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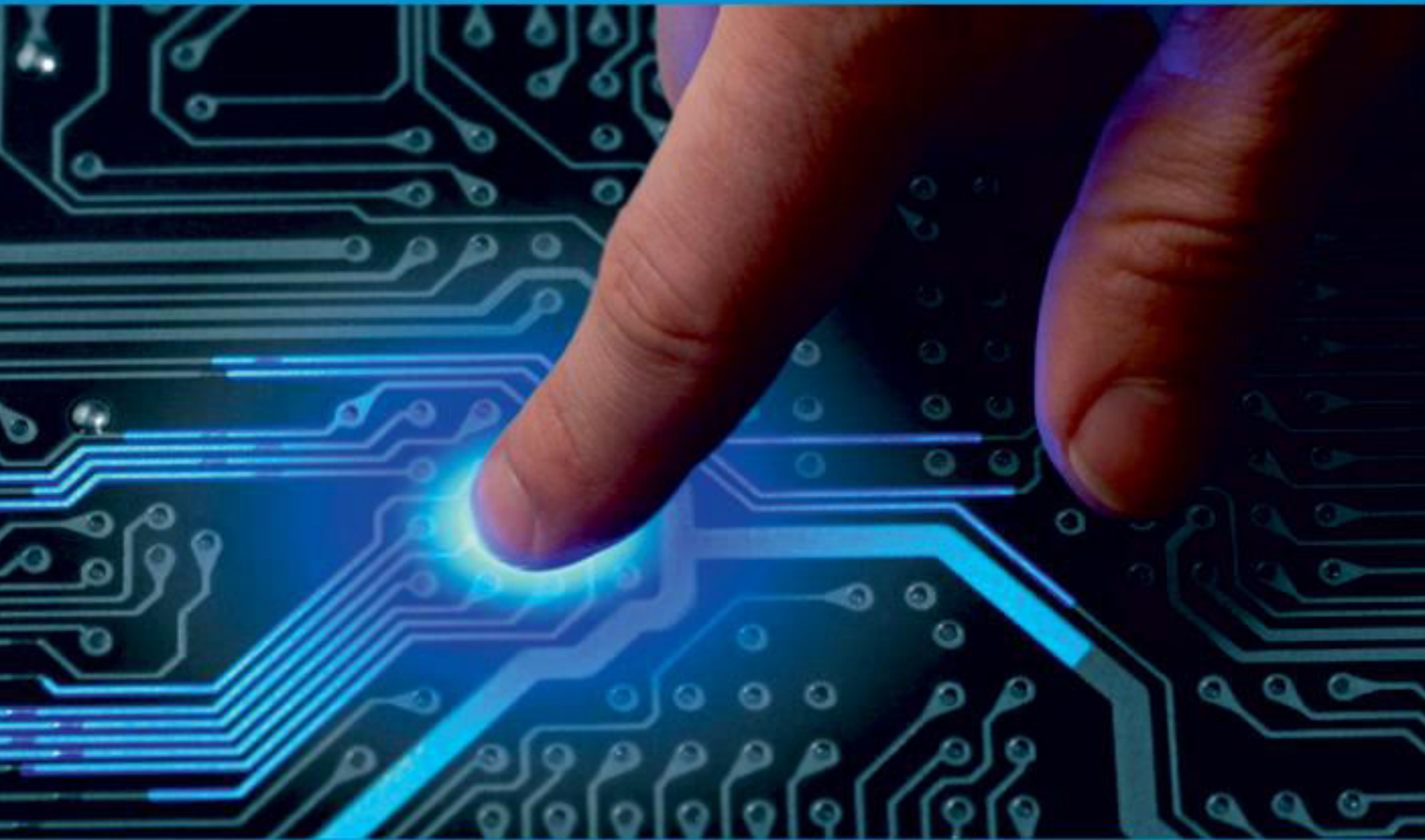

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Automated Identification of Fish Species Using CNN

