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Application of EfficientNet Deep Learning with Wiener Filter for Freshwater Fish Disease Image Classification

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Abstract:
Challenges pertaining to the timely and accurate diagnosis of diseases in freshwater fish have adversely impacted the productivity of the aquaculture industry. Image classification using deep learning techniques has the potential to overcome such challenges. However, this potential has not been realized due to such problems as image noise, motion blur, and small dataset sizes. Most prior studies in this area employ the same Convolutional Neural Network (CNN) architectures and, while using the same or similar techniques, generic to the studies, to preprocess the images. The focus of this study is to compare and benchmark the image classification performance of the EfficientNet architectures (B0 to B7) using the Wiener Filter as a preprocessing technique for the classification of diseases in freshwater fish. The experiments used a publicly available dataset of 1,750 images of seven diseases in fish, while maintaining identical training parameters to yield sixteen different experimental configurations. Metrics such as accuracy, precision, recall, and F1-score were exercised while evaluating model performance. The data show that medium-scale architectures surpass both smaller and larger size variants. The optimal performance was achieved by EfficientNet-B4 and Wiener Filter with an accuracy of 94.89%, precision of 95.15%, recall of 94.92%, and an F1-score of 94.89%. The results confirm that preprocessing with Wiener Filter improves performance on classification tasks using medium-sized models and further elucidate the applicable value of the model developed in this study in aquaculture and its related interventions.

Keywords: ***Freshwater Fish Disease**, **EfficientNet, Wiener Filter**, **Image Classification***.

1. Introduction

Aquaculture is one of the most important aspects of the global food production system as it involves breeding, rearing, and harvesting of organisms. The segment of freshwater aquaculture is growing rapidly, particularly in Asia as well as in Africa, which are the two leading producers of freshwater fish [1]. However, the farming of freshwater fish still contends with fish diseases which cause substantial losses in productivity and the quality of the crops [2]. Fish diseases are the most significant cause of the estimated USD 6 billion losses annually in global aquaculture [3]. The economic losses are attributed to the high fish mortalities, and the declining quality of aquaculture products which impact the business viability of aquaculture enterprises [4], [5].

Numerous health conditions like Red Spot Disease, Aeromoniasis, Bacterial Gill Disease, Saprolegniasis, White Spot Disease, and White Tail Disease share similar and sometimes identical visual symptoms that complicate the identification process [6], [7]. Currently, the diagnosis of fish ailments is primarily done by hand or through lab testing which is time-consuming, expensive, labor-dependent, and is prone to diagnostic errors [2]. Hence, there is a pressing need for an automatic, fast, and accurate fish disease identification system that utilizes images.

The enhancements made to deep learning, for instance Convolutional Neural Networks (CNN) have unequivocally shown greater understanding of image classification, inclusive of diseases in fishes. Automatic feature extraction is a stronghold for CNN, commanding greater success in image classification tasks than traditional feature engineering based methods [8], [9], [10]. A number of researches have demonstrated the ability of CNN architectures to successfully classify fish diseases even with small datasets through transfer learning by employing pretrained visual feature representations [11]. One such model is EfficientNet, an architecture that balances model depth, width, and resolution of the model based on compound scaling [12]. Ironically, while EfficientNet has been shown to effectively tackle classification of diseases in fishes, the predominant number of research has limited itself to one variant and even on that has not satisfactorily addressed image quality concerns in fish disease datasets [5].

The primary step in the classification of images of diseased fish is the removal of visual impairments, such as motion blur, Gaussian noise, and low light. This is important since such imperfections can diminish classification accuracy. The Wiener Filter is a preprocessing method that performs Gaussian noise and motion blur reduction and is reported to be superior to CLAHE, Unsharp Masking, and Median Filter in achieving a balanced removal of motion blur and noise [13], [14], [15]. The application of the Wiener Filter in the preprocessing stage of classification of images of diseased freshwater fish, however, remains largely unexplored. Consequently, this study intends to assess the Wiener Filter within the context of preprocessing and determine the classification accuracy levels of the assorted variants of EfficientNet between B0-B7 to provide a model for the classification of diseased freshwater fish that is more accurate, stable, and efficient. In contrast to prior studies that concentrated exclusively on one of the variants of the EfficientNet or on nonspecific preprocessing methods, this study assesses, in a more complete manner, the outcomes of employing EfficientNet B0-B7 in combination with the Wiener Filter for preprocessing.

