

Fish Detection and Species Classification of Low Quality Fishes Pictures using CNN

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Abstract: *A new technique has been developed to automatically detect and classify various species of fish, which could help combat illegal and unsustainable fishing practices. Around half of the world relies on seafood as their main source of protein, so it is crucial to protect marine life. The new method could provide researchers with a way of monitoring fish populations and determining which species are being overfished. It is hoped that this technology will lead to more sustainable fishing practices and help to preserve our oceans for future generations. The implemented system helps investigators and nature conservationists to analyze images captured by boat-cameras of fishes, overcoming hindrances such as varying degrees of luminosity and opacity. The system is capable of detecting and classifying the fishes into different species, aiding in conservation efforts and research. This technology provides a useful tool for researchers and scientists working in marine biology, making it easier to analyze and understand the behavior of marine life. The fish detection system comprises of two phases – augmentation and detection. The augmentation phase involves using data augmentation techniques to enhance real-time images captured by boat- cameras and send them to the detection module. The detection phase uses the enhanced images to search for fish regions and identify fishes. With this system, the fishing industry can monitor fish populations accurately and efficiently.*

Keywords: CNN, Deep Learning, Image Processing, Machine Learning

I. INTRODUCTION

Human activities such as overfishing, pollution, and climate change. Overfishing has caused a decline in fish populations, while pollution has led to the degradation of aquatic habitats. Climate change has warmed ocean waters, leading to issues such as coral bleaching and the displacement of fish populations. These problems not only affect the aquatic environment but also have significant impacts on the global economy and human livelihoods. It is necessary to take immediate action to address these issues and protect the fish environment before it is too late. Machine learning techniques and technology can aid in the classification of fish types and identifying vulnerable strains at the risk of extinction. By comparing and determining their distinctive features, the characteristics of different fish species can be analyzed efficiently. This will enable proactive measures to be taken towards preventing the extinction of these strains by developing targeted conservation plans and regulations. The application of these techniques can contribute significantly towards the conservation of marine biodiversity. Classification experts are exploring better techniques to improve the classification process. Newer methods include digital image processing and pattern recognition technology. Pattern recognition is employed in various fields to classify a range of things, from insects to satellites. This technology offers a fast, reliable, and accurate classification strategy, which could be applied to more complex and diverse datasets. With improved classification efficacy, organizations can better manage, analyze, and understand large volumes of information, ultimately giving them a competitive edge within their respective industries.

Real-time inspection of fisheries is crucial to preserve marine ecosystems in coastal areas where detrimental uncultured practices occur. It is important to study the size and diversity of fish species in order to conserve them. By utilizing effective monitoring and enforcement mechanisms, fisheries can be sustainably managed to ensure the long-term viability of marine ecosystems. This will protect ecosystems, improve livelihoods, and promote the responsible use of marine resources. Previously, real-time detection and classification of captured fishes required manual inspection by an expert on-

board. However, there has been a lack of automatic methods to perform this task until now. Some methods involve bringing the captured fish to the lab for analysis. But there is a need for more efficient and real-time methods to support fishery management and conservation efforts. The project is aimed at using pisciculture and species preservation techniques. The future goal is to improve results by using R-CNN in the detection and classification stages. The project could be expanded to include other fish species. Identifying fish would assist in the export market.

This paper provides a brief introduction to the topic of system problems and presents a survey conducted to detect the underlying problem. The process represented by a diagram in Section II is discussed in detail in Section III.

II. REVIEW LITERATUR

Composited FishNet: Fish Detection and Species Recognition From Low-Quality Underwater Videos Thus, the interference of underwater environmental information on the object characteristics is reduced, and the output of the main network to the object information is strengthened. In addition, to better integrate the high and low feature information output from CBresnet, the enhanced path aggregation network (EPANet) is also designed to solve the insufficient utilization of semantic information caused by linear upsampling. The experimental results show that the average precision (AP)0.5:0.95, AP50 and average recall (AR) $\max=10$ of the proposed Composited FishNet are 75.2%, 92.8% and 81.1%, respectively. The composite backbone network enhances the characteristic information output of the detected object and improves the utilization of characteristic information.

Fish Detection and Classification Using Convolutional Neural Networks.

