Automatic Analysis of Fish Farm Environment

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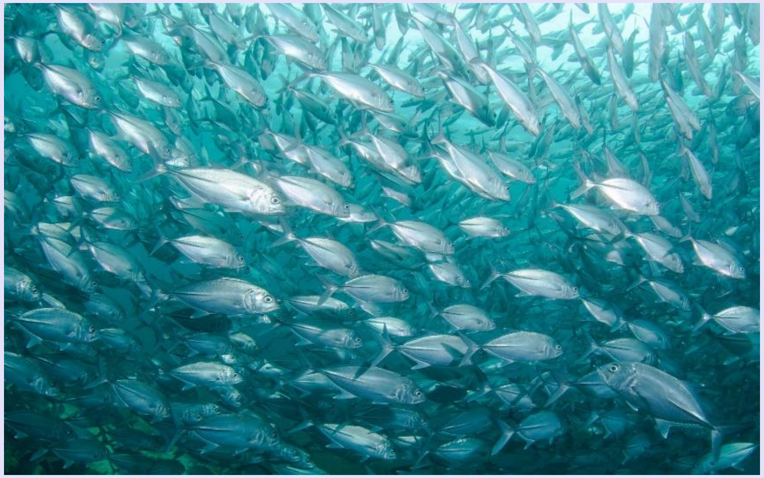
  Eng.Radwa Samy

Introduction 1/4

Fish farm environment strongly affects fish behavior and health. An uncontrolled environment may cause fish mortality.

The proposed system serves this field by analyzing fish farm environment and is presented in three consequent stages.



Introduction 2/4

First Stage

The system contains interface circuit that connects reality and computer recognition systems. The interface circuit consists of three main parts.

1) Raspberry Pi 3

2) Sensors

Temperature

PH

3) Camera

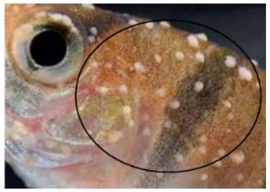
Introduction 3/4

Second Stage

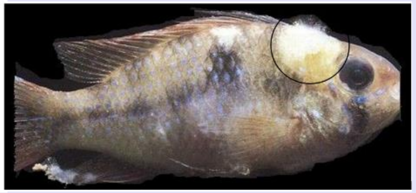
Fish Disease Classification

Our system classify three different types of fish diseases

EUS



ICH



COLUMNARIS

Fish Tracking

Our system tracks fish movements to hep in expectation of fish behavior

Introduction 4/4

Third Stage

The system sends a notification through an android application to inform users of any improper farm conditions and any detected infections.

Related Work I

Approach → Automatically detects or diagnoses the EUS diseased fish

Algorithm → Canny’s edge detection, Fast algorithm, PCA, Neural Network

Result → 86% on images taken from sources as NGRF, Lucknow and CIFRI

Related Work II

Approach → Detects or diagnoses the EUS diseased fish.

Algorithm → PCA, K-Means Clustering and HSV

Result → 90% on images collected from the different part of the Barak Valley, Assam

Related Work III

Approach

Extract pathogen area of infected fish and send notification about diagnosed disease and to the fish farmers

Algorithm

3x3 mean filter, edge sharpening filter, Morphological erosion and dilation operations, Polar and geometric feature, PCA

Result

90% on images collected from 8 different aquaculture farms in the Wando, Jindo, and Yosu areas of Korea

Problem Statement

- ❖ Building a system that **achieves higher accuracy** than manual checking.
- ❖ **Prevent** fish diseases from spreading in fish farms.
- ❖ **Solve** problem that experts may face such as to Fast fish movement and unclear vision.

Challenges

- There is no published public dataset
  - Fish4knowledge only and the site is for sale.
- Color segmentation approaches
  - Specify 1 odd color
- Limited human vision due to earthen ponds
- Concerns on diagnosing one disease at time
- A lot of measurements should be controlled
- Inaccurate Segmentation (As Color Segmentation).
- Fish Fast Movement

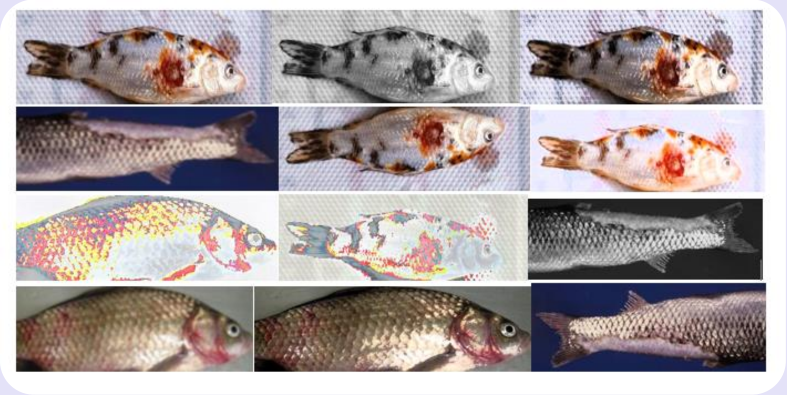
Dataset 1/2

Our data-set includes images of fish with the three types of fish diseases. Our data-set were collected from different internet resources. We also collected some images from “Africa Aquaculture Research and Training Center (AARTC), Abbassi, Egypt”

Prof. Dr. Ayman Anwar Ammar
Central Laboratory for Aquaculture Research (CLAR)
Egypt

Dataset 2/2

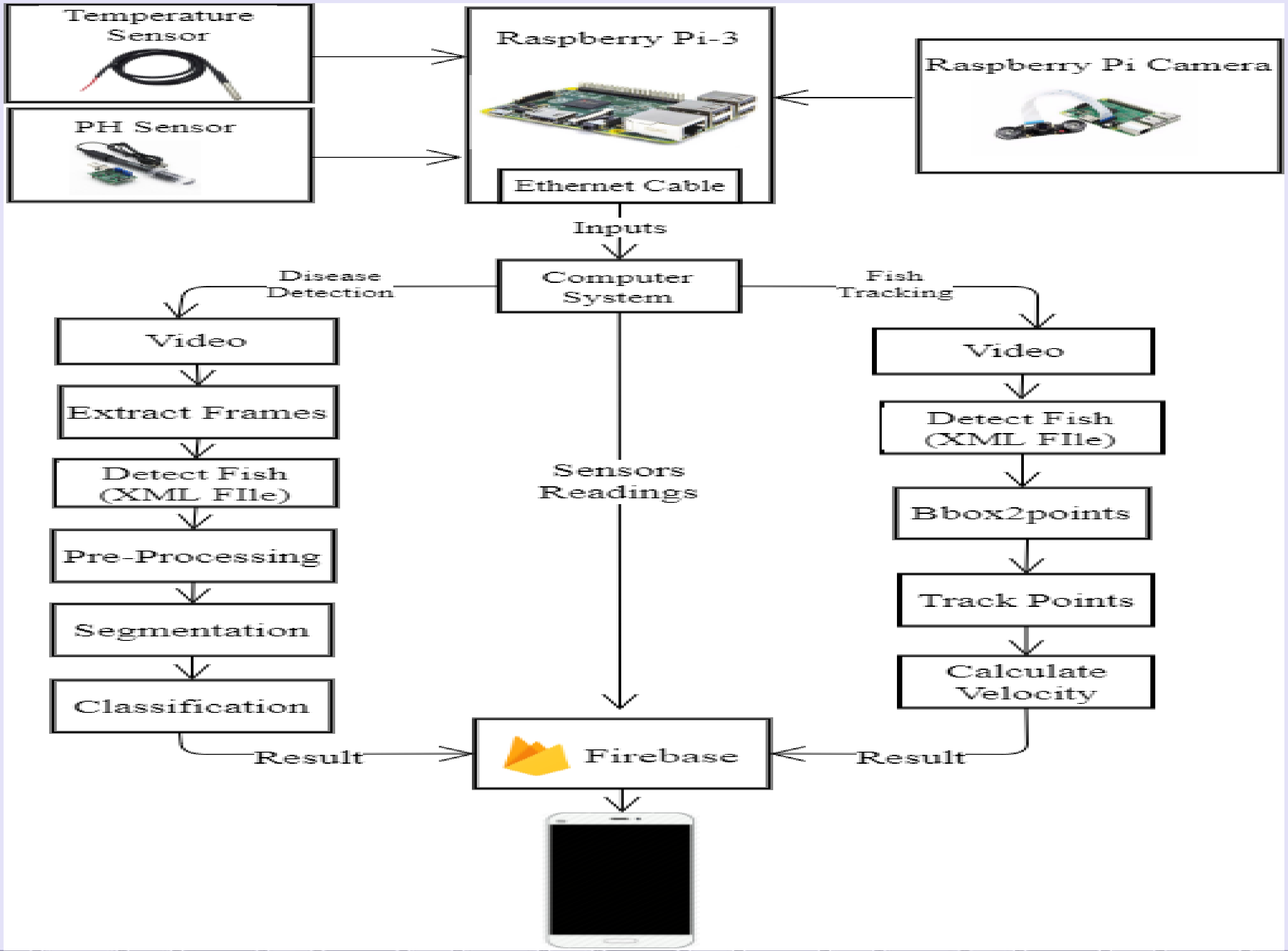
However, the number of images collected is not large enough to train the system. Therefore, we applied data augmentation to increase our samples because the collected images are not sufficient for training purpose.



