Automatic Fish Classification Using Lanczos Resampling and Deep Learning

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Abstract—**The development of automation in the fish industry, a vital sector of the food industry, is a highly relevant and essential topic. This development is essential for boosting output and mitigating the risk of future food shortages brought on by the world's population expansion. Automatic fish classification using computer vision has been widely developed in fish industry automation, and a lot of research on that topic has been published. However, while some research has produced promising results using complex methods, others have applied simpler approaches with less satisfactory outcomes. This study suggests a straightforward but efficient technique for differentiating between fish species by concentrating on their main characteristics, such as body form and scale patterns. To effectively support these image capturing properties, the Lanczos re-sampling technique is used in this study. Additionally, our basic deep learning model can correctly learn and identify fish species thanks to a fish picture categorization engine created using Google Teachable Machine. Utilizing the Fish-Pak dataset, a popular fish picture dataset frequently used in studies on fish species classification, the suggested approach successfully overcomes the difficulty and attains a high accuracy rate of 97.16%.**

Index Terms—**automatic fish classification, Fish-Pak dataset, Lanczos resampling, deep learning, Google Teachable Machine (GTM)**

I. Introduction

The development of automation in the fish industry, which is part of the food industry, is a topic of great interest and critical necessity [1]. One of the main goals of automation in the food industry, including the fish industry, is to increase productivity. It is felt to be urgently needed to anticipate the threat of food scarcity in the future, due to the continued growth of the human population as well as the impact of climate change and global warming [2].

Automatic fish classification using machine and computer vision with deep learning has been widely developed in fish industry automation, and a lot of research on that topic has been published [3–5]. Table I. summarizes the recent state of the art of automatic fish classification for farming fish based on deep learning in the last 5 years. In the table, we can observe that each work is detailed with the dataset used, the proposed method, and its advantages and disadvantages.

Improving food production methods, like fish farming, is crucial to solving future food shortages as the world's population rises and environmental problems are exacerbated by climate change [6, 7].

Among the automation technologies utilized in the fish sector are automated fish identification and classification systems, automated water quality monitoring, and automated feeding systems [8]. These technologies are particularly useful for creating automatic sorting systems that minimize human participation and cut down on manual stages [9].

Recent advances in deep learning technology, a branch of artificial intelligence focused specifically on image processing, have significantly enhanced the capabilities of automation, especially for detection and classification tasks. Deep learning-based solutions have gained popularity due to their superior accuracy and real-time processing capabilities. This research aims to develop a deep learning algorithm integrated with image processing techniques for classifying farmed fish. The resulting system will support the advancement of automated sorting systems and other potential technologies in the fisheries industry, reducing human labor and decreasing the time required to sort fish by size and species using automated machinery, leading to a more efficient and sustainable future for aquaculture.

II. Related Work

Numerous research has been published on the topic of automatic fish categorization using computer vision and machine vision combined with deep learning, as was previously noted. This has led to substantial breakthroughs in the field of automation within the fish business [10–12].

Rauf H.T. *et al*. (2019) [6] employed the Fish-Pak dataset [7]. They proposed a CNN (Convolutional Neural Network) with 32 layers by modifying the standard VGGNet network by adding four convolutional layers. They could achieve fairly good accuracy results (96.94%), while the network model they offer has a large architecture.

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The Fish-Pak dataset was also used by Abinaya N.S. *et al*. [8]. In addition to a variety of image processing methods (background removal using BLOB, auto-rotation using MSEE, and picture segmentation), they employed three AlexNet networks for each body, scale, and head. Lastly, they used an NBF (Naive Bayesian Fusion) to add up the results. MSEE stands for Multi-Stage Exhaustive Enumerative Optimization, and BLOB stands for Binary Large Object Analysis. Using a combination of these methods, they achieved a high accuracy of 98.64%. This method requires several intricate processes despite its remarkable precision. In a similar vein, Xu *et al*. used SE-ResNet152 with a class-based balanced focal loss function to transfer learning from ImageNet, and while it achieved a 98.80% accuracy rate, it required a significant amount of processing power and training time. Shammi S.A. used a more straightforward, traditional CNN that same year, which produced a lesser accuracy of 88.96% but was simpler to deploy.

A Deep Convolutional Autoencoder (DCA) was suggested by Banerjee A. *et al*. (2022) [10] to categorize fish. They applied it to a dataset they collected themselves of three Indian local carp, consisting of 1,500 images. They succeeded to obtain fairly good results (97.33% of accuracy).

