Image processing Model with Deep Learning Approach for Fish Species Classification

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Abstract: Fish image classification is seemingly simple yet a convoluted process. Moreover, the scientific research of population counts and geographical behaviour is substantial for progressing the current developments in this field. We've tried several approaches to find the optimum-performing approach using advanced computer vision and data mining techniques with limited research scope and difficulties. Its performance was compared to the state-of-art models like CNN, EfficientNet etc., to validate the credibility of the proposed model. Eventually, it was observed that the empirical approach using the ANN confirmed the DNN model to be the leading model with an accuracy of 100%.

Keywords: Image Processing; ResNet; EfficientNet; Deep Learning model; Fish Image Classification; Feature Extraction; Convolutional Neural Network.

1. Introduction

Image processing is the boon in every field which not only reduces the workload but also significantly reduces the time without compromising the accuracy of the classification of certain object [1,2]. Such is the case with the fish species classification using image processing . Fish classification is an important process in many widespread domains such as monitoring ecological and behavioural state of the marine species, or estimate the food reserves and its trend for human consumption [3-5] . Although, much scientific research has not been performed yet which is credible enough to completely eradicate human supervision. Recently various machine learning algorithm gain popularity to accurately classify fish species based on their images and that successfully eliminate the need for human intervention in assisting or classifying fish species [6,7].

1.1 Real-life Implications

Classifying fish into different classes is essential for various applications that are not limited to the sustainability of different species and ecological impacts and utilized for determining the census of marine fish species and speculating the deportment of the fish [8-10]. Classical methods implemented in this field are dependent on user interference and cumbersome. Although there have been apparent advancements and the introduction of several new learning methods, they lack accuracy and limited fish detection capabilities [11-15]. Fish species classification can play a major role in determining fishing practices based on legal restrictions. The identification of endangered species in water bodies of all sizes is also required by concerned institutions, and hereby the proposed model can solve the problem.

Moreover, even with the complements made in improving the resolution of images and gathering a large amount of real-time data is tedious and often problematic. The problem of creating a model that can provide high accuracy and significantly detect objects in pictures with distortion, low-light, and low-light segmentation errors persist [16-17]. Furthermore, even though different image processing and recognition approaches have been applied, the models neglect each feature's impact and adapt a smaller number of features [18-19]. To solve the above problems, there is a need for a system with feature variability. Many researchers proposed different models for this problem by using different data mining techniques with machine learning.

1.2 Related Work

Muhammad et al. recently presented a deep CNN-based model for categorising fish species. It used AlexNet, reduced the number of layers, and added a dropout layer to improve accuracy from 86.65 percent to around 90.48 percent. [20]

Kristian et al. proposed a deep learning method for efficiently processing many images and detecting fishes without pre-filtering. It begins by detecting fish in a single image and then employs CNN with a squeeze-and-excite architecture. The Model is then trained with ImageNet for fish detection, with pre-training and post-training accuracy (with image augmentation) of 99.27 percent and 87.74 percent, respectively. [21].

Ahsan et al. created a model for detecting fish and populations with computer-based solutions. A hybrid model is used in this method, which combines optical flow and Gaussian mixture with the deep learning method. It employs a YOLO-based system, which takes into account only fish that are clearly visible. This model's accuracies on two different datasets were 91.64 percent and 79.8 percent, respectively. [22].

Ahmad et. Al. Proposed a low-cost method for segmenting fish species from the images with poor visual cues like turbidity, luminosity etc. He used gaussian mixture with pixel-wise posteriors method to distinguish fish from complex scenarios. The results showed an accuracy of 84.3% in minimizing missed detections of marine species.[23].

Vaneeda et al. proposed using synthetic data to identify fish species in the absence of training data. Acoustic-trawl surveys were used to capture images and collect acoustic data. She used a deep learning method with a novelty training regime to simulate images realistically. The results showed a range of accuracy with a maximum accuracy of around 94 percent for this approach. [24].

Praba et al. proposed a method for developing effective fish recognition models using various image processing sets. It employs VGG-16, which was trained using the ImageNet classifier. The model was trained on four different types of datasets, one of which was an RGB colour space image. Results showed the best GAR value of 96.4% on RGB trained model while exhibited the lowest of 75.6% on the blending image trained dataset [25].

Alaa et al. proposed a biometric-based fish identification model. It begins with feature extraction. Following that, LDA was used to reduce features, which were then trained with the AdaBoost classifier. The model produced promising results, with a 96.4 percent accuracy rate. [26].

Muhammad et al. proposed a model for classifying fish using low-resolution images. It is made up of unsupervised learning, feature extraction, and data augmentation. This two-layer model was 99 percent accurate. [27].

Yakup et al. developed a multi-stage fish classification system. Morphometry was used to extract features in this method, and a three-stage classifier was used in the model. The nearest neighbour algorithm was used, which has a 99 percent accuracy rate. [28].

Daramola et al. proposed a system for categorising fish into distinct classes. This system makes use of SVD and feature extraction. ANN is used to train the model. On the testing dataset, correctly identifies images with a 94 percent accuracy. [29].

Ahmad et al. used novel techniques to develop a method for accurately detecting fish in videos. This method employs regional-CNN to train the model before applying background subtraction and optical flow to raw images to generate fish movement regions. On two different dataset repositories, this method yielded accuracy of 87.44 percent and 80.02 percent. [30]

Vincent et al. used an artificial neural network in conjunction with a feature selection algorithm to solve the fish classification problem. He used a classification tree algorithm to select features, which were then fed into a 100 hidden layer ANN model. The results showed a 78.0 percent testing accuracy. [31]

Sebastien et al. conducted research on accurately identifying fishes using CNN and comparing it to humans. According to the results, CNN had an accuracy of 94.9 percent compared to human identification, which had an accuracy of 84.9 percent. [32].

1.3 State-of-art work

In the above literature review, it can be observed that most of the research have implemented the feature-extraction based classification combined with simplified classification techniques like SVM and KNN, while some of them have utilized pre-defined image processing algorithms like VGG-16 and AlexNet [33-34].

As per the two major categories i.e., image processing models and feature extraction models, the state-of-art image processing is 99.27% using the CNN Model. However, feature-extraction algorithms when combined with ANN implementation can only fetch the maximum accuracy up to 99% that too for low resolution fish images, although none of the proposed research could comprehensively extract the important features from the image.