This step involves the segmented image of fishes to be passed to the classifier model which specifies to which species the detected fish belongs to. CNN (Convolutional neural network) is used at the detection and classification phase, with different architectures, to extract and analyze features. The system provides confidence quotients on each image, expressed on a 0–1 scale, indicating the likelihood of the image belonging to each of the following eight categories ALB, BET, YFT, LAG, DOL, Shark, Other and None. The system provides detection and classification with an accuracy of 90% and 92% respectively.

Detection, Localization and Classification of Fish and Fish Species in Poor Conditions using Convolutional Neural Networks.

In this work the initial steps towards a system capable of parametrising fish schools in underwater images are presented. For this purpose a deep convolutional neural network called Optical Fish Detection Network (OFDNet) is introduced. This is based on state-of-the-art deep learning object detection architectures and carries out the task of fish detection, localization and species classification using visual data obtained by underwater cameras. Based on experiments on a dataset obtained at sea, OFDNet is shown to successfully detect 66.7% of the fish included and furthermore classify 89.7% of these correctly.

Underwater Fish Species Classification using Convolutional Neural Network and Deep Learning.

The target of this paper is to propose a method for Automated classification of Fish species. A high accuracy fish classification is required for greater understanding of fish behavior in Ichthyology and by marine biologists. Maintaining a ledger of the number of fishes per species and marking the endangered species in large and small water bodies is required by concerned institutions. Majority of available methods focus on classification of fishes outside of water because underwater classification poses challenges such as background noises, distortion of images, presence of other water bodies in images, image quality and occlusion. In this work, a novel method based on Convolutional Neural Networks, Deep Learning and Image Processing to achieve an accuracy of 96.29%.

III. METHODOLOGY

System Architecture

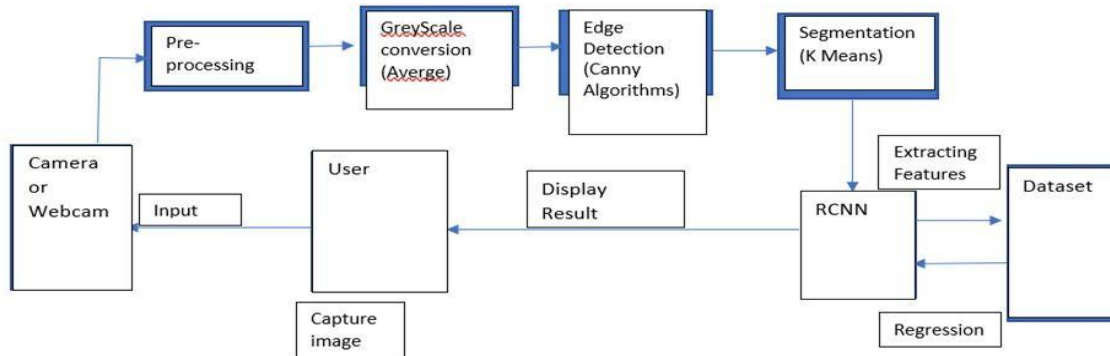


Fig 1: System Architecture

The diagram shows the major components of the system, which are:

- **Input:** A webcam or phone camera will be the primary input device to capture images for this project. The images captured will undergo pre-processing techniques including erosion, dilation, and noise cancellation. These steps are necessary to enhance the quality of the input image and improve the accuracy of subsequent image recognition algorithms. The pre-processed image will then be used as input for further processing and analysis.
- **Image Processing:** The input image is processed using an algorithm called CNN and various operations like grayscale conversion, edge detection, image segmentation, and feature extraction. These processed images are then matched with templates to identify the object or pattern in the image. The output of this process can be used for various tasks like object recognition, face recognition, and image classification. This technology has revolutionized various industries, including healthcare, automotive, and security, where it is used for various applications like inspection, diagnosis, surveillance, and autonomous driving.
- **Template matching:** Template matching is a technique used for locating small parts of an image that need to be compared with a pre-existing template or dataset. This quality control measure ensures that images are of a high standard by comparing the desired parts with a pre-existing standard. The technique helps to streamline processes by accurately identifying similarities and differences between images. Overall, template matching is an essential tool for minimizing margin of error in image processing and ensuring that visual outputs meet desired quality standards.

Algorithm

Convolution Neural Network(CNN):

A CNN, or convolutional neural network, is specifically designed to process images and convert them into a vector code. It draws on fully-connected neural networks and is structured with multiple layers that process signals and propagate them through the network. In simpler terms, a CNN is a type of neural network that helps computers recognize and interpret visual data, such as pictures or videos. They have become widely used in areas such as computer vision and image recognition, as they can accurately identify patterns and features within an image.

