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A COMPARATIVE STRATIFICATION OF FISH SPECIES USING TRANSFER LEARNING ON PRE-TRAINED DEEP LEARNING NETWORKS JUXTAPOSED WITH SHUFFLERES – A HYBRID DEEP NETWORK CLASSIFIER

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SUMMARY

The marine ecoculture is an evolving realm that necessitates thorough scrutiny of the diverse species it comprises, along with the explicit identification of the species classes that form, to be crucial for aquaculture and the ecological conservation of fish diversity. The stratification through image classification is a well-studied area of research using various conventional algorithmic methods. However, the need to progressively identify deep features to stratify the multiple species of fish unambiguously remains the pivotal study of this investigation. Deep learning methodologies utilize various pre-trained networks that enable the identification of fish species through a systematic, layered approach of non-linear activation functions, which delineate feature patterns and thereby achieve higher classification accuracy. The study proposes a new method for stratifying fish species by applying transfer learning to pre-trained deep learning networks, namely AlexNet, InceptionV3, and Resnet-18, along with the application of ShuffleRes, a hybrid deep network classifier. To address the specified research question, the work employs transfer learning, which enables the exploitation of knowledge from large image datasets by fine-tuning pre-trained models. This approach enhances classification performance in fish species, despite the limited availability of annotated data. Furthermore, the proposed ShuffleRes architecture combines the advantages of residual connections and shuffle layers, promoting improved feature representation, discriminative capacity, and surpassing classification accuracy compared to individual pre-trained networks. The simulations are implemented in MATLAB, and the results for the study are successfully procured.

Key words***:*** *fish classification, deep learning, pre-trained networks, alexnet, inceptionv3, resnet-18, shuffleres, MATLAB.*

INTRODUCTION

The realms of marine biology, fisheries conservation, and aquaculture management, along with meticulous monitoring of oceanic biodiversity, necessitate the comprehensive incorporation of precise species stratification [1]. Among the vast number of aquatic species that populate the world, it is incredibly challenging to identify and classify fish species. Conventional ways of classification of species are highly based on manual observation [1], morphological characteristics, or genetic analysis, which can be time-consuming, labour-intensive, and prone to errors, especially when dealing with large-scale datasets or species with subtle morphological variations [2]. The application of advanced algorithmic approaches from various domains has effectively addressed the above challenges [1]. The advent of deep learning techniques [3] has firmly revolutionized the multiple phases of image classification, thereby broadening the scope for automated and accurate species recognition based on visual cues extracted from images. Deep learning models have demonstrated impressive potential when applied to learning discriminative features from raw databases, thereby leading to unparalleled performance in various processes that accelerate classification competence. Harnessing the computational efficiency of deep learning networks forms the crux of this study. The transfer learning mechanism enables the efficient refinement of data interpretations while capturing low-level features of the image to deliver higher accuracy [17]. The significance of this research paper lies in its proposal of an innovative method for fish species classification, utilizing the capabilities of deep learning techniques. This is achieved by exploring the practice of transfer learning on pre-trained deep learning networks [4], combined with the implementation of ShuffleRes – a hybrid deep network classifier. Transfer learning, used in this investigation, enables us to effectively capitalize on the knowledge encoded in pre-trained models by training them on large-scale image datasets, thereby further enhancing the classification performance of fish species.

Furthermore, the ShuffleRes architecture is introduced by combining the efficacy of residual connections and ShuffleNet layers, thereby improving the robustness of performance and the feature characteristics extracted from the constructed image datastore. To compare the efficiency of the suggested methodology, the comparative performance is clarified with the help of the accuracy metrics received with the pre-trained models [3] and the hybrid ShuffleRes architecture. Simulations of the investigation through comparative analyses with state-of-the-art deep learning classifiers highlight the superiority of the ShuffleRes architecture in capturing intricate patterns inherent in fish species imagery [6]. The findings suggest that the fusion of transfer learning and hybrid deep network architecture presents a promising avenue for accurately and efficiently stratifying fish species, with potential implications for ecological monitoring and biodiversity conservation, thereby optimizing effective management.

This paper aims to depict the progression of this research through the adept explanation of Decision Learning techniques in categorizing fish species using the layered convolutional and pooling approach of the networks. The sectioning of the paper is presented, with Section II elaborating on the literature review about fish species classification. Section III outlines the proposed methodology for this study, followed by the presentation of results and conclusion in Sections IV and V, respectively.

