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FISH DISEASE DETECTION OF EPIZOOTIC ULCERATIVE SYNDROME USING DEEP LEARNING IMAGE PROCESSING TECHNIQUE

Rachman F*, Akbar MNS and Putera E

eFishery, Multidaya Teknologi Nusantara, Indonesia

Abstract: Early detection of fish disease is a vital acknowledgment in Fish Cultivation since it could track later effects on the fish ponds since the disease could be contagious. Visual identification is the common method that is used by the majority of conventional cultivators in Indonesia. By applying Image Recognition technology, disease identification could be executed efficiently from process latency and the amount of batch that could be identified. Our limitation in this paper is EUS (Epizootic Ulcerative Syndrome) developed by a pathogenic fungus, *Aphanomyces invadans.* Common identifiers of infected fish could be identified by visual inspection acknowledging red blotches in the fish bodies. This research used Object Segmentation Inference MobileNetV2 as model system architecture and Image Processing. Using HSV Threshold base to identify which part of the fish is infected by the disease. Object Segmentation will separate the disease area from the fish's whole body. Meanwhile, the HSV Threshold setting in will identify red blotches in fish bodies. Then fish bodies that have been infected by EUS will be shown by the binary result of the HSV Threshold. To see the performance of the system we could see the indicators shown by the F1 score, as the result of the image identification from 80 augmented data we have an average score is on 84% accuracy. That means we could assist conventional fish farmers by identifying diseases faster and helping cultivators with minimum knowledge about identifying fish diseases.

Keywords: object segmentation, HSV, Epizootic Ulcerative Syndrome, MobileNetV2

Introduction

Fisheries have become one element that is quite important, especially in improving the economy. Especially for fish farming has become a source of livelihood for people living in rural areas (Chakravorty, 2015). Just like other living things, fish are also often exposed to various diseases, especially since almost all fish can carry pathogens and parasites (Lyubchenko, 2016). Epizootic Ulcerative Syndrome (EUS) is an ulcerative symptom of a destructive disease that attacks freshwater fish in brackish water. This disease is caused by fungal pathogens attached to the fish (Malik et al., 2017). The initial symptoms of the disease are marked by the presence of red dots on the fish's body, then within a few days, the fish infected with EUS will lose their scales and show muscles in fish, then the fish will die within a few days, also spreading the disease to the other fish in the same pool (Chakravorty, 2015).

Traditionally, the fish diseases diagnosis is still ambiguous because it leads to the experience of each fish cultivator or fish expert. In the end, it will lead to the individual skill and experience of the expert with the disease they have studied (Chakravorty, 2015). Detecting and diagnosing fish disease is very time-consuming and not easy because it requires an analysis of the microorganisms that carry the

*Corresponding Author's Email: faishal.rachman@efishery.com

disease (Nayak, 2014). Therefore, the ability to diagnose quickly and accurately is needed to control various diseases. Moreover, detecting certain diseases effectively and accurately can help prevent the spread of disease to other fish; otherwise, it will affect human health when consuming these fish (Tacon, 2013).

In response to this limitation, in this study, we will use a digital image processing approach to speed up diagnosing EUS disease areas in fish. The segmentation method has been successful in a wide variety of fish images. This method will be used as image feature extraction to take the EUS area on the body of the fish infected with the disease. Several other studies apply this method.

Lyubchenko et al. (Malik et al., 2017). in their research, detect and mark the infected area, also separating the normal part of the fish by using color characteristics. We will use several logical methods, such as Intersection over Union (IoU), to help perform feature extraction on the segmentation. Also, employ several deep learning architectural system models to help automate the analysis of diseased fish areas in the digital image data.

Related Works

Chakravorty et al. (Chakravorty, 2015). Made a system to help recognize fish diseases from a digital image using a method called Principal Component Analysis (PCA). In the process, segmentation of the fish disease area in the image is carried out based on the color characteristics by using K-Means Clustering. Also, The HSV image renders the image of the fish in black and white (hue and tint) to make it easier to detect areas affected by EUS. Chakravorty's research provides extensive results of areas affected by EUS disease once images of fish with EUS are included in their program (Chakravorty, 2015).