Step 1: The dataset consists of images of human faces that have been captured by a camera. The images may vary in terms of lighting, angle, and facial expression. This dataset can be used for a variety of purposes, such as face recognition, emotion detection, or studying facial features. It may also be used for research and development of machine learning algorithms or computer vision techniques that involve processing and analyzing image data.

Step 2: A convolutional neural network (CNN) is a type of neural network that is commonly used as an encoder to extract image features. As the CNN processes the image, it extracts features pixel by pixel, using filters that detect specific patterns or features in the image. This allows the CNN to learn important characteristics of the image, which can then be

used for tasks such as object recognition, classification, and segmentation. The features extracted by the CNN are typically passed on to other layers of the neural network for further processing and analysis.

Step 3: Matrix factorization is a technique used to break down a matrix of size $m \times n$ into two smaller matrices, typically of sizes $m \times k$ and $k \times n$. These smaller matrices can be used to represent the original matrix in a more efficient and meaningful way. In the context of image processing, the matrix of extracted pixels can be factorized to identify patterns and relationships between pixels. This can be useful for tasks like image compression and reconstruction, anomaly detection, and feature extraction for machine learning algorithms.

Step 4: Max pooling is a technique used in convolutional neural networks (CNN) to reduce the spatial dimensions of a feature map. In this technique, a matrix is divided into non-overlapping regions and the maximum value within each region is selected to form a new matrix. This new matrix has a smaller width and height compared to the original matrix, but the same depth. Max pooling is useful in reducing the computational complexity of CNNs and extracting important features while retaining spatial information.

Step 5: When performing normalization, any negative values in the dataset are converted to zeros. This step ensures that the data falls within a certain range, typically between 0 and 1, making it easier to compare and analyze. This process is particularly important when dealing with variables that have vastly different scales, as it allows for fair comparison between them. By converting all negative values to zero, any potential biases introduced by negative numbers are eliminated, creating a level playing field for analysis.

Step 6: In order to convert input values into a more useful format for neural networks, researchers have developed the concept of zero rectified linear units, or ReLUs. This involves filtering each value through a function that sets any negative values to zero, effectively "rectifying" the data. This approach has been found to improve the speed and efficiency of neural network computation, and has been widely adopted across the field. By using ReLUs, researchers can effectively eliminate extraneous data and ensure that their models focus only on the relevant inputs.

Step 7: The hidden layers in a neural network are responsible for processing and analyzing input values from the visible layers. They apply mathematical operations to these inputs and determine the appropriate weights for each one in order to calculate the maximum probability of a specific output. These layers are important for machine learning, as they help to extract features and patterns from the input data that can then be used to make predictions or classifications. The number and size of hidden layers in a neural network can vary depending on the complexity of the problem at hand.

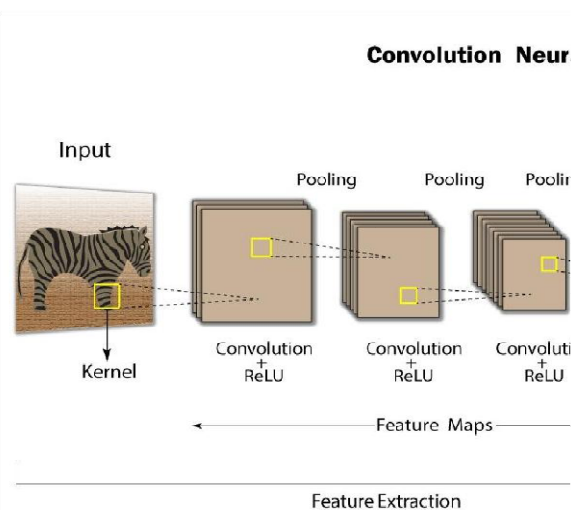
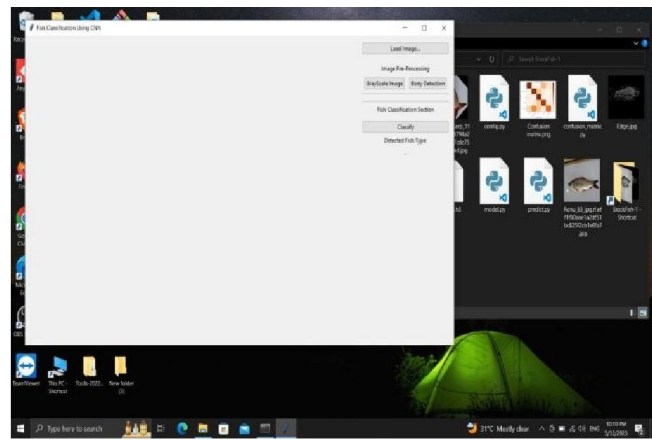
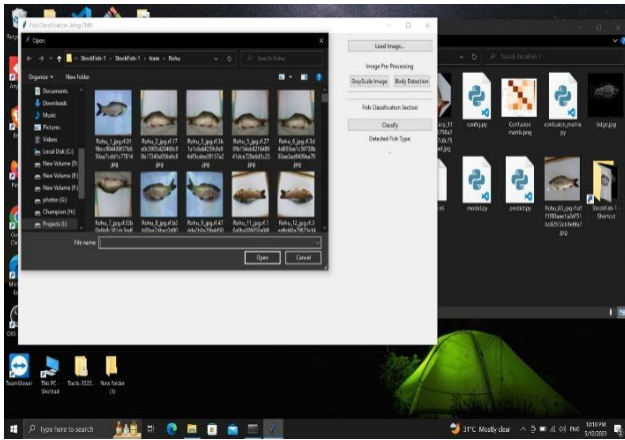