2. Literature Review

The value of research focusing on the image-based recognition of fish diseases in freshwater aquaculture has scaled new heights. This is attributed to the growing demand for robust diagnostic solutions that are also scalable. A stream of scholarly works has discussed the capacity of CNNs to competently detect complex visual patterns in fish diseases caused by bacterial, fungal, parasitic, and viral infections. These works have also highlighted the possibility of using CNN approaches to replace manual visual assessments and laboratory tests, which are often expensive, slow, and are conducted by an experienced specialist [2], [7].

With respect to increasing the ease and accuracy of classification, research has graduated to exploring a variety of complex deep learning structures. Some works have demonstrated that the fusion of multiple CNN architectures and transfer learning has the potential to improve the representation of the embedded features of fish disease images [16]. Other fish disease classification works have also reported that EfficientNet due to its capacity to address multiple visual complications in an aquatic ecosystem is a good fit for the classification of disease images [5]. In most of these works, however, only one EfficientNet variant has been studied, which is the reason the difference in model scales has been underexplored, even with identical dataset conditions. EfficientNet employs a compound scaling method that simultaneously adjusts network architecture in depth and breadth with an optimization in image resolution. This results in a network with strong feature extraction capability and computational efficiency [12]. This architecture has demonstrated strong performance in image classification within a variety of domains, such as the medical and biological imaging fields, suggesting robust performance across various datasets [17], [18]. However, the different versions of EfficientNet with respect to computational resource allocation have not been studied in detail within the context of noisy freshwater fish disease images.

The uncontrolled imaging conditions of the datasets from the freshwater aquaculture sector continue to attract criticism because of the problems caused by motion blur, low-light imaging, and the presence of Gaussian noise within the images. The literature review suggests that feature learning by neural networks would be facilitated by better image preprocessing. Wiener filters take noise out of images and the structural features of the images remain intact and biomedical images [13]. Wiener filters have been shown to be better than the Gaussian blur and noise dismissal of the mean and median filters. [15].

The use of Wiener filters for the classification of fish diseases is in publications. Most of the works in the literature use generic/default preprocessing tools and do not take the noise and blur characteristics of fish disease datasets into account. Also, some publications have analyzed the preprocessing and the use of some contemporary convolutional neural networks in particular EfficientNet and freshwater aquaculture. Several gaps exist in literature review. First, a comprehensive evaluation comparing the multiple variants of EfficientNet (B0–B7) on the classification of freshwater fish diseases has yet to be conducted. Second, the absence of an in-depth investigation on the Wiener Filter as a specialized preprocessing method for fish disease images has been recognized. This is an attempt to assimilate the Wiener Filter preprocessing technique and EfficientNet B0–B7 in an effort to determine their relevance to the classification of diseases in freshwater fish and, consequently, provide a stronger and more efficient framework for actual aquaculture.

3.Methods

This study utilizes a publicly available image dataset titled Freshwater Fish Disease Aquaculture in South Asia, which can be accessed through Kaggle.com (https://www.kaggle.com/datasets/subirbiswas19/freshwater-fish-disease-aquaculture-in-south-asia). The dataset was created by Subir Biswas and is widely used in research on freshwater aquaculture disease classification. It consists of 1,750 images divided into seven classes, namely Bacterial Diseases – Aeromoniasis, Bacterial Gill Disease, Bacterial Red Disease, Fungal Diseases – Saprolegniasis, Parasitic Diseases, White Tail Disease (Tail Rot), and Healthy Fish. Each class contains 250 images. Sample images from each class are shown in Figure 1.