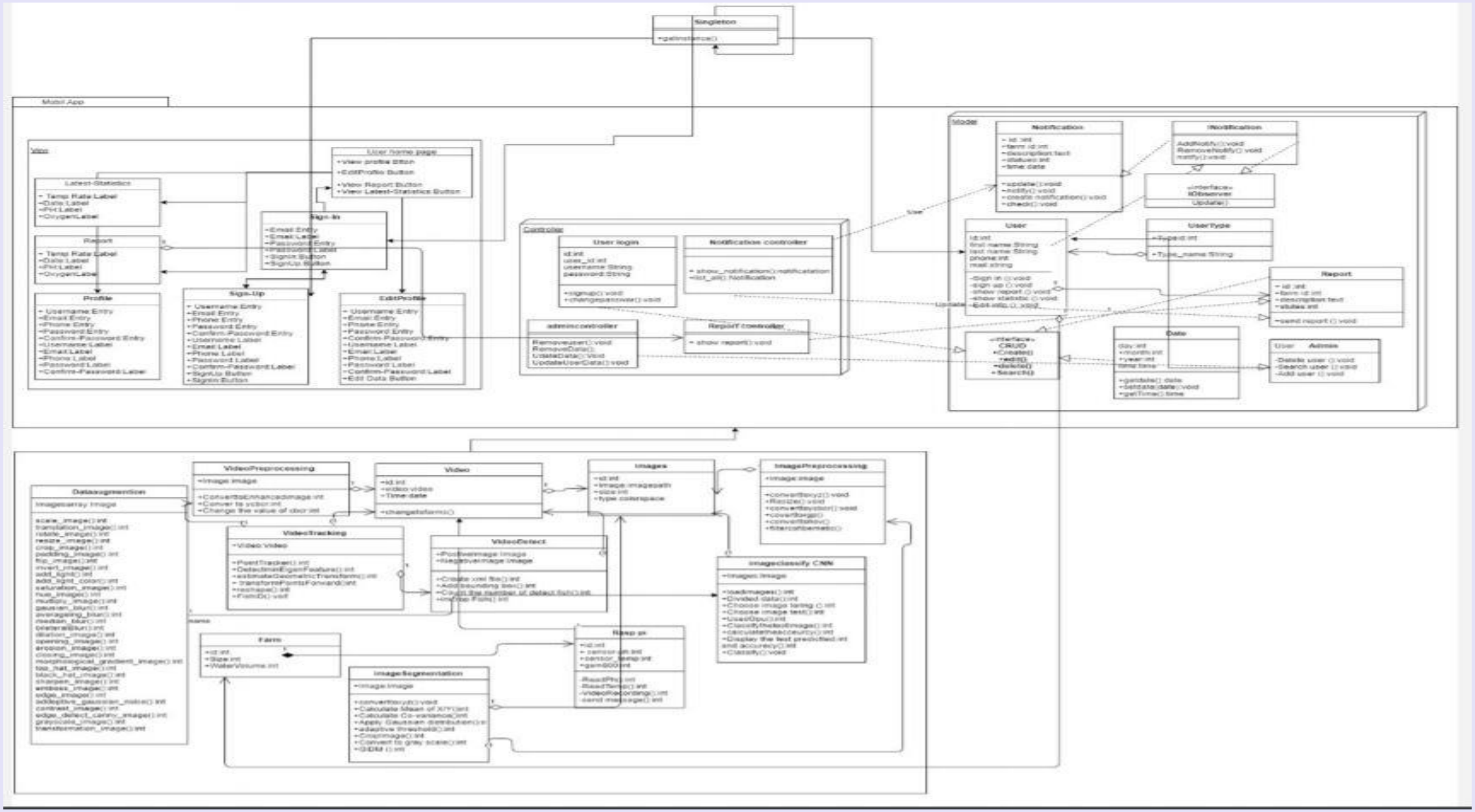
Motivation

- In Egypt, The intensive aquaculture farming has grown increasingly,
- especially in the deserts of northern Sinai. Fish farms are distributed through the
- Nile Delta region and concentrated mainly in the Northern lakes

System Overview



Class Diagram



Algorithms used

❖ Segmentation:

- Gaussian Distribution

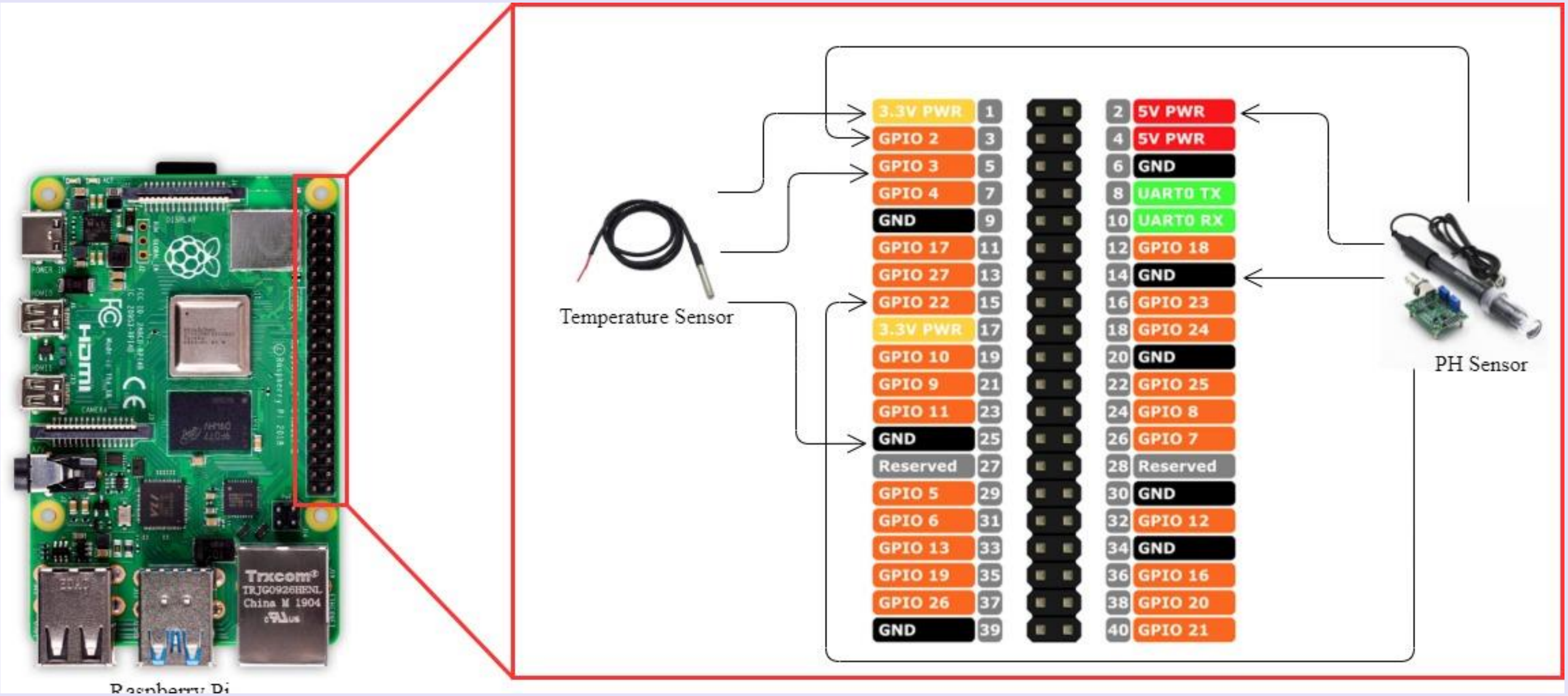
❖ Classification:

- Different architectures of convolutional neural network

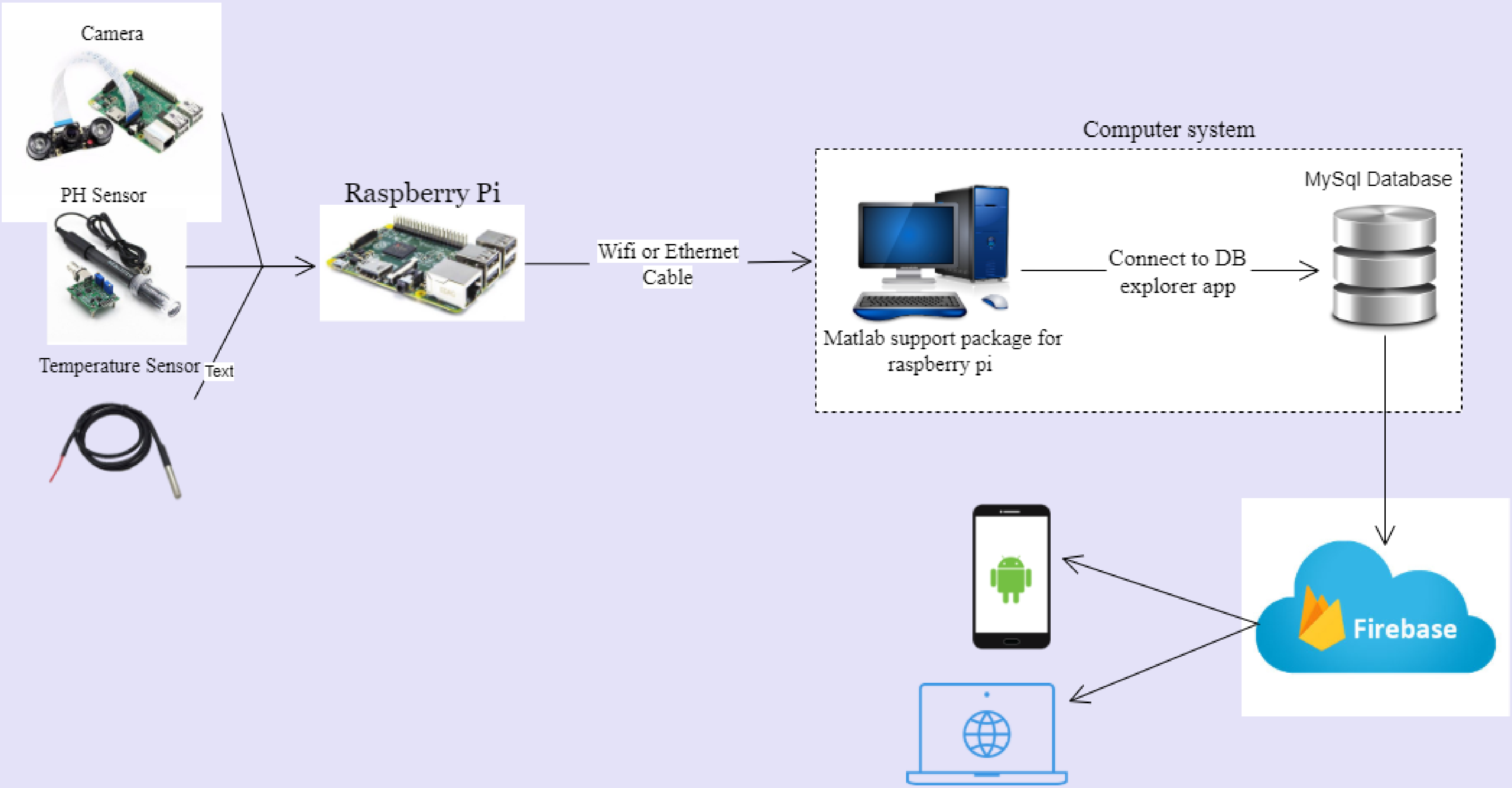
❖ Tracking

- Vision Point Tracking using Kanade-Lucas-Tomasi (KLT) feature-tracking algorithm

Raspberry Pi connection with sensors



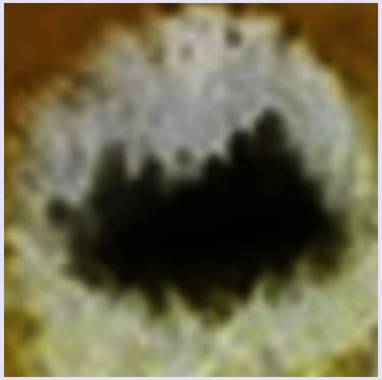
Hardware-circuit



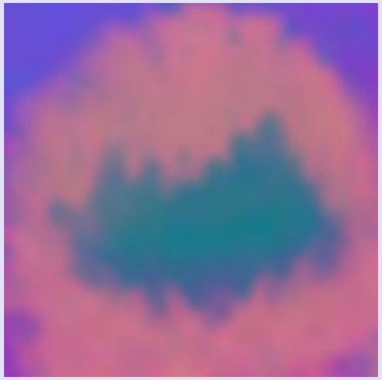
Pre-processing

During the pre-processing phase, Three different color spaces were applied; RGB, YCbCr, XYZ and LAB.

RGB



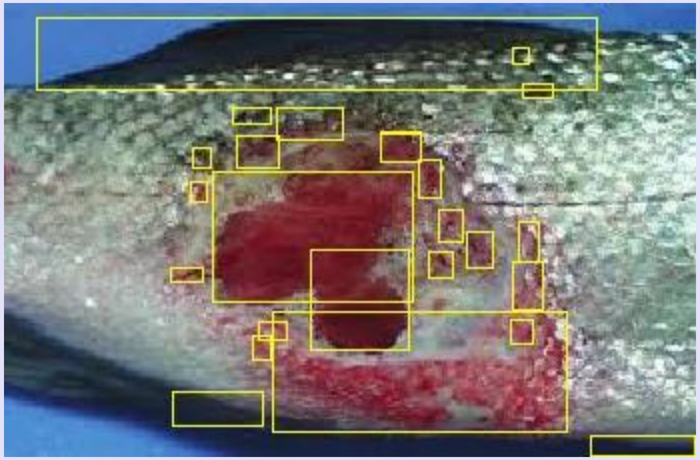
XYZ



YCBCR

Segmentation

For segmentation, we built a Gaussian distribution in three different color space, Building an effective Gaussian distribution requires a suitable computed means and covariances.



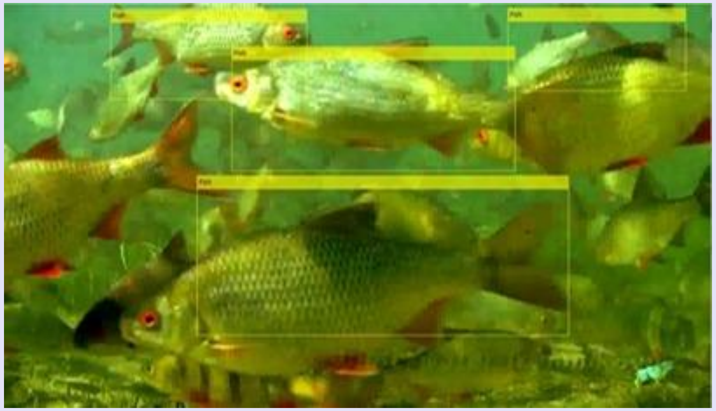
CNN Classification

- ❖ ResNet18
- ❖ ResNet50
- ❖ ResNet101
- ❖ Alex-Net
- ❖ VGG16
- ❖ VGG19
- ❖ mobilenetv2
- ❖ Xception
- ❖ Inceptionresnetv2
- ❖ Shufflenet
- ❖ Nasnetmobile
- ❖ Nasnetlarge
- ❖ Squeezenet
- ❖ Inceptionv3
- ❖ Densenet-201
- ❖ Googlenet

Model	Versions	Layers	Activation function	Input size	Convolution kernel size	Innovative point	Applications
ResNet ??	18 50 101	18 layers 50 Layers 101 Layers	RelU	224x224x3	ResNet initial convolution: 7×7. Resnet 50 and 101: 1×1, 3×3 and 1×1. ResNet 18: 3x3	ResNet overcomes degradation and vanishing gradient problems residual blocks that increases the number of hidden layers. The core idea of ResNet is introducing "identity shortcut connection" that skips one or more layers	ImageNet 2012 dataset ?? and Automatic Spoofing Detection [1]
VGG [2]	16 19	16 layers 19 layers	ReLU non-linear	224x224x3	VGG: 3x3	This network uses only 3x3 convolutional layers stacked on top of each other in increasing depth. VGG makes improvement over AlexNet by replacing large kernel-sized	ImageNet (ILSVRC-2012) and Classifying Cooking Object's State [3]
SqueezeNet [4]		18 layers	RelU	227x227x3	SqueezeNet: 1×1 and 3×3	SqueezeNet goal was to create small neural network with fewer parameters. It was able to achieve a 50X reduction in model size compared to AlexNet. SqueezeNet has advantage of fire module, which uses less filters to decrease number of parameters	ImageNet dataset, fine-grained object recognition [5] and Generic Visual Recognition [6]
DenseNet [7]	201	201 layers	ReLU	224x224x3	DenseNet: 7×7	In DenseNet, the feature-maps of all preceding layers are used as inputs, and its own feature-maps are used as inputs into all subsequent layers. DenseNet alleviate the vanishing-gradient problem and reduce the number of parameters	ImageNet (ILSVRC-2012) [8] and optical flow []
AlexNet [9]		8 layers	ReLU non-linear	227x227x3	Alexnet: 11x11, 5x5 and 1x1	AlexNet has large number of filters to perform the convolution operation of sizes 11×11, 5×5 and 3×3	ImageNet(LSVRC-2010) and high Spatial Resolution Remote Sensing [10]
GoogleNet [11]		22 layers	ReLU	224x224x3	GoogleNet: 5X5, 3X3 and 1X1	GoogleNet increases the depth of the network and gain a higher performance level. It is based on the concept of the inception module, it is the collection of convolution and pooling operation performed in a parallel manner so that features can be extracted using different scales	ImageNet(ILSVRC14) and High performance offline handwritten Chinese character recognition [12]
Mobilenetv2 [13]	2	54 layers	ReLU6	224x224x3	Mobilenetv2: 1x1, 3x3	Mobilenetv2 improves the performance of mobile models on multiple tasks. Mobilenetv2 is based on an inverted residual structure	ImageNet, Face Attribute Detection [14]
Xception [15]		71 layers	ReLU	299x299x3	Xception: 1x1,3x3	Xception involves Depthwise Separable Convolutions,it is supposed to be more efficient than classical convolution in terms of computation time. Xception relies on Shortcuts between Convolution blocks	ImageNet datase [16], Audio Event Detection and Tagging [17]
Inceptionv3 [18]	3	48 layers	ReLU	299x299x3	Inceptionv3: 3×3	In inceptionv3, computational efficiency and fewer parameters are realized	ImageNet(ILSVRC 2012) and flower classification [19]
ShuffleNet [20]			RelU	224x224x3	Shufflenet: 1x1,3x3	Shufflenet aim to explore a highly efficient architecture specially designed for limited computing ranges. Shufflenet allows more feature map channels and it is especially critical to the performance of very small networks. ShuffleNet achieves 13× actual speedup over AlexNet while maintaining comparable accuracy	ImageNet, Mobile devices [21] .

Object Detection

- In our proposed approach, we applied vision.CascadeObjectDetector System object, It detects objects in images by sliding window over the image. Then uses a cascade classifier to decide whether the window contains the object of interest.