EMPIRICAL REVIEW

Sambit Dash et al. [11] presented a paper that enhances the Convolutional Neural Network combined with ResNet-50 for fish species classification, providing insights into classification accuracy across different epochs. The results were satisfactory.
Jayashree Deka et al. [9] elaborated on fish classification using AlexNet and ResNet-50 architectures. The study presented the training and testing of the incorporated fish dataset, demonstrating the higher accuracy obtained with AlexNet [10] compared to the ResNet framework [12]. The future work of the study involves the use of live classification monitors to enhance the accuracy of fisheries stratification, while aiding in the conservation and management of aquaculture.

PROPOSED METHODOLOGY

The proposed methodology utilizes fish image data from Kaggle, comprising 430 images, which include various classes of species. The procedures for training and testing the deep learning networks are separated into 70% and 30% segmentation of the entire image data captured in this study. The overall architecture for this study is depicted in Figure 1 below.

The various classes of species include Black Sea Sprat, Gilt Head Bream, Horse Mackerel, Red Mullet, Red Sea Bream, Sea Bass, Shrimp, Striped Red Mullet, and Trout. The image datastore, consisting of diverse images of various species, is loaded into MATLAB. Deep Learning networks hold a combination of pre-trained networks depending on the type of data to be processed [5]. This investigation incorporates an image database, and therefore, the selection of pre-trained image networks is made. For this study, three pre-trained networks are chosen primarily because of their optimality in terms of time, number of layers, and total learnable parameters. The training and testing sets are segregated according to the ratio above. The three chosen pre-trained models for this study are AlexNet [13], InceptionV3, and ResNet-18. The process of transfer learning is initiated in conjunction with data augmentation [14], which enables a higher score of classifier accuracy. The purpose of implementing transfer learning is to engage the learnable layers to acquire more knowledge of the current dataset while efficiently training the layers to enhance accuracy. The explication of transfer learning utilized in AlexNet is illustrated in Figure 2 as follows:

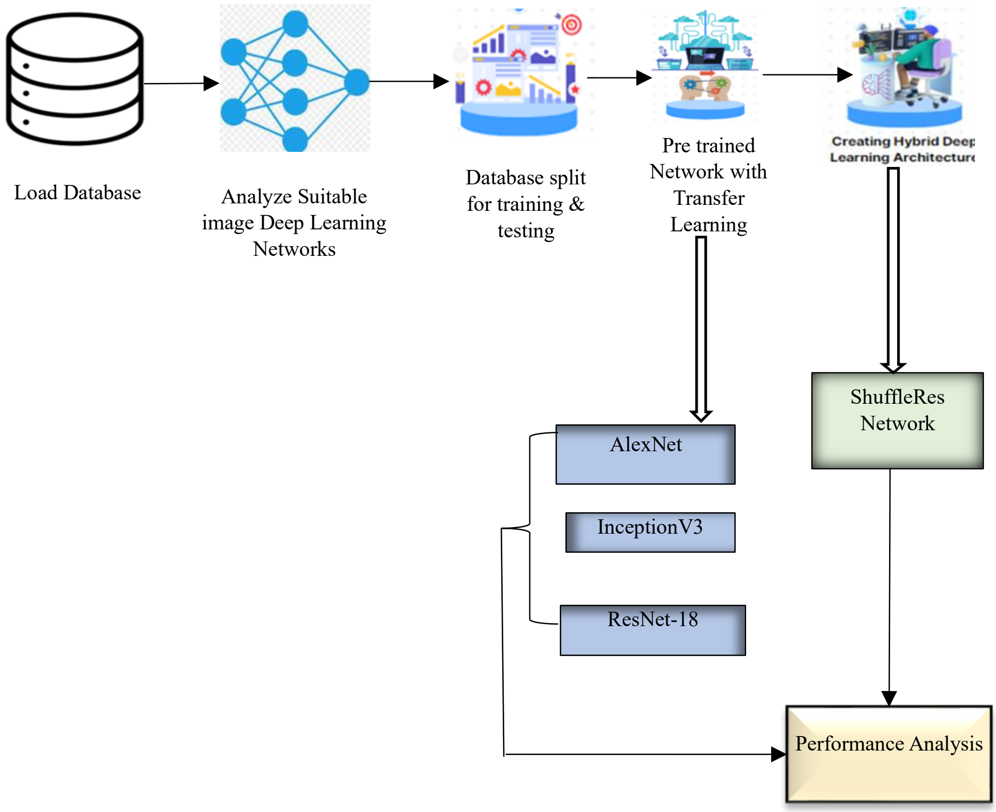

Figure 1. Architecture flow for this study

The network InceptionV3 is another image deep learning network incorporated with transfer learning in this study [10]. The implementation of the InceptionV3 network is initiated by loading the network and the image dataset, while subsequently altering the pre-trained network layers to adopt transfer learning. Similar to the previous implementation, data is augmented to enhance classifier accuracy. The training options and network delineations are presented in Figure 3 as illustrated below:

The Resnet-18 network is a directed acyclic graph network [18], which is incorporated using transfer learning, along with pre-training the network. The network contains an input layer, a combination of convolution and pooling layers that process the loaded database. This network uses the Rectified Linear Units (Relu) activation layer in these units [15]. The activation works through a thresholding mechanism initiated at 0 for any given f(x) = max (0, x). Thus, the classification throughput exhibits linear functionality, rendering 0 when x < 0, and linearly stratifies when the value of x is greater than 0. The network is constructed with 72 layers, utilizing the previously specified training options. The network is constituted with epochs set to 10 and a learning rate of 0.0001. The results obtained after training and validation are presented in the subsequent section of this paper.

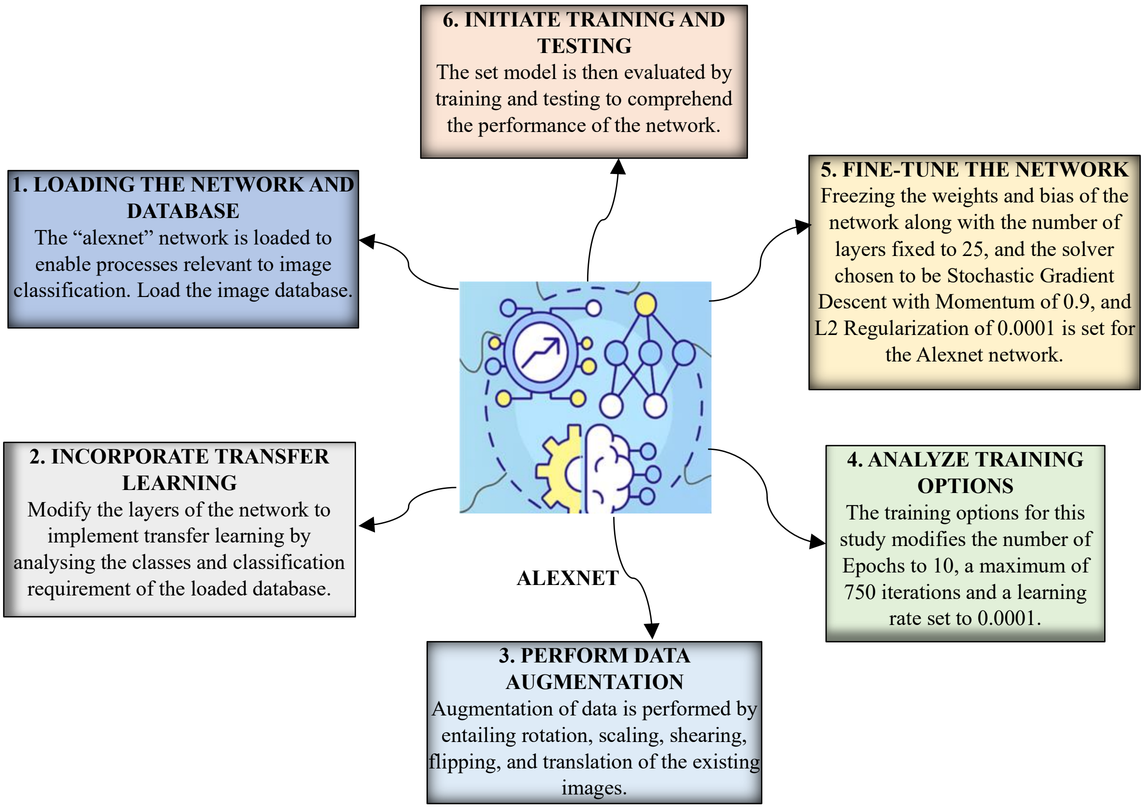

Figure 2. Alexnet implementation with transfer learning

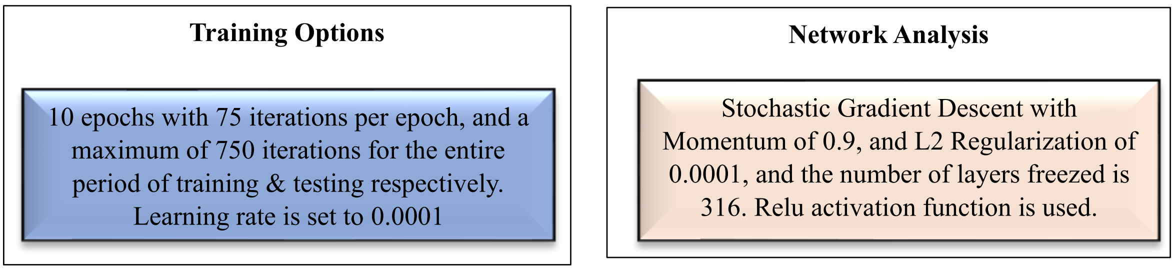

Figure 3. Training and network analysis of inceptionv3 network

The ShuffleRes deep learning architecture is built by combining the ShuffleNet and ResNet architectures to obtain a hybrid image classifier network. This hybrid network is built using the layers demonstrated below, as depicted in Figure 4.

The training and network analysis options are selected in conjunction with a similar training option, stochastic gradient descent with momentum of 0.9, but with adjustments to the number of epochs and the learning rate. The learning rate is set to 0.01, and