1.4 Problem Statement

To introduce a fish species classification technique immune to overfitting without compromising the capability of identifying species of fish, which is capable enough to eradicate user interference and compare the results of all the state-of-art classification approaches to provide the optimum performance.

1.5 Proposed Solution

In this paper, proposed research models depict a thorough investigation of 7 different computer vision techniques embedded with data mining algorithms based on their performance implemented on 9000 images of fish belonging to 9 distinct categories representing nine different fish species. Out of which, the highest accuracy was yielded to be 100%. Some species like shrimp had a conspicuous shape, making it easy to tag, although all other fish were found to have a similar structure, making the fish image classification a challenging task. The proposed research involves a customized computer vision approach involving the segmentation of the fish from the image. It fine-tunes the pre-trained models like VGG19 Model, Inception V3 model, Xception model, ResNet150 V2 model, EfficientNetB0 model with customized top-up architecture, and a personalized CNN model, a data mining ANN model which was built on the 20 features extracted from the images. A complete comparison is implemented on the above computer vision techniques, out of which the ANN Deep Learning model is observed to outperform every other computer vision technique.

Furthermore, the statistical dimensions were recorded based on the image classification report (Accuracy, Precision, F1-Score, and Recall). The models are implemented using an algorithm that undermines the likelihood of over-fitting and prevents any user interference in detecting fish species.

1.6 Research Contribution

Current Developments in finding the solution to the problem is not yet progressed and the existing solutions neither provide efficiency and robustness. We provide a novel alternative solution with utmost 100% accuracy to the above problem taking a thorough account of all the RGB characteristics and Stochastic Gradient of the image in vertical as well as the horizontal virtue. Furthermore, the RGB channels and Stochastic gradient were subjected to statistical operations which were not utilized in any of the earlier proposed research. The proposed model is flexible enough to take consideration of all images of different sizes, as it is size independent unlike many of the image processing models which require a uniform size. The model is robust enough to work with even grayscale images. Moreover, the ANN model which is utilized is optimal enough to provide fastest results without compromising the accuracy of the classification. We also provide the list of subtle difference in the performance comparison of the proposed model with the custom mounted image processing models to juxtapose the significance of the proposed model.

The rest of the paper is as follows: II) Material and Methods, III) Results and Discussion IV) Conclusion.

2. MATERIAL AND METHODS

2.1 Experimental Setup

The machine utilised for implementing the research have the following requirements:

Table. 1.TESTBED ENVIRONMENT

OS	Windows 10
RAM	8 GB
GPU	4 GB
IDE	Pycharm (Python)

The entire used algorithm implemented with above configuration. As we can observe from the above table, the physical requirements are negligible and the proposed model can be compatible with almost any physical machine.

2.2 Pre-Processing:

2.2.1 Segmentation and Masking

The outline of the fish segmentation provided with the dataset was used as a mask on the original images, so the background can be removed from the image, which can act as a potential noise and filter the necessary fish image.

2.2.2 Resizing:

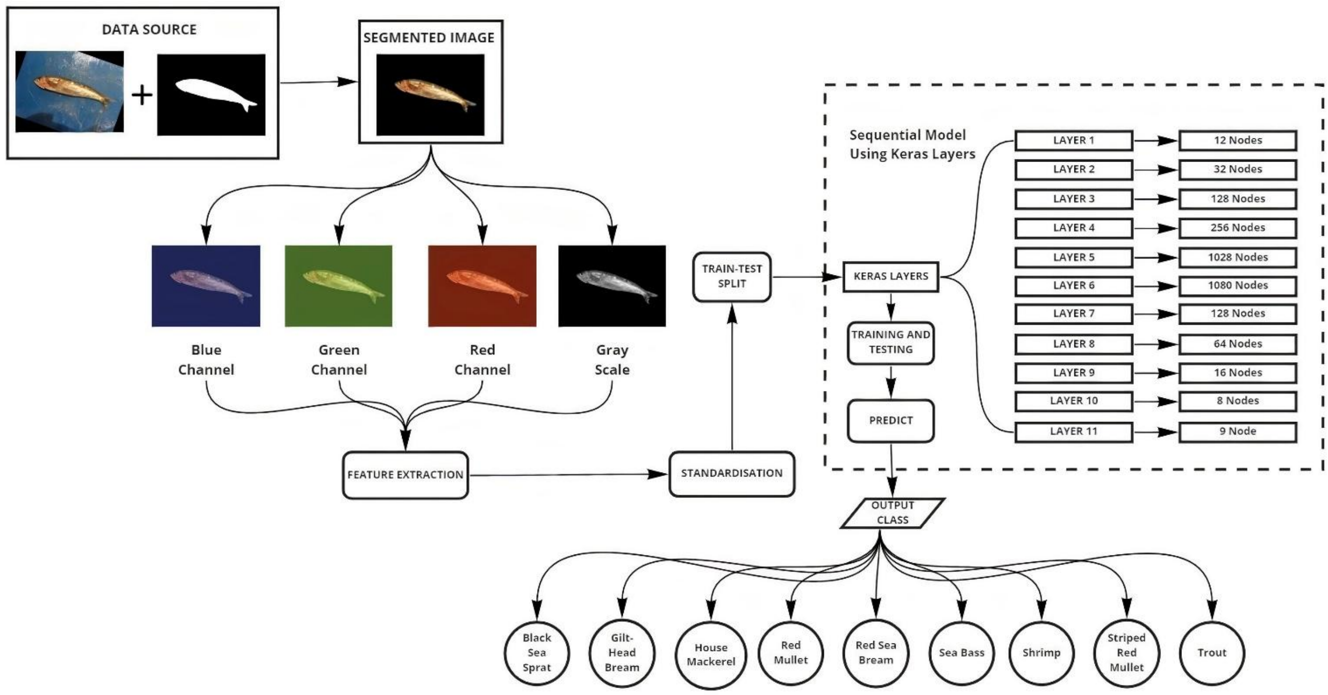
All the images were resized to 75px * 75 px size to optimize the performance level and take care of the execution time and resource utilization.

2.2.3 Standardization:

All the entries of the CSV dataset were applied for standardization so that the resulting average is calculated as 0, and a unit standard deviation can be observed.