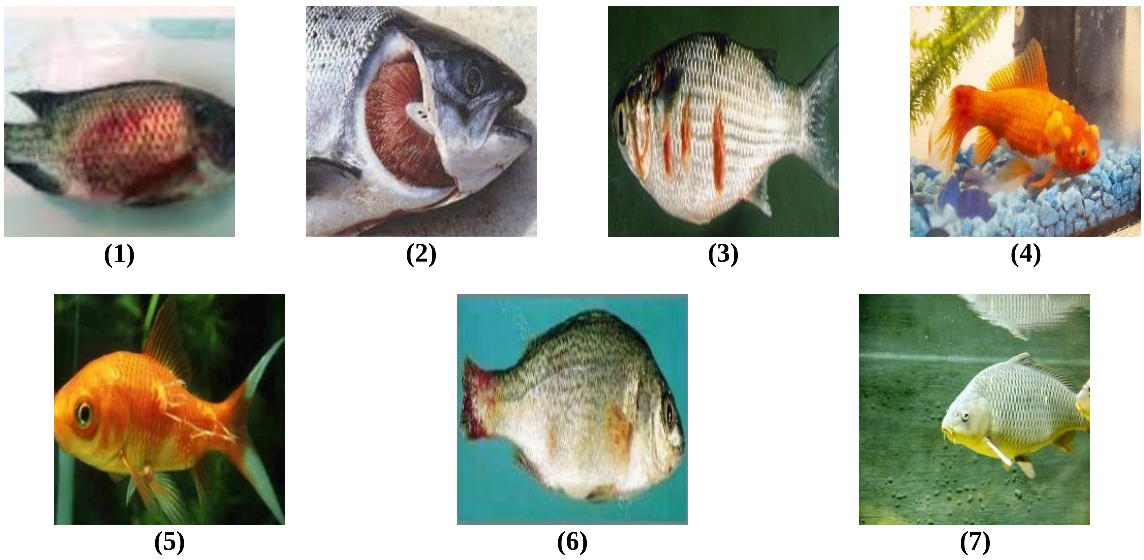


Figure 1. Sample images of: **(1)** Bacterial diseases - Aeromoniasis, **(2)** Bacterial gill disease, **(3)** Bacterial Red disease, **(4)** Fungal diseases Saprolegniasis, **(5)** Parasitic diseases, **(6)** White tail disease (Tail Rot), **(7)** Healthy Fish

At this point, structured system design was created to facilitate a systematic and reproducible process of conducting research. The dataset was partitioned into three subsets, comprising 80% of the dataset for training, 10% for validation, and 10% for testing. To ensure an unbiased assessment of the performance and to minimize the risk of data leakage between training and testing periods, this fixed data splitting method was uniformly applied to all experiments.

Having established the dataset partitioning, the Wiener Filter was used to mitigate the presence of noise and motion blur that characterize, for example, images depicting examples of diseases affecting freshwater fish. In this research, the Wiener Filter was used in the spatial domain via the wiener filter function in the SciPy library, and applied to each of the three RGB channels in an isolated manner, with a local window of 5×5 that varied the noise amount based on local statistical data. This approach of working in the spatial domain of the images was such that the significant visual characteristics that relate to the diseases in the images, such as lesions, scale textures, and edges, were retained as the noise and blur were suppressed.

In order to strengthen model generalization, augmentation only on training datasets was done. Random Flip, Random Rotation, Random Zoom, and several other processes were done as augmentation. These actions, to an extent, allow the model to become more optimal to differing orientations and scales changes to be present in actual aquaculture environments. Thus, the classification models were built using EfficientNet B0 to B7 architectures. Each EfficientNet model utilized transfer learning by initializing the weights from ImageNet and speeding the model's convergence. To adjust to the freshwater fish disease dataset, a fine-tuning procedure was used by freezing the initial layers to keep the basic low-level feature representations, and the remaining layers were trained to learn features specific to the disease. In Figure 2, the model architecture is shown.