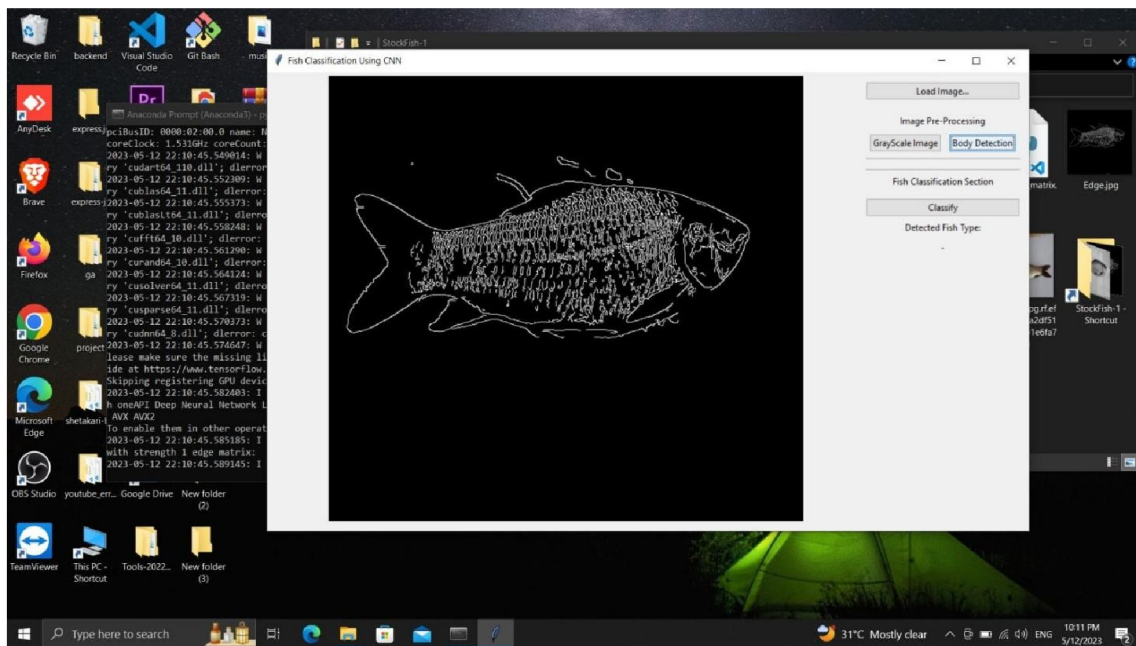
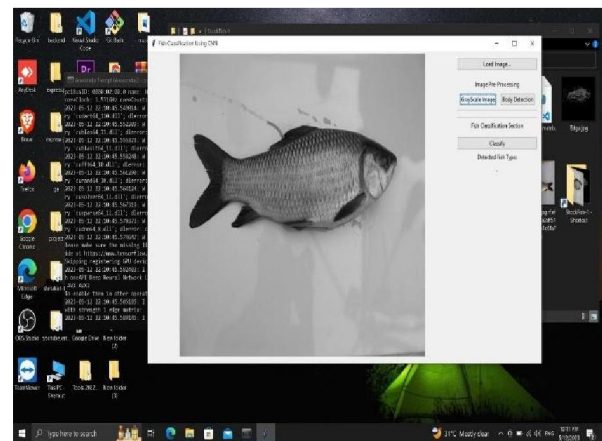
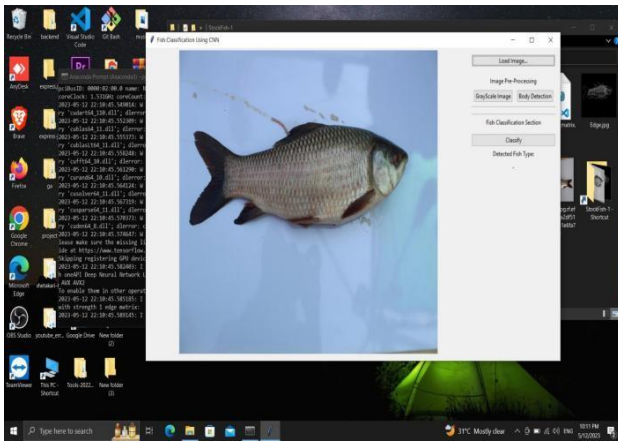
Fig3: CNN Algorithm