the point at which the epoch is scheduled is set to 30, with each epoch repeated twice. Batch normalization scales the mini-batches of images and also calculates the mean and variance of features within the batch. The pooling layer, however, is realized by finding the maximum among the matrix of values obtained as a result of extracting the values in the image; thus, achieving an effective dimension reduction process where the image retains its pixel efficiency. The following occurs after applying ReLU activation and pooling [19]. A fully connected convolutional layer is introduced using CNN. This is done to address bottlenecks caused by overfitting. The fully connected CNN layer regularizes the data vectorization from the previous layer. The SoftMax classification output layer [16] employs a probabilistic dissemination method to address multi-class classification problems. The number of layers combined for the hybrid architecture, including the input, convolutional, pooling, normalization, activation, feature analysis, and output layers, totaled 171. The throughput from this architecture, after loading the database, is found to be most optimal among the existing pre-trained architectures used in this study. The results thus procured are illustrated in Section.

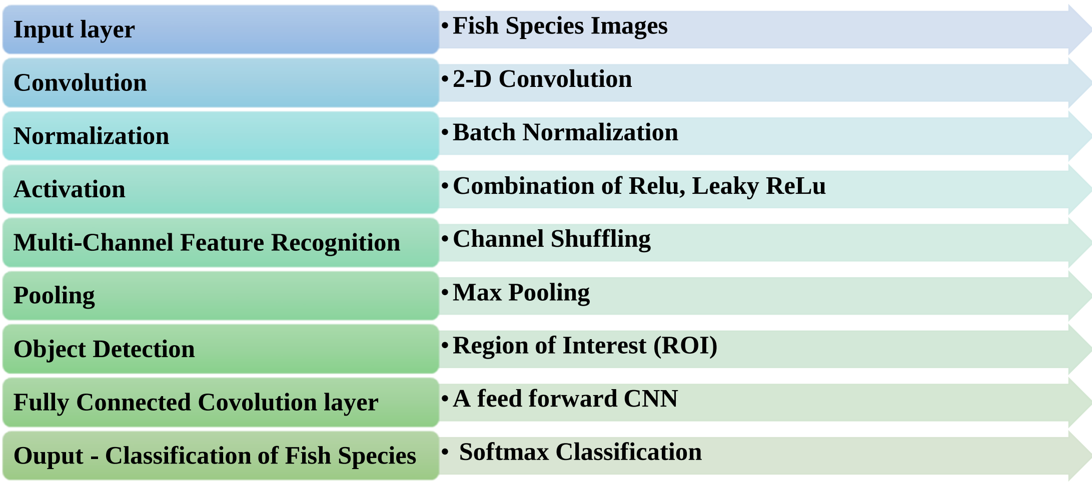

Figure 4. ShuffleRes layer overview

RESULTS AND DISCUSSION

The stratification accuracy of networks and the performance of deep learning networks are delineated in this section, presenting the performance results of training and validation for the pre-existing networks.

