International Journal on Advanced Science Engineering Information Technology

Vol.11 (2021) No. 3
ISSN: 2088-5334

Local Freshwater Fish Recognition Using Different CNN Architectures with Transfer Learning

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Abstract— **Bangladesh has its profusion of water resources, but due to environmental issues and some other significant causes, the quantity of water resources is lessening continuously. As a result, many of our local freshwater fishes are being abolished, leading to a lack of knowledge about freshwater fish among the new generation of people in Bangladesh. It is also very difficult to recognize freshwater fish because of their nature, color, shape, and structure. To recognize the local freshwater fish efficiently, transfer learning can be used, one of the significant parts of deep learning that concentrates on storing knowledge gained while solving one problem and employing it to a distinct but related problem. This paper has used six CNN-based architecture with transfer learning, namely DenseNet201, InceptionResnetV2, InceptionV3, ResNet50, ResNet152V2, and Xception. A total of seven freshwater fish image data is used here, which is collected from the various local fish markets of Bangladesh. To check the effectiveness of the working approach, we have calculated the accuracy, precision, Recall, and F1-Score. The approach InceptionResnetV2 and Xception achieved the highest accuracy with 98.81% over the other approach which is a very significant result.**

Keywords— **Freshwater local fish; recognition; transfer learning; CNN.**

Manuscript received 30 Dec. 2020; revised 9 Feb. 2021; accepted 16 Feb. 2021. Date of publication 30 Jun. 2021.

I. INTRODUCTION

Bangladesh is a riverine country with bunches of waterways jumbled from East-West-North-South. The outpouring of water from Bangladesh is the third most elevated on the planet, close to the Amazon and Congo frameworks. From 2000 and 2016, aquaculture production increased from 712,640 and 2,060,408 metric t, a much larger quantity than wild capture production (1.023 million t) in 2016. Total fish production in Bangladesh in 2014–2015 was reported to be 3,684,245 MT, of which 1,023,991 MT (27.79%) were from inland open waters, 2,060,408 MT (55.93%) from inland closed waters and 599,846 MT (16.28%) from marine fisheries [1]. Almost 795 native species of fish and shrimp species of fishes cultivate in Bangladesh [2]. Everyday people must have some fish on their food plate. Many of the freshwater fishes of Bangladesh are being abolished for several reasons, which leads to a lack of knowledge about freshwater fish among the people in Bangladesh. Recently a lot of work has been done to recognize fishes though fish recognition is mainly restricted to constrained environments. As fish recognition is a challenging issue, researchers continuously applied several novel approaches to find the best results.

Alsmadi *et al.* [3] proposed a methodology to recognize fishes using neural networks. In this work features are extracted by combining the size and shape of the fish images. The system has been done on distinct 350 fish images of 20 fish families and in the overall work acquired 86% accuracy applying the neural network incorporated with the back-propagation algorithm. Rahman *et al.* [4] proposed a methodology to recognize the Local birds of Bangladesh using MobileNet and Inception-V3. They used 7 types of local birds and augmented the imagedata using image processing techniques. The highest accuracy is found for MobileNet model with transfer learning technique.

A Computer vision-based approach and neural network is applied to recognize fish species by Storbeck and Daan [5]. This method achieved the accuracy of 98% but they did not mention anything about the dataset. Montalbo and Hernandez [6] proposed a methodology to recognize fish species using VGG16 Deep Convolutional Neural Network (DCNN). Though this approach gets 98.67% accuracy, they have used synthetic augmented data for training and testing the proposed model for three different fish species. Deep and Dash [7] have intended a hybrid Convolutional Neural Network (CNN) framework that uses CNN for feature extraction and classification SVM and k-NN. This framework gives 98.79% accuracy by using only a standard dataset.

Qin *et al.* [8] have used a cascaded deep learning architecture to recognize underwater fish from live videos. In this system, principal component analysis (PCA) is applied in two convolutional layers, and to extract information, spatial pyramid pooling (SPP) is used. This architecture gives an accuracy of 98.64%. A combined technique like ANN and Decision Tree is used by Alsmadi *et al.* [9] with global feature extraction, image segmentation, and geometrical parameters to recognize fishes. This prototype has been done with a total of 1513 types of fish images, and this approach gives an accuracy of 96.4%.

Hridayami *et al.* [10] applied VGG16 DCNN, which is pre-trained on ImageNet via transfer learning method to recognize fish images. In this approach, 50 species of fishes are recognized with different accuracies on four different datasets. An aquarium family fish species identification with eight family fish species and 191 sub-species systems has been proposed by Khalifa *et al.* [11] using DCNN. The whole work has been done by comparison with AlexNet and VggNet, whereas Alexnet trained on 1521 images with an accuracy of 85.59%. A machine vision-based local fish recognition is done by Sharmin *et al.* [12]. In this work, they have considered six species of fish, and among fourteen features, four types of features are considered, and these features are extracted, and image segmentation is done by the histogram-based method. The whole work has been completed with a low amount of 180 images, and three classifiers like SVM, k-NN, and Ensemble are applied, whereas SVM proffers an accuracy of 94.2%.

From the above analysis of the related work, it was found that very few research works have been done on local fish recognition in the context of Bangladesh. Though some related work has been found, most of the work is done with traditional methods whereas our work is done with a novel approach and a large number of datasets.

To recognize the local freshwater fish, we have applied six CNN based architectures with transfer learning techniques namely DenseNet201, InceptionResnetV2, InceptionV3, ResNet50, ResNet152V2, and Xception. We have classified seven types of freshwater fish of Bangladesh. To check the effectiveness of the applied models, performance evaluation metrics have been calculated here.

II. Materials and Method

This section is divided into six sub-sections: the acquisition of the image, image data pre-processing, dataset splitting, and CNN architecture with transfer learning, training and testing, and calculation performance metrics. The working procedure of local fish recognition is shown in Fig. 1.

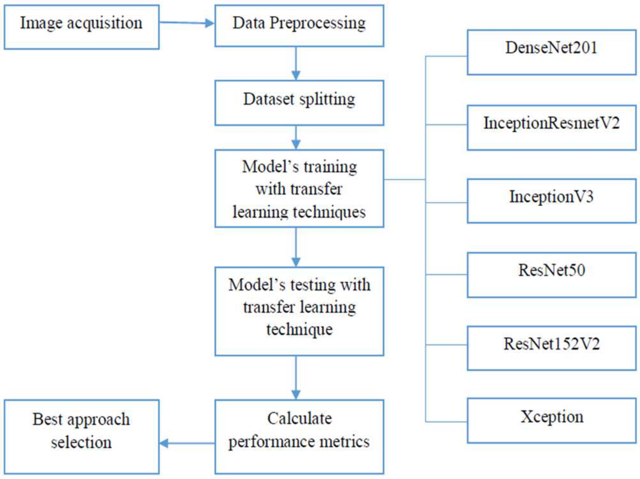

Fig. 1 Working procedure of local fish recognition

A. Acquisition of Image

We have collected 100 images of data for each class of fish. As seven fish species are utilized for recognition, the amount of collected data size is about seven hundred. Table 1 exhibits the details of local fishes that have been utilized here, referring to the local name, English name, and scientific name [13].

TABLE I
DATASET OF LOCAL FISH WITH LOCAL NAME, ENGLISH NAME, SCIENTIFIC NAME AND IMAGE

Local name	English name	Scientific name	Image
Puti	Onespot Barb	Puntius terio	
Batasi	Potasi	Pachypterus atherinoides	
Bou	Bengal Loach	Botia dario	
Baim	Zig-Zag Eel	Mastacembelus armatus	
Kajuli	Gangetic Ailia	Ailia coila	
Kakila	Freshwater Garfish	Xenentodon cancila	
Pabda	Pabdah Catfish	Ompok pabda	

B. Image Data Preprocessing

The collected data is pre-processed by applying various techniques. We need many data to train the CNN model. As our collected data is not sufficient to train the CNN model, data augmentation is performed to increase the size of data. Various operations are available for data augmentation, namely cropping, rotation, zooming, contrast enhancement, and exacerbate color space. Applying data augmentation techniques, we have gathered 300 data per class and 2100 image data for seven classes.

C. Dataset Splitting

Augmented data is also resized and split randomly into two sets: the training and testing image data set. A total of 1680 augmented data which is 80% used for training the model. A total of 420 augmented data which is 20% used for testing the model.

D. CNN Architecture with Transfer Learning

Convolution Neural Network (CNN) is mainly used to analyze the visual imagery adopting deep learning algorithms. In CNN, the neurons are partitioned into three-dimensional structures in which each partitioned neuron analyses the small region of the image. The final output is predicted using the layers on CNN. The CNN structure comprises numerous layers: the input layer, convolution layer, pooling layer, fully connected layer, and a fully connected output layer exhibited in Fig. 2 [14].

The input layer, which is the first layer for every convolutional neural network, is used to reserve the image pixel's value of the input image. Feature extractions are accomplished from the input image in the convolutional layer which is also known as the major building block. Various kernels or filters are used for performing convolutional operations that extract high-level features from input images in convolutional layers. In the convolutional layer, hyperparameters are used where filter size and strides are included. The generation of output is known as a feature map or activation map. The convolutional output is defined as in Eq. (1) [14].

$$x_j^l = f\left(\sum_{i\in p_j} x_i^{l-1} \times Q_{ij}^l + b_j^j\right) \quad (1)$$

Where xj, Pj, Qij, and bj denote the set of output feature maps, input maps, the kernel for convolution, and bias term, respectively. The output feature map size is given by the following Eq. (2),

$$O = \frac{W-K+2P}{S} + 1 \quad (2)$$

O, W, K, P and S denote the output length/height, input length/height, filter size, padding, and stride. Strides refer to the number of pixels that are used to move by the window after each process, and zeros padding refers to adding P zeros in each side of input boundaries. Then the pooling layer is applied for reducing the parameter number when the size of the image is massive. For reducing the dimension of every map, spatial pooling is used. It intercepts the necessary information. Spatial pooling is categorized into different ways, namely max pooling, average pooling, and sum pooling. Utilizing rectified feature maps, max pooling and average pooling apprehend the largest element. The summation of all elements available in a feature map is referred to as sum pooling.

Then the fully connected layer is called for further process. FC layer is used to flatten the input feature into vectors. This function performs high-level reasoning to create the model. The last layer of CNN is the output layer used to predict the output from each given input class.

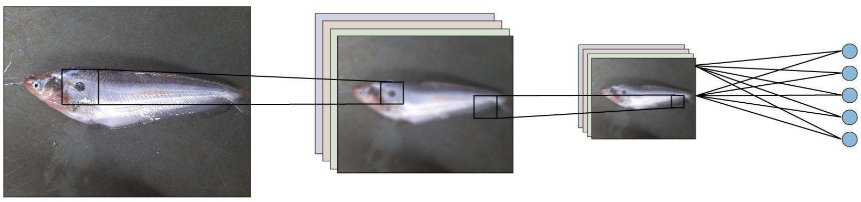

Fig. 2 CNN structure for recognizing local fish

For obtaining the output probability, the softmax function is used here as it produces well-performed probability distribution. The softmax function is also known as Normalized Exponential that is expressed by following Eq. (3).

$$P(C_r|x,\theta) = \frac{P(x,\theta|C_r)P(C_r)}{\sum_{i=1}^{k} P(x,\theta|C_i)P(C_i)} \quad (3)$$

Where ≤ P (Cr|x, Θ) ≤ 1 and $\sum_{i=1}^{k} P(C_i|x,\theta) = 1$ $P(x,\theta|C_r)$ is the conditional probability of class r and prior probability respectively.

There are numerous models in convolutional neural networks. We have adopted six models namely DenseNet201, InceptionResnetV2, InceptionV3, ResNet50, ResNet152V2, and Xception with transfer learning techniques to accomplish this work. Transfer learning is a technique of machine learning where a trained model on a task is reused for a second relevant task. For transfer learning, the domain must be the same. There are two ways to use transfer learning: developing the model approach and pre-trained model approach [15]. Here, the pre-trained model approach has been utilized.

When the dataset is little compared to the imagenet dataset, it is not a good idea to fine-tune the CNN due to the chance of overfitting. As our working dataset is little, the top layer of pre-trained base CNN has been removed. Then the FC layer with some dropout and output layers for matching the classes have been added. After that, the weights of the new FC layer have been randomized, and those weights are trained in the pre-trained network. Finally, training of the network is performed to update the weights of the new FC layers.

E. Training and Testing

To train the data of local fish, we have fixed the epochs with batch size. The number of the epoch that has been used to train the image data is 100 of 8 batch size. As we have utilized transfer learning techniques, the pre-trained weight of imagenet has been used here and test set is utilized as the validation set. The initial learning rate is 0.001 during training the image data. The optimizer named rmsprop and crossentropy loss function are also utilized to train the models. After completion of training the models, the test data has been used to test the models and 7*7 confusion matrices are generated by each model.

F. Calculate Performance Metrics

For the measurement of the performance of each model, it is necessary to calculate the performance evaluation metrics for each class. We have calculated some prominent performance evaluation metrics. The following mathematical from Eq. (4) to Eq. (7) is applied for calculating performance evaluation metrics.

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{TP+FN+FP+TN}} \times 100\% \quad (4)$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}} \times 100\% \quad (5)$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP+FN}} \times 100\% \quad (6)$$

$$\text{F1 Score} = 2 \times \frac{(\text{Precision} \times \text{Recall})}{(\text{Precision+ Recall})} \times 100\% \quad (7)$$

III. RESULTS AND DISCUSSION

As we have worked with the seven types of local freshwater fish, namely Puti, Batasi, Bou, Baim, Kajuli, Kakila, and Pabda, so all the applied CNN models with transfer learning generated 7*7 matrix here. The generated confusion matrix for DenseNet201, InceptionResnetV2, InceptionV3, ResNet50, ResNet152V2 and Xception model presented in Table 2 to Table 7. The following confusion matrices adopted to calculate and visualize the significant predictive analytics like accuracy, precision, Recall, and F1-score that indicates the classification model's performance on a set of test datasets for which the true/real values are known.

TABLE II
GENERATED 7*7 CONFUSION MATRIX FOR DENSENET201

DenseNet201	**Puti**	**Batasi**	**Bou**	**Baim**	**Kajuli**	**Kakila**	**Pabda**
Puti	57	0	0	0	0	2	1
Batasi	0	60	0	0	0	0	0
Bou	0	0	60	0	0	0	0
Baim	1	0	0	57	0	2	0
Kajuli	0	0	0	0	60	0	0
Kakila	0	0	0	0	0	60	0
Pabda	0	0	0	0	0	0	60

TABLE III
GENERATED 7*7 CONFUSION MATRIX FOR INCEPTIONRESNETV2

InceptionResnetV2	**Puti**	**Batasi**	**Bou**	**Baim**	**Kajuli**	**Kakila**	**Pabda**
Puti	60	0	0	0	0	0	0
Batasi	0	60	0	0	0	0	0
Bou	1	0	59	0	0	0	0
Baim	1	0	0	59	0	0	0
Kajuli	0	0	0	0	60	0	0
Kakila	0	1	0	1	0	57	1
Pabda	0	0	0	0	0	0	60

TABLE IV
GENERATED 7*7 CONFUSION MATRIX FOR INCEPTIONV3

InceptionV3	**Puti**	**Batasi**	**Bou**	**Baim**	**Kajuli**	**Kakila**	**Pabda**
Puti	60	0	0	0	0	0	0
Batasi	1	58	1	0	0	0	0
Bou	0	0	60	0	0	0	0
Baim	1	0	0	59	0	0	0
Kajuli	0	1	0	0	59	0	0
Kakila	0	0	0	1	0	59	0
Pabda	1	0	0	0	0	0	59

TABLE V
GENERATED 7*7 CONFUSION MATRIX FOR RESNET50

ResNet50	**Puti**	**Batasi**	**Bou**	**Baim**	**Kajuli**	**Kakila**	**Pabda**
Puti	57	0	0	1	0	2	0
Batasi	2	58	0	0	0	0	0
Bou	0	0	60	0	0	0	0
Baim	1	0	0	56	0	3	0
Kajuli	0	1	0	0	59	0	0
Kakila	2	0	0	6	0	52	0
Pabda	2	0	0	0	0	0	58

TABLE VI
GENERATED 7*7 CONFUSION MATRIX FOR RESNET152V2

ResNet152V2	**Puti**	**Batasi**	**Bou**	**Baim**	**Kajuli**	**Kakila**	**Pabda**
Puti	57	3	0	0	0	0	0
Batasi	1	59	0	0	0	0	0
Bou	0	0	60	0	0	0	0
Baim	1	15	0	42	0	2	0
Kajuli	0	1	0	0	59	0	0
Kakila	12	1	0	4	0	43	0
Pabda	0	1	0	0	0	0	59

TABLE VII
GENERATED 7*7 CONFUSION MATRIX FOR XCEPTION

Xception	**Puti**	**Batasi**	**Bou**	**Baim**	**Kajuli**	**Kakila**	**Pabda**
Puti	60	0	0	0	0	0	0
Batasi	0	60	0	0	0	0	0
Bou	0	0	60	0	0	0	0
Baim	1	0	0	59	0	0	0
Kajuli	0	0	0	0	60	0	0
Kakila	0	1	0	3	0	56	0
Pabda	0	0	0	0	0	0	60

Table 8 represents the accuracy and other evaluation metrics measurements of DenseNet201 to recognize the local freshwater fish. The overall accuracy of DenseNet201 to recognize the local freshwater fish is 98.57%. DenseNet201 achieved 100.00% precision for Batasi, Bou, Baim, and Kajuli freshwater fish class. The highest Recall of 100.00% has been found for Batasi, Bou, Kajuli, Kakila, and Pabda fish. The highest F1-Score of 100.00% has been found for Batasi, Bou, Kajuli fish.

TABLE VIII
ACCURACY AND EVALUATION METRICS OF DENSENET201

Class	Accuracy	Precision	Recall	F1 Score
Puti		98.28%	95.00%	96.61%
Batasi		100.00%	100.00%	100.00%
Bou		100.00%	100.00%	100.00%
Baim	98.57%	100.00%	95.00%	97.44%
Kajuli		100.00%	100.00%	100.00%
Kakila		93.75%	100.00%	96.77%
Pabda		98.36%	100.00%	99.17%

The accuracy and other evaluation metrics measurements of InceptionResnetV2 to recognize the local freshwater fish is present in Table 9. The overall accuracy of InceptionResnetV2 to recognize the local freshwater fish is 98.81%. InceptionResnetV2 achieved 100.00% precision for Bou, Kajuli, and Kakila freshwater fish class. The highest Recall of 100.00% has been found for Puti, Batasi, Kajuli, and Pabda fish. The highest F1-Score of 100.00% has been found for Kajuli fish.

TABLE IX
ACCURACY AND EVALUATION METRICS OF INCEPTIONRESNETV2

Class	Accuracy	Precision	Recall	F1 Score
Puti		96.77%	100.00%	98.36%
Batasi		98.36%	100.00%	99.17%
Bou		100.00%	98.33%	99.16%
Baim	98.81%	98.33%	98.33%	98.33%
Kajuli		100.00%	100.00%	100.00%
Kakila		100.00%	95.00%	97.44%
Pabda		98.36%	100.00%	99.17%

Table 10 presents the accuracy and other evaluation metrics measurements of InceptionV3 to recognize the local freshwater fish. The overall accuracy of InceptionResnetV2 to recognize the local freshwater fish is 98.57%. 100.00% precision for Kajuli, Kakila, and Pabda freshwater fish class has been achieved using InceptionV3. The highest Recall of 100.00% has been found for Puti and Bou fish class. The highest 99.17% F1-Score has been found for Bou fish.

TABLE X
ACCURACY AND EVALUATION METRICS OF INCEPTIONV3

Class	Accuracy	Precision	Recall	F1 Score
Puti		95.24%	100.00%	97.56%
Batasi		98.31%	96.67%	97.48%
Bou		98.36%	100.00%	99.17%
Baim	98.57%	98.33%	98.33%	98.33%
Kajuli		100.00%	98.33%	99.16%
Kakila		100.00%	98.33%	99.16%
Pabda		100.00%	98.33%	99.16%

The accuracy and other evaluation metrics measurements of ResNet50 are presented in Table 11. The overall accuracy of ResNet50 to recognize the local freshwater fish is 95.24%. 100.00% precision for Bou, Kajuli, and Pabda freshwater fish class has been achieved using ResNet50. The highest Recall of 100.00% has been found for only one class which is Bou fish class. The highest 100.00% F1-Score has been found for only Bou fish class using RasNet50.

TABLE XI
ACCURACY AND EVALUATION METRICS OF RESNET50

Class	Accuracy	Precision	Recall	F1 Score
Puti		89.06%	95.00%	91.94%
Batasi		98.31%	96.67%	97.48%
Bou		100.00%	100.00%	100.00%
Baim	95.24%	88.89%	93.33%	91.06%
Kajuli		100.00%	98.33%	99.16%
Kakila		91.23%	86.67%	88.89%
Pabda		100.00%	96.67%	98.31%

In Table 12, the accuracy and other evaluation metrics measurements of ResNet152V2 are presented. The overall accuracy of ResNet152V2 to recognize the local freshwater fish is 90.24%. 100.00% precision for Bou, Kajuli, and Pabda freshwater fish class has been obtained using ResNet152V2. The highest Recall of 100.00% has been found for only one class which is Bou fish class. The highest 100.00% F1-Score has been found for only Bou fish class using ResNet152V2.

TABLE XII
ACCURACY AND EVALUATION METRICS OF RESNET152V2

Class	Accuracy	Precision	Recall	F1 Score
Puti		80.28%	95.00%	87.02%
Batasi		73.75%	98.33%	84.29%
Bou		100.00%	100.0%	100.0%
Baim	90.24%	91.30%	70.00%	79.25%
Kajuli		100.00%	98.33%	99.16%
Kakila		95.56%	71.67%	81.90%
Pabda		100.00%	98.33%	99.16%

The accuracy and other evaluation metrics measurements of Xception are presented in the following Table 13. The overall accuracy of Xception to recognize the local freshwater fish is 98.81%. 100.00% precision for Bou, Kajuli, Kakila and Pabda freshwater fish class has been obtained using Xception. The highest Recall of 100.00% has been found for class Puti, Batasi, Bou, Kajuli, and Pabda. The highest 100.00% F1-Score has been found for Bou, Kajuli, and Pabda fish class using Xception.

TABLE XIII
ACCURACY AND EVALUATION METRICS OF XCEPTION

Class	Accuracy	Precision	Recall	F1 Score
Puti		98.36%	100.00%	99.17%
Batasi		98.36%	100.00%	99.17%
Bou		100.00%	100.00%	100.00%
Baim	98.81%	95.16%	98.33%	96.72%
Kajuli		100.00%	100.00%	100.00%
Kakila		100.00%	93.33%	96.55%
Pabda		100.00%	100.00%	100.00%

Roc curve of the best model in this context named Xception is presented in Fig. 3. Roc curve is an essential metric that is used to observe the classifier's output quality. In Roc curve, the top left corner of the plot is the ideal point as here the true positive rate remains high and the false positive rate remains low. The larger the AUC, the better the model's performance is.

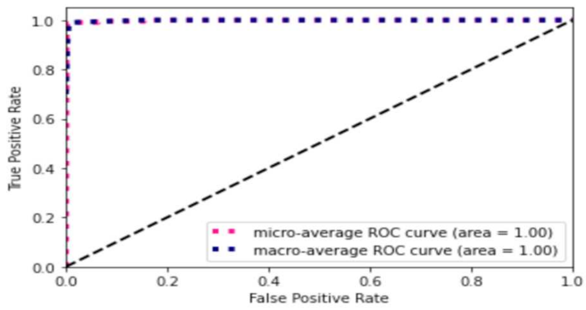

Fig. 3 ROC curve of the Xception to recognize the local fish.

IV. Conclusion

Here, we have used six CNN models with transfer learning to recognize seven types of freshwater fish (namely Puti, Batasi, Bou, Baim, Kajuli, Kakila, and Pabda) of Bangladesh and performed the comparative analysis among the six working approaches. Total 80% of the data is used for the training purposes and the rest of the 20% is used for the testing purposes. In this work, InceptionResnetV2 and Xception obtained the highest accuracy of 98.81% to recognize the local freshwater fish. On the other hand, ResNet152V2 achieved 90.24% accuracy which is the lowest among all the working approaches. In the future, we will add more types of freshwater fish to the dataset and apply both the traditional machine learning approach and deep learning approach to recognize the freshwater fish efficiently.

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