2.3 Proposed Model Architecture

Figure. 1 Proposed Architecture diagram



The proposed model includes a Keras Sequential model, one of the most basic yet effective data mining techniques to approach the problem using the transitioning layers having different weights, signifying a flow of function till the output layer. The proposed Deep Learning Model contains an input layer with 12 nodes connected to 9 hidden layers preceding the output layer with nine nodes signifying nine different classes.

2.4 Image Data Source

The publicly available Image dataset was initially collected from the Department of Electrical and Electronics Engineering, Izmir University of Economics, Turkey. The dataset comprised 9000 images belonging to 9 different fishes, depicting 1000 images for each species.

2.5 Feature Extraction from Images for Data Mining Algorithm

For the Deep Learning Model, A CSV file was created by extracting the following features from the images. The number of effective features can play an effective role in determining the technique's performance [26-28]. And thus, statistical operations like the average, standard deviation, unique quantities and maximum are applied to the pixelated values of the image, which were originated from the image in the form of an RGB list. Moreover, the image gradient is also utilised by extracting the Sobel horizontal and vertical gradients, further subjected to the same statistical operations. Which included the following attributes:

1. **STD_IMG:** The Standard Deviation of the Gray Scale pixelated values is determined
2. **Unique_clrs:** The total number of Unique colours that can be identified from the Gray Scale image
3. **ABS_Mean_x:** The Absolute average value of horizontal descent of the image using the Sobel operator
4. **ABS_STD_x:** The Absolute standard deviation of horizontal descent of the image using the Sobel operator
5. **ABS_MAX_x:** The Absolute maximum value of horizontal descent of the image using the Sobel operator
6. **ABS_Mean_y:** The Absolute average value of vertical descent of the image using the Sobel operator
7. **ABS_STD_y:** The Absolute standard deviation of vertical descent of the image using the Sobel operator
8. **ABS_MAX_y:** The Absolute maximum value of vertical descent of the image using the Sobel operator
9. **RedMax:** The maximum pixel value generated from the Red channel of the image
10. **GreenMax:** The maximum pixel value generated from the Green channel of the image
11. **BlueMax:** The maximum pixel value generated from the Blue channel of the image
12. **RedMean:** The mean pixel value generated from the Red channel of the image
13. **GreenMean:** The mean pixel value generated from the Green channel of the image
14. **BlueMean:** The mean pixel value generated from the Blue channel of the image
15. **RedUnique:** The total distinct pixel value generated from the Red channel of the image
16. **GreenUnique:** The total distinct pixel value generated from the Green channel of the image
17. **BlueUnique:** The total distinct pixel value generated from the Blue channel of the image
18. **RedSTD:** The standard deviation of pixel value generated from the Red channel of the image
19. **GreenSTD:** The standard deviation pixel value generated from the Green channel of the image
20. **BlueSTD:** The standard deviation pixel value generated from the Blue channel of the image

2.6 Parameters and Customizations for Computer Vision Models

Table 1 shows the various parameters setting for Computer Vision Models.

Table.2. PARAMETERS SETTING FOR COMPUTER VISION MODELS

Model Name	**Epoch Pre**	**Epoch Fine**	**Batch Size Pre**	**Batch Size Fine**
CNN	20	-	32	-
Inception	10	5	32	16
Xception	10	5	32	16
VGG-19	10	10	32	16
ResNet150	10	10	32	16
EfficeintNet	8	10	32	16

Table.3. PARAMETERS SETTING FOR COMPUTER VISION MODELS

Model Name	**Learning Rate Pre**	**Learning Rate Fine**	**Input Shape**	**weights**
CNN	-	-	(75,75,3)	-
Inception	0.0001	0.0001	(75,75,3)	imagenet
Xception	0.0001	0.0001	(75,75,3)	imagenet
VGG-19	0.0001	0.0001	(75,75,3)	imagenet
ResNet150	0.0001	0.0001	(75,75,3)	imagenet
EfficeintNet	0.0001	0.0001	(75,75,3)	imagenet

2.6.1 Convolutional Neural Network Model

The custom-tailored CNN Model was implemented on the dataset with the following architecture [20,35-37].

- Input Layer: Convolutional Layer with 32 Nodes and kernel Size of (3, 3)
- Max pool Layer: Kernel size of (2, 2)
- Flattening Layer: to convert the 2D representation down to 1D format
- Dense Layer: 128 Nodes, and Rectified Linear Unit as Activation function
- Dense Layer: 64 Nodes, and Rectified Linear Unit as Activation function
- Output Layer: with 9 Nodes and Softmax as Activation function

The model is further compiled with Adam Optimizer. The Learning Rate reduction is implemented to reduce the learning rate when the model fails to gain accuracy in 5 epochs and the early stop method to prevent overfitting.

2.6.2 EfficientNet Model

EfficientNet is a robust pre-trained Convolutional Neural Network architecture-based technique. The technique has eight different sub-models. Out of which, the B0 is the most straightforward model. The traditional B0 model is complemented by a Global Average Pooling layer, 1024 nodes embedded dense layer, and a Rectified Linear Unit as an Activation function. Furthermore, a final layer with 9 nodes for the nine species is added to the model [38-40].

2.6.3 Inception V3 Model

Inception v3 is one of the most widely used computer vision techniques with about 42 layers deep with good performance levels. The pre-trained Inception v3 used in research is further augmented with a Global Average Pooling layer followed by 1024 nodes embedded dense layer having the Rectified Linear Unit and an output layer with nine nodes the total of 9 species [31-43].

2.6.4 ResNet150 V2 Model

This model is the leading model in terms of model complexity with 152-layer deep architecture and thus is difficult to mount or recognize data patterns. A Global Average Pooling layer is added to the pre-trained ResNet model is utilized in the study, proceeded by 1024 nodes embedded dense layer with Rectified Linear Unit and an output layer comprising nine nodes indicating the total of nine species [44-46].

2.6.5 VGG-19 Model

VGG19 is a 19-layer variation of the VGG model comprising 16 convolution layers, three fully connected layers, 5 MaxPool layers, and a SoftMax layer. The paper includes the VGG-19 Model with a Global Average Pooling layer, followed by 1024 nodes embedded dense layer and Rectified Linear Unit as an Activation function and an outlet layer with 9 nodes for the nine species [47-48].