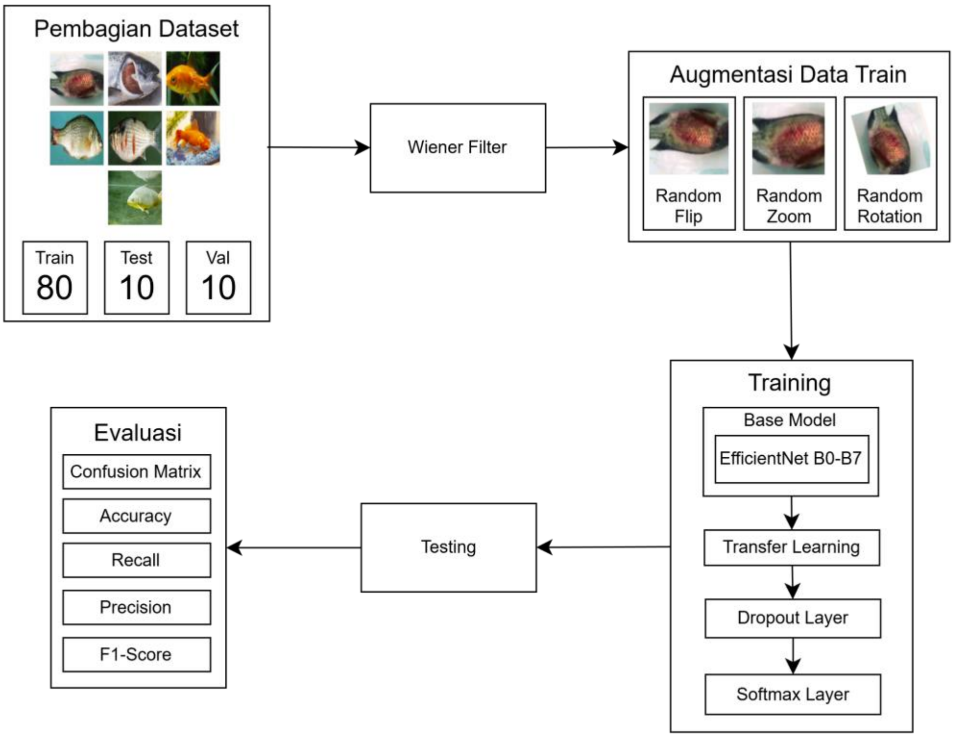


Figure 2. Model Design

In order to ensure a fair comparison across different architectures, all EfficientNet models were trained using the same training configuration. The models were optimized using the Adam optimizer with a learning rate of 3×10^{-5}, a batch size of 32, and a maximum of 15 training epochs. Sparse categorical cross-entropy was employed as the loss function, and transfer learning was applied by freezing the first 40 layers of each pretrained EfficientNet model. A fixed random seed of 42 was used to ensure reproducibility, and all experiments were implemented using the TensorFlow/Keras framework. The complete training configuration, including hyperparameter settings and model-specific input image resolutions, is summarized in Table 1.

Table 1. Training configuration

	Configuration	B0	B1	B2	B3	B4	B5	B6	B7
1	Input Size	224 × 224	240 × 240	260 × 260	300 × 300	380 × 380	456 × 456	528 × 528	600 × 600
2	Batch Size	32							
3	Number of Epochs	15							
4	Loss Function	Sparse Categorical Cross-Entropy							
5	Fine Tuning Strategy	First 40 layers frozen							
6	Random Seed	42							
7	FrameWork	Tensorflow/Keras							

To evaluate model performance, sixteen experimental scenarios were designed, consisting of EfficientNet B0–B7 without preprocessing and EfficientNet B0–B7 combined with Wiener Filter preprocessing. The complete list of experimental scenarios and model configurations evaluated in this study is summarized in Table 2.

Table 2. Experimental Scenarios

	Scenarios	Configuration
1	Scenario 1	EfficientNet-B0
2	Scenario 2	EfficientNet-B1
3	Scenario 3	EfficientNet-B2
4	Scenario 4	EfficientNet-B3
5	Scenario 5	EfficientNet-B4
6	Scenario 6	EfficientNet-B5
7	Scenario 7	EfficientNet-B6
8	Scenario 8	EfficientNet-B7
9	Scenario 9	EfficientNet-B0 + Wiener Filter
10	Scenario 10	EfficientNet-B1 + Wiener Filter
11	Scenario 11	EfficientNet-B2 + Wiener Filter
12	Scenario 12	EfficientNet-B3 + Wiener Filter
13	Scenario 13	EfficientNet-B4 + Wiener Filter
14	Scenario 14	EfficientNet-B5 + Wiener Filter
15	Scenario 15	EfficientNet-B6 + Wiener Filter
16	Scenario 16	EfficientNet-B7 + Wiener Filter

Model performance was evaluated using a confusion matrix. Accuracy and macro-averaged precision, recall, and F1-score were used as the primary evaluation metrics, as macro averaging provides a fair assessment of per-class performance in multi-class classification [19] problems with balanced datasets.

To sustain the integrity of the results of the experiment, the models were all trained and tested on the same data splits, data setup and data evaluation, processed in the same manner, and analyzed in the same way. This controlled setup in the experiments allows for the objective analysis of the techniques proposed and tested on the several architectures of EfficientNet allowing for fair comparisons.

4. Results and Discussion

This study was able to record results from experiments carried out in sixteen different settings for EfficientNet B0–B7, both with and without the Wiener Filter. The average performance for each of the experiments is contained in Table 3 and the macro averaged results for all the experiments.