TABLE I: RECENT STATE OF THE ART OF AUTOMATIC FISH CLASSIFICATION FOR CULTIVATED FISH BASED ON DEEP LEARNING IN RECENT 5 YEARS

Work	Dataset	Method	Advantage	Disadvantage
H.T. Rauf *et al*. (2019) [6]	Fish-Pak [7]	Proposed a CNN with 32 layers by modifying the standard VGGNet network by adding four convolutional layers.	Achieved good accuracy (96.94%).	Big network model. Number of parameters: 404.4M.
N.S. Abinaya *et al*. (2021) [8]	Fish-Pak	Using three AlexNet networks for each body, scale, and head, as well as a number of image processing techniques. Then finally, it is summed the results using an NBF.	High classification result (98.64%).	requires many techniques and complicated methods.
Xu *et al*. (2021) [13]	Fish-Pak	With a class-balanced focal loss function, they employed SE-ResNet152 to transfer learning from ImageNet to the Fish-Pak dataset.	Good acuracy (98.80%).	Training SE-ResNet152 ImageNet needs big computation (long time, high hardware specification, etc.).
S. A. Shammi *et al*. (2021) [9]	Fish-Pak	Using a classic CNN.	Simple algorithm (a Classic CNN).	Achieved an accuracy of less than 95% (88.96%).
A. Banerjee *et al*. (2022) [10]	1,500 photographs of three native carps from India	used a DCA, or deep convolutional autoencoder.	Achieved good accuracy (97.33%).	* Requires quite a lot of pre-processing data and is not reported as fully automatic or not. Without it, the accuracy results may change significantly. * With data pre-processing, the proposed method is quite complex.
Kuswantori Ari, *et al*. (2022) [11]	Fish-Pak	Using YOLOv4	Simple method.	Achieved an accuracy of less than 95% (77.42%) in the complete class.
Md. Asif Ahmed *et al*. (2023) [12]	Eight different classes of fish, which they created on their own (BD Fish)	CNN + Convolutional LSTM.	Achieved good accuracy (97%).	The dataset and input data seem to have a few challenges. Images in the dataset have a white constant background, and no augmentation was reported.
Bo Gong *et al*. (2023) [14]	Fish-Pak	Using transfer learning and vision transformers.	Achieved good accuracy (98.34%).	Complicated methods.

However, in their research, quite a lot of pre-processing data was needed, and it was not reported whether it was fully automatic or not. Without it, the accuracy results may change significantly. In addition, with data pre-processing, the proposed method is quite complex. Previously, the author published work on fish classification on the Fish-Pak dataset using YOLOv4 [11]. The proposed method is quite simple, with YOLOv4 optimized using several techniques. However, the accuracy results obtained were quite low (77.42%) for the entire class. Md. Asif Ahmed, *et al*. (2023) [12] used a convolutional LSTM (Long Short-Term Memory) in conjunction with CNN and applied it to their dataset, which comprises eight fish classifications. In their research, they could reach a good accuracy result (97%). However, the dataset and input data seem to have a few challenges. Images in the dataset have a white constant background, and no augmentation was reported. The last work was presented by Bo Gong *et al*. (2023) [14]. They proposed the dataset of Fish-Pak as well, and suggested a transfer learning followed by a vision transformer. The accuracy result was reported as very good (98.34%), while the method proposed is complicated.

According to the review of the state of the art of automatic farming fish classification based on deep learning, the Fish-Pak dataset is the most frequently used. This dataset has many advantages. It has many types of fish species (classes), the fish pictures contained are quite challenging, etc. Meanwhile, other fish datasets have limited classes, or the fish images contained are less challenging, such as having a constant background, etc. Furthermore, the aforementioned review concludes that good accuracy results are delivered by complicated methods, while employing simple methods results in poor accuracy.

In our work, we propose an approach that is simple but is expected to produce good classification results. In other words, we propose a simple but effective approach for the automatic classification of farmed fish based on image processing and deep learning. The main idea is that we focus on the main distinguishing features, namely body shape and scale patterns, to classify fish species. We utilize Lanczos resampling, which adequately supports this process, allowing our proposed deep learning model to effectively learn and recognize fish species based on these key features. We also created the deep learning model ourselves, which is remarkably simple. In comparison to previous relevant research, the deep learning network model only has two layers and a much smaller number of parameters. In the end, it is hoped that this work can contribute to the development of automatic fish classification for farmed fish based on computer vision and deep learning.