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ABSTRACT: Fish species identification is very explanatory to the study of fish bionomics and management of fisheries. There are many ways and consistent tools that are used by the marine community for the identification of fish.Conventionally, dichotomous keys are used for fish identification. In this process, fish identification is an important decision-making process having steps to be followed sequentially in which any wrong decision in the order would affect the reaching species. To make this process more accurate and protect from the wrong decision using Transfer Learning, it has become the more favorablesolution to overcome the ecology gap and make accurate identification of Fish species. For learning the identification of fishes, information websites, such as Fishbase are used but still, the information is scattered across diverse sources and is unvaried to access. Algorithms like VGG16, VGG19, Resnet50, and InceptionV3 are applied usingTransfer Learning for automatic fish species classification over the data taken from FishBase. A proposed system is developed to identify fish species, according to their common name so that a fisherman selling his/her product to the vendor can easily crossly verify the originality of the product.The data(images) is augmented using different augmentation methods. The proposed system is developed to identify the fish species which contain 14 different fish species considered as 14 parameters that are trained on different CNN architectures. Fish species are considered in such a way that they are found near the Indian subcontinent. The identification system demonstrates the best results with the VGG16 algorithm with an accuracy of 89.38%.

KEYWORDS: Deep Learning, Convolution Neural Networks, Fish Species Identification, Transfer Learning, VGG16, Data Augmentation, Aquaculture Industry.

I. INTRODUCTION

Fish, an edible and mostly non-toxic aquatic animal, consumed by humankind for ages. It's been one of humanity's extremely healthiest food as it contains low-fat high-quality protein that fulfills 15% of protein demand around the world.This aquatic species is packed with countless essential nutrients and a great source of minerals that are vital for the human body. For example, it fulfills human's omega-3 fatty acid intake that helps to develop the brain and eye and keeps the heart and liver healthy, thus reducing the risk of many diseases including diabetes and heart attack.Therefore, an intelligent seafood monitoring system and tools are greatly needed that can easily detect fish and classify their type for biomass estimation, monitoring ecosystem, species population assessment, species quality control, counting fish, and assessing associations. Furthermore, such tools can also help in regulating legal restrictions on fishing practices by determining endangered species existence.

The aquaculture industry provides a livelihood for billions of people around the world and does an important part to boost the local economy of the coastal region in many countries but due to illegal and harmful fishing practices, and pollution the marine industry is in danger. The healthy key fish stocks should be managed and observed for an efficient ecosystem, to increase the economy of fishers and global food security. The identification of key healthy fish stock and management is required to increase the economic goals without impacting a certain kind of fish with overfishing or mismanagement which would lead to declines in fish stock and impact badly the economy of fishers

The consumption of fish is increasing in India due to various reasons like health benefits in improving skin health, enhanced metabolism, and effective digestion which are increasing the aquaculture market. Also, the customer shift from high-calorie meat items to a protein-rich diet has given an additional boost to the sector. With the support of government initiatives to build a stronger framework and reduce the economic gap by providing required infrastructure like cold chain facilities and fish seed for farming. The main market for the aqua industry is mainly the export business.

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The aqua sector has moved from unorganized retail channels, like wet markets, to organized retail channels, like supermarkets,and has also supported its vast growth because of rising disposable incomes,health consciousness, and more feedstock availability. The fish caught volume also increased for several years and reached 12.18 million metric tons in 2020, according to the Ministry of Fisheries, Animal Husbandry & Dairying. Indian aqua feed mills can produce 2.9 million metric tons. The rise in aquafeed showsan increase in fish caught-up volume which is the factor driving the market growth.
India with a vast aquaculture market has reached 12.4 million tons in 2022. In the future, the IMARC group predicts to reach 19.9 million tons by 2028, which in turn will provide a growth rate (CAGR) of 8.1% during 2023-2028.

II. PROPOSED WORK

A system is developed for the identification of Fish species by using Convolution Neural Networks inDeep Learning algorithmslike VGG16, VGG19, Resnet50, and InceptionV3 in the python programming language which is having a frontend GUI to communicate with the algorithms in python and gives the identified name of the specie given for identification.Frontend is developed using the stream-litframework in python. Image is selected and it is uploaded to predict the fish specie The algorithms pre-trained on the dataset made by collecting images of 14 different species for the FishBase website, further augmenting the collected images to create a larger dataset for training the algorithms. Here by using the transfer learning process to get better results during the identification process. The highest accuracy achieved with VGG16 is 89.38%.

