Fish Species Identification and Classification: A Deep Learning Approach

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ABSTRACT

Real-time classification of fish species plays a real-time role in preserving diverse marine species in fisheries management. However, the general method gives imprecise results and is time-consuming. Broad classification of fish is a difficult task for fish experts. To solve the problem, we propose a deep-learning model that classifies and predicts any fish image. Our model uses various deep-learning tools to extract features from fish images. We trained our model on the "Fish Image Dataset" and achieved 98.5 per cent accuracy with testing images with this model. Our applied model is suitable for fisheries, marine biological research, and aquaculture.

Keywords –Deep Learning, Fish Species, aquaculture, classification.

INTRODUCTION

Accurate identification and classification of fish species are the main tasks of the management protection of fish stocks. However, the traditional methods used to identify fish species face challenges due to the diversity of marine species found in India. These approaches often result in inaccuracies and time-consuming processes that hinder usefulness and complicate large-scale monitoring efforts. Manual detection by experts becomes particularly labor intensive and resource-intensive under such conditions.

To overcome the limitations of methods of fish species identification, we propose an innovative deep-learning method. We have developed deeper learning capabilities, especially the "Image Data Generator" software, which extracts robust features from fish images during training and validation. In addition, we apply a fish classification model to accurately identify fish species based on the extracted features. Deep learning provides an accurate and efficient solution for identifying and classifying fish species.

We trained our proposed model over the "Fish Image Dataset" (collection of rich fish species). In the testing phase, our model gains an accuracy of 98.5 per cent on fish species identification.

The implemented deep learning model is in various domains (such as Fisheries management, fish preservation, marine biology research, and aquaculture. To improve our model accuracy, we contribute our proposed work.

In the research paper, we included the details of our proposed deep-learning model for fish species classification and identification. We put our methodology behind our deep learning model. In addition, we report experimental results and discuss the application of our approach in the context of fisheries management.

Overall, our research copy demonstrates the potential of deep learning approaches to improve fish species classification and identification.

DEFINITIONS

Image Data Generator:

A Software Component or Library that automates the creation of synthetic and enhanced image data is called an Image Data Generator. It can generate a new image by applying different transformations, augmentations and adjustments to existing images or by generating entirely new Synthetic Images based on defined criteria.

Random rotation:

Random rotation, in the context of image processing and computer vision, refers to a technique in which an image is rotated at a random angle within a specified range.This technique is commonly used for data augmentation, a process in which additional training examples are generated by applying different transformations to existing data.Random rotation is especially useful when training machine learning models, especially in tasks like image classification, object detection, and image segmentation.

Random Flip:

Random flip, in the context of image processing and data enhancement, refers to the technique of randomly flipping or mirroring an image horizontally or vertically.

This technique is often used when training machine learning models, especially in computer vision tasks such as image classification, object detection, and face recognition.

Random image flip is a form of data enhancement, which increases the diversity of the training dataset and improves the generalizability of the model to different directions and scenarios.

Random Zoom:

Random rotation, in the context of image processing and computer vision, refers to a technique in which an image is rotated at a random angle within a specified range.
This technique is commonly used for data augmentation, a process in which additional training examples are generated by applying different transformations to existing data.
Random rotation is especially useful when training machine learning models, especially in tasks like image classification, object detection, and image segmentation.

Conv 2D:

Conv2D stands for Convolution 2D and it is a fundamental operation in convolutional neural networks (CNNs)usedtoprocesstwo-dimensionaldata,suchasimagesConv2D layers are an essential part of the CNN architecture and play an important role in feature extraction.

Max-pooling 2D:

Max pooling 2D is a popular layer in Convolution Neural Networks used to sample or reduce the spatial size of feature maps generated by Convolution layersIt is a form of aggregation layer that can reduce the computational complexity of the network, control overfitting, and increase translation invariance.
Special,

Average pooling 2D:

Average Pooling 2D, commonly known as AveragePooling2D, is a convolutional neural network (CNN) layer used to down-sample or reduce the spatial size of feature maps generated by convolutional layers.It is a kind of pooling layer, similar to MaxPooling2D, but instead of choosing the maximum value in each pooling window, it calculates the average.

Maximum Layer:

It seems like there might be some confusion regarding the term "maximum layer" in the context of neural networks or deep learning.There is no commonly used class or operation called a "maximum layer" in a standard deep learning architecture.Maximum clustering classes select the maximum value from a group of values in a small region of the feature map to reduce the spatial size and capture the dominant features.If you have a specific question or context regarding the "maximum layer" or another layer in a neural network, please provide more details and I will be happy to help you further.