III. Materials and Methods

A. Dataset and Image Augmentation

The dataset of Fish-Pak [7] is considered very fit for use in this experiment. It consists of six types (classes) of cultivated freshwater fish that are often found in Pakistan and sur-rounding countries: 1. Thala (Catla); 2. Silver (Hyperphthalmichthys molitrix); 3. Rohu (Labeo rohita); 4. Mori (Cirhinus mrigala); 5. Common carpio (Cyprinus carpio); and 6. Grass carp (Ctenopharyngodon Idella).

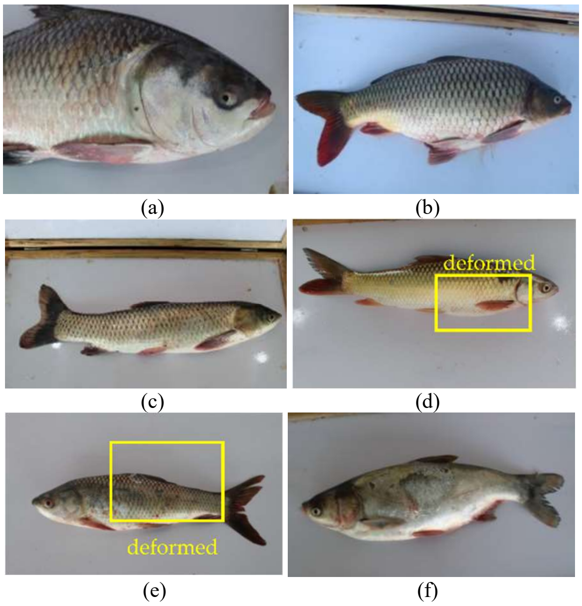


Fig. 1. Example images for every class in the Fish-Pak dataset: (a) Catla; (b) C. Carpio; (c) G. Carp; (d) Mori; (e) Rohu; and (f) Silver [7].

Fig. 1 displays samples of fish photos for each category (class) in this dataset. As mentioned previously, this dataset is the most commonly utilized for developing automatic fish classification for farmed fish based on image processing and deep learning.

Additionally, this dataset is also quite challenging for several reasons: each image in the dataset is original (not processed), the background remains natural (also not processed) and is not constant, the number and condition of fish in each class are large and varied, the visual appearance is similar for several classes (such as Catla-C. Carpio and G. Carp-Mori, which have similar body shapes and scale patterns), and the condition of many fish is damaged or deformed (as an example in parts (e) and (f)). Among the main features of fish that can differentiate between one species and another species in general, also included in the fish in this dataset, are body shape and scale patterns [7]. For this reason, we use it as the basic concept of our approach.

However, the number of fish images in each class in this dataset is low and not balanced. So augmentation is then carried out to enrich and balance the data in each class. The small number of images (less than 100) and the unbalanced number in each class make deep learning algorithms less effective in the learning process [8]. Flip, rotation, and translation are the augmentation techniques employed in this work, because they make sense and are appropriate for classifying fish [8, 11, 14]. The augmentation process is carried out as described in Eqs. (1) to (4) [11].

I_f^C is the fish image in each class, which consists of I_f^{1C}, I_f^{2C}, to $I_f^{N_C C}$. The multiplication factor m_f is then determined by the ratio between the class target image N_T with the number of class images N_C. This multiplication factor is then applied to each class m_f^C with the target image per class N_T determined to be 100 [8, 11]. In this way, image augmentation per class I_{af}^{nC} can be generated using flip F_a, rotation θ_a, and translation T_a techniques. Finally, the original and augmented images are collected and become a new dataset I_{Nf}^C. The new dataset is presented in Table II.

$$I_f^C = \left\{ I_f^{1C}, I_f^{2C}, ..., I_f^{N_C C} \right\}, \tag{1}$$

$$m_f^C = \left| 1 - \frac{N_T}{N_C} \right|, C \in \left[1, 2, \cdots C \right], N_C < N_T, \tag{2}$$

$$I_{af}^{nC} = H\left(I_f^{nC}, F_a, \theta_a, T_a \right) \Big| a \in \left[1, 2, \cdots, m_f^C \right] \Big|, \tag{3}$$

$$I_{Nf}^C = \left\{ I_f^{1C}, I_f^{2C}, \cdots, I_f^{N_C C}, I_{af}^{1C}, I_{af}^{2C}, \cdots, I_{af}^{N_C C} \right\}. \tag{4}$$