2.6.6 Xception Model

Xception model is a 71 layered architecture, an extended version of the Inception model, but with an exceptional performance capability. The traditional VGG-19 model is complemented by a Global Average Pooling layer, 1024 nodes embedded dense layer, and a Rectified Linear Unit as an Activation function. Furthermore, a final layer with 9 nodes for the nine species is added to the model [49].

3. RESULTS AND DISCUSSIONS

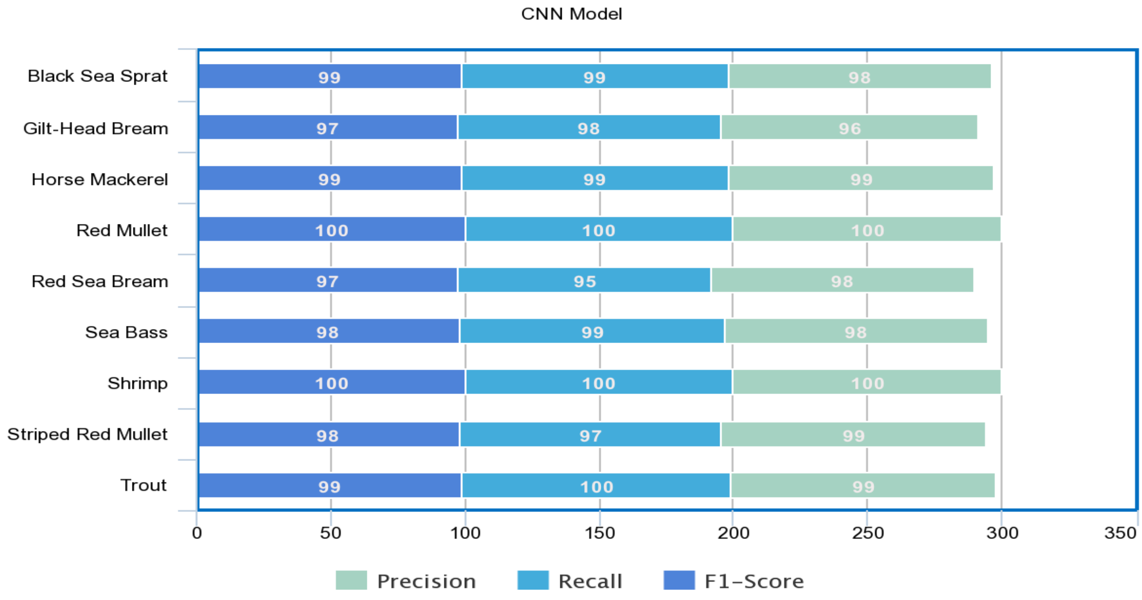
Here the dataset was split into two distinct sub-arrays by the Train-Test split approach. The Training component comprised 70% of the original data, while the Testing component accounted for 30% of the original dataset. After processing the details of all the models, an investigation using performance was conducted to identify the best model out of 7 classification models. In this comparison analysis, the parameter metrics utilized for distinguishing models were Accuracy, Precision, F1-score, and Recall, which can be calculated from the confusion matrix. All the models' output is depicted via the likelihood of belonging to a specific class. Which can be in the form of a fraction between 0 and 1. The one is allotted to the max value of the label list, while all others are allotted 0. Further, the hot encoded labels are converted to a single integral column coded as:

- 0: Black Sea Sprat
- 1: Gilt-Head Bream
- 2: Horse Mackerel
- 3: Red Mullet
- 4: Red Sea Bream

- 5: Sea Bass
- 6: Shrimp
- 7: Striped Red Mullet
- 8: Trout

3.1 Convolutional Neural Network Model

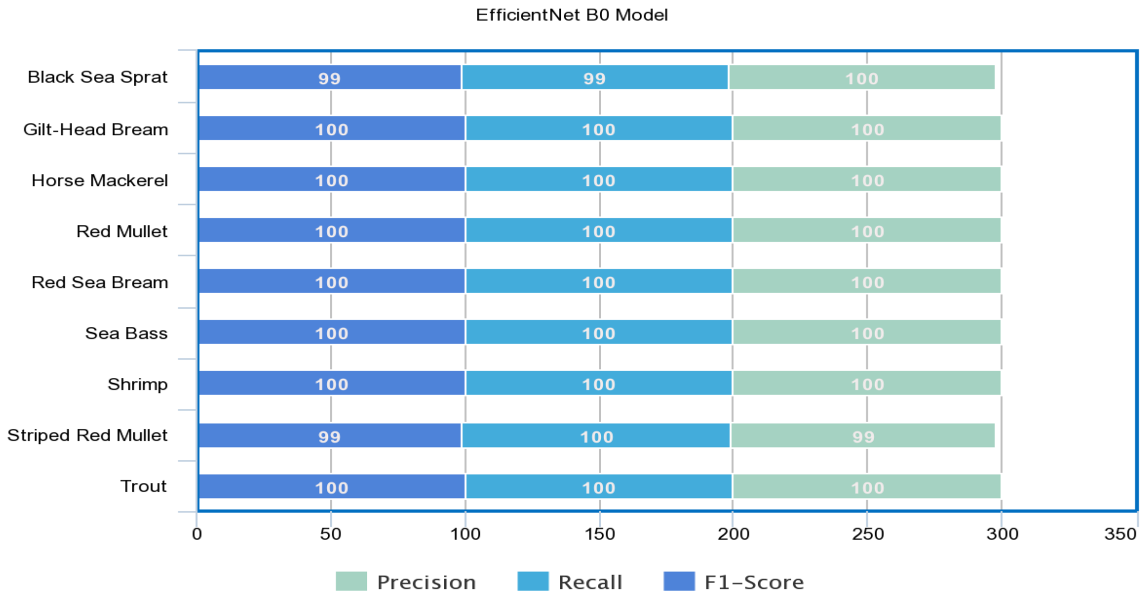
Figure. 2 Comparison of metrics- (Precision, Recall, F1-score) for each of the 9 classes for the CNN Model



This graph of figure 2 shows the performance of the CNN model on different fish classes. It detects Red Mullet & Shrimp classes with utmost precision, recall and the highest F1-score. Trout class has a high recall score.