Huber loss:

Huber loss, also known as Smooth L1 loss, is a type of loss function used in machine learning; especially inregression problems.It is designed to be less sensitive to outliers than the original mean square error (MSE) loss function.

Flatten layer:

The Flatten layer is a common layer in neural networks and deep learning, especially in convolutional neural networks (CNNs) and some types of fully connected networks.Its main purpose is to convert a multidimensional tensor (e.g. 2D or 3D tensor) into a one-dimensional vector, which can then be used as input to fully connected layers for tasks such as analysis category or regression.

Dropout Layer:

It is applied during training and consists of randomly "dropping" (disabling) a portion of a neuron or neural network unit at each training step.

Dense layer:

The dense layer, also known as a fully connected layer or fully connected neural network, is one of the basic components of artificial neural networks including deep learning models. It plays an important role in connecting neurons or units from one layer to another.

GELU activation function:

TheGaussianErrorLinearUnit(GELU)functionisanactivationfunctioncommonlyusedindeeplearningmodels,

The formula of the GELU activation function follows:

GELU(y) = 0.5 * y * (1 + tanh(sqrt(2/pi) * (y + 0.044715 * y^3)))

SoftMax function:

It takes as input a vector of real numbers and turns them into a probability distribution over some classes.The SoftMax function is especially useful when you need to assign probabilities to each class in a classification task.

PROPOSED WORK

Our proposed model is divided into two parts (such as the training phase (Classification) and the testing phase (Prediction)). Subsequently, we divided the training phase into Testing and validation of image data. The split ratio of our proposed model is 8:2, whereas the trainable size is 80 per cent and the validation size 20per cent.

Training Phase:

In the training phase, we implement an image data generator. We set the rotation range at 5 degrees with the zoom range at 20 per cent. We also implement horizontal flip into True value and rescale the image data generator one upon 255 in float data type.

Then, we scan image directories for loading images with batch size set to 16 and the target size of input images 100 (image height and image width are equal).

In the validation phase, we implement an image data generator. We set the rotation range at 5 degrees with the zoom range at 20 per cent. We also implement horizontal flip into True value and rescale the image data generator one upon 255 in float data type.

Then, we scan image directories for loading images with batch size set to 16 and the target size of input images 100 (image height and image width are equal).

After training and validation sub-phases, we get our pre-processed image data. We proceed with the following steps:

1. We implement an input layer to take data from fish images.
The target of the input data sets to a random rotation layer.
2. In the random rotation layer, we set the factor to one upon 360 values with "nearest" interpolation.
3. We pass this data into a random flip layer with horizontal and vertical flip modes.
4. We use a random zoom layer with height and width factor set to 0.2 with "nearest" interpolation.
5. We use convolution layers with 16 units, 32 units, and 64 units, and the kernel size of this layer is (2, 2) with "Gelu" activation. The initial convolution layer takes input from the random zoom layer.
5. Then, we use a two-dimensional max-pooling layer with pool size (3, 3). It takes input from the last convolution layer.
6. Also, we use a two-dimensional average pooling layer with pool size (3, 3) with the last convolution layer.
7. We maximize the values between the max-pooling and average pooling layer. This layer takes input from the maximize layer.
8. We use a flattened layer to optimize the input size.

9. Dropout layer takes input from the flattened layer by setting a 0.5 value.
10. Hidden layers implemented with 128 units, 64 units, and 32 units with the "Gelu" activation function, respectively.
11. The dropout layer implements over the last hidden layer by setting a 0.25 value.
12. Lastly, the output layer uses a SoftMax activation function taking input from the dropout layer with 31 units.

We use Huber loss with a set delta of 0.1 value and use "Adam" optimizers by setting the learning rate with 0.00001 and epsilon with 0.00000001. Therefore, the trainable batch size is 16. The epoch is set to 50.

Hence, the overall training accuracy is 99 per cent.

Testing Phase:

Then, we scan image directories for loading images with batch size set to 16 and the target size of input images 100 (image height and image width are equal) with the nearest interpolation. Then, we divide it into 255.0 image tensors.Then, we reshape the tensor and, predict the testing image data.

RESULT ANALYSIS

We evaluated the performance of the proposed deep learning framework for fish species identification on a dataset of 10,000 fish images collected from various regions of India.
The dataset includes 31 different fish species, with an equal number of images for each species.

To compare the performance of our framework with other approaches, we also tested the traditional fish recognition methods and two different deep learning methods:CNN is based on VGG16 and CNN is based on ResNet50.Both deep learning methods are widely used for image classification tasks.

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