Table II: New Dataset after Augmentation

Fish	Number of Images (body)	Multiplication Factor	Number of Augmented Images	New dataset (Body)	Training (70 %)	Testing (30 %)
Catla	20	4	80	100	70	30
C. Carpio	50	1	50	100	70	30
G. Carp	11	9	99	110	77	33
Mori	70	1	70	140	98	42
Rohu	73	1	73	146	102	44
Silver	47	2	94	141	99	42
Total	271	–	466	737	516	221
Average	45	–	78	123	86	37
Standard Deviation Average	23.16	–	–	19.87	–	–

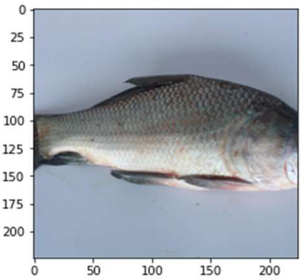
Table II reveals that each class now has a minimum of 100 images. The number of images for each class is also more balanced, as indicated by the standard deviation average value, which has decreased quite significantly from 23.16 to 19.87. In this way, the images in each class meet the minimum number and are more balanced, so that the learning process can run effectively [8, 11]. Then the images in each class are split into 70% for training and 30% for testing [8, 9, 14].

B. Resizing and Lanczos Resampling

The input image is resized to 224 × 224 using the Lanczos resampling technique [15]. Lanczos resampling is frequently used as a low-pass filter, but it may also be used to seamlessly interpolate a digital signal's value between its samples. In the latter scenario, each sample of the provided signal can be mapped to a scaled and translated version of the Lanczos kernel. The central lobe of a second, longer sinc function windowed a sinc function is the Lanczos kernel. After evaluation, the sum of these translated and scaled kernels can be added to get the necessary points. A fraction of the sample interval will cause the digital signal's sampling rate to change or rise. Usually, these are employed for Lanczos resampling.

In another function, it is often used for multivariate. Among several simple filters for resampling purposes, the "best compromise" is considered for the Lanczos technique. A Lanczos kernel is obtained from Eq. (5) and Eq. (6). For interpolation, it is obtained by Eq. (7), and the two-dimensional interpolation is expressed by this process is shown in Fig. 2.

(a)



(b)

Fig. 2. (a) Input image with original size and (b) after applying resizing and Lanczos resampling (224 × 224)

$$L(x)=\begin{cases}\sin c(\pi x)\sin c(\pi x/a), & \text{if } -a<x>a\\ 0, & \text{otherwise}\end{cases} \tag{5}$$

Equivalently,

$$L(x)=\begin{cases}1, & \text{if } x=0\\ \dfrac{a\sin(\pi x)\sin(\pi x/a)}{\pi^2x^2} & \text{if } -a\le x<a \text{ and } x\neq 0\\ 0, & \text{otherwise}\end{cases} \tag{6}$$

The Lanczos kernel $L(x)$ is formed from the sinc function $\sin c(x)$ after normalization, then multiplied by the Lanczos window (or sinc window). This sinc window is the central lobe of a horizontally stretched sinc function of $\sin c(x/a)$ for $-a \le x \le a$.

$$S(x)=\sum_{i=\lfloor x\rfloor-a+1}^{\lfloor x\rfloor+a} s_i L(x-i) \tag{7}$$

where the discrete convolution of those samples with the Lanczos kernel for integer values of i yields the value $S(x)$ interpolated at an arbitrary real argument x. This is the sample of a one-dimensional signal.

$$L(x,y)=L(x)L(y) \tag{8}$$

C. Data Array and Normalization

$$z=\frac{x-\min(x)}{\max(x)-\min(x)} \tag{9}$$

D. Deep Learning Model and Training Process

Google's teachable machine, or simply teachable machine, powered by convolutional neural networks, is a no-code machine learning platform and a web-based application created by Google that allows users to learn and perform basic machine learning without writing additional code. Teachable machine offers three options for creating machine learning models: image classification, voice classification, and gesture classification. In the hyperparameters section of teachable machine, there are three settings: epoch, batch size, and learning rate.

Epochs refer to the number of trainings rounds the machine undergoes. In each round, all data is fed to the learning model. The more rounds, the more accurate the model becomes.