Malik et al. (Malik et al., 2017). Divided the research into two parts: the first part is the segmentation of image data, and the second parts is extracting features from image data fish infected by the EUS diseases. For segmentation, they apply image enhancement, a preparation to improve image quality before segmentation is carried out, then use edge detection to retrieve the morphological patterns in the fish image data. Next is the second parts, they extracting image features from image data of fish infected with EUS disease using Histogram of Gradient (HOG) and Features from Accelerated Segment Test (FAST). After that, the image dataset will go through two processes to classify images to determine which fish were infected with EUS and which were not infected with EUS. The accuracy results obtained from combining several approach techniques with the flow (application of segmentation methods - dimension reduction - and classification methods) are as follows: HOG-PCA-KNN (56.32%), FAST-PCA-KNN (63.32%), HOG-PCA -NN (65.8), and FAST-PCA-NN (86%).

From the previous studies, segmentation has proven suitable for detecting necrosis areas in EUS-infected fish. Therefore we will try to do image segmentation for the EUS-infected fish combined with several deep learning computing methods to predict EUS-infected disease and obtain new accurate analysis results.

Proposed System

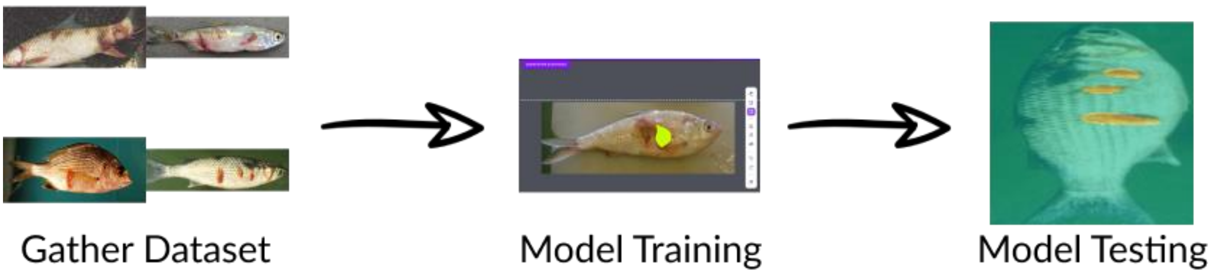

Figure 1: Proposed design system

This research will create a system to detect EUS disease in fish body parts. Before detection begins, several method approaches must be passed. First, we collect datasets of fish infected with EUS. In the second stage, we will conduct training models, such as implementing evaluations of datasets. The last stage is model testing, which involves implementing several architectural scenarios from deep learning computing algorithm such as FCN-32-MobileNet, Resnet50-Unet, Mobilenet-Unet, and Mobilenet-Segnet. After several stages of the proposed system, EUS disease detection in the fish dataset can be seen. The flow of the proposed system can more or less be seen in Figure 1.

Dataset Gathering

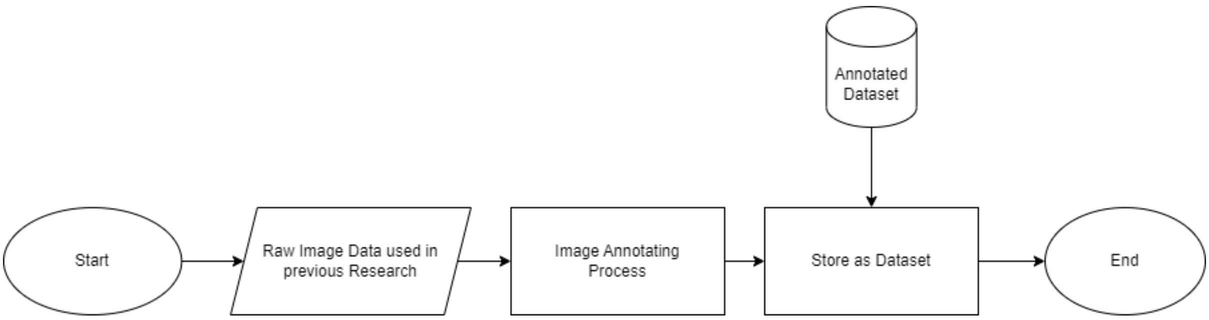

Figure 2: Gathering dataset process.