Tracking

- Benchmark Trajectories for Multi-Object
- Tracking Histogram-based object
- Tracking vision. Point Tracker using KLT Algorithm

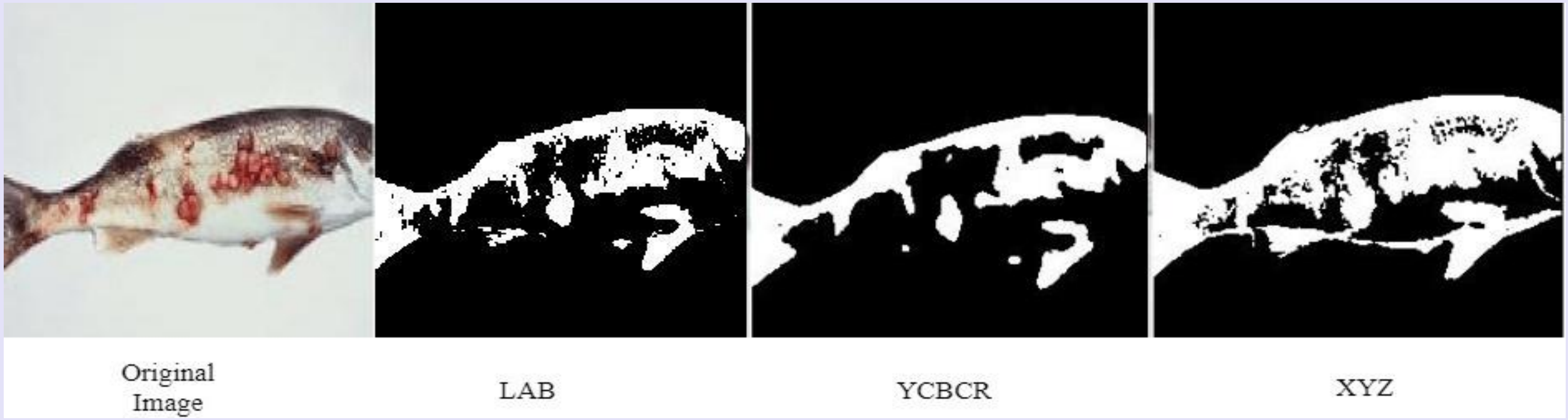
Segmentation Experiments 1/2

- For segmentation, we build the Gaussian model on XYZ, LAB and YCBCR color spaces. We found that EUS achieved good results in LAB color space, while ICH achieved good results in YCBCR color space and Columnaris in XYZ.

Table 5.2: Segmentation Experiment on different color spaces

Color Spaces	EUS	ICH	Columnaris
XYZ	51.9%	74.5%	85.8%
YCBCR	60.1%	79.8%	30.3%
LAB	79.7%	64.9%	16.1%

Segmentation Experiments 2/2



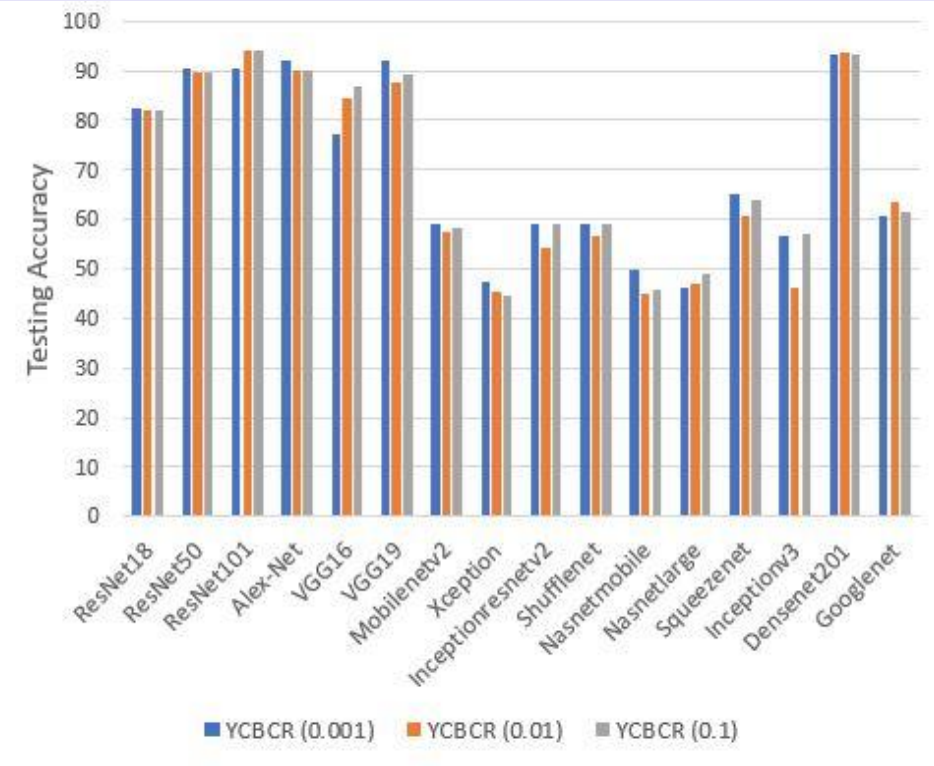
Cnn Experiments 1/3

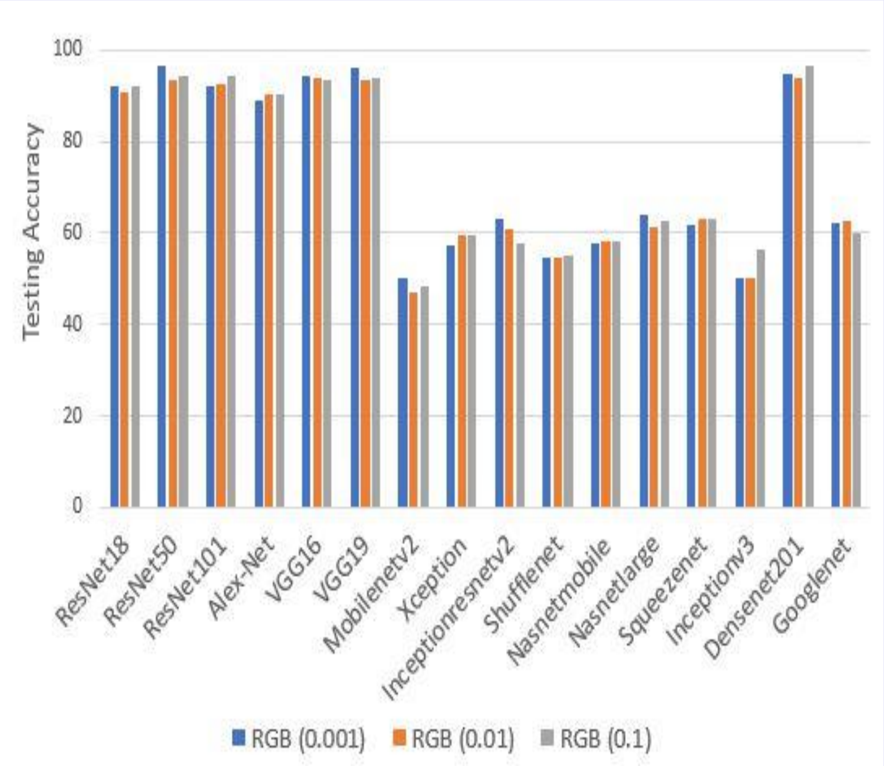
Achieved training accuracy result

Cnn Architectures	RGB(0.001)	RGB(0.01)	RGB(0.1)	YCBCR(0.001)	YCBCR(0.01)	YCBCR(0.1)	XYZ(0.001)	XYZ(0.01)	XYZ(0.1)
ResNet18	17,60%	14,50%	24,60%	13,60%	12,50%	12,50%	17,70%	18,50%	15,50%
ResNet50	18,70%	18,60%	15,60%	14,60%	15,50%	15,50%	24,50%	16,50%	16,50%
ResNet101	16,**80**%	14,%	16,50%	13,50%	14,50%	14,50%	15,50%	16,50%	19,50%
Alex-Net	12,60%	7,50%	9,60%	7,60%	9,50%	9,50%	8,50%	8,50%	8,60%
VGG16	14,50%	14,60%	14,50%	15,50%	18,40%	18,50%	16,60%	16,50%	15,50
VGG19	14,50%	14,60%	15,50%	21,50%	17,60%	14,60%	16,50%	15,50%	15,50%
Mobilenetv2	13,50%	7,60%	8,50%	17,60%	7,40%	7,40%	10,60%	9,60%	9,60%
Xception	12,50%	12,50%	11,50%	11,50%	16,60%	13,50%	13,50%	12,50%	12,60%
Inceptionresnetv2	11,50%	16,60%	12,60%	12,60%	11,50%	11,60%	15,50%	12,50%	12,60%
Shufflenet	7,50%	7,60%	7,50%	7,60%	7,50%	8,50%	21,50%	19,60%	15,60%
Nasnetmobile	9,50%	7,50%	7,60%	7,50%	7,50%	8,60%	15,60%	15,60%	15,60%
Nasnetlarge	13,60%	13,50%	15,50%	14,50%	14,60%	13,60%	14,50%	14,60%	14,60%
Squeezenet	7,50%	7,60%	7,50%	7,50%	7,50%	8,50%	8,60%	11,50%	8,50%
Inceptionv3	15,50%	14,40%	12,50%	15,60%	11,60%	11,50%	14,50%	16,50%	13,50%
Densenet201	**6.53**,60%	13,50%	7,60%	16,60%	7,50%	10,60%	12,60%	10,50%	7,60%
Googlenet	15,60%	14,50%	14,50%	14,50%	14,50%	16,50%	20,50%	16,50	19,50%