FishBase. FishBase is a database of fish species containing all the global species, mostly the fish which has fin. It is the highest extensively approached online database and the largest information on adult finfish on the web. FishBase provides overall species data, including information on taxonomy, biometrics and morphology, behavior and habitats, geographical distribution, bionomics, and population effectiveness as well as reproductive, metabolic, and genetic data. Access to tools such as biogeographical modeling, trophic pyramids, identification keys, and fishery statistics and there are direct species-level links to information in other databases such as LarvalBase, GenBank, the IUCN Red List, and the Catalog of Fishes. FishBase included descriptions of 35,100 species, with 325,900 common names, 62,200 pictures, and 2,500 collaborators contributing data for information availability and sharing.

Data-set. The dataset used for the study contains images that were taken from the FishBase website. Images samples of 14 different species which are extensively found near the Indian subcontinent are used in the dataset. The fish species that are used in the dataset for the proposed systemto train and develop our models are Rawas, Katla, Rohu, Bangda, Rani, Sumrai, Pomfret, Hilsa, Sardine, Jhinga, Bombay Duck, Crab, Tilapia, Catfish, and GarraRufa.

Data Augmentation.

In total, after data augmentation, the data set has a total of 6000 images for all 14 classes. For augmentation, the ImageDataAugmentor and ImageDataGenerator libraries are used in python. Different augmentation techniques applied

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are Horizontal Shift, Horizontal Shift with Rotation, Vertical Shift, Vertical Shift with Rotation, Dark & Bright, Horizontal Flip, Horizontal Flip with Rotation, Vertical Flip, Vertical Flip with Rotation, and Random Zoom.
After the augmentation of data, themodel is trained and then saved in the form of model_name.h5 which is accessed by the front end to process the identification of fish and show the identified specie.

Transfer Learning. Transfer learning is the method known as reusing pre-trained networks, as it applies pre-trained network weights to a hefty dataset. As Pre-trained network models have already mastered the art of capturing low-level characteristics such as edges, lines, and curves. With convolutional layers, which are normally the highest computationally intensive part of the process, the implementation of these weights helps the network to come to an outstanding score more efficiently and quickly than training from scratch.

A Algorithms

Pre-trained Deep CNNs. There are many pre-trained CNN models accessible that have obtained good results in image processing and analysis. The important models are VGG, ResNet, Inception, Alexnet, and Google Net. In the proposed work, the utilized models are VGG16, VGG19, ResNet50, and InceptionV3 models.

VGG16 Model. The extensively used models VGG16 & VGG19 contain 16 and 19 layers respectively. VGG16 model is very efficiently trained on the ImageNet database and got 75.3% top-1 accuracy and won the ILSVRC classification competition in 2014, it has a huge database containing around 14 million images divided over 20000 classes. VGG16 model contains 5 convolution blocks. In which, all 5-convolution block has 2 convolutional layers and I max-pooling layer. The fully connected layers undertake the prediction as well as classification tasks. VGG16 and VGG19 are very deep CNN models that can handle enormous-size image identification tasks. For variable VGG configuration, different numbers of layers are used, VGG16 has 16 layers, whereas VGG19 uses 19 layers. An important characteristic of VGG16 is that the depth of volume increases due to the increasing number of filters in each layer, which results in a double number of filters after each max pooling. The last layer of architecture contains a flattened vector of 4096 elements that are successively connected to the FC layer having 1000 elements and a softmax activation function. These many neurons communicate to total ImageNet categories.

ResNet50 Model. ResNetis a short form for Residual Networkswhich is a very in-depth CNN model, trained on ImageNet and achieved an 80.62% top-1 accuracy, and won the ILSVRC classification competition in 2015. The ResNet-50 model contains 50 layers. To make the network deeper, an instinctiveidea could be used simply to stack layers. However, this solution guides to reachingmore training errors with regard to state-of-art methods. A correct way to stack layers for increasing performance is to executeasimilar mapping to the output of the following layer.ResNet50 model useda deep residual learningframework in which the layers fit a residual mapping rather than stacking layers immediately. This solves the problem of mortification of training accuracy butit gets immersed as the depth of the neural network increases.