The dataset used is an image of fish infected by EUS and necrosis experienced from the sample images of previous studies. Then, the necrotic part of the fish image is masked to get a binary image of the fish disease segmentation section. In addition, the dataset image augmentation is done in with the form of 90° Image Rotation, Random Saturation, Random Blur, and Random Mosaic to make the dataset more varied and to avoid overfitting in the model training process (Shorten & Khoshgoftaar, 2019). Figure 2 will give a little overview of the gathering dataset.

Image Segmentation

Haralick *et al*., (1985) refer to digital image processing. Image Segmentation is a process of partitioning a digital image into several image segments, also known as image regions or image objects (sets of pixels). The purpose behind segmentation is to simplify and change the representation of an image into something more meaningful and straightforward to analyze. Image segmentation is frequently used in several studies, especially in the medical case, to separate parts affected by specific diseases and give visualization information so the doctors or specialists can easily distinguish each type of disease (Pham *et al*., 2000, Sharma *et al*., 2010, Masood *et al*., 2015). Figure 3 will be shown the example of a segmentation image application.

In this research, the segmentation that will be used is to segment the body parts of healthy fish undergoing necrosis due to EUS.

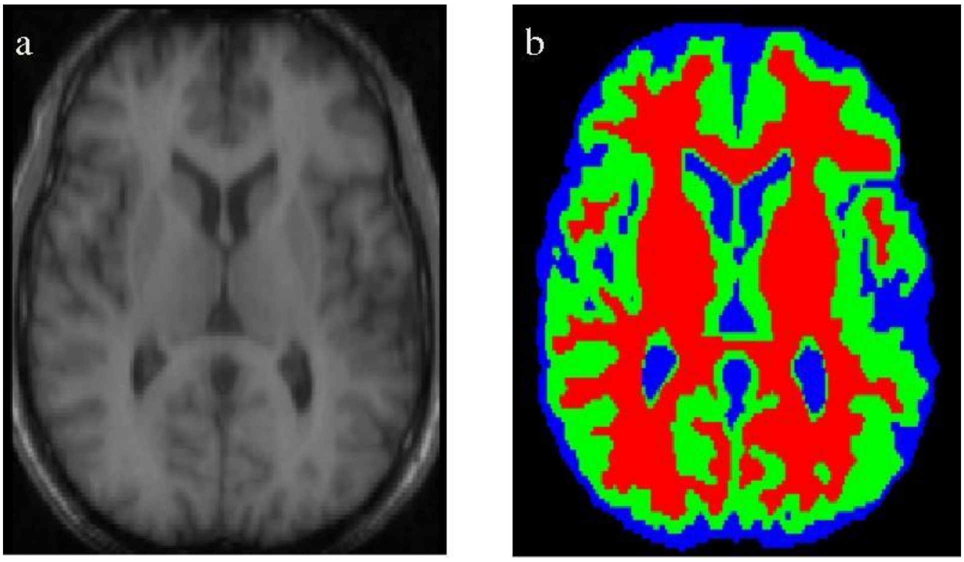

Figure 3: Examples of image segmentation applications in the medical studies

Intersection over Union (IoU)

Intersection Over Union (IOU) is a value based on statistical similarity and diversity of sample sets. Aims to develop an overlapping area (the area that intersects) between two segmentations, namely segmentation of prediction results and segmentation of ground truth (truth). So, the requirement to apply IOU is to have both bounding boxes. Starting with applying the IOU, we can find other evaluation values, such as precision, recall, and continuously (van Beers et al., 2019). Figure 4 will show, how to calculate IoU

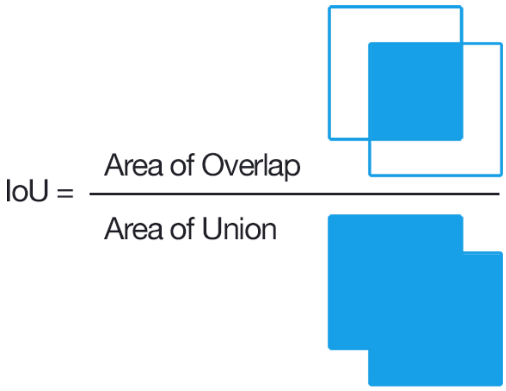

Figure 4: IoU Calculation illustration

Deep Learning Architecture

In this study, several Deep Learning Architectures will be used to help strengthen the computing system in assisting segmentation methods such as Fully Convolutional Network (FCN), ResNet, and MobileNet, by explaining the implementation as follows:

1. FCN-32-MobileNet

A fully Convolutional Network, commonly abbreviated as FCN, is a matrix convolution method that detects every pixel of an image. In the process, FCN excels because it avoids pooling, so the learning process takes less time (Shelhamer et al., 2017a). Figure 5 will show the illustration of FCN architecture.

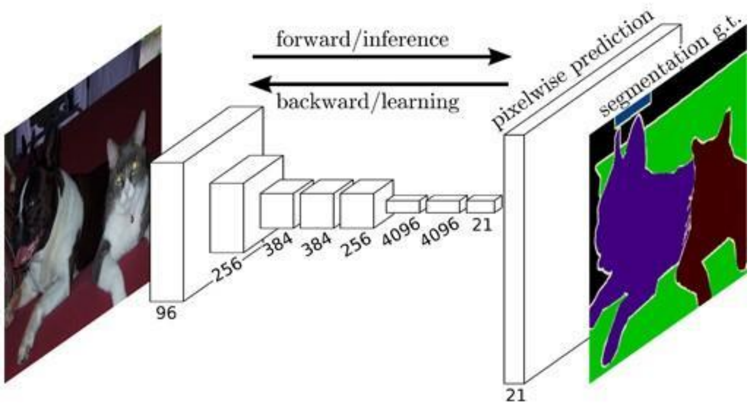

Figure 5: Illustration of FCN architecture

2. ResNet50-Unet

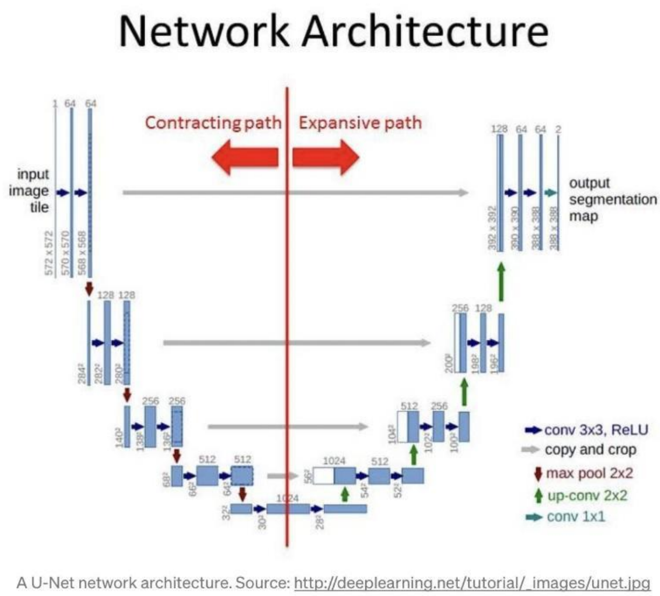

Figure 6: UNet architecture illustration

UNet is a kind of Convolutional Neural Networks (CNN) approach, first proposed to make better segmentation of biomedical images. The architecture is effective for applications that want the same output image size as the input image size. Therefore, the image is downsampling (encoder) using Convolution Layers and upsampling (decoder) to retrieve the image with segmentation. The encoder path captures the context of the image, producing feature maps. The decoder path is used to enable precise localization using transposed convolutions. By using the Unet architecture, the input image will be estimated from each pixel. This process will provide conclusions that are very suitable for the feature extraction task in task (Beers, F. v., 2019). UNet architecture looks more or less like figure 6.

ResNet (Residual Network) is a neural network used as the backbone for many computer vision models. Under normal circumstances, training the deeper neural network is quite challenging. There seem to be increased error rates in training deep neural networks due to the vanishing gradient problem. In theory, training error should decrease when multiple Convolution Neural networks are stacked. However, in practice, adding more layers to the Convolution Neural Network increases the training error. Optimization or corruption problems occur here.