Cnn Experiments 2/3

Achieved test accuracy result





Cnn Experiments 3/3

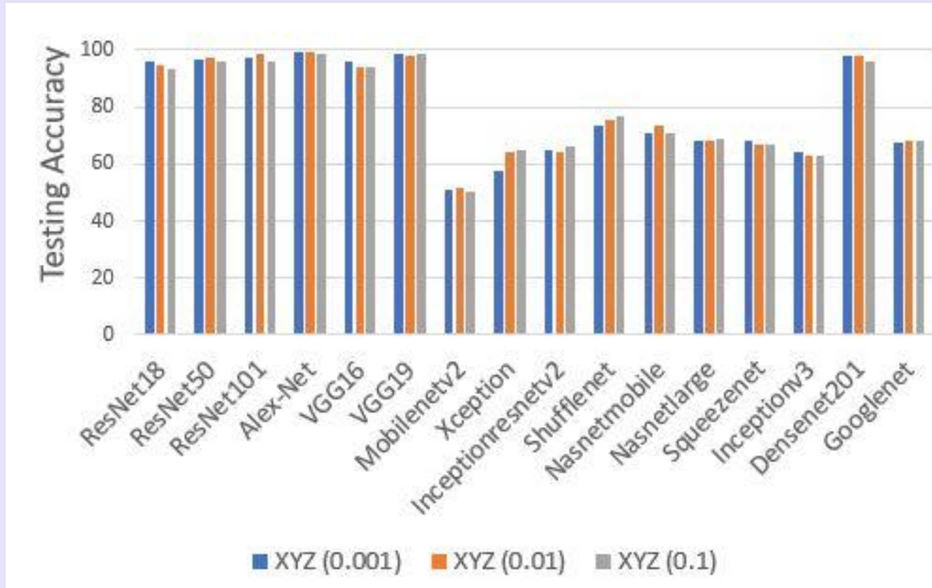
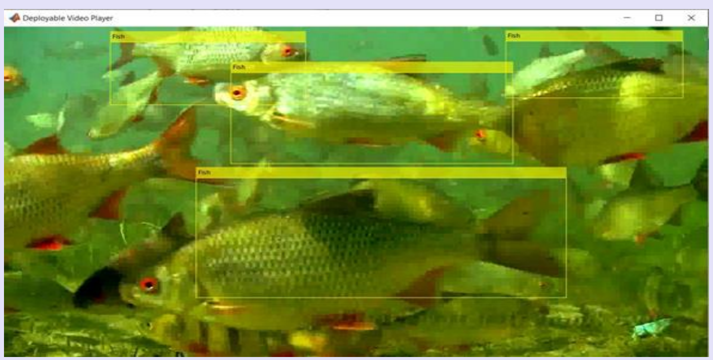


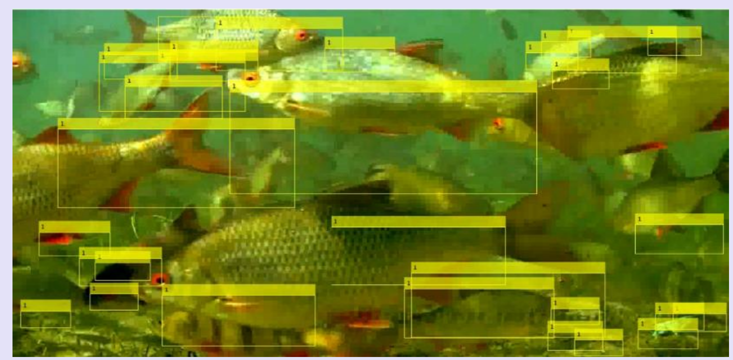
Table 5.4: Highest achieved results when applying different CNN architectures

CNN Architecture	Colorspace-Learning rate	Testing accuracy	Training accuracy	Traning time
AlexNet	XYZ-0.01	99.0446%	50%	7min,51sec
DenseNet-201	RGB-0.001	94.9045%	60%	6min,53sec
ResNet101	RGB-0.001	92.3567%	80%	16min,46sec

Object Detection Experiments

HOG Feature	Haar Feature
HOG features are often used to detect objects such as people and cars. They are useful for capturing the overall shape of an object.	Haar features are often used to detect faces because they work well for representing fine-scale textures.

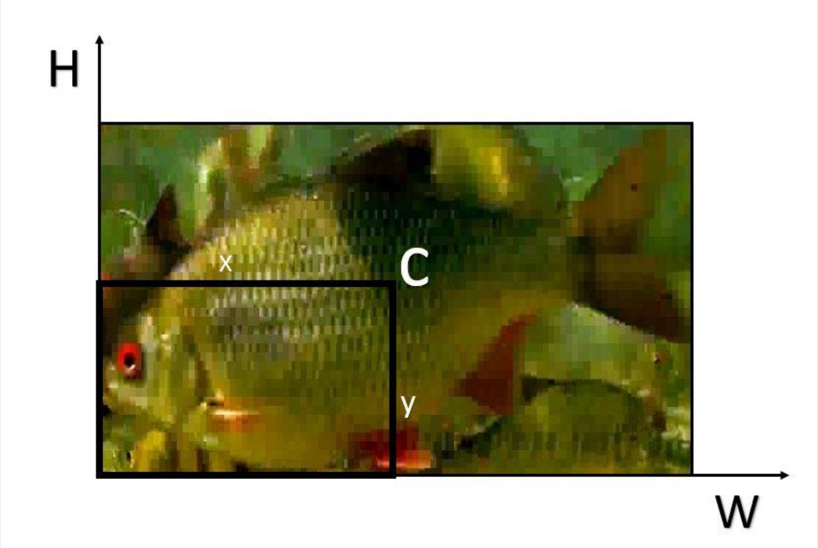




In our experiment, HOG feature outperformed haar feature and it achieved good accuracy when applying 'MinSize' and 'Threshold' to enhance the detection to be more accurate

Video Trajectory Experiments

Matrix Creation



matrix2

181x2 double

	1	2	3
1	372	102.5000	
2	1.0745e+03	94	
3	670	199	
4	687	458	
5	458.5000	104.5000	
6	682.5000	197	
7	578	526	
8	288	331.5000	
9	428.5000	105.5000	
10	279	138.5000	
11	719	191	

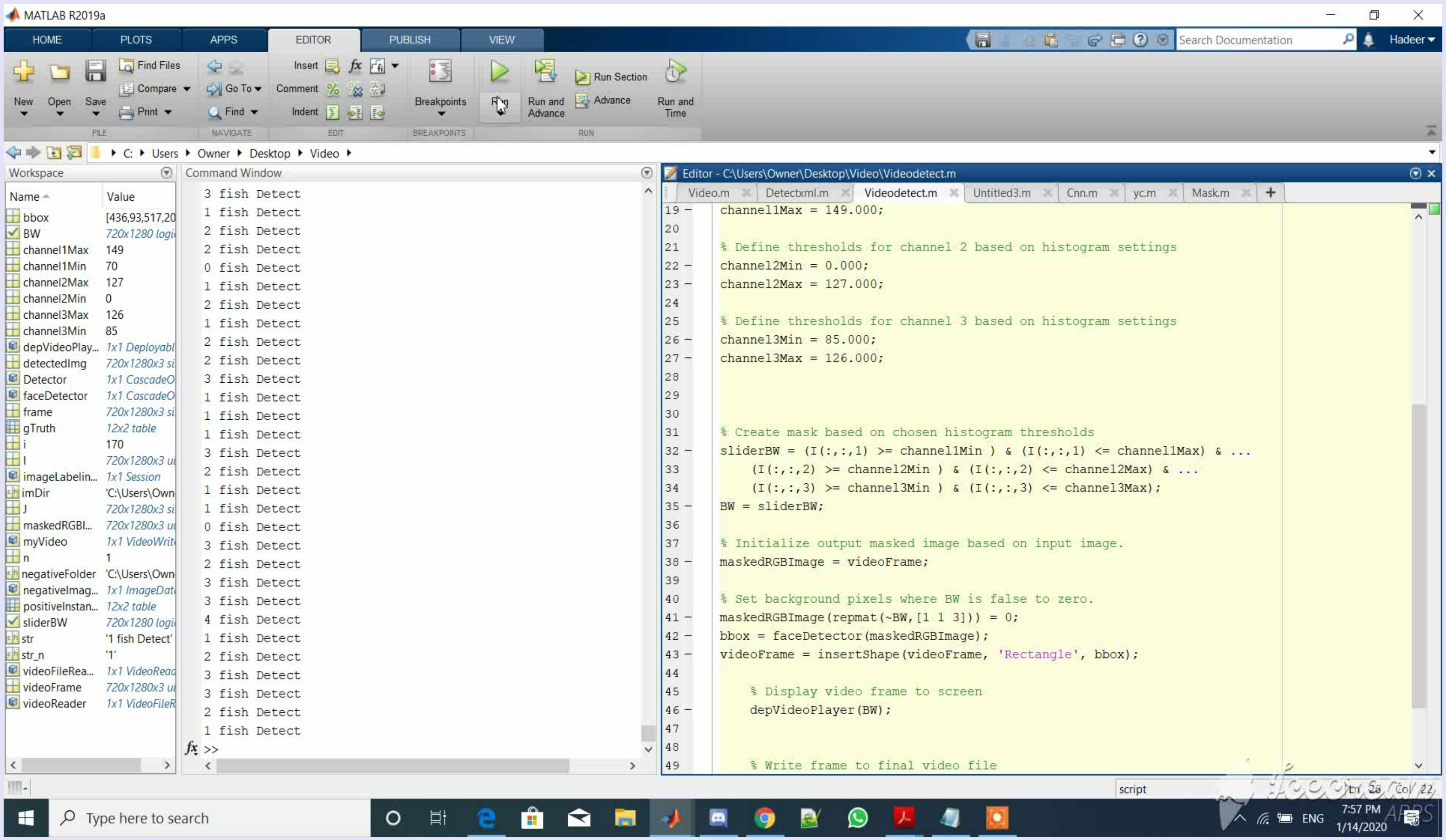
Tracking-Scenario

- Waypoints: calculate the position for each bonding box in the matrix

- Velocity in the navigation coordinate system at each way point in meters per second, specified as an N-by-3 matrix