InceptionV3 Model. Inception v3 is a DL model based on CNN, used for image classification. Inception V3 is the greater version of the basic model of inception V1 with higher efficiency. It has a total of 42 layers with a lower error rate. The layers are Convolution, convolution padded, pooling, Inception, linear, and softmax. The model is made of symmetric and asymmetric building blocks with average pooling and max pooling, concatenation, dropouts, and fully connected layers. Inception v3 has attained 78.1% accuracy on the imagenet dataset.

Methodology

In this proposed system, CNN-based algorithms and their in-depth learning frameworks have been used to identify fish using transfer learning methods, by employing the profound models VGG16, VGG16, ResNet-50, and InceptionV3. Transfer Learning is applied as it helps to handle insufficient data and performance duration to the models.
Batch normalization is a widely used technique for normalizing input features on models that can lead to a substantial reduction in convergence time.Normalization happens during training, but come evaluation time,the classification result of an image should depend solely on the input image and not the set of images that are being fed to the model.
Activation inputs are normalized by subtracting the mean and dividing by the standard deviation. To keep things balanced in the presence of backpropagation, two trainable parameters are introduced in every layer. An activation layer is created using the ReLU class following the dense layer. The ReLU function will directly pass the positive data as output, and give zero if the input data is negative.

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B Different libraries used

TensorFlow. It is an open-source platform containing trained deep learning models and API which any be used for desktop, mobile,web, and cloud.

Keras. Keras applications are big libraries that have premade architectures models with pre-trained weights.

import Sequential. The sequential model is used for a plain stack of layers that has exactly one input tensor and one output tensor.

import Dense, Flatten, Dropout. These are the types of layers modified. The dense layer is used to change the values of the matrix. It adds the fully connected layer to the neural network. Flatten converts the pooled feature map into a single column that is input as fully connected layers. The dropout layer helps to regularise randomly set dimensions of the input vector to zero.

convolutional import Conv2D, MaxPooling2D. The 2D convolution layer has filters and a kernel that goes through the 2D image data and gives single output pixels by performing elementwise multiplication. Max pooling 2D gives a tensor of rank representing the maximum pooled values as output from the input window by downsampling the spatial dimension by taking the maximum value.

applications.vgg19 import VGG19. The vgg19 model is loaded and initiated to work on the dataset.

optimizers import Adam. An optimizer is one important argument required for compiling the model. In VGG19, the Adam optimizer is used, which is a stochastic gradient descent method that is based on adaptive estimation of first-order and second-order moments.

import Input, Lambda, Dense, Flatten. The first layer is constructed using the Input layer. The lambda layer helps to pass more than one tensor to the lambda layer. The input data of the lambda layer can be transformed.

models import Model. With this, the dataset is loaded into the model for the purpose of training

applications.vgg16 import VGG16. The vgg16 model is loaded for keras and initiated to work on the dataset.

vgg16 import preprocess_input. The preprocess_input function is used to transform the image to the format the model requires.Some models use images with values ranging from 0 to 1. Others from -1 to +1. Resnet is using the Caffe style.

resnet50 import ResNet50. The Resnet50 model is loaded for keras and initiated to work on the dataset.

inception_v3 import InceptionV3. The inceptionV3 model is loaded for keras and initiated to work on the dataset.

III. RESULTS

The output is obtained as follows using 5 Epoch and 5 Epoch step size in the given algorithms.

Model	**Epoch**	**EPoch Step Size**	**Accuracy**
VGG16	5	5	89.38
VGG19	5	5	25.00
ResNet50	5	5	12.11
Inception V3	5	5	55.62

The identification system demonstrates the best results with the VGG16 algorithm with an accuracy of 89.38%. the amount of loss of VGG16 is also recorded which gets reduced at each epoch as the model gets trained effectively with respect to the dataset, which all together increases the identification capacity of the model. VGG16 loss function graph shows that as the model gets trained the loss gradually decreases.