3.2 EfficientNet Model

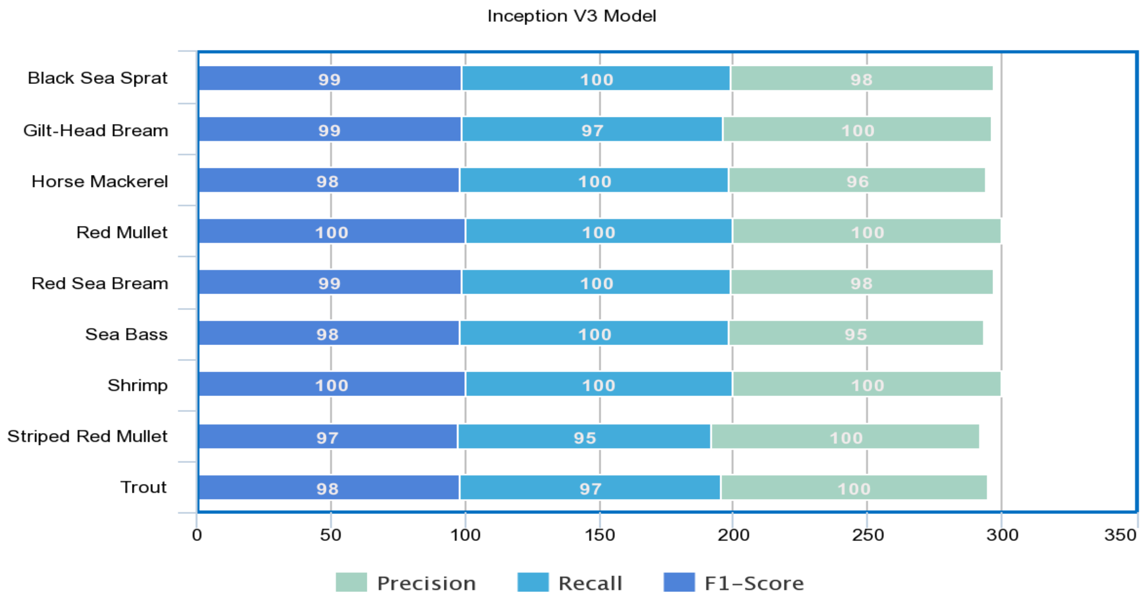
Figure. 3 Comparison of metrics- (Precision, Recall, F1-score) for each of the 9 classes for the EfficientNet B0 Model



This graph of figure 3 shows the performance of the EfficientNet model on different fish classes. This model shows the highest precision on 7 out of 9 classes and a perfect recall score on 8 out of 9 classes. Almost all of the classes display a high F1-score value for this model.

3.3 Inception V3 Model

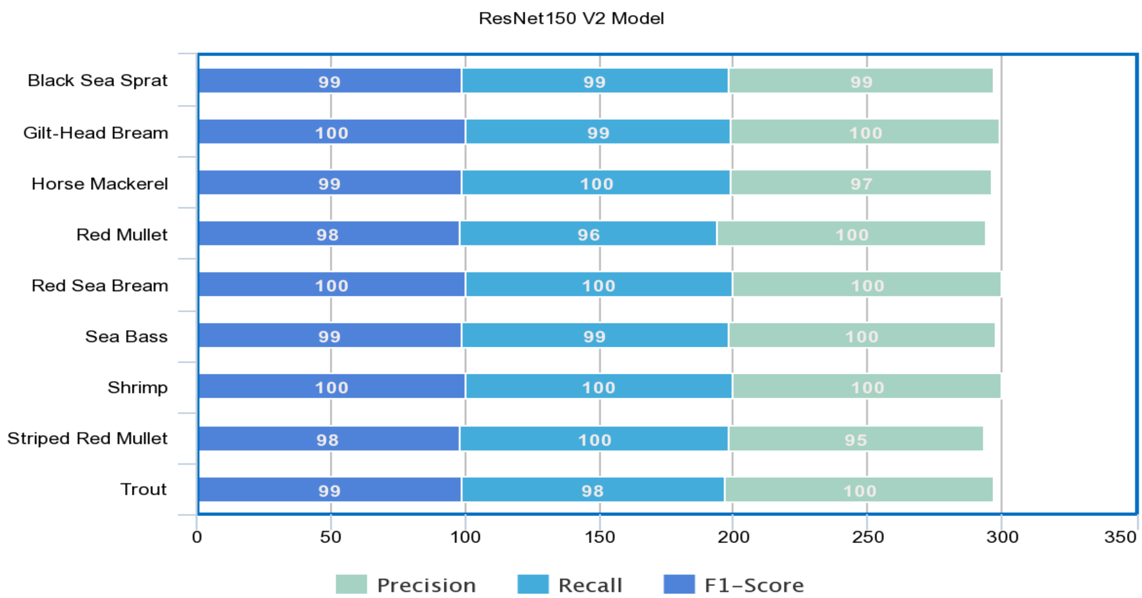
Figure. 4 Comparison of metrics- (Precision, Recall, F1-score) for each of the 9 classes for the Inception V3 Model



This graph of figure 4 shows the performance of the Inception model on the different fish classes. This model offers a high precision rate on red mullet and shrimp images similar to the CNN model. In the case of recall score, it shows a good performance in 7-out-of-9 classes.

3.4 ResNet150 V2 Model

Figure. 5 Comparison of metrics- (Precision, Recall, F1-score) for each of the 9 classes for the ResNet150 V2 Model



This graph of figure 5 shows the performance of the ResNet150 model on the different fish classes. The maximum precision score is detected in gilt-head bream, while red mullet and shrimp classes offer the highest numbers in all three metrics. Peak F1-score is achieved in 6-out-of-9 types.