Batch size is the number of data samples sent to train the machine at one time. When all data has been processed, one round is considered complete.

Learning rate is a variable that controls the learning speed in each round. Even small adjustments to this value can significantly affect machine learning performance. To improve the detection accuracy of Teachable Machine, users can customize the hyperparameters before training the model.

The deep learning model is very simple; it only consists of two sequential layers. The total parameters are 539,008, consisting of 524,928 train-able and 14,080 non-trainable. The first layer has an output shape of [none, 1280], and the second layer has [none, 7]. The number 7 shows the number of classes in the final classification (0–6). In this work, we separated C. Carpio Red from the C. Carpio class into a new class so that the total class was 7. This separation was proven to be able to increase model performance quite significantly in this class and in all classes in our previous work [11]. We generated this model with the help of the Google Teachable Machine (GTM) [16], which was previously introduced to recognize other objects [17–19]. Fig. 3 describes the architecture of the deep learning model created.

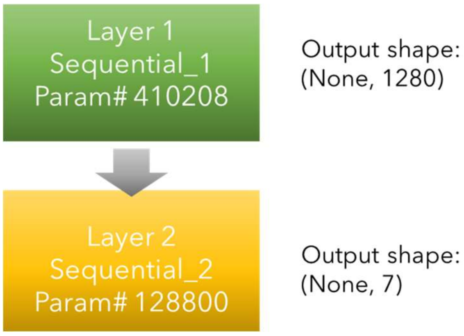


Fig. 3. The model's architecture

With a batch size of 16, the learning process requires just 50 epochs which is satisfactory for learning rate of 0.001, using image training for 70% of the new dataset. It's interesting to note that the learning process was finished successfully in less than two minutes. We do not require high-specification hardware because Google's giant cloud computer handles this training process. The fact that this service is free to use is even more

E. Confusion Matrix

In this paper, the experimental results are validated using a confusion matrix. True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) are the four building components that make up this matrix. When the model successfully classifies the fish, it is referred to as a TP. TN refers to a situation in which the model fails to categorize a fish because it does not exist, which it is assumed to be 100% in this work. When a fish is incorrectly classified by the model, especially when it makes two or more classifications, it is categorized as a FP. When the model fails to classify the fish despite its existence, it is categorized as a FN [20].

From those building blocks, this confusion matrix can evaluate the model with accuracy and other performance parameters such as precision, recall or sensitivity, specificity, and F1 score, as described with equations Eq. (10) to Eq. (15) [21].

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \times 100\% \tag{10}$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \times 100\% \tag{11}$$

$$\text{Recall / Sensitivity} = \frac{\text{TP}}{\text{TP} + \text{FN}} \times 100\% \tag{12}$$

$$\text{Specivity} = \frac{\text{TN}}{\text{TN} + \text{FP}} \times 100\% \tag{13}$$

$$\text{F1 Score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \times 100\% \tag{14}$$

As an alternative, the accurateness of the model can alternatively be stated as follows:

$$\text{Accuracy} = \frac{\sum_i^N P_i}{\sum_i^N |Q_i|} \times 100\% \tag{15}$$

where $\sum_i^N P_i$ refers to the total of correct predictions, while $\sum_i^N |Q_i|$ refers to the total predictions [11].

IV. Results and Discussion

A. Experimental Results

The learning and testing process, as well as the entirety of this work, is depicted in Fig. 4. The testing process is carried out with image testing (30% of images from the new dataset), which is chosen randomly. In this work, the threshold is set to 50%. Table III displays the detailed classification results for each class.