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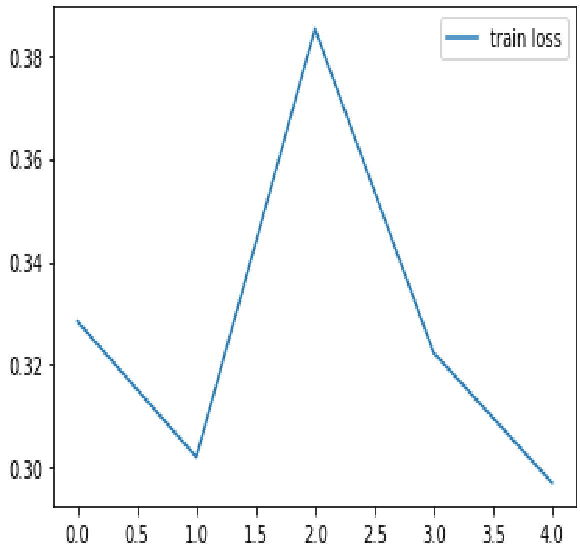

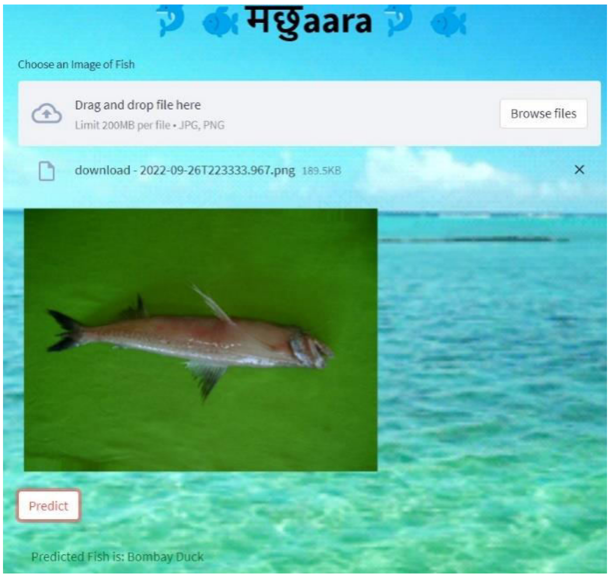

IV. CONCLUSION

The paper, have proposed a method to identify fish species using different algorithms like VGG16, VGG19, Resnet50, and InceptionV3 and found that VGG16 gives the most precise predictions with an accuracy of 89.38%. The main idea was to explore and study pre-trained VGG16 and convolutional neural network models which would contribute in image classification as well as identification.The system can be used to provide detailed captured information to the fisherman as well as vendors and consumers which will create business transparency.

REFERENCES

1. Yuandalei Cao, Qujiang Lei, Tongfan Wei, Haozhe Zhong (2021) A computer vision program that identifies and classifies fish species.
2. Weiguo Yi, Siwei Ma, Heng Zhang, Bin Ma (2022) Classification and improvement of multi label image based on vgg16 network
3. Dena F. Mujtaba and Nihar R. Mahapatra (2021) Fish Species Classification with Data Augmentation
4. Francesco Rossi, Alfredo Benso, Stefano Di Carlo,GianfrancoPolitano, Alessandro Savino and Pier Luigi Acutis (2016) FishAPP: a Mobile App to Detect Fish Falsification through Image Processing and Machine Learning Techniques
5. B Vikram Deep, Ratnakar Dash (2019) Underwater Fish Species Recognition using Deep Learning Techniques
6. Jawad Rasheed (2021) A Sustainable Deep Learning based Computationally Intelligent Seafood Monitoring System for Fish Species Screening
7. Yuhang Li, Daqi Zhu, HaoDong Fan (2021) An Improved Faster RCNN Marine Fish Classification Identification Algorithm
8. Zhenxi Zhao , Yang Liu , Xudong Sun , Jintao Liu , Xinting Yang , and Chao Zhou (2021) Composited FishNet: Fish Detection and Species Recognition From Low-QualityUnderwater Videos
9. Dena F. Mujtaba and Nihar R. Mahapatra (2021) Convolutional Neural Networks for Morphologically Similar Fish Species Identification
10. Ambuj Kumar Agarwal, Raj Gaurang Tiwari, Vikas Khullar, Rajesh Kumar Kaushal(2021) Transfer Learning Inspired Fish Species Classification.