3.5 VGG-19 Model

Figure. 6 Comparison of metrics- (Precision, Recall, F1-score) for each of the 9 classes for the VGG-19 model

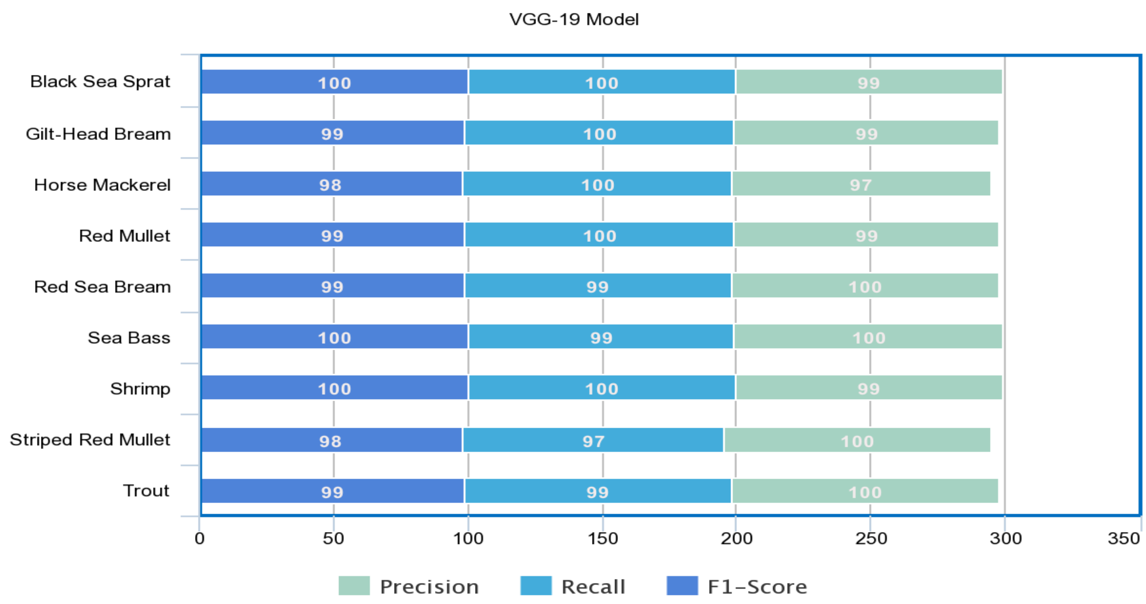
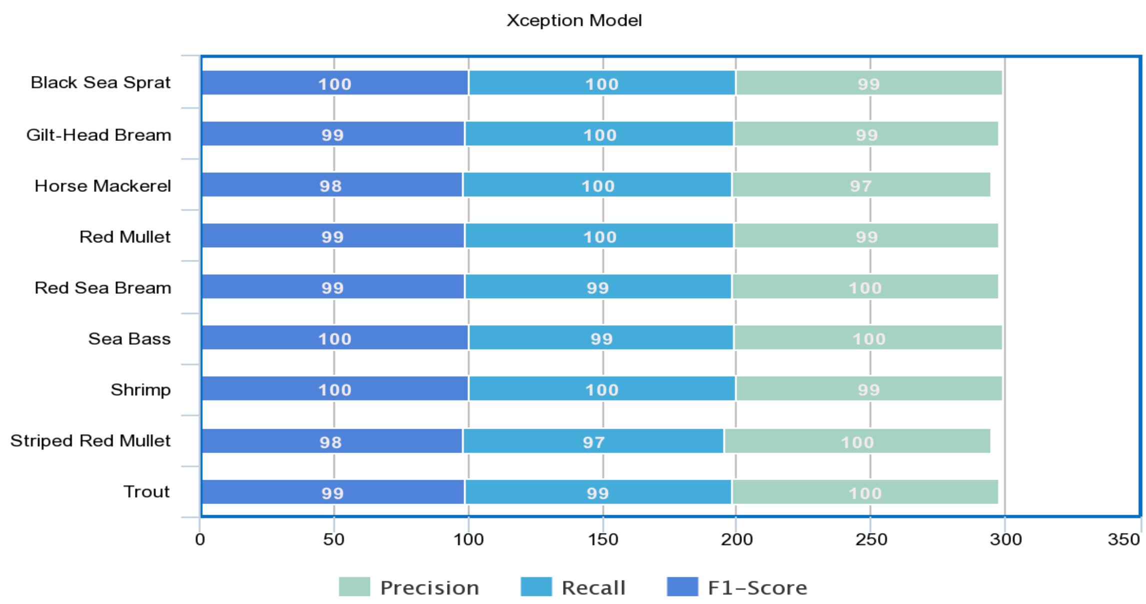


Figure 6 depicts the performance of the VGG-19 model on various fish classes. Horse-mackerel and shrimp classes have a perfect score in metrics. This model has a high recall value for the black sea sprat, red sea bream, and trout classes.

3.6 XceptionModel

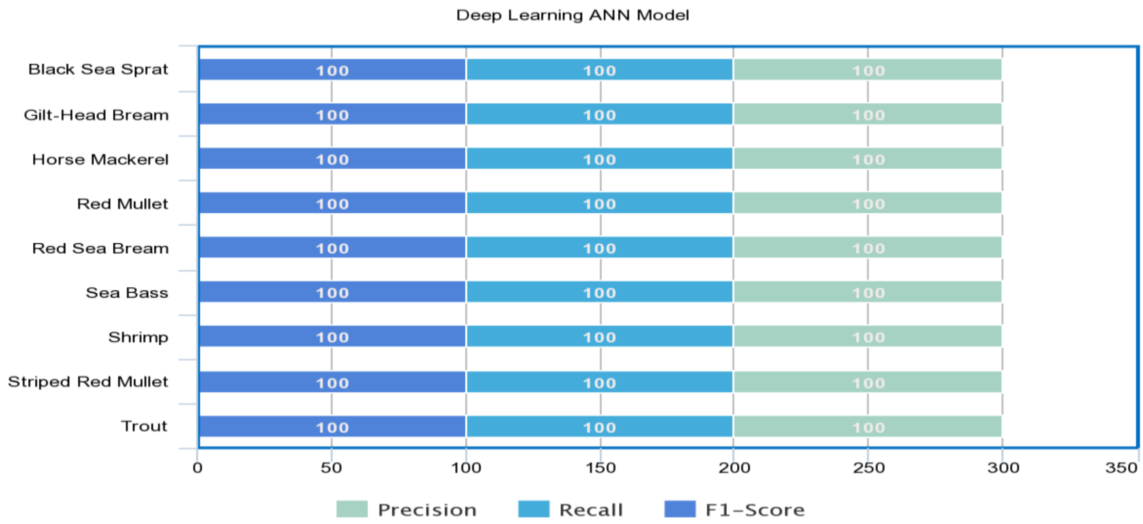
Figure. 7 Comparison of metrics- (Precision, Recall, F1-score) for each of the 9 classes for the Xception Model



This graph of figure 7 shows the performance of the Xception model on different fish classes. Black sea sprat & shrimp show high values of precision & recall. At the same time, other classes are also detected with low error per c