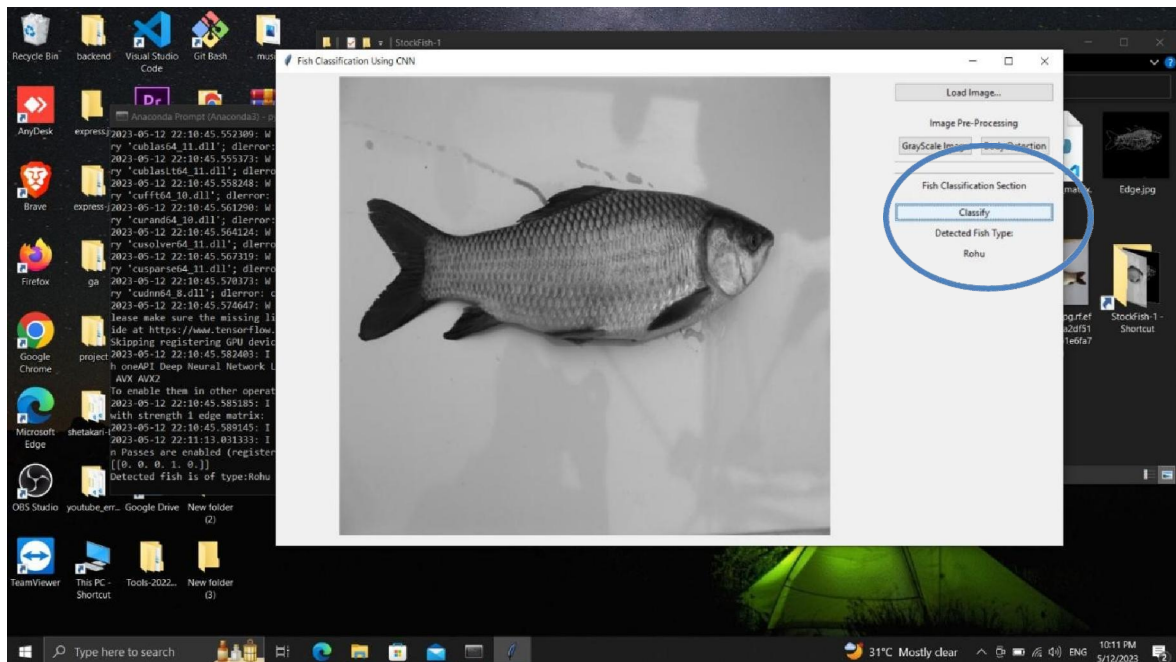


IV. RESULT & ANALYSIS



Load Image for classification. The steps Followed show the results of grey conversion and edge detection





V. CONCLUSION

Using CNNs for detection and classification has resulted in impressive outcomes, surpassing traditional image processing techniques that relied on manual feature extraction. The accuracy levels achieved through these networks have exceeded expectations. However, the process as a whole requires careful consideration and management to ensure optimal results. To achieve better results in production and improve the accuracy of the network, the training should be done on limited datasets and better aggregation tools. Future scope includes the implementation of R-CNN for enhanced results in the detection and classification phases. Possible extensions to the project include the detection of objects using advanced techniques.

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