ResNet solves this problem by resorting to shortcuts. This is a technique called skip connection. Skip connection skips several layers and connects directly to the output. In this way, the exploding/vanishing gradient problem is avoided. There are many different ResNet architectures. It is named according to the depth layers. The example can be seen in figure 7.

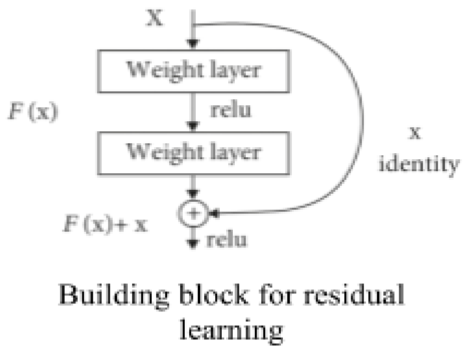

Figure 7: Example of Resnet depth layer.

3. MobileNet-Unet

MobileNet is a family of convolutional neural networks (CNN) for image classification proposed by a team of researchers at Google (Masood et al., 2015). Through its different versions, MobileNet introduced many novel ideas that aim to reduce the number of parameters to make it more efficient for mobile devices while achieving high classification accuracy. These novel ideas include depthwise convolution, Squeeze- Excitation (SE) modules, skip connections, and a new activation function, called Swish (Alsenan et al., 2021). The main idea of this work is to build a deep image segmentation model based on the UNet architecture combined with the pre-trained MobileNetV3 model to exploit its strong feature extraction capabilities. The question is how to best combine these two models, which is the main contribution of our work in this paper. We show the proposed model's architecture named MobileNet-V3-UNet, including the different blocks of the MobileNetV3 architecture and the input feature maps. Figure 8 shows the MobileNet architecture for the feature extraction.

4. MobileNet-Segnet

Semantic segmentation has made progress in recent years with deep learning. The first prominent work in this field was fully convolutional networks(FCNs). FCN was proposed as an end-to-end method to learn pixel-wise classification, where transposed convolution was used for upsampling. This architecture was used to refine the segmentation output, which utilized higher resolution feature maps. That method paved the road to subsequent advances in segmentation accuracy. Multi-scale approaches, structured models, and Spatio-temporal architectures introduced different directions for improving accuracy. Multi-scale approaches, structured models, and Spatio-temporal architectures introduced different directions for improving accuracy. All of the above approaches focused on the accuracy and robustness of segmentation. Well-known benchmarks and datasets for semantic segmentation, such as Pascal, NYU RGBD, Cityscapes, and Mapillary, boosted the competition toward improving accuracy (Siam et al., 2018)

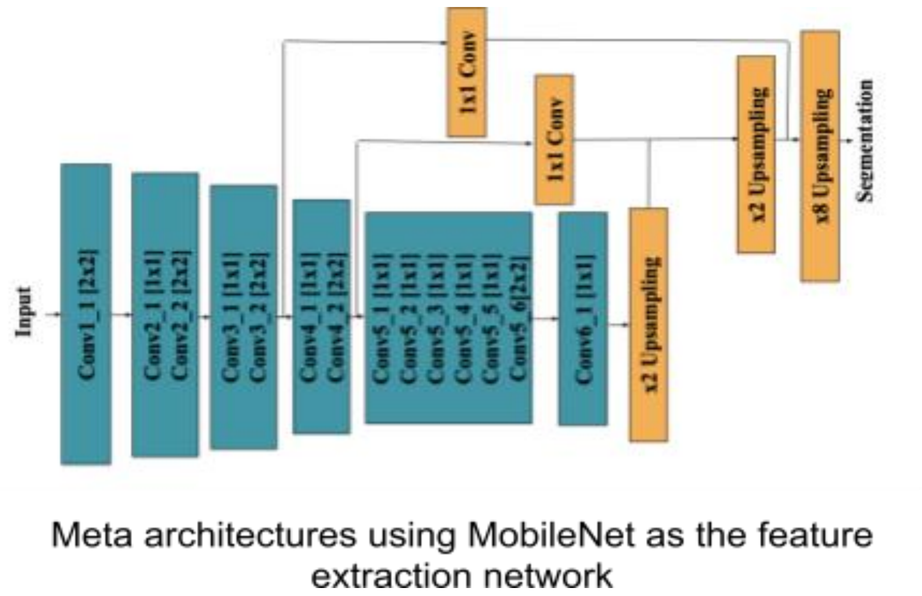

Figure 8: Mobilenet architecture as the feature extraction.