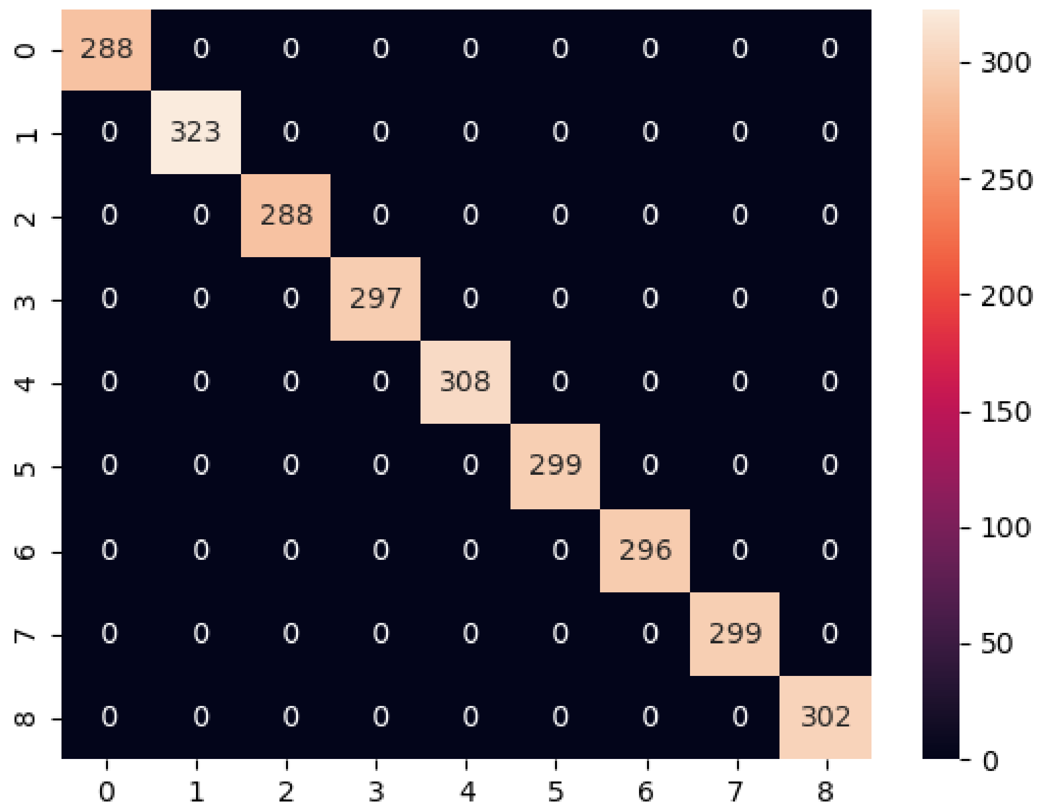
3.7 Deep Learning Artificial Neural Network Model

Figure. 8 Comparison of metrics- (Precision, Recall, F1-score) for each of the 9 classes for the Deep Learning ANN Model



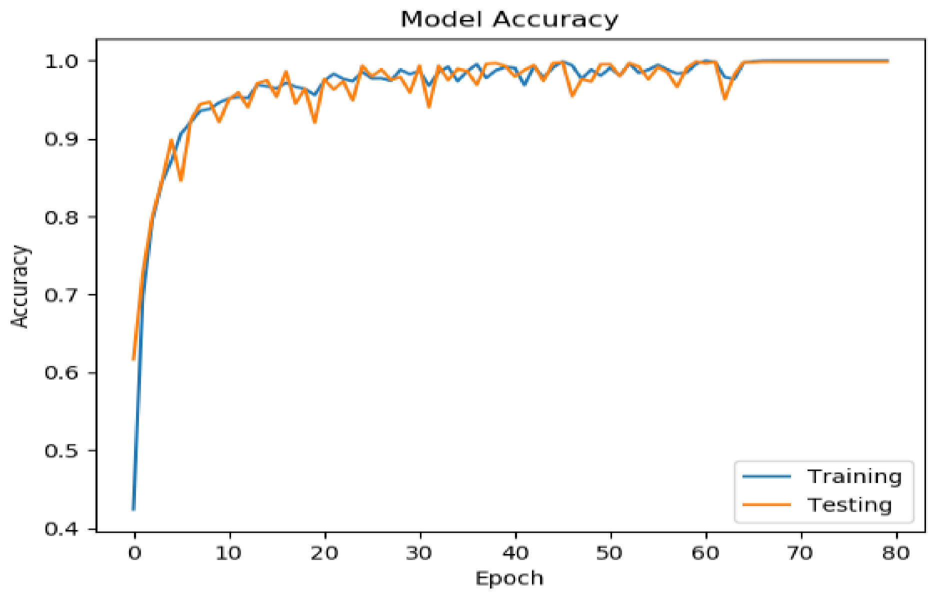
This graph of figure 8 shows the performance of the Deep Learning ANN model on different fish classes. This model perfectly detects all classes of fish with utmost precision & recall value. It also has the highest F1-score of any fish species.

Figure. 9 Confusion matrix for the 9 classes in the Deep Learning ANN Model



The above matrix shows that all values except diagonal ones are zero, which depicts that this model correctly identified all fish species without any outliers or errors.

Figure. 10 Training and Testing Accuracy vs Epochs for the Deep Learning ANN Model



The above line chart of figure 10 depicts the behaviour of accuracy and the increment of every epoch, suggesting the high robustness of the model. The parallel training and testing accuracy also indicate that the overfitting did not occur.