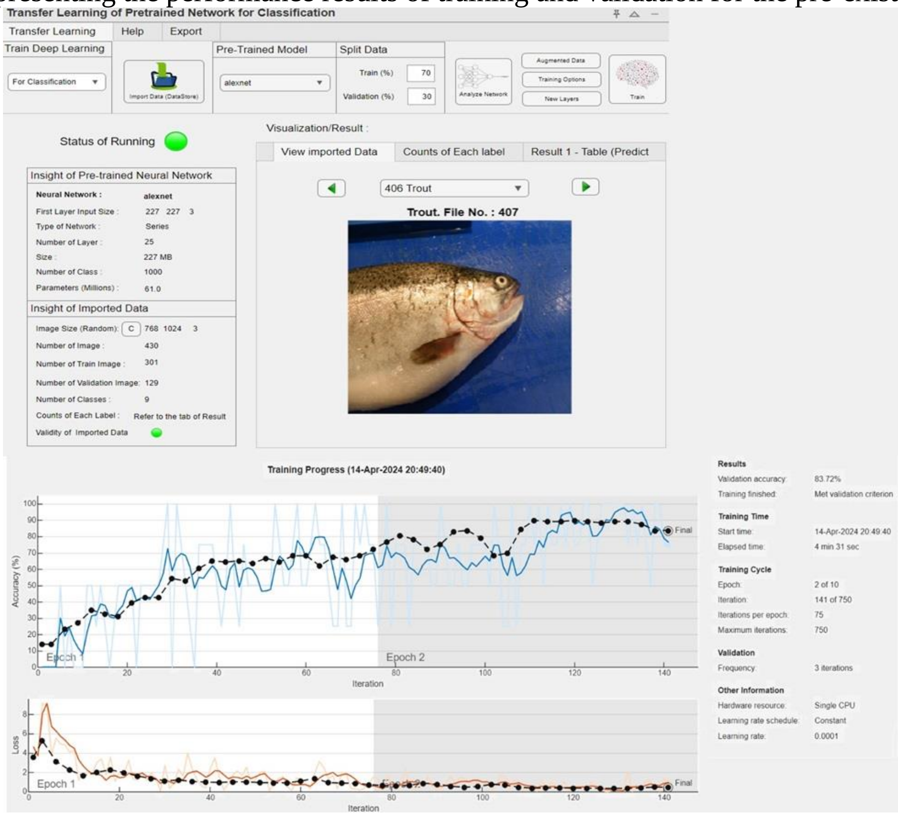

Figure 5. AlexNet implementation and performance analysis

Figure 5 illustrates the process of transfer learning with the AlexNet model of fish classification. A training set comprising 30% of 430 images was used, with 30% of the data reserved as the validation set. The training progress graph indicates that the training accuracy is indeed on the rise, with a validation accuracy of 83.72% achieved in the second epoch. The values of loss decreased gradually, indicating better learning. The image displayed illustrates a correctly classified sample of trout, and the training has passed the validation criterion in 4 minutes and 31 seconds.