Experimental Result

Preprocessing

In this research, the dataset goes through 2 stages of preprocessing, namely: resizing the image to 2048 x 2048 and cropping the image into four parts (Tile). One of the factors that can improve the accuracy of the test is the number of datasets provided. However, if there are only a few available datasets, the augmentation process on the dataset can be used as an alternative. That is, increasing the diversity of available data without collecting new data. The augmentation process carried out includes

- Rotation: Rotates data in the range of -15° to 15°.
- Saturation: Adjusts the sharpness of the image in the range of -25% to 25%.
- Brightness: Adjust the image's brightness level from -25% to 25%.
- Blur: Makes the image appear blurry up to 10px.
- Noise: Makes the image look like it has dents/color grains up to 5% of its pixels.

The above process resulted in 1056 datasets from the 24 data. The dataset is divided into 960 training sets, 64 validation, and 32 testing sets. Figure 9 will show the result of the preprocessing phase.

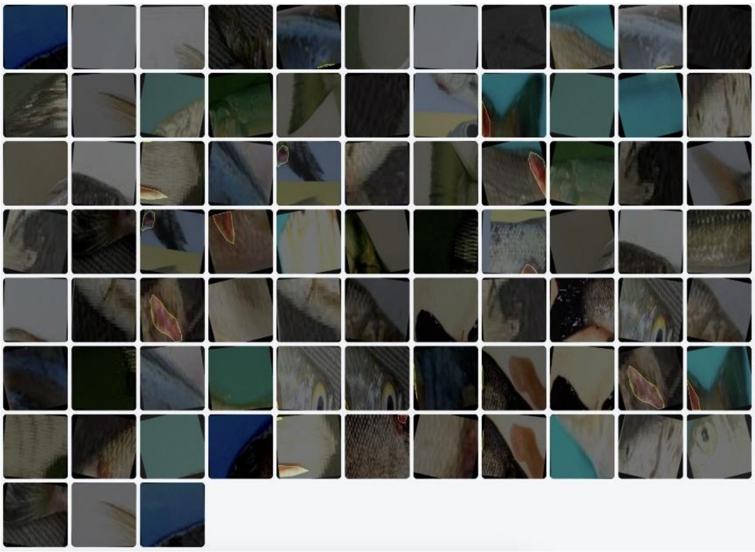

Figure 9: Preprocessing phase result.

Segmentation Labelling

The segmentation process is carried out manually using the polygon feature to mark areas that are characteristic of the onset of disease in fish in each photo in the dataset as shown in figure 10. This process generates a disease area to create masking label of the image dataset.