Table 3. Performance Comparison of EfficientNet B0–B7

	Scenario	Accuracy	Recall	Precision	F1-Score	Parameter	Training time
1	Scenario 1	90,34 %	90,37 %	90,59 %	90,24 %	4.214.442	6,70 m
2	Scenario 2	93,18 %	93,23 %	93,33 %	93,16 %	6.740.110	7,67 m
3	Scenario 3	92,61 %	92,65 %	93,14 %	92,60 %	7.949.824	9,40 m
4	Scenario 4	92,04 %	92,08 %	92,49 %	92,07 %	10.981.174	11,85 m
5	Scenario 5	**93,75** %	**93,80** %	**94,06** %	**93,70** %	17.904.230	17,25 m
6	Scenario 6	92,04 %	92,06 %	92,39 %	92,06 %	28.776.702	24,40 m
7	Scenario 7	92,04 %	92,08 %	92,01 %	91,95 %	41.256.086	32,75 m
8	Scenario 8	91,47 %	91,43 %	91,51 %	91,49 %	64.426.398	40,10 m
9	Scenario 9	89,20 %	89,23 %	89,90 %	89,23 %	4.214.442	9,40 m
10	Scenario 10	91,47 %	91,51 %	91,85 %	91,43 %	6.740.110	11,10 m
11	Scenario 11	93,75 %	93,75 %	94,04 %	93,78 %	7.949.824	12,40 m
12	Scenario 12	93,18 %	93,18 %	93,41 %	93,19 %	10.981.174	14,80 m
13	Scenario 13	**94,88** %	**94,92** %	**95,14** %	**94,88** %	17.904.230	18,95 m
14	Scenario 14	92,61 %	92,63 %	93,04 %	92,67 %	28.776.702	29,70 m
15	Scenario 15	92,61 %	92,63 %	92,67 %	92,60 %	41.256.086	38,0 m
16	Scenario 16	92,04 %	92,12 %	92,14 %	92,00 %	64.426.398	51,10 m

According to the information provided in Table 3, EfficientNet-B4 with Wiener Filter is the only one that has an accuracy of 94.88%, recall of 94.92%, precision of 95.14%, and an F1-score of 94.88%, which is the best overall performance achieved. No preprocessing EfficientNet-B4 is also a good performer, and performance is stable, although a little lower than the Wiener Filter results. These results thus confirm EfficientNet-B4 is the best architecture to use in this research, both with or without Wiener Filter.

The performance trend suggests that there is even greater discrimination of visual features pertaining to disease across medium sized networks spanning from EfficientNet-B0 to EfficientNet-B4. In contrast to this, larger networks such as EfficientNet-B5,B6, and B7 demonstrate negligible to even decreased performance due to the implication that classification accuracy does not improve with greater or more complex models, especially with smaller datasets. This isas evident from the computational characteristics presented in Table 3 to illustrate that as EfficientNet-B0 to EfficientNet-B7 training time and number of parameters increases greatly. Moreover, larger networks such as EfficientNet-B5, B6, and B7 take exceedingly longer to train and still do not surpass the performance of EfficientNet-B4. Thus overall, these results validate that EfficientNet-B4 achieves the best classification performance and retains efficient computational usage. The benefits of the Wiener Filter preprocessing can also be seen in the results in Table 3. Wiener Filter consistently improves the performance of several variants of EfficientNet, with EfficientNet-B2 through EfficientNet-B4 being the most affected. One example is EfficientNet-B4, which showed an increase in accuracy from 93,75% to 94,88% with the use of Wiener Filter. The results show that the Wiener Filter is able to reduce noise and motion blur, which in turn improve the visualization disease-related features and assist the network to extract these features more effectively.

The performance of models without preprocessing improves moderately in these networks compared to EfficientNet-B0 and EfficientNet-B1, which are smaller architectures. For smaller networks, preprocessing seems to remove some fine details in images which are important for correct classification. The results therefore depict that the capacity and the size of the model influence the efficiency of the use of the Wiener Filter. Additional to the Wiener Filter preprocessing, two other image enhancement techniques namely CLAHE and Median Filter, were also considered as baseline preprocessing methods with the EfficientNet-B4 architecture. Considering its overall performance, EfficientNet-B4 was picked as a representative model among all the evaluated EfficientNet variants, and the results of these preprocessing methods are compared in Table 4.

