Defence Science Journal, Vol. 71, No. 2, March 2021, pp. 200-208, DOI : 10.14429/dsj.71.16236

Deep Convolutional Neural Network based Ship Images Classification

Narendra Kumar Mishra*, Ashok Kumar, and Kishor Choudhury

Weapons and Electronics Systems Engineering Establishment, New Delhi - 110 066, India

**E-mail: narendra.lal@hqr.drdo.in*

ABSTRACT

Ships are an integral part of maritime traffic where they play both militaries as well as non-combatant roles. This vast maritime traffic needs to be managed and monitored by identifying and recognising vessels to ensure the maritime safety and security. As an approach to find an automated and efficient solution, a deep learning model exploiting convolutional neural network (CNN) as a basic building block, has been proposed in this paper. CNN has been predominantly used in image recognition due to its automatic high-level features extraction capabilities and exceptional performance. We have used transfer learning approach using pre-trained CNNs based on VGG16 architecture to develop an algorithm that performs the different ship types classification. This paper adopts data augmentation and fine-tuning to further improve and optimize the baseline VGG16 model. The proposed model attains an average classification accuracy of 97.08% compared to the average classification accuracy of 88.54% obtained from the baseline model.

Keywords: Ship classification; Convolutional neural network; Transfer learning; VGG16

1. INTRODUCTION

Apart from their conventional roles, modern naval forces are also actively involved in maritime security operations, including monitoring, tracking, detecting, and identifying ocean traffic, efficiently and effectively.

Vessel movements are currently monitored using automatic identification system (AIS)[1], synthetic aperture radar (SAR)[2], satellite-based images[3-4], and optical images captured by cameras. SAR or satellite images give the full view of maritime vessels and cover larger ocean areas than optical images. For maritime surveillance, the optical image-based classification would be an efficient solution due to its simplicity and easy availability. However, its successful realisation using conventional methods faces many challenges such as degraded quality of images due to environmental factors, the resemblance in the look and form of the class of ships, and the vastness of the ocean environment.

These factors call for a more reliable technology or system which can automatically classify ships based on their features, where artificial intelligence (AI) can play a significant role. AI system is capable of automatic identification and recognition of marine vessels and objects around it, like navigation-aids, boats, etc. that can lead to the enhanced situational awareness.

1.1 Convolutional Neural Network

With the advancement in technology, in terms of more robust algorithms, availability of large volume of structured datasets, and the capability of handling large volumes of data more efficiently through graphical processing units (GPUs), AI has turned up as one of the most promising technologies across diverse fields. In this paper, CNN based deep learning algorithm has been studied, and its performance is evaluated and analysed.

In CNN based models, input images are minimally processed and fed directly to the system, where a suitable group of features is extracted through a learning[5]. This CNN capability allows for the cascading of several CNN layers making it a "Deep" feature extractor while learning the essential features for the particular problem of interest. In Deep learning models, convolutional layers learn more generic features in the initial stages and learn features specific to the input training dataset in deeper stages that are further utilised to classify the test images that were not part of the training dataset. It is predominantly used in a broad range of image recognition applications due to its automatic high-level feature extraction capabilities and exceptional performance[6].

Fundamentally, CNN architecture consists of sequences of layers that transform the pixel values of input images through various processes to final class scores. The process flow architecture of a typical CNN, and its basic building blocks are shown in Fig. 1. The details of fundamental blocks of CNN[7] are described as follows:

(i) *Convolutional Layer:* This layer is responsible for learning the important features from input images. It consists of several learnable filters or kernels that slides spatially across the input image and calculates the dot products as a response called the feature maps. A schematic implementation of the convolution operation is shown in Fig. 2. Two important features of the convolutional layer are local connectivity (at a time, filter weights are multiplied to only a local area of the input image) and

Received : 25 August 2020, Revised : 19 January 2021
Accepted : 01 February 2021, Online published : 10 March 2021

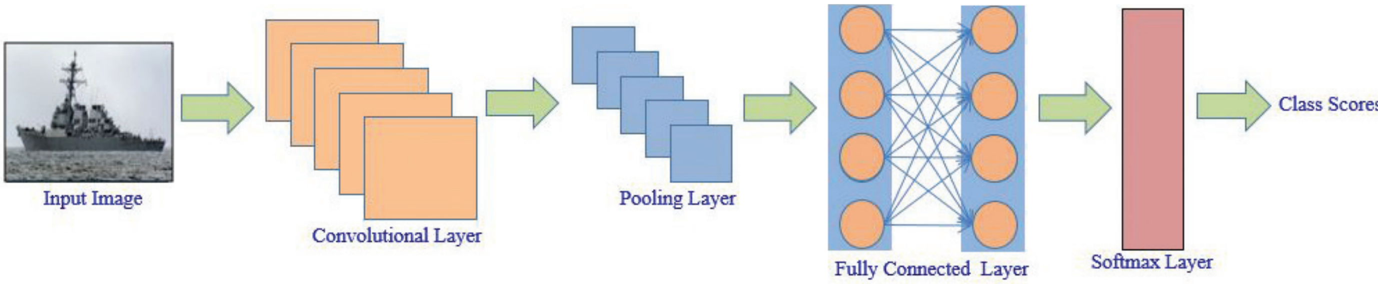

Figure 1. Process flow architecture of typical convolution neural network.