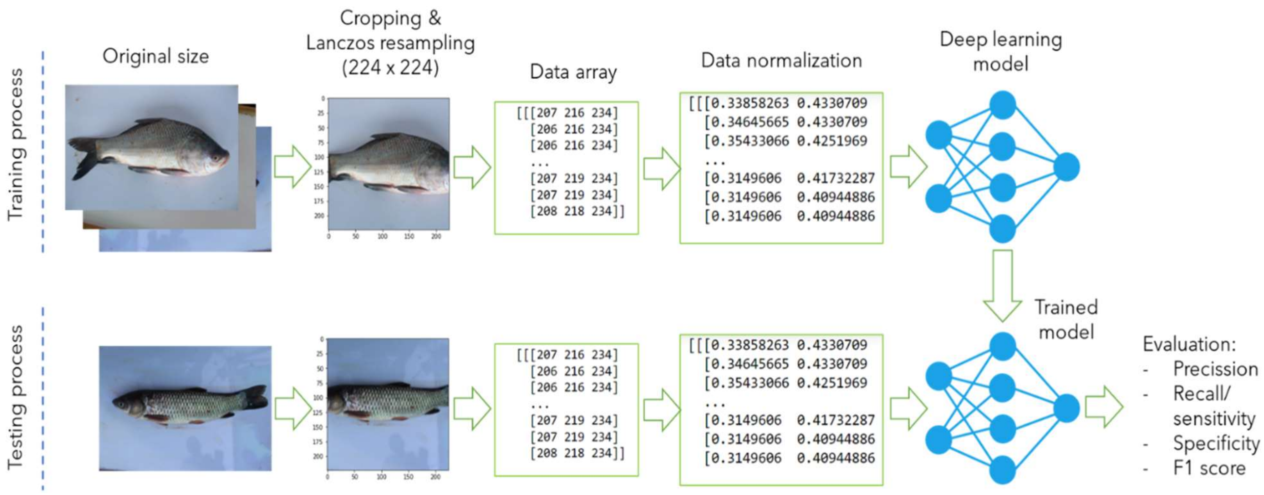


Fig. 4. The workflow for the training and testing process.

TABLE III: EXPERIMENTAL RESULTS

Class	Correct classification (TP)	Wrong classification (FP)	Fail Classification (FN)	Accuracy (%)	Precision (%)	Recall/ Sensitivity (%)	Specificity (%)	F1 score (%)
Catla	29	1	0	96.67	96.67	100.00	96.77	98.31
C. Carpio	28	1	1	93.33	96.55	96.55	96.77	96.55
G. Carp	33	0	0	100.00	100.00	100.00	100.00	100.00
Mori	40	1	1	95.24	97.56	97.56	97.67	97.56
Rohu	43	1	0	97.73	97.73	100.00	97.78	98.85
Silver	42	0	0	100.00	100.00	100.00	100.00	100.00
Average	-	-	-	97.16	98.08	99.02	98.17	98.54

For example, class C. Carpio has a total of 30 test images. From the experimental results, 28 images could be classified correctly as C. Carpio, 1 image was classified incorrectly (classified as another class), and 1 image failed to be classified (the model could not classify). By the confusion matrix, the accurateness for class C. Carpio can be determined at 93.33%, and other performance parameters can also be determined, such as precision at 96.55%, re-call/sensitivity at 100%, specificity at 96.77%, and an F1 score of 98.31%. From the results of this experiment, the final average results for all classes were 97.16% for accuracy, 98.08% for precision, 99.02% for recall/sensitivity, 98.17% for specificity, and 98.54% for F1 score. Fig. 5 describes the classification results in the confusion matrix. There we can see the distribution of actual class vs. classified class, especially to see which class is in the wrong or double classification. For example, the Rohu class has one misclassification where it is classified as C. Carpio. Fig. 6 presents the classification results for each class for accuracy and other performance (precision, recall/sensitivity, specificity, and F1 score) in comparison [22].

Actual Class \ Classified Class	Catla	C. Carpio	G. Carp	Mori	Rohu	Silver
Catla	29				1	
C. Carpio		28	1			
G. Carp			33			
Mori				40	1	
Rohu		1			43	
Silver						42

Fig. 5. Confusion matrix result for the model's output.

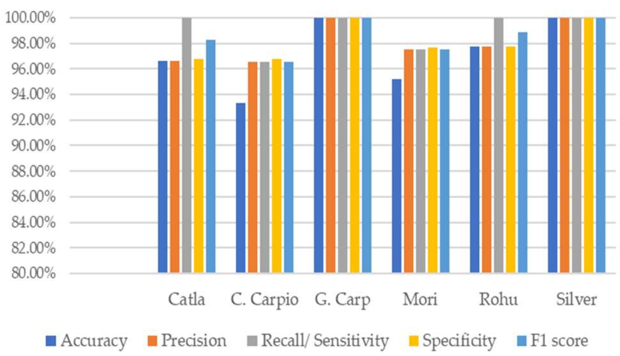


Fig. 6. Experimental results for accuracy and other performance.

