than learning to generalize. This phenomenon underscores the importance of ongoing refinement and optimization in the training process, possibly through techniques such as data augmentation or regularization methods to improve the model's robustness and generalization capabilities. Addressing these aspects is crucial for enhancing the VGG model's effectiveness in real-world applications, where accurate vessel classification is vital for operational efficiency and safety in maritime contexts.

4. Conclusion

The VGG model demonstrates promising performance in classifying vessel types, achieving a commendable accuracy of 94% and maintaining high precision and recall metrics. However, the findings also reveal critical limitations, particularly concerning overfitting and misclassification of specific vessel types. As the maritime industry increasingly relies on automated systems for operational efficiency, addressing these challenges will be essential. Future work should focus on enhancing the model's generalization capabilities through techniques such as data augmentation and optimization of hyperparameters. By doing so, the vessel classification system can be improved, ultimately contributing to more effective port operations and increased maritime safety.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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