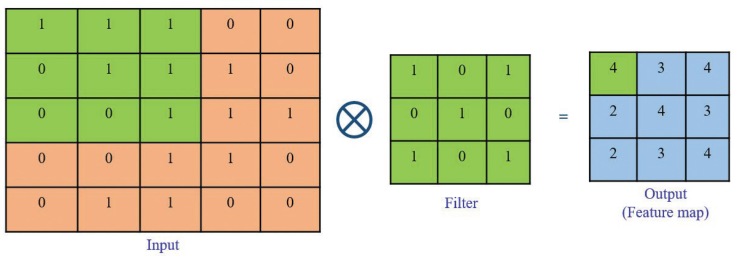

Figure 2. Schematic representation of convolution operation in a convolutional layer.

Weight Sharing (the same filter weights are multiplied to every spatial location of the input image). A Convolutional layer output is fed to the activation function (e.g., ReLU) that introduces non-linearity into the artificial neural network. The output size of the convolutional layer depends on the following four Hyperparameters:

- Number of filters, K
- Filter size, FxF
- Amount of zero padding, P
- Stride, S

For an input volume of size $W1$x$H1$x$D1$, the convolutional layer results in an output volume of the size $W2$x$H2$x$D2$ that can be calculated as

$$W2 = \frac{W1 - F + 2P}{S} + 1$$

$$H2 = \frac{H1 - F + 2P}{S} + 1$$

$$D2 = K$$

(ii) *Pooling Layer:* This layer downsamples the input image's spatial dimension and is placed in-between two convolutional layers. Pooling minimises the computational complexity by reducing the learnable network parameters. MaxPooling and AveragePooling are two prominently used Pooling techniques, as depicted in Fig. 3.

(iii) *Fully-Connected Layer:* This layer performs the actual prediction (classification or regression) job. It consists of fully connected layers as a regular artificial neural network followed by a Softmax layer (final output layer) that provides the class scores. It consists of input layer, output layer and number of hidden layers as shown in Fig. 4. The number of hidden layers and number of nodes in each layer are Hyperparameters.

1.2 Transfer Learning

It is very uncommon to train a convolutional network from scratch because it needs a sufficiently large training dataset and GPU to execute and evaluate the deep learning model. Alternatively, a transfer learning approach can be used for a new classification task. In the transfer learning-based approach, the pretrained model weights, which have already been trained optimally on similar problems, are used for the new image recognition task. A transfer learning approach is schematically represented in Fig. 5. In transfer learning, either a convolutional network pretrained using millions of images could be used as a fixed feature extractor (where pretrained weights of the convolutional blocks are used as it is for the particular classification task of interest), or weights of the pretrained network can be fine-tuned for the specific dataset/problem. The selection of a specific transfer

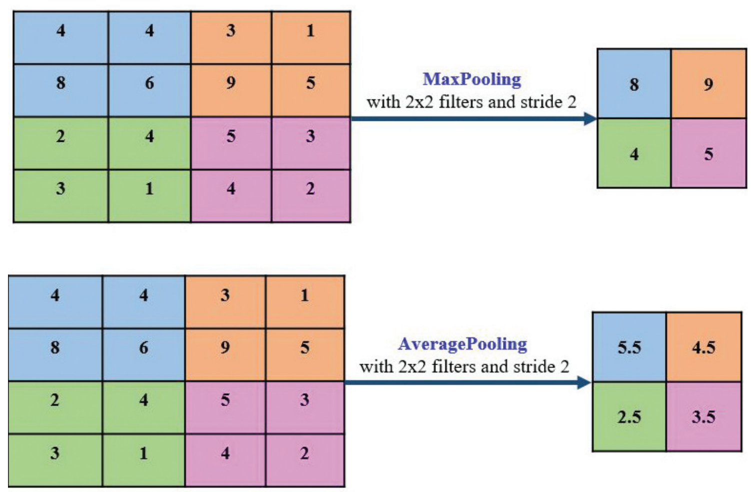

Figure 3. Schematic representation of pooling operation in a convolutional layer, maxpooling (top), and AveragePooling (bottom).

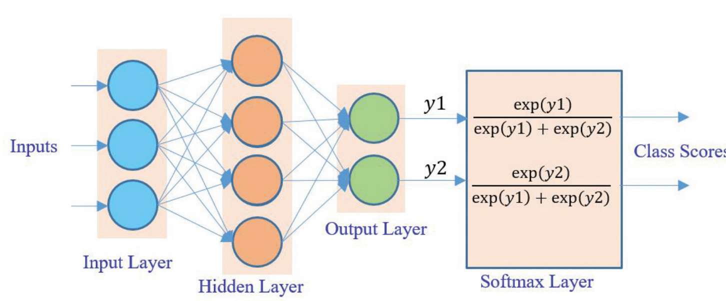

Figure 4. Schematic representation of neural network with fully connected layers.