With the concept of focusing on the main features of fish body shape and scale patterns, simple methods, and deep learning models, this work can deliver quite good results. It can be proven from the resume of experimental results that have been described above. Thus, the author is confident that it is also very possible that the proposed approach can be applied to the classification of other fish outside the Fish-Pak dataset or to other fish in general.

B. Comparison with Contemporary Deep Learning Models and The Recent-State-of-the-Art

We compare our approach with other popular deep learning models for image classifiers and the recent state of the art in the last 5 years that also utilize the Fish-Pak dataset. This comparison can be seen in Table IV. The models and approaches are ordered from those that produce the lowest level of accuracy to the highest, and the parts in bold indicate the best.

From Table IV, it can be concluded that the approach we proposed does not have the best level of accuracy but can be categorized as good (97.16%). In addition, our approach is significantly superior in terms of the number of layers, number of parameters, and training time. This advantage means our deep learning models are much simpler and can be applied to lower specification hardware devices.

TABLE IV: COMPARISON WITH OTHER POPULAR DEEP LEARNING MODELS FOR IMAGE CLASSIFIERS AND THE RECENT STATE-OF-THE-ART

Model/ Approach	Classification accuracy (%)	No. of layers	No. of parameters	Training time (hrs)
Kuswantori Ari *et al.* [11] (YOLOv4)	77.42	164 [23]	63.9 M [24]	10
S.A. Shammi *et al.* [9] (Classic CNN)	88.96	9	-	-
GoogLeNet [8]	90.91	144	404.4 M	0.42
AlexNet [8]	92.32	25	62.3 M	0.20
ResNet-18 [8]	93.20	72	11 M	0.35
H.T. Rauf *et al.* [6]	96.94	32	404.4 M	-
Our approach	97.16	2	539,008	0.025
ResNet-50 [8]	97.26	177	23 M	1.66
Inception-v3 [8]	98.20	316	25 M	1.15
Bo Gong *et al* [14]	98.34	-	85.81 M	-
N. S. Abinaya*et al.* [8]	98.64	76	186.9 M+	0.62
Xu *et al.* [9]	**98.80**	152	60.3 M	-

C. Limitation and Future Direction

The main limitation of this work is that the approach to recognizing the fish is only based on scale patterns and body shape, not including the head shape, which is also one of the main factors in identifying the fish species [25]. So, it might be less effective if this approach is applied to other datasets, especially if the main factor determining the fish's differentiation is based on its head shape. So, in future work, this approach can be developed by combining or adding the feature of head shape, so it could be more promising to be applied to all other datasets or all fish in general, and it is expected to increase the performance as well.

V. Conclusion

The primary purpose of this experiment is to automatically classify fish utilizing image processing and deep learning, and we propose a simple approach that should yield good classification results. The main idea is that we focus on the main distinguishing features, namely body shape and scale patterns, to classify fish species. The input image is resized and resampled using the Lanczos technique, and then the scale pattern and body shape features of the fish are extracted using a custom deep learning model that was created using GTM. By utilizing the Fish-Pak dataset, this approach was able to produce a total average accuracy of 97.16%.

These results are considered quite good, and when compared with other popular contemporary deep learning models and the recent state of the art, our proposed approach has the advantages of a simple method, much fewer layers, and only a minimal training time. With this concept, it is also very possible that the suggested methodology can be utilized to classify other fish outside the Fish-Pak dataset or to other fish in general. However, since this work does not address this aspect, which is its main limitation, the approach may be less effective for fish that require classification based on their head characteristics. To enhance this technique, future work is planned to incorporate the head features of the fish. This improvement is expected to increase efficiency and make the approach more adaptable to other datasets or fish species in general. For future work, this algorithm will be developed on an embedded system, such as a Raspberry Pi, to operate alongside a fish sorter, providing greater convenience to users.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Conceptualization, Taweepol Suesut (T.S.) and Ari Kuswantori (A.K.); methodology, Worapanya Suthanupaphwut (W.S.) and A.K.; software, T.S. and A.K.; validation, T.S., Worapong Tangsrirat (W.T.) and Navaphattra Nunak (N.N.); formal analysis, T.S. and N.N.; investigation, T.S. and N.N; resources, T.S.; data curation, W.S.; writing original draft preparation, A.K. and T.S.; writing review and editing, W.T. and N.N.; visualization, T.S.; supervision, T.S.; project administration, T.S.; funding acquisition, N.N. All authors have read and agreed to the published version of the manuscript.

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