Table 4. Performance of EfficientNet-B4 with Different Image Preprocessing Methods

	Preprocessing	Accuracy	Recall	Precision	F1-Score
1	No Preprocessing	93,75 %	93,80 %	94,06 %	93,70 %
2	Wiener Filter	**94,88** %	**94,92** %	**95,14** %	**94,88** %
3	CLAHE	93,75 %	93,80 %	93,90 %	93,71 %
3	Median Filter	94,32 %	94,37 %	94,41 %	94,27 %

The results shown in Table 3 show that the pre-processing results on the EfficientNet-B4 architecture show that the enhancement of the images shows positive results, whereas the pre-processing baseline results show no consequences. The baseline results, with no pre-processing, achieved results of 93.75% and F1 score equal to 93.70%. On the other hand, CLAHE presents similar results with a few insignificant differences on precision and F1 score attribute. The Median Filter shows even a greater enhancing results on accuracy with 94.32% and F1 score equal to 94.27%.This means that it greatly improved the reduction of the noise, and that the preservation of the features was moderate to it. On the contrary, the Wiener Filter provided the best results with the highest accuracy (94.88%) and highest results in recall (94.92%), highest the precision (95.14%), and equal F1 score (94.88%). This shows that the Wiener Filter has the greater capabilities of noise and blur suppression, of the overall greater features of disease discrimination within the visual images.To further investigate the class-wise behavior underlying the aggregate results reported in Table 4, a detailed per-class performance analysis was conducted for representative small sized and medium sized models, namely EfficientNet-B1 and EfficientNet-B4, both with and without Wiener Filter preprocessing, using class-wise precision, recall, and F1-score, as shown in Table 5. The refinement of the class-wise behavior underpinning the overall results in Table 4 was an abstract of the total class performance for small and medium-sized models in the EfficientNet B1 and B4 with and without Wiener Filter preprocessing. This was carried out using class-wise precision, recall, and F1-score that are provided in table 5.

Table 5. Class-wise Precision, Recall, and F1-score of EfficientNet-B1 and EfficientNet-B4

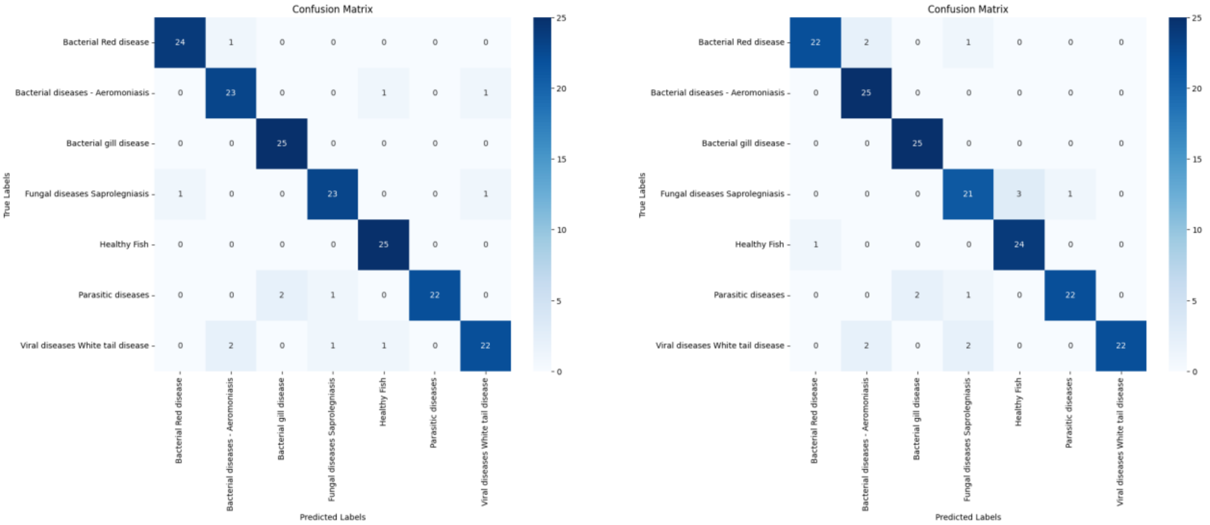
	Scenario	Class	Precision	Recall	F1-Score
1	Efficientnet B1	Bacterial Red Disease	96,00 %	96,00 %	96,00 %
		Aeromoniasis	88,46 %	92,00 %	90,20 %
		Bacterial Gill Disease	92,59 %	100 %	96,15 %
		Saprolegniasis	92,00 %	92,00 %	92,00 %
		Healthy Fish	92,59 %	100 %	96,15 %
		Parasitic Diseases	100 %	88,00 %	93,62 %
		White Tail Disease	91,67 %	84,62 %	88,00 %
2	Efficientnet-B1 + Wiener Filter	Bacterial Red Disease	95,65 %	88,00 %	91,67 %
		Aeromoniasis	86,21 %	100 %	92,59 %
		Bacterial Gill Disease	92,59 %	100 %	96,15 %
		Saprolegniasis	84,00 %	84,00 %	84,00 %