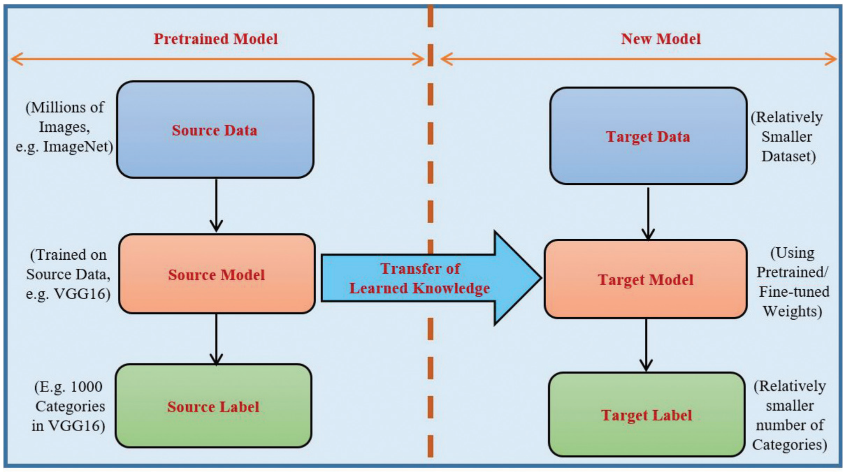

Figure 5. Schematic representation of the Transfer Learning approach.

learning approach depends upon several factors[8] that includes size and similarity of the new dataset compared to the original dataset and is tabulated in Table 1. Due to the inadequacy of a sufficiently large dataset and GPU availability, transfer learning has been used in the present study considering Case 3 for implementation.

There are several freely accessible top-performing models, like VGG16[9], ResNet50[10], Inception[11], Xception[12], InceptionResNet[13], and DenseNet[14], which can be readily integrated into a new image recognition task. In the present study, the transfer learning approach based on the standard VGG16 model has been used as a baseline model for ship image classification. Originally, VGG16 was trained using ImageNet that consists of millions of images with 1000 categories. In our study, the marine vessel images are smaller in numbers and dissimilar in relation to the original dataset. Therefore, the standard VGG16 could not be used as a fixed feature extractor, where pretrained weights of the convolutional blocks can be used as it is for the particular classification task. Therefore, to make the VGG16 model more relevant and specific to the classification of ship's images, the last convolution block of the VGG16 network has been re-trained. However, a relatively small number of images in the training of the model leads to overfitting of the model that has been verified empirically also. To mitigate this issue, we have used two important process improvement techniques; the first is 'BatchNormalisation'. The second is 'Dropout.' It is pertinent to mention that process improvement techniques, BatchNormalisation and Dropout, were not implemented in the standard VGG16 model.

Process improvement techniques cannot be incorporated directly into the pretrained convolutional blocks of the standard VGG16 model. Therefore, an additional convolutional block similar to the convolutional blocks of standard VGG16 has been appended in the proposed model to incorporate process improvement techniques. An extra convolutional block would also lead to learning more specific features of the input training dataset as the convolutional layer goes into deeper stages. Process improvement techniques have also been incorporated into the classification block consisting of Fully-Connected Layers. The VGG16 model has been further built upon by data augmentation and fine-tuning of the network Hyperparameters. Proposed model has been evaluated against the baseline model.

2. RELATED WORK

In the recent past, several efforts have been made to classify maritime vessels' optical images using CNN based deep learning algorithms. In reference[15], CNN trained on

Table 1. Choice of transfer learning approach depending upon the similarity and size of the images in the new problem of a statement as compared to the original dataset

Case	Factors (of new dataset compared to the original dataset)		Choice of transfer learning approach	Explanation
	Similarity	Size		
(1)	Similar	Smaller	Train only a classifier layer using pretrained weights	Fine-tuning of the pretrained weights would lead to the overfitting problem due to the small dataset. As images in the new problem of interest have similarities with the original dataset, features learned by the pretrained weights would still be relevant.
(2)	Similar	Larger	The model can be fine-tuned through the full network.	Since the new dataset is sufficiently large, re-training would not suffer overfitting issues.
(3)	Dissimilar	Smaller	Few convolutional layers, including the classifier layer, can be fine-tuned.	Since the new dataset is small, only the classifier layer to be re-trained. However, due to the new dataset's difference compared to the original dataset, few convolutional layers need to be re-trained to learn the features specific to the new dataset.
(4)	Dissimilar	Larger	A model can be developed from scratch, or transfer learning can be utilised by fine-tuning through the entire network.	A model can be trained from scratch due to the availability of a large data set. Alternatively, transfer learning can be utilised by fine-tuning through the entire network.

AlexNet, Inception, and ResNet50 has been developed using the MARVEL dataset[16], a large-scale image dataset for maritime vessels. MARVEL dataset is a huge collection of marine vessels consisting of 2 million images from ship photos and ship tracker website[17]. Ship classification[18] using AlexNet model for ten categories of vessels using images from the same website has been developed. More studies[19-20] have been undertaken using images from the same website. Although these studies have used transfer learning based architectures and have used images from the same website, one-to-one performance comparison with the present study cannot be undertaken due to lack of uniformity in the datasets.

3. EXPERIMENTAL DESIGN

3.1 Dataset

The first challenge in training and validating the proposed model was the availability of authentic and labelled images of ships for classification purposes. To ensure this, for our experiment purpose, we obtained the dataset by downloading ship images from the aforementioned website.