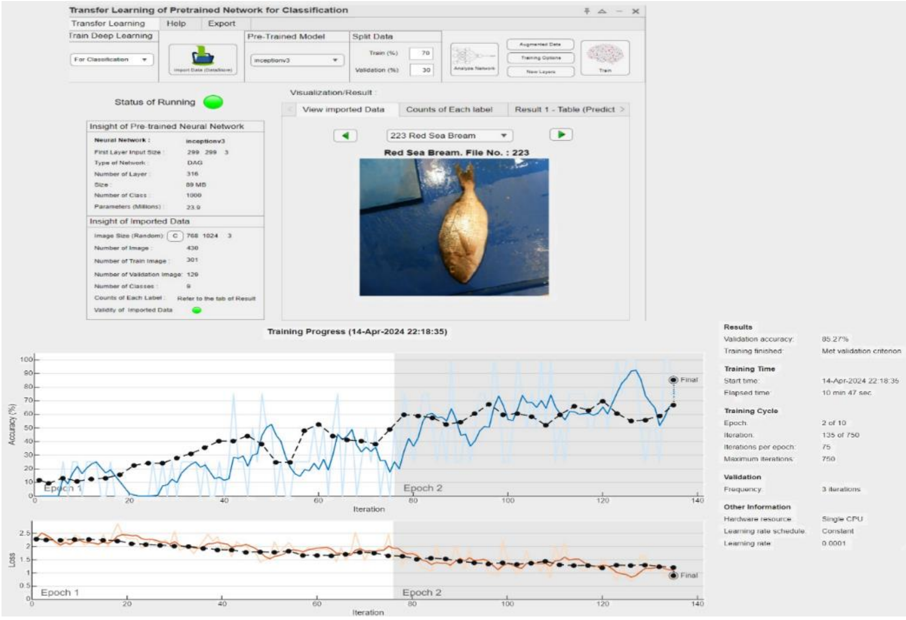

Figure 6. InceptionV3 implementation and performance analysis

Figure 6 illustrates the transfer learning application in fish classification using the Inceptionv3 model. The 430 training images were divided into 70% training and 30% validation sets. As indicated by the accuracy graph, there is a gradual increase in accuracy, with validation reaching 85.27 percent accuracy in the second epoch. The successive decrease in loss values indicated efficient learning processes. The pictured object is a properly labeled Red Sea Bream, and the model passed the test with the validation criterion after 10 minutes and 47 seconds of training.

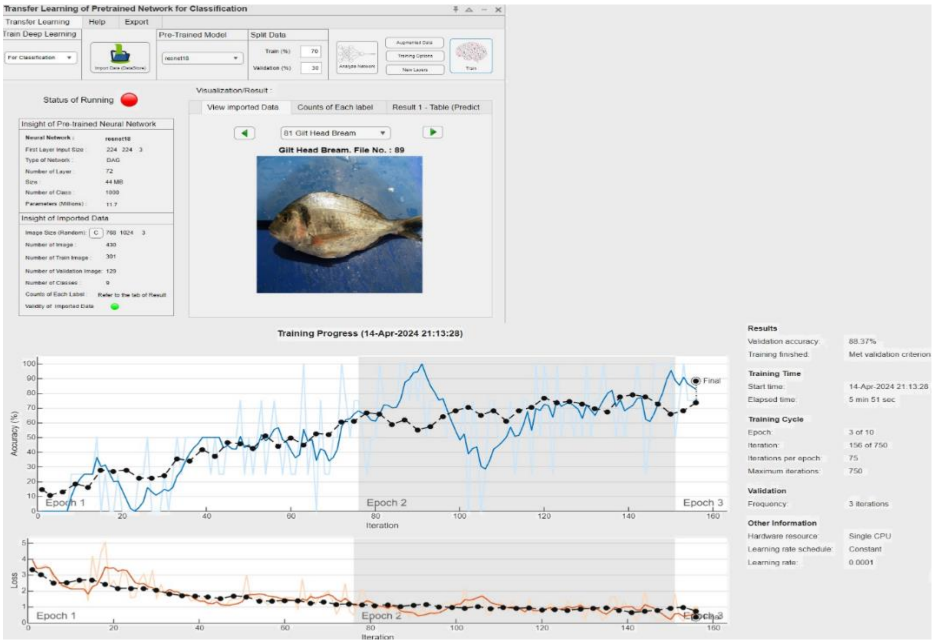

Figure 7. Resnet implementation and performance analysis

Figure 7 illustrates the transfer learning of the ResNet18 model for fish classification. The 430-image dataset was split into 70 % for training and 30% for validation. The accuracy curve also demonstrated stable progress, with a validation accuracy of 88.37% reached after the third epoch. Loss figures consistently showed a decline, which confirmed effective learning. The image presented is of a successfully identified Gilt Head Bream, and the model satisfied the validation criterion in 5 minutes and 51 seconds during training.