Figure. 11 Training and Testing Loss vs Epochs for the Deep Learning ANN Model

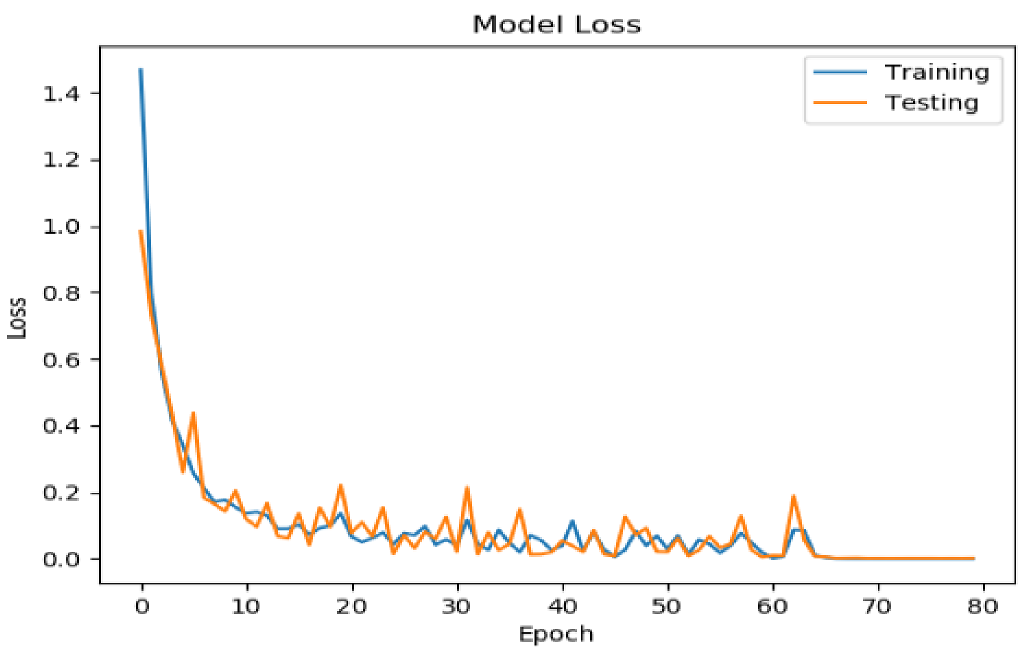
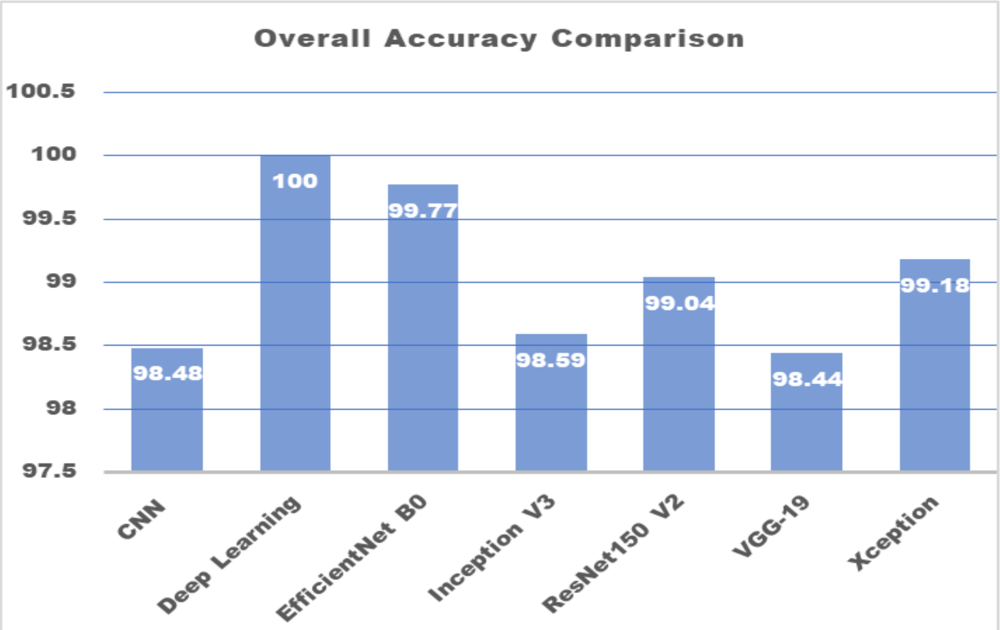


Figure 11 shows the behaviour of loss and the increment of every epoch approaching loss as 0, indicating the model's high robustness. The parallel training and testing accuracy indicate that overfitting did not occur.

After a thorough comparison and contrast, it is empirical that the proposed model surpassed all the other classification techniques, with an accuracy of 100%, and the side metrics of Precision, F1 score, and Recall score were found to be 100% (figure 12).

Figure. 12 Comparison of metrics- (Precision, Recall, F1-score) for each of the 9 classes for the CNN Model



4. Conclusion

This research work analyses different algorithms to propose the best possible model to subjugate the problems of existing methods. The research utilized the segmentation of fish images obtained from the dataset and extracted 20 features from 3 color channels and the grayscale filtered images. In the attributes derived from the color channel, the statistical operation of mean, max, unique and standard deviation were applied. The gray scale mapping was further processed via the horizontal and vertical gradient sobel operator, further subjected to the same statistical analysis operation. Furthermore, the Sequential Model with 11 distinct layers was applied to the dataset after smoothening data using the standardization function.

The feature extraction performance was furthered compared to the modern image processing techniques like CNN, VGG-19, Inception, Xception, ResNet and EfficientNet Model to bolster the integrity of the proposed model. Eventually, it was observed that the empirical approach affirmed the Deep Learning Image Processing model to be the premier model with an accuracy of 100%.

We propose a new alternative solution with utmost accuracy to the aforementioned issue taking a comprehensive consideration of all the RGB features and Stochastic Gradient of the picture in vertical as well as the horizontal direction. The suggested model is flexible enough to take account of all pictures of various sizes, since it is size independent unlike many of the image processing models which mandates a uniform size. The model is strong enough to deal with even grayscale pictures. Moreover, the ANN model which is used is optimum enough to give quickest results without sacrificing the accuracy of the classification. We also offer the list of minor variation in the performance comparison of the proposed model with the custom mounted image processing models to juxtapose the importance of the suggested model.

The deployed version can effectively reduce the reliance of human supervision while also effectively lowering the cost factor without compromising time constraints or thorough accuracy. This model will be extremely useful for the marine industry, ecological research who need to examine the population of fishes in marine ecology of a specific area because it requires very little computational power and can work with images of any size and resolution. Currently we proposed the research for up to 9 fish species, but in the future, we will expand the classifying capability to more and more species. Thus, this application can be utilized as a business model to aid many budding industries dependent on marine ecological resources, and consequently contribute to the scientific research.

4.1 Future work

The applications of the proposed model are endless and can be expanded to include new categories like plants and animal species. Therefore, the model will be tested on new datasets and the scope of identifying species will be generously expanded to embed comprehensive functionalities. The model would also be exposed to hyperspectral images to comprehend more features as possible to effectively classify species. The proposed model will also be deployed on a website to ensure the availability to the users.

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