The website consists of a large number of vessel images for each category. To reduce our model's processing complexity; we have compiled a class balanced dataset comprised of 2400 images of four classes: aircraft carrier, Crude oil tankers, Cruise ships & liners, and Destroyers. A few images from the training dataset for each category are demonstrated in Fig. 6. The complete dataset has been distributed in a proportion of 80:20 for training and testing of the proposed model. Twenty percent of the training dataset has been further utilised for validation purposes. Description of a number of the training and testing images from the dataset are enumerated in Table 2. All the images were saved by keeping the pixel size of 224 of the image's largest dimension without affecting the pixel qualities as the standard VGG16 model was developed using an input image size of 224x224.

Figure 6. Sample images of four classes of ships from the dataset.

Table 2. Description of a number of training and test images from the dataset.

Class	Train	Test
Aircraft carriers	480	120
Crude oil tankers	480	120
Cruise ships and liners	480	120
Destroyers	480	120
Total	1920	480

3.2 Neural Network Architecture

In this part, the baseline model based on VGG16 architecture and various techniques that we incorporated in the proposed model to improve the classification performance has been described.

3.2.1 Baseline Model (VGG16)

VGG16 model has been used as a baseline model developed by the Visual Graphics Group (VGG) at Oxford. It comprises of series of Convolutional layers and MaxPooling layers as its primary element connected in a pattern, as shown in Fig. 7. Convolution Blocks 1 and 2, each comprise two convolutional layers and one MaxPooling layer in succession, as a feature extractor. Similarly, Convolution Blocks 3, 4, and 5, each include three convolutional layers and one MaxPooling layer in sequence. The final Block 6 consists of three fully connected layers and a Softmax layer in succession as a classifier. It is important to note that the Dropout and Batch Normalisation steps were not implemented in the standard VGG16 model. Since data augmentation does not form part of the actual VGG16 model, it has been also incorporated into the baseline model.

3.2.2 Data Augmentation and Fine-tuning of VGG16 Model

The performance of the VGG16 model has been further improved upon by incorporating various process improvement techniques, as discussed below:

(a) Data Augmentation: Data augmentation has been employed to achieve diverse feature learning by adding individual variations in the images so that the same kinds of images are not fed in each epoch during the learning process. Data augmentation has been applied very carefully to generate a new set of images to augment the training dataset while preserving the basic features. The various kinds of random variations incorporated into the training dataset include zooming, rotation, shift, and horizontal/vertical flips.

(b) Re-train the weights of the VGG16 model: VGG16 was designed to extract fine-grained features of objects from 1,000 categories. As the higher-order features learned by the model corresponds to the ImageNet dataset that may not be directly relevant to the classification of optical images of the ships, we have re-trained some convolution blocks of VGG16 to fine-tune the weights for our classification task.

(c) Fine-Tuning the Model: Following Hyperparameters have been fine-tuned to improve the performance of the baseline model:

(i) *Number of Layers:* Classification accuracy may be improved by increasing the number of hidden layers and

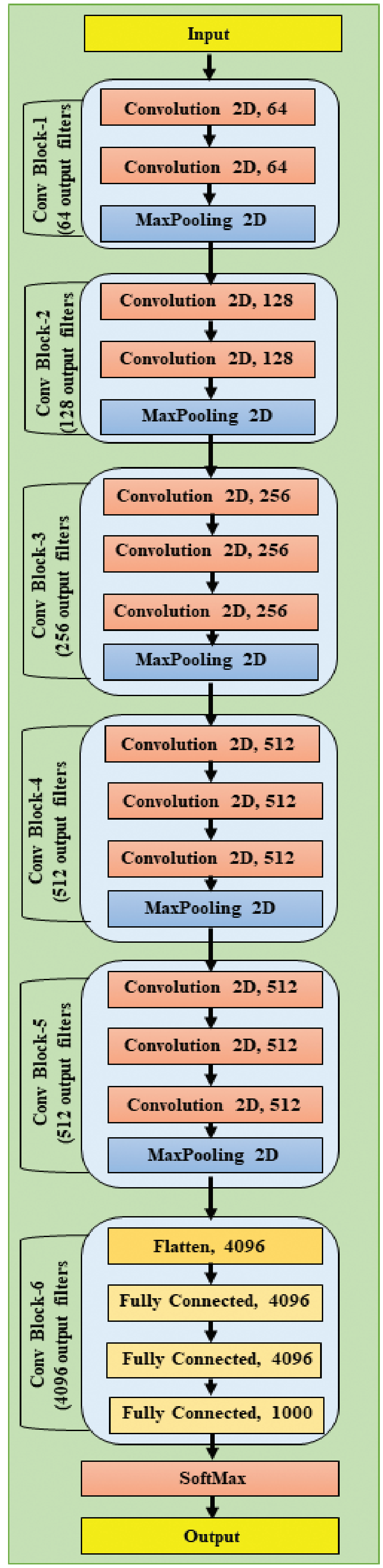

Figure 7. Process flow architecture of standard VGG16 model.

numbers of nodes in each layer as it enhances the model capacity. However, it has been observed empirically that a deeper network lead to the overfitting of the model, higher complexity, and more training time due to the increased number of learnable parameters. Therefore, the impact of the number of hidden layers and nodes in each layer is evaluated empirically, and optimal numbers were chosen accordingly.