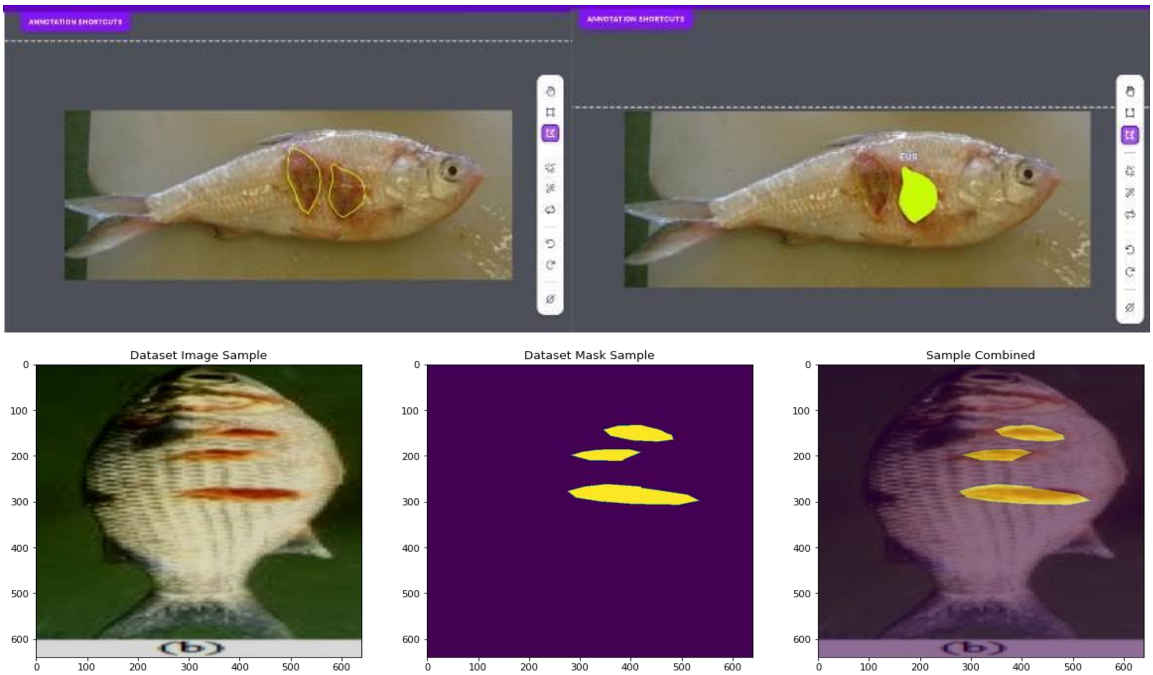

Figure 10: Segmentation label process using polygon feature mark.

Training Process

In the training process phase, we will use several computing algorithm approach scenarios for the data that has been segmentation labeled, the purpose of these various training processes, among others, is to find the results of which scenario is the best to use for fish data resulting from segmentation labels. So that in the future, if we want to make an application, we can find out what method is best to use. The scenarios that we will use in this study:

- FCN-32 combined with MobileNet
- Resnet50 combined with Unet
- MobileNet combined with Segnet
- MobileNet combined with Unet

These scenarios are not only applied to the training phase, but also applied to the testing and validation phase so that the system is more consistent and optimal.

Results

Table 1: System experiment performance results.

Model Arch	Phase	Mean IoU	Frequency Weighted IoU
fcn_32_mobilenet	train	87.28%	98.17%
resnet50_unet	train	89.64%	98.52%
mobilenet_segnet	train	93.77%	99.06%
mobilenet_unet	train	98.75%	99.82%
fcn_32_mobilenet	test	52.82%	91.09%
resnet50_unet	test	59.33%	92.36%
mobilenet_segnet	test	53.69%	91.26%
mobilenet_unet	test	55.33%	91.52%
fcn_32_mobilenet	validation	57.97%	95.89%
resnet50_unet	validation	59.74%	95.75%
mobilenet_segnet	validation	65.35%	96.20%
mobilenet_unet	validation	62.33%	96.04%

From the results of the system experiment in table 1, we used the scenarios that have been defined previously. In the training phase, we got the best result from the scenario between MobileNet and Unet and obtained an accuracy of 98.75%. We have the lower accuracy in the training phase from the FCN-32 and MobileNet scenario which have 87.28%. Meanwhile, the scenarios at the testing phase have a stagnant value with an average accuracy of 54.75%. The highest accuracy at this phase is the combination of Resnet50 and Unet, which gets an accuracy of 59.33%. As for the validation phase, the highest accuracy value is obtained from the MobileNet scenario with Segnet, which is 65.35%.

Using the defined scenarios in the training phase of the system looks like quite good results. However, the accuracy drops drastically when turning into the testing and validation phase. This can cause with various things. One of them is the poor quality of the dataset, which causes the test and validation results to be inaccurate as in the training stage. Therefore, in further research, we will improve the image dataset of EUS-infected fish quality that needs to be taken directly.

Conclusion

This study concludes that the proposed approach can be used to carry out early detection solution of EUS disease in fish by Image Processing using Deep Learning, with the best architectural computing model using Segnet with MobileNet Backbone, which gets the best Mean IoU and Frequency Weighted IoU using validation data at 65.35% and 96.2%.

In future research we will use more datasets and better quality images to make precision value increased and used to detect other diseases, especially those that could be visible.

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