		Healthy Fish	88,89 %	96,00 %	92,31 %
		Parasitic Diseases	95,65 %	88,00 %	91,67 %
		White Tail Disease	100 %	84,62 %	91,67 %
3	Efficientnet-B4	Bacterial Red Disease	100 %	96,00 %	97,96 %
		Aeromoniasis	92,59 %	100 %	96,15 %
		Bacterial Gill Disease	89,29 %	100 %	94,34 %
		Saprolegniasis	89,29 %	100 %	94,34 %
		Healthy Fish	91,67 %	88,00 %	89,80 %
		Parasitic Diseases	95,65 %	88,00 %	91,67 %
		White Tail Disease	100 %	84,62 %	91,67 %
4	Efficientnet-B4 + Wiener Filter	Bacterial Red Disease	100 %	92,00 %	95,83 %
		Aeromoniasis	92,31 %	96,00 %	94,12 %
		Bacterial Gill Disease	92,59 %	100 %	96,15 %
		Saprolegniasis	96,00 %	96,00 %	96,00 %
		Healthy Fish	89,29 %	100 %	94,34 %
		Parasitic Diseases	95,83 %	92,00 %	93,88 %
		White Tail Disease	100 %	88,46 %	93,88 %

Table 5 shows that there is almost no impact from the Wiener Filter on Efficient Net models for high value Recall classes such as the Bacterial Gill Disease, Bacterial Red Disease classes. These classes all achieved high value Recall even without preprocessing. Other classes like Bacterial Red Disease, Aeromoniasis, Skin Redness Disease overlap greatly in features. Once Wiener Filter preprocessing is applied, Aeromoniasis, with zero Recall jumps to 100% Recall at the expense of Bacterial Red Disease's Recall and F1 score decreasing from around 96% to 88% and F1 score from 96% to 91.67%. Aeromoniasis and Bacterial Red Disease differ from each other in subtle texture and color, which Wiener filtering seems to be removing in these high Recall classes.

The same pattern can be seen for Parasitic Diseases and Saprolegniasis, as they share similar texture and morphological traits. Even without any preprocessing, Saprolegniasis sustains a balanced precision and recall standing at 92%. When applying a Wiener Filter, precision and recall drop to 84%. This drop in performance suggests that the Wiener Filter may compress high frequency texture details that are important for the smaller sized models for both parasitic and fungal infections which explains the inconsistent class wise improvements for EfficientNet-B1.

In comparison, EfficientNet-B4 shows an almost uniformly good and steady class wise performance with and without preprocessing. Not using Wiener Filter, EfficientNet-B4 records considerably high precision and recall values for visually similar classes like Bacterial Red Disease with 100% precision, 96% recall and Aeromoniasis with 92.59% precision, 100% recall, which shows good discrimination for the closely related bacterial infections. With Wiener Filter preprocessing, this separation becomes even more pronounced, as illustrated by more even precision–recall trade-offs and greater F1 scores across the majority of the classes. Most importantly, the distinction between Parasitic Diseases and Saprolegniasis is further enhanced, with Saprolegniasis attaining 96% precision and recall, implying that the suppression of noise and blur allows one to enhance more discriminative morphological features without smoothing out the relevant texture information for medium sized architectures. These results corroborate that Wiener Filter pre-processing has a greater impact when paired with high performing models, resulting in better and more uniform class-wise classification. To analyze class-wise error patterns further, confusion matrix analysis was performed with representative models. EfficientNet-B1 without preprocessing and EfficientNet-B1 with Wiener Filter confusion matrices are shown in Figure 3.