(ii) *Learning Rates:* Learning rate is one of the vital Hyperparameter that needs careful selection. Through experiments, it has been observed that a small learning rate causes the trapping and slow down of the learning process; whereas, a large value of learning rate leads to quick and non-optimal convergence. An optimal value of the learning rate has been chosen empirically.

(iii) *Batchsize:* Batchsize is the number of training samples fed to the gradient descent algorithm in determining the error gradient. It is a vital Hyperparameter that influences the learning algorithm's dynamics.

(iv) *BatchNormalisation:* BatchNormalisation performs the normalisation (shifting and scaling) of the output from a convolutional layer before feeding it to the next layer that reduces the covariance shift of the network[21]. It speeds up the learning process of an artificial neural network with enhanced stability.

(v) Regularisation: A major challenge in the development of any deep learning model is to overcome the overfitting problem so that it may generalize well on the new dataset. To mitigate this issue, two prominent regularisation techniques, Dropout[22] and Early Stopping, have been used in this paper. These techniques not only reduce overfitting but can also lead to the faster optimisation and better overall performance.

3.2.3 *Proposed Model*

During the performance analysis of the baseline model, several significant observations have been made. During the training process, cross-entropy loss was first decreasing; however, it started increasing after a certain number of epochs. It is also observed that there exists a substantial gap between the graph of training and validation accuracy. The model achieved very high training accuracy but performed poorly on the test dataset. This behaviour clearly indicates the overfitting of the model. To further improve the performance, the following modifications were incorporated in the proposed model:

(a) Weights of the convolution Block-5 are re-trained so that the model will be more suitable and efficient for the ship classification task.

(b) An additional convolution block consisting of three consecutive convolutional layers and a MaxPooling layer has been inserted before the block of fully connected layers. This block has been primarily used to incorporate BatchNormalisation and Dropout to avoid overfitting in the model and assist in learning of higher-order features.

(c) Batch Normalisation and Dropout have been embedded into the Block-6 consisting of fully connected layers.

The process flow architecture of the proposed model is presented in Fig. 8.

3.2.4 *Experimental Parameters*

The proposed model has been trained and evaluated on the Google Colab cloud server. The Hyperparameter values have been tuned optimally in multiple iterations while training our model. Details of the final experimental parameters are tabulated in Table 3.