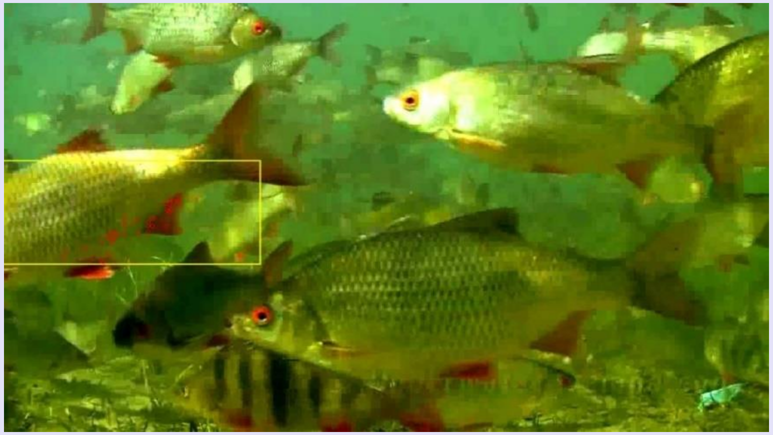
1 Time	2 Position			3 Velocity		
0	-10.0800	202.6500	33.9418	-11.2800	8.8100	-0.0588
1.9608	-21.1200	211.2700	33.8846	-11.2500	8.7900	-0.0577
2.9412	-32.1300	219.8800	33.8287	-11.2100	8.7800	-0.0565
3.9216	-43.1000	228.4900	33.7738	-11.1600	8.7800	-0.0554
4.9020	-54	237.1000	33.7201	-11.0900	8.7900	-0.0543
5.8824	-64.8500	245.7300	33.6674	-11.0300	8.8100	-0.0531
6.8627	-75.6200	254.3800	33.6158	-10.9500	8.8400	-0.0520
7.8431	-86.3100	263.0700	33.5654	-10.8600	8.8800	-0.0510
8.8235	-96.9100	271.8000	33.5159	-10.7600	8.9300	-0.0499
9.8039	-107.4100	280.5800	33.4676	-10.6600	8.9900	-0.0488
10.7843	-117.8100	289.4300	33.4202	-10.5500	9.0500	-0.0478
11.7647	-128.0900	298.3400	33.3739	-10.4200	9.1300	-0.0467
12.7451	-138.2500	307.3200	33.3286	-10.2900	9.2100	-0.0457
13.7255	-148.2700	316.3900	33.2843	-10.1500	9.2900	-0.0447
14.7059	-158.1500	325.5400	33.2410	-10	9.3800	-0.0437
15.6863	-167.8800	334.7900	33.1987	-9.8400	9.4800	-0.0427
16.6667	-177.4500	344.1400	33.1574	-9.6700	9.5900	-0.0417
17.6471	-186.8500	353.5900	33.1170	-9.5000	9.6900	-0.0407
18.6275	-196.0600	363.1500	33.0776	-9.3100	9.8100	-0.0397
19.6078	-205.1000	372.8200	33.0391	-9.1100	9.9200	-0.0388
20.5882	-213.9300	382.6100	33.0016	-8.9100	10.0400	-0.0378
21.5686	-222.5500	392.5100	32.9649	-8.6900	10.1600	-0.0369
22.5490	-230.9600	402.5400	32.9292	-8.4600	10.2800	-0.0360
23.5294	-239.1400	412.6800	32.8944	-8.2300	10.4100	-0.0351
24.5098	-247.0900	422.9400	32.8604	-7.9800	10.5300	-0.0342

Track Segmentation



Final result

- In the tracking phase, Vision.pointTracker is applied by using the Kanade-Lucas-Tomasi (KLT) algorithm . The Estimate Geometric Transformation is then applied to determine the transformation between the point locations in the previous and current frames

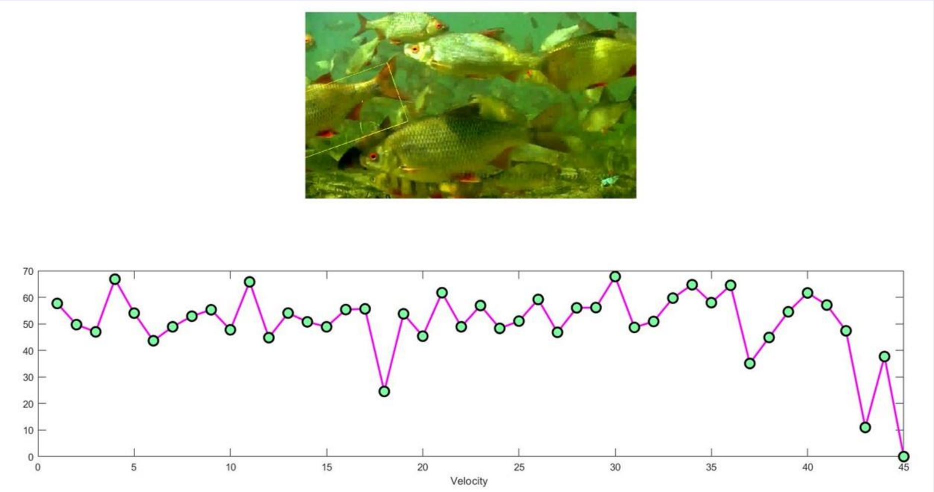


Fish Tracking Experiments

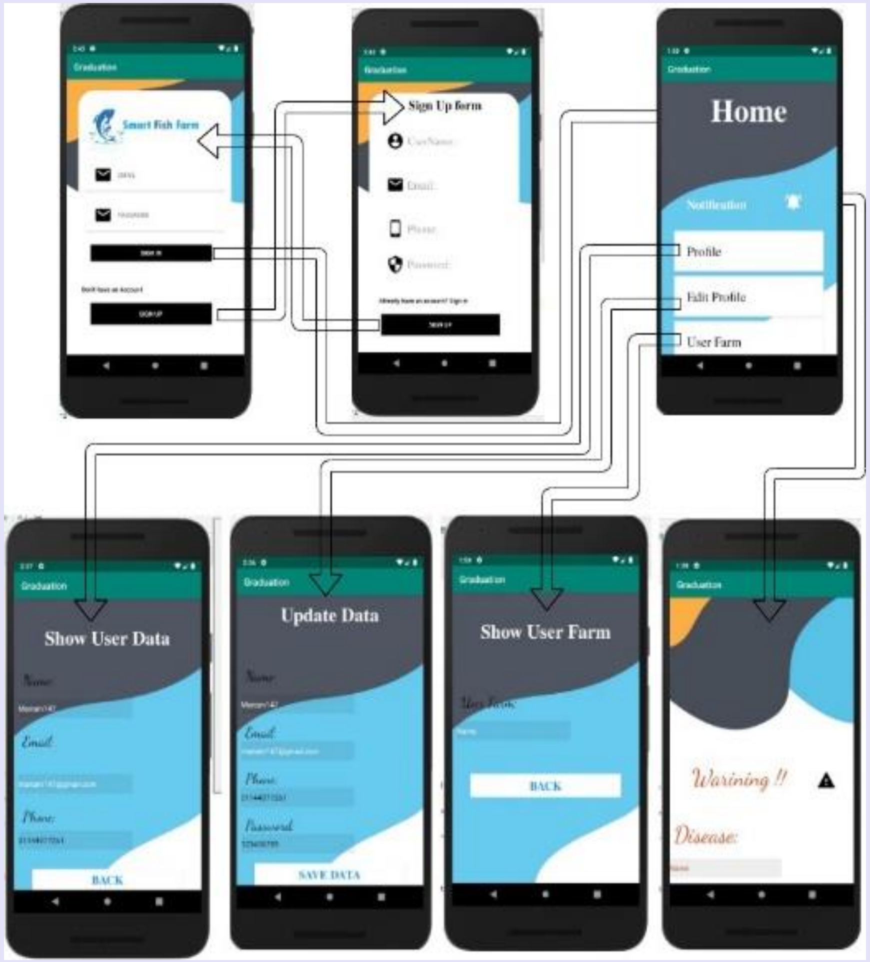
After applying fish tracking, fish velocity is then calculated to help in the expectation of fish behavior.