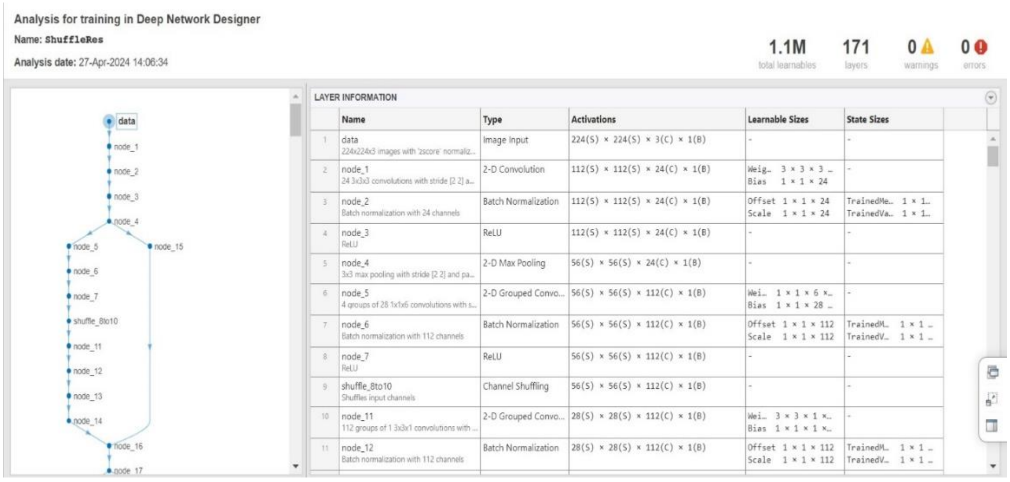

Figure 8. Layer overview and analysis of the shuffleres architecture

Figure 8 shows the Network structure analysis of the ShuffleNet model in MATLAB Deep Network Designer. The framework consists of 171 layers and 1.1M parameters to learn. It involves the input of images in size 224-224-3, which is then processed through a convolution, batch normalization, ReLU, max pooling, grouped convolution, and channel shuffling procedure. The design effectively downsizes dimensions in space while preserving opportunities, and no warnings or errors are reported, which signifies appropriate settings in training.

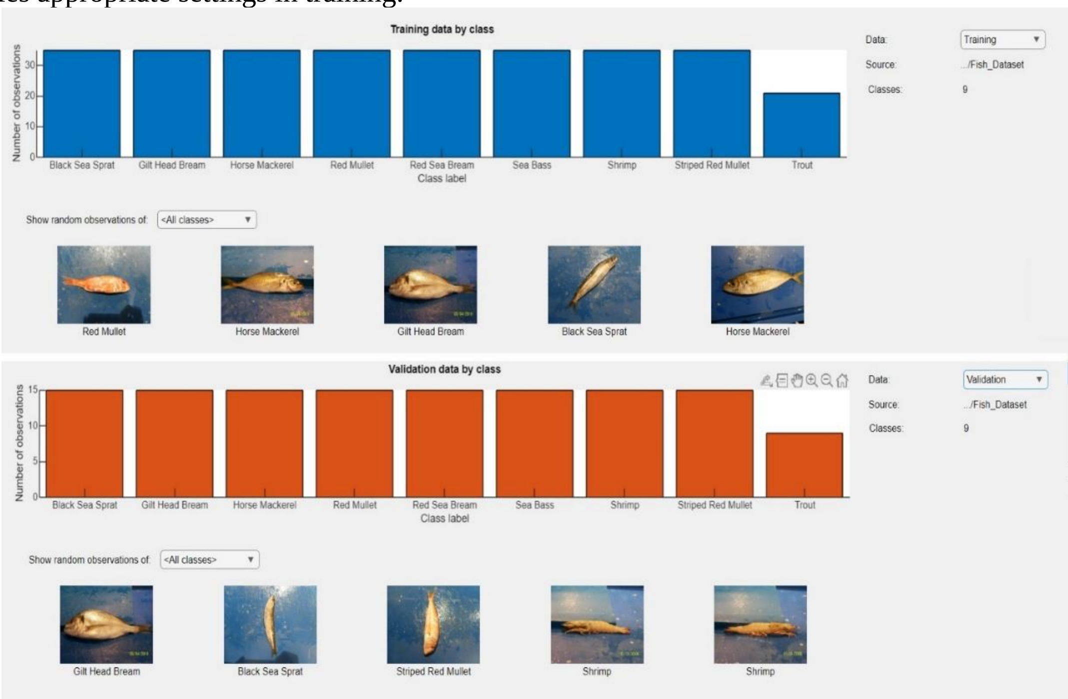

Figure 9. Training and validation classes

Figure 9 illustrates the distribution of training and validation images from a fish classification dataset with nine classes, including the Black Sea Sprat, Gilt-Head Bream, Red Mullet, Sea Bass, Shrimp, and Trout. The blue Bar chart at the Top shows training data, with approximately 30 images in each class.

The orange Bar chart at the Bottom indicates validation data, which has approximately 15 images in each class. The diversity of the dataset can be demonstrated through sample images shown below each chart, which depict small examples of fish species at different orientations and under various lighting conditions, thereby representing the dataset relatively evenly and aiding in the training and assessment of the model.