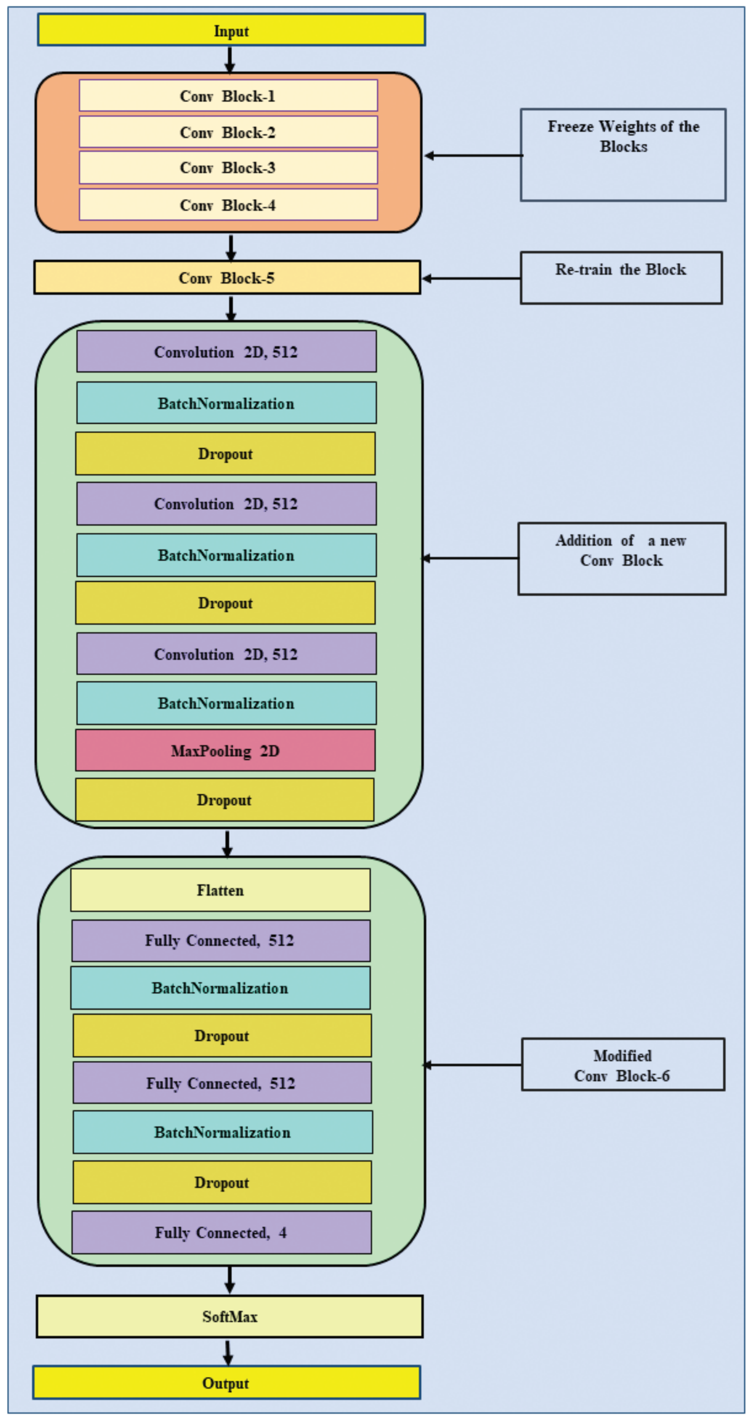

Figure 8. Process flow architecture of the proposed model.

4. ANALYSIS AND RESULTS

Both baseline and proposed models have been trained on Google Colab using Hyperparameters as listed in Table 3 for the same input dataset. The details of classification performance measures for both the models are tabulated in Table 4. It is to be noted that the Early Stopping criterion takes almost twice the number of epochs to exit the training process in the proposed model. A gap of 4.3% between training and validation accuracy in the baseline model was further reduced to 2.4% in the proposed model, showing reduced overfitting and better convergence. Evaluation of the test dataset shows a performance improvement of 8.54% in terms of classification accuracy compared to the baseline model.

The performance has been also evaluated by analysing the graphs of classification accuracy and cross-entropy loss during the training process. In the baseline model, through the analysis of graphs of classification accuracy and cross-entropy loss, as shown in Fig. 9, it has been observed that there exists a considerable gap between the training and validation, which confirms overfitting in the model. Regularisation (through Dropout) and Early Stopping has been included into the baseline model to reduce the impact of overfitting. The corresponding graph for the proposed model showing improved performance and better convergence between training and validation is shown in Fig. 10.

The confusion matrix[23], which provides the matrix of true labels vs. predicted labels, is shown in Figs. 11 and 12 for the baseline and the proposed models. It represents the number of true classifications in each category through the diagonal elements. It has been observed that significant confusion occurs between the aircraft carrier and destroyer category of images, and the same has been predicted due to the similarity of features between the two categories. Six aircraft carrier images have been incorrectly predicted to destroyer-class in

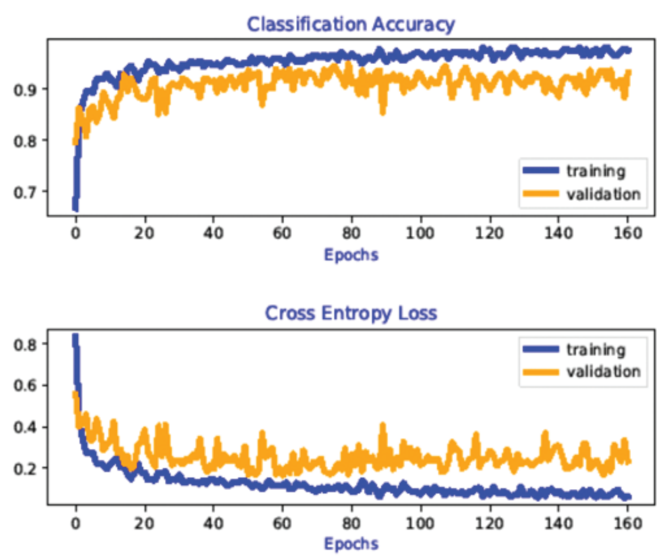

Figure 9. Graphs of classification accuracy and cross-entropy loss for the baseline model.

Table 3. Hyperparameters selected for the training of the baseline and the proposed model.

Experimental parameters	Values
Learning rate	0.0001
Momentum	0.99
Batchsize	32
Number of epochs	500 with early stopping
Dropout	0.2-0.5
Optimizer	Adam

Table 4. Classification performance measures for the Baseline and the Proposed Model.

Model	Performance Measures						Epochs (max 500)
	Training		Validation		Testing		
	Loss	Accuracy (%)	Loss	Accuracy (%)	Loss	Accuracy (%)	
Baseline	0.0609	97.53	0.2321	93.23	0.4856	88.54	161
Proposed	0.0068	99.80	0.1728	97.40	0.1347	**97.08**	327

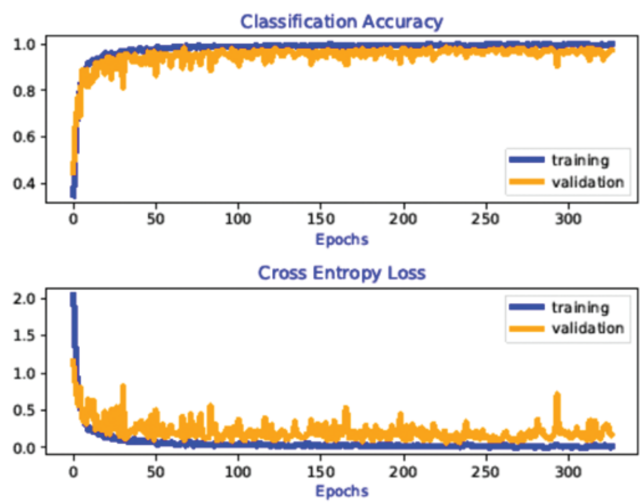

Figure 10. Graphs of classification accuracy and cross-entropy loss for the proposed model.