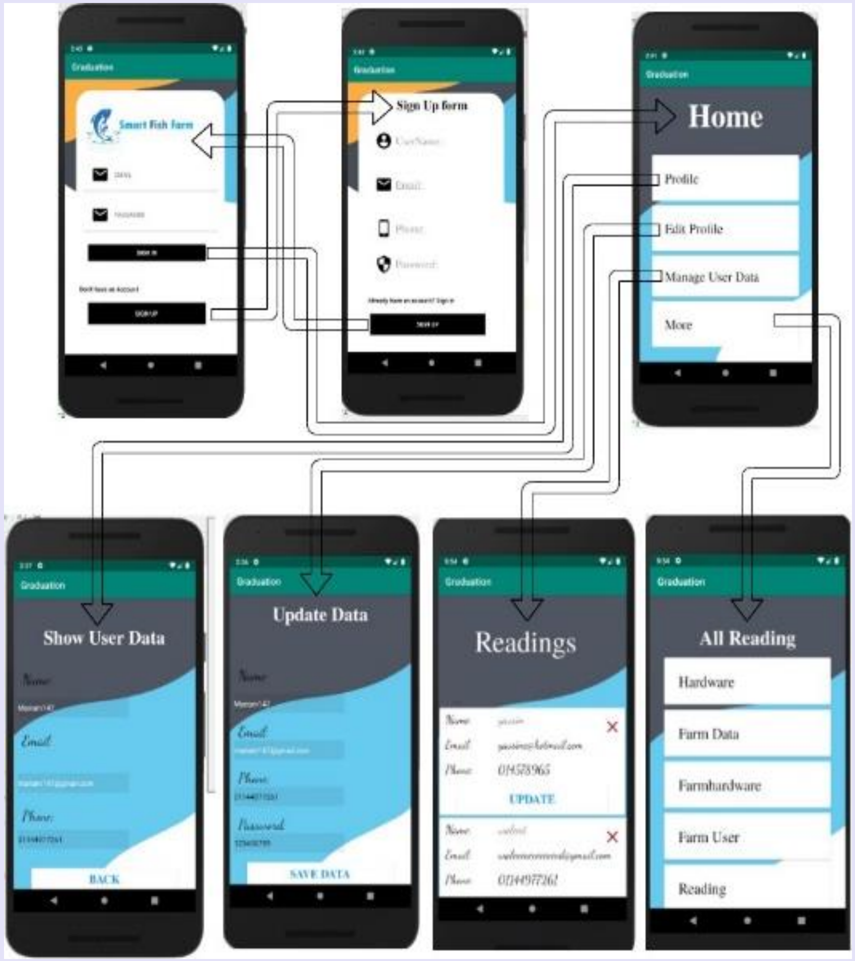
The velocity is calculated my multiplying the distance of centroids between previous frame and current frame.

This is done by getting the video frame rate (frame/second), the video scale (meter/pixel).