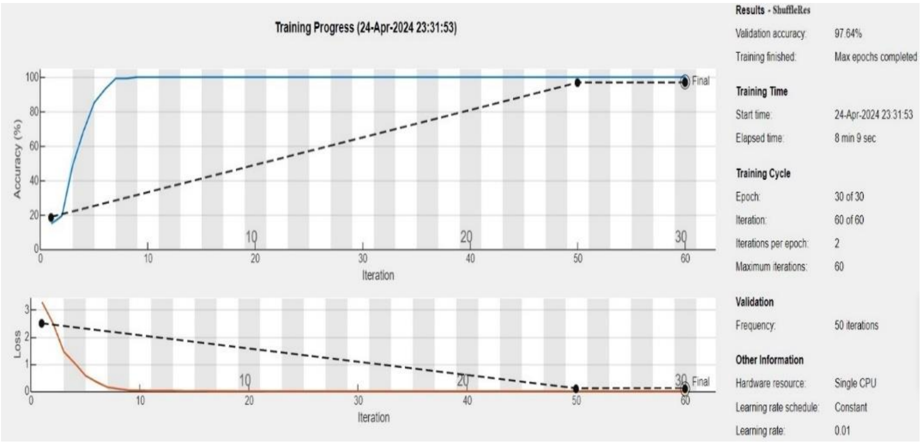

Figure 10. Performance of shuffleres architecture

The Figure 10 training progress plot indicates that the model, ShuffleRes, achieved a very high validation score of 97.64 after completing 30 training epochs using 60 iterations. Within the initial few iterations, accuracy increased quickly and settled at around 100%, with the loss steeply decreasing to near zero, indicating highly effective learning. The training began on April 24, 2024, at 23:31:53 with a duration of 8 minutes and 9 seconds, utilizing one CPU. The learning rate was set to 0.01, and there were two iterations per epoch. It was validated after every 50 iterations. The stable accuracy and low level of loss imply that the model is appropriately trained without overfitting much.

A comparative chart of the various performance metrics relevant to the incorporated networks utilized in this study is tabulated in Table 1 below.

Table 1. Performance chart of deep learning image networks

S. No	Deep Learning Networks	Number of Layers	Number of Epochs	Learning Rate	Process Time	Classification Accuracy
1	Alexnet	25	10	0.0001	4 Min 31 Sec	83.72%
2	InceptionV3	316	10	0.0001	10 Min 47 Sec	85.27%
3	Resnet-18	72	10	0.0001	5 Min 51 Sec	88.37%
4	ShuffleRes	171	30	0.01	8 Min 9 Sec	97.64%

The results obtained from the deep learning networks unambiguously demonstrate that the hybrid ShuffleRes deep learning architecture, which combines the ShuffleNet and ResNet architectures, requires a higher processing time but achieves the pinnacle of classification accuracy compared to transfer-learned, pre-built deep learning image networks.

CONCLUSION

Aquaculture, conservation, and fisheries management are crucial aspects of an economy. The need for developing accurate identification and feature decision boundary forms is cardinal in protecting the various species of aquatic life. This study utilizes deep learning networks to analyze the features of species [7], [8] while effectively stratifying them into different classes. The other image networks in deep learning incorporate the transfer learning mechanism into pre-trained networks, while constructing a hybrid architecture using the layers of ShuffleNet and ResNet-18. The depth of layers in each of the image networks used in this study differs, along with variances observed in terms of processing time, number of epochs, and learning rate. But the training solver used is fixed to stochastic descent with momentum of 0.9. The classification accuracy of various image networks thus procured indicated that

AlexNet yielded 83.72%, followed by InceptionV3 at 85.27%, and then ResNet-18, which delivered 88.37%. The hybrid ShuffleRes architecture, which combines normalization, feature analysis, and SoftMax classification, remains the highest classifier generator, achieving an overall stratification accuracy of 97.64%. The deep learning technique of feature identification, analysis, and classification thus accelerates insight into aquaculture species, enabling practitioners and researchers to develop optimized monitoring standards and effectively utilize advanced computational methods for future research developments. Future work can pivot on real-time fish datasets that further challenge the data acquisition process, while significantly requiring high-performance graphics processing units (GPUs) that can improve classification in the utilized deep learning networks.

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