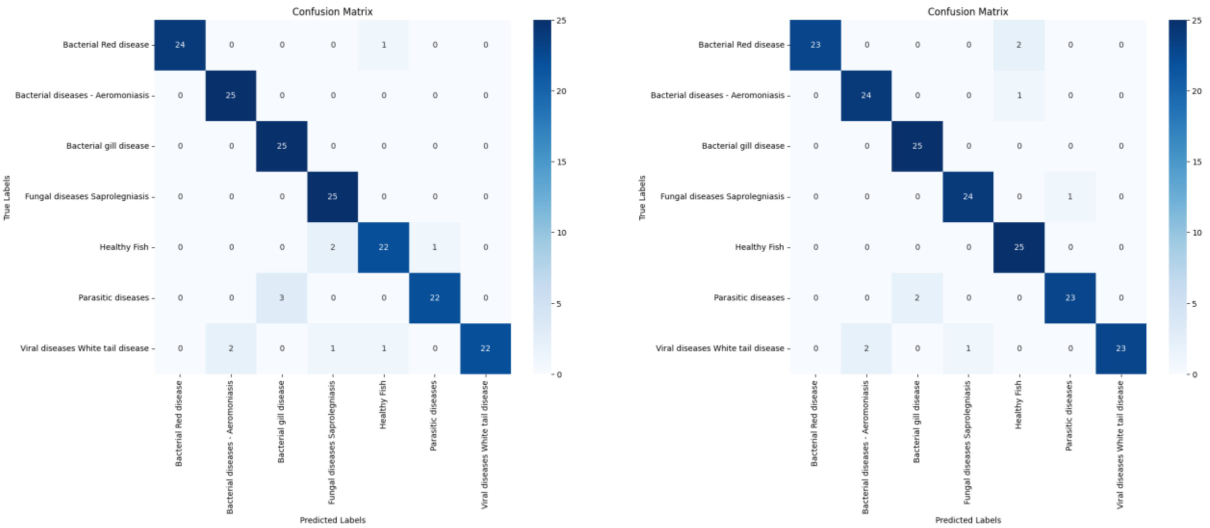


(1) **(2)**

Figure 3. Confusion Matrix of: **(1)** EfficientNet-B1, **(2)** EfficientNet-B1 + Wiener Filter

As shown in Figure 3, EfficientNet-B1 without preprocessing shows classification errors mainly in visually similar categories, particularly white tail disease, parasites, and viruses. After applying Wiener Filter preprocessing, several classes such as Healthy Fish and Bacterial Red Disease show better results, indicating an improvement in background noise suppression. However, an increase in classification errors was observed in Aeromoniasis and White Tail Disease, suggesting that Wiener filtering may suppress the subtle color and texture cues required by small sized models. These results indicate that Wiener Filter preprocessing does not consistently benefit small sized architectures and may degrade classification performance for certain disease categories.

The confusion matrices of EfficientNet-B4 without preprocessing and with Wiener Filter are shown in Figure 4.



(1) **(2)**

Figure 4. Confusion Matrix of: **(1)** EfficientNet-B4, **(2)** EfficientNet-B4 + Wiener Filter

As shown in Figure 4, EfficientNet-B4 without preprocessing already demonstrates strong class-wise classification performance, as indicated by dominant diagonal elements across most disease categories. After applying Wiener Filter preprocessing, predictions become more concentrated along the main diagonal, with reduced inter-class confusion, particularly between fungal and parasitic diseases. Although a slight increase in misclassification is observed for the Healthy Fish class, the overall class-wise performance improves, confirming the positive impact of Wiener Filter on medium sized architectures.

To evaluate stability, EfficientNet-B4 with and without Wiener Filter preprocessing was subjected to additional assessment through repeated training runs with different seeds (42, 123, and 999). EfficientNet-B4 with Wiener Filter displayed a mean accuracy of 0.9508 ± 0.0027 and thus demonstrated an equitable and consistent performance through all runs, whilst EfficientNet-B4 without preprocessing displayed an accuracy of 0.9470 ± 0.0097 and performance across runs was inconsistent. These findings affirm the fact that Wiener Filter preprocessing improves the accuracy of model predictions and simultaneously improves the robustness of the model by making it less sensitive to its initialization.

5. Conclusions

This study showed that a medium-sized EfficientNet architecture, in particular EfficientNet-B4 with Wiener Filter preprocessing is the best performing configuration for the classification of images depicting the diseases of freshwater fishes. EfficientNet-B4 with Wiener Filter achieved the best overall performance with an accuracy of 94.88%, a recall of 94.92%, a precision of 95.14%, and an F1 score of 94.88%, whereas larger EfficientNet variants did not provide any further improvements, suggesting that a greater model complexity does not equate to a greater classification accuracy.

This study’s novelty is derived from the comprehensive assessment of the stylistic and class level computational efficiencies of the EfficientNet variants B0-B7 after preprocessing using the Wiener Filter. It was shown that the Wiener Filter is more useful with models of medium size and that it is less effective with smaller models because of the visual detail losses. These conclusions are certainly interesting, yet the research was constrained by reliance on a single publicly available databased where image quality was also fairly consistent as well as the constrained sample size of approximately 250 images per class. Additional work will build on the proposed methodology and analyze larger and more hetergenous databases with diverse, real-world images from aquatic farming. Other deployment related features, such as efficient computational resource utilization and inference delays for faster responses, will also be considered more deeply.

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