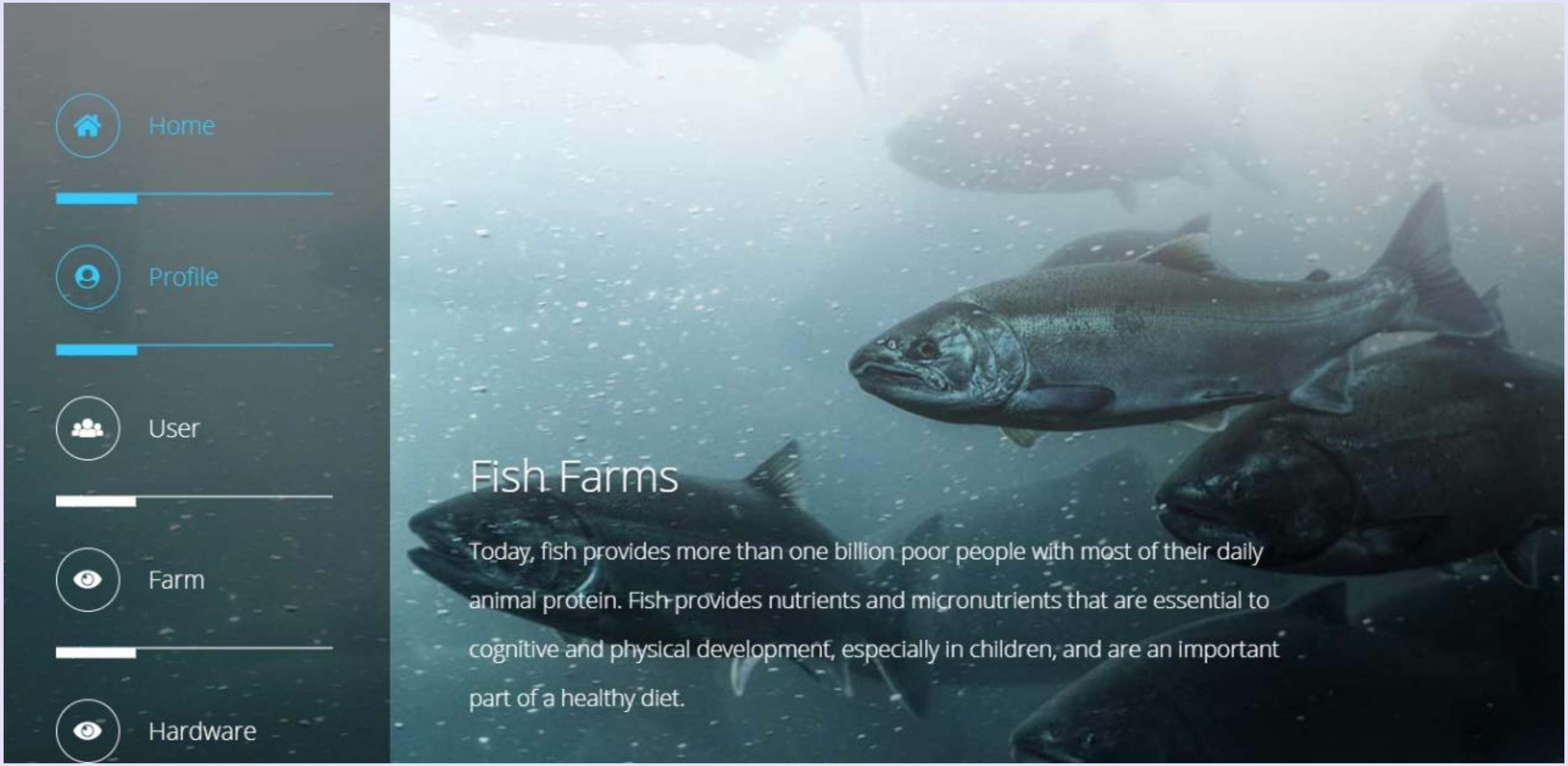


User interface Android

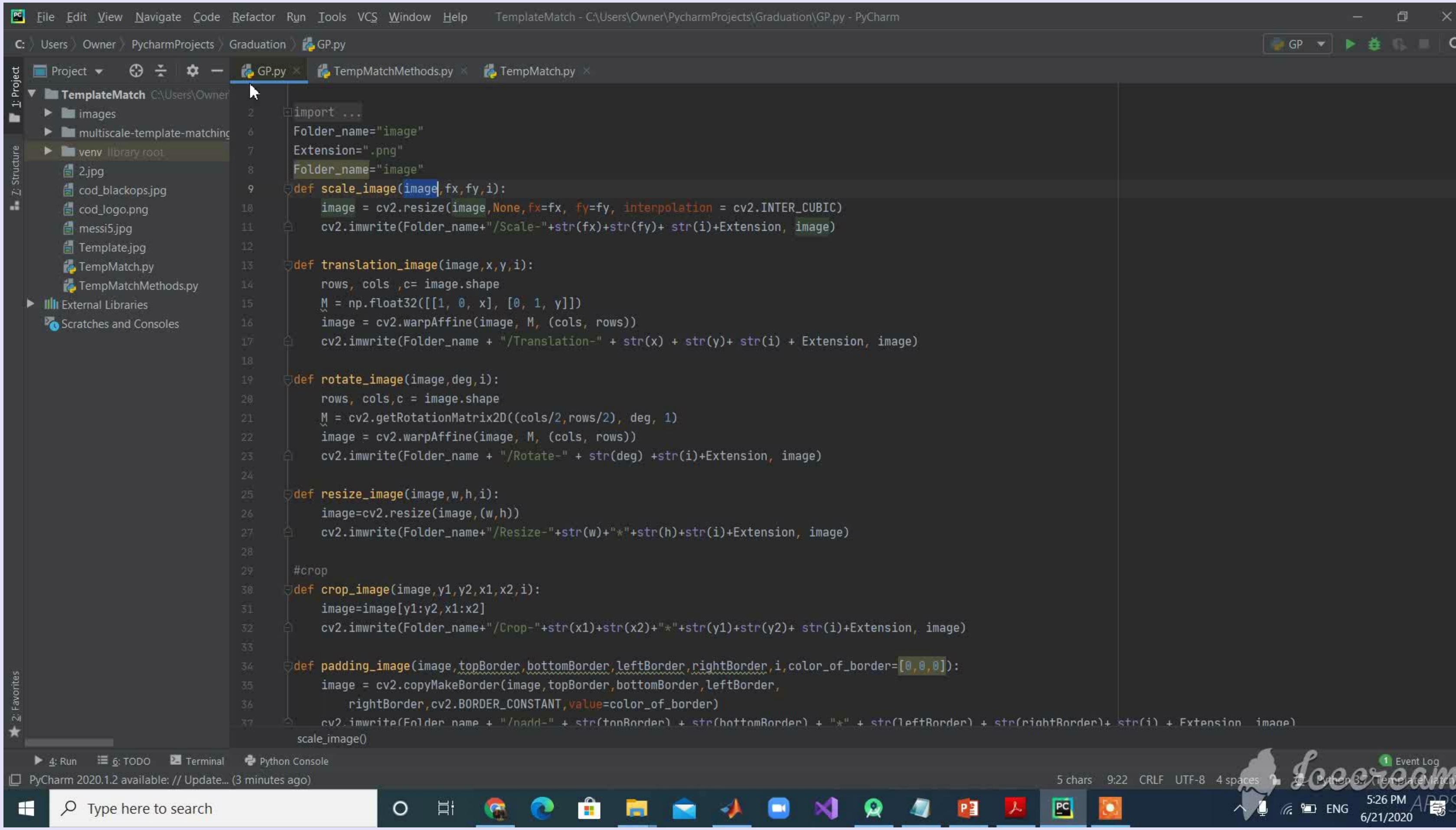




User interface Web



Data Augmentation Demo



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User Expert

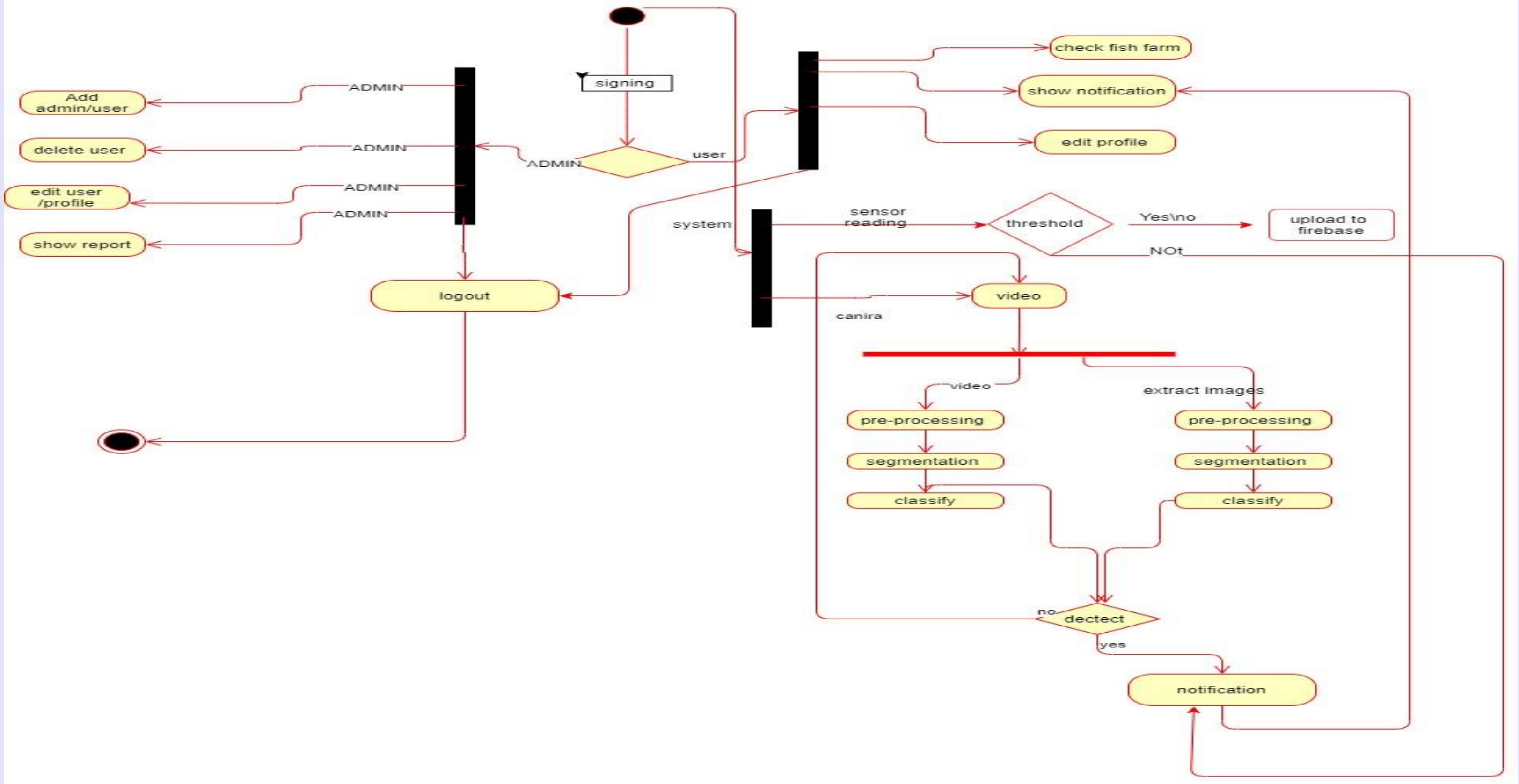
أ.دكتور خالد احمد السيد

رئيس مجلس إدارة الهيئة العامة للثروة السمكية

Thank You

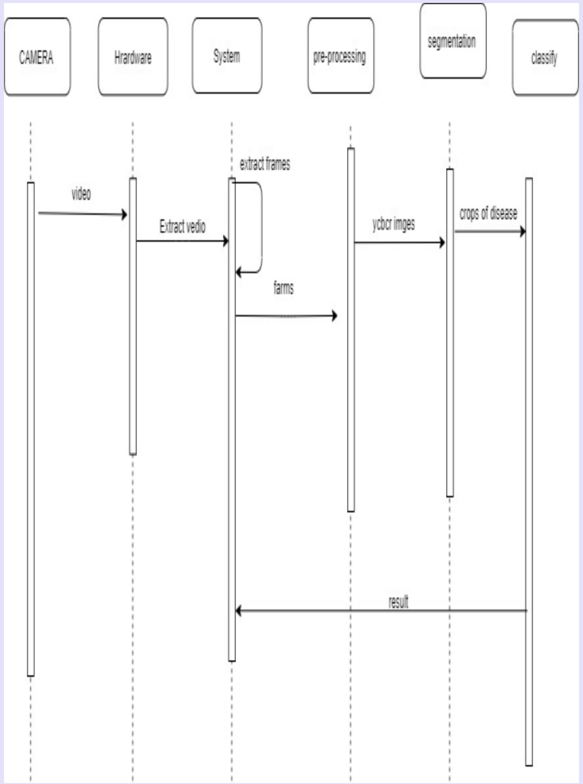
Appendix

Activity Diagram

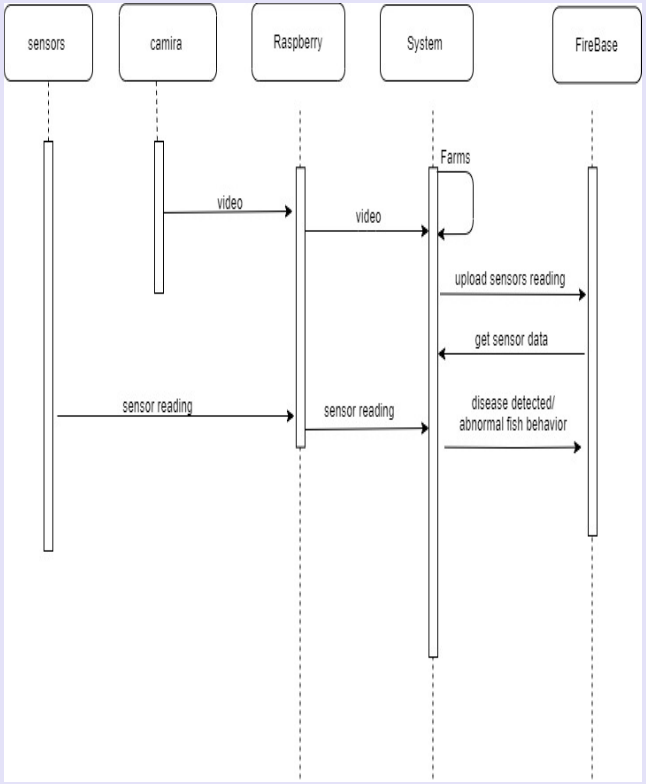


Sequence Diagram

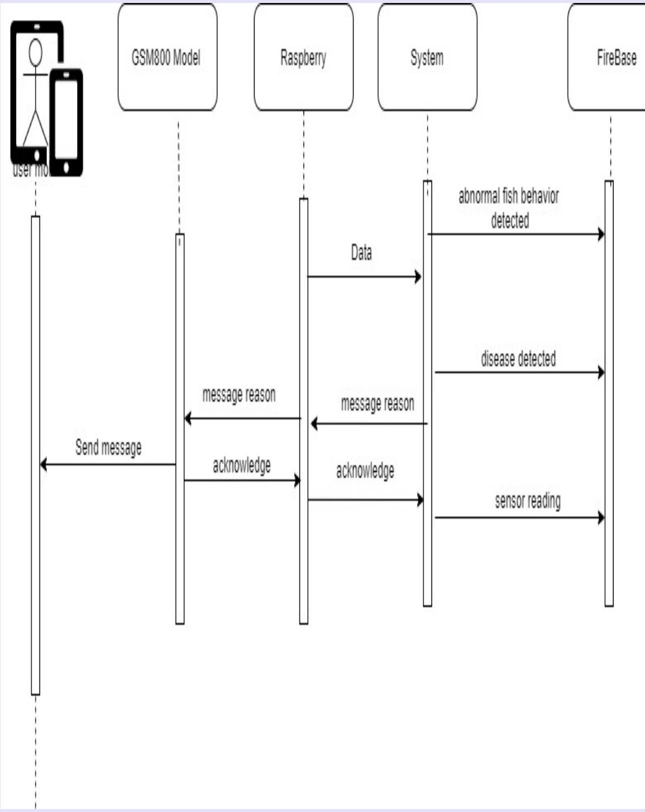
1