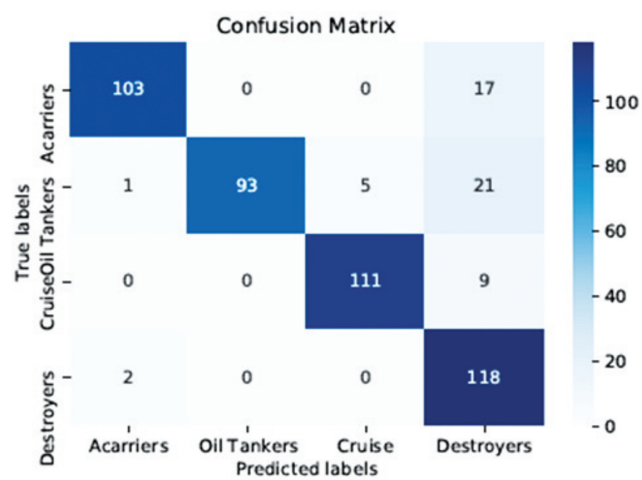

Figure 11. Confusion matrix for the baseline model.

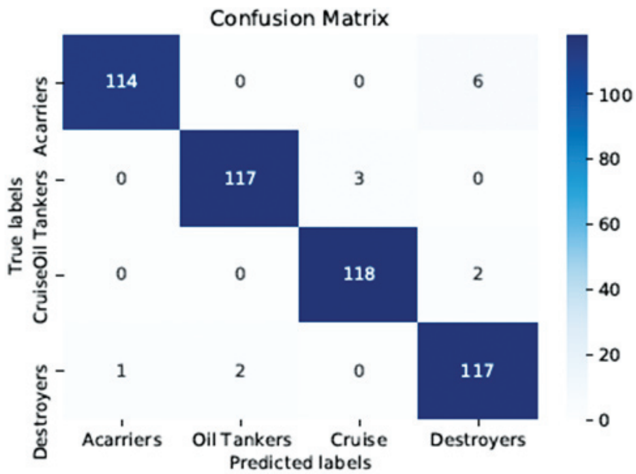

Figure 12. Confusion matrix for the proposed model.

the proposed model. Another significant observation is that out of 120 test images for the destroyer-class, 118 images have been correctly classified using the baseline model, while the number is 117 for the proposed model. However, the overall classification accuracy has improved significantly in the proposed model.

5. CONCLUSION

In the present study, ship classification has been addressed using VGG16 based transfer learning architecture. Further, the addition of several performance improvement techniques and fine-tuning of neural network Hyperparameters have been carried out to improve the baseline model. Evaluation and analysis of the proposed model have been carried out for four categories of ship images using a limited dataset. CNN based proposed model shows promising results with a classification accuracy of 97.08%, making it suitable for maritime security applications.

In all the experiments, it has been assumed that the input images belong only to one of the four categories. However, if the input image does not belong to any of the four categories, it can be classified as a member of the 'unknown' class by assigning a suitable threshold value (say, 0.5) to the class scores. Class scores is the values of associated probabilities at the output of Softmax layer that is the final output layer in artificial neural network. If the value of the highest class score is lower than the threshold value, then that particular output can be marked as 'unknown' class.

As a future work, this model can be further fine-tuned for use with satellite-based or SAR based ship images to create a robust system for ship classification. The study can be further extended to the case of multiple ships or objects in each input image.

REFERENCES

1. http://www.imo.org/en/OurWork/safety/navigation/pages/ais.aspx [Accessed on 28 Jun 2020].
2. Bentes, C.; Frost, A.; Velotto, D. & Tings, B. Ship-iceberg discrimination with convolutional neural networks in high resolution SAR images. *In* Proceedings of EUSAR 2016: 11th European Conference on Synthetic Aperture Radar, Hamburg, Germany, 2016, 1-4.
3. Rainey, Katie; Reeder, John D. & Corelli, Alexander G. Convolution neural networks for ship type recognition. *In* Proc. SPIE 9844, 12 May 2016, Automatic Target Recognition XXVI, 984409.
doi:10.1117/12.2229366
4. Shi, Qiaoqiao; Li, Wei; Tao, Ran; Sun, Xu & Gao, Lianru. Ship classification based on multifeature ensemble with convolutional neural network. *Remote Sens.*, 2019, **11,** 419.
doi: 10.3390/rs11040419.
5. Lecun, Y.; Haffner, P.; Bottou, L. & Bengio, Y. Object recognition with gradient-based learning. *In* Shape, Contour and Grouping in Computer Vision, Springer-Verlag, Heidelberg, Berlin, 1999, 319-345.
doi: 10.1007/3-540-46805-6_19
6. Gonalez, R.C. Deep convolutional neural networks [Lecture Notes]. IEEE Signal Processing Magazine, Nov 2018, **35**(2), 79-87.
doi: 10.1109/MSP.2018.2842646
7. https://cs231n.github.io/convolutional-networks/ [Accessed on 14 Nov 2020].
8. https://cs231n.github.io/transfer-learning/ [Accessed on 14 Nov 2020].
9. Simonyan, Karen & Zisserman, Andrew. Very deep convolutional networks for large-scale image recognition. 2015.
arXiv 1409.1556v6
10. He, K.; Zhang, X; Ren S. & Sun J. Deep residual learning for image recognition. *In* Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR), Las Vegas, NV, USA, Jun 2016, 770–778.
doi: 10.1109/CVPR.2016.90
11. Szegedy, C.; Vanhoucke, V.; Ioffe, S.; Shlens, J. & Wojna, Z. Rethinking the inception architecture for computer vision. *In* Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR), Las Vegas, NV, USA, Jun 2016, 2818–2826.
doi: 10.1109/CVPR.2016.308
12. Chollet, F. Xception: Deep learning with depthwise separable convolutions. *In* Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR), Honolulu, HI, USA, Jul 2017, 1800–1807.
doi:10.1109/CVPR.2017.195
13. Szegedy, C.; Ioffe, S.; Vanhoucke, V. & Alemi, A. Inception- v4, inception-resnet and the impact of residual connections on learning. *In* Proc. AAAI Conf. Artif. Intell., San Francisco, CA, USA: AAAI Press, 2017, 4278–4284.
doi: 10.5555/3298023. 3298188
14. Huang, G.; Liu, Z.; Van Der Maaten, L. & Weinberger, K.Q. Densely connected convolutional networks. *In* Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR), Honolulu, HI, USA, Jul 2017, 2261–2269.
doi: 10.1109/CVPR.2017.243
15. Leclerc, M.; Tharmarasa, R.; Florea, M. C.; Boury-Brisset, A.; Kirubarajan, T. & Duclos-Hindié, N. Ship classification using deep learning techniques for

maritime target tracking. 21st International Conference on Information Fusion (FUSION), Cambridge, 2018, pp. 737-744.
doi: 10.23919/ICIF.2018.8455679
16. Solmaz, Berkan; Gundogdu, Erhan; Yucesoy, Veysel & Koc, Aykut. Generic and attribute-specific deep representations for maritime vessels. IPSJ Transactions on Computer Vision and Applications, 2017.
doi: 10.1186/s41074-017-0033-4
17. Ship photos and ship tracker. http://www.shipspotting.com[Accessed on 22 May 2020].
18. Bartan, Burak. Ship classification using an image dataset. 2017. Corpus ID: 29004678
19. Milicevic, Mario; Zubrinic, Krunoslav; Obradovic, Ines & Sjekavica, Tomo. Data augmentation and transfer learning for limited dataset ship classification. *WSEAS Trans. Syst. Control*, 2018, **13**, 460-465.
20. Dao, Cuong; Xiaohui, Hua; Morère, Olivier. Maritime vessel images classification using deep convolutional neural networks. *In* proceedings of the Sixth International Symposium on Information and Communication Technology, 2015, 276-281.
doi:10.1145/2833258.2833266
21. Ioffe, Sergey & Szegedy, Christian. Batch normalisation: accelerating deep network training by reducing internal covariate shift. 2015.
arXiv:1502.03167
22. Srivastava, Nitish; Hinton, Geoffrey; Krizhevsky, Alex; Sutskever, Ilya & Salakhutdinov, Ruslan. Dropout: A simple way to prevent neural networks from overfitting. *J. Mach. Learning Res.,* 2014, **15**(56), 1929-1958.
23. https://en.wikipedia.org/wiki/Confusion_matrix [Accessed on 28 Jun 2020].

CONTRIBUTORS

Mr Narendra Kumar Mishra received his MTech in Communication Engineering from IIT Delhi, in 2018. He is presently working as Scientist 'D' at DRDO - Weapons and Electronics Systems Engineering Establishment, New Delhi. His field of research includes Embedded Systems, Systems Integration, Signal Processing and Machine Learning. He has contributed in the design and development of interface solutions for various ships and submarines.
In the current study, he conceived and designed the experiment, optimised the deep learning techniques used in the experiment, performed software-coding, results analysis and prepared the manuscript.

Mr Ashok Kumar received his MTech in Radio Frequency Design and Technology from IIT Delhi, in 2017. He is presently working as Scientist 'D' at DRDO-Weapons and Electronics Systems Engineering Establishment, New Delhi. His field of research includes Embedded Systems, Data Communication and Systems Integration. He has contributed in the design and development of interface solutions for various ships and submarines.
In the current study, he performed data preparation, helped in formulation of the experiment and preparation of the manuscript.

Mr Kishor Choudhury received his MTech in Computer Technology from IIT Delhi, in 2012. He is presently working as Scientist 'F' at DRDO - Weapons and Electronics Systems Engineering Establishment, New Delhi. He has received CNS Commendation in 2006 and DRDO Technology Group Award in 2008. His field of research includes algorithms, embedded systems and computer vision. He has contributed in the design and development of interface units for various ships and submarines.
In the current study, he provided overall guidance in conceptualisation & realisation of the experiment and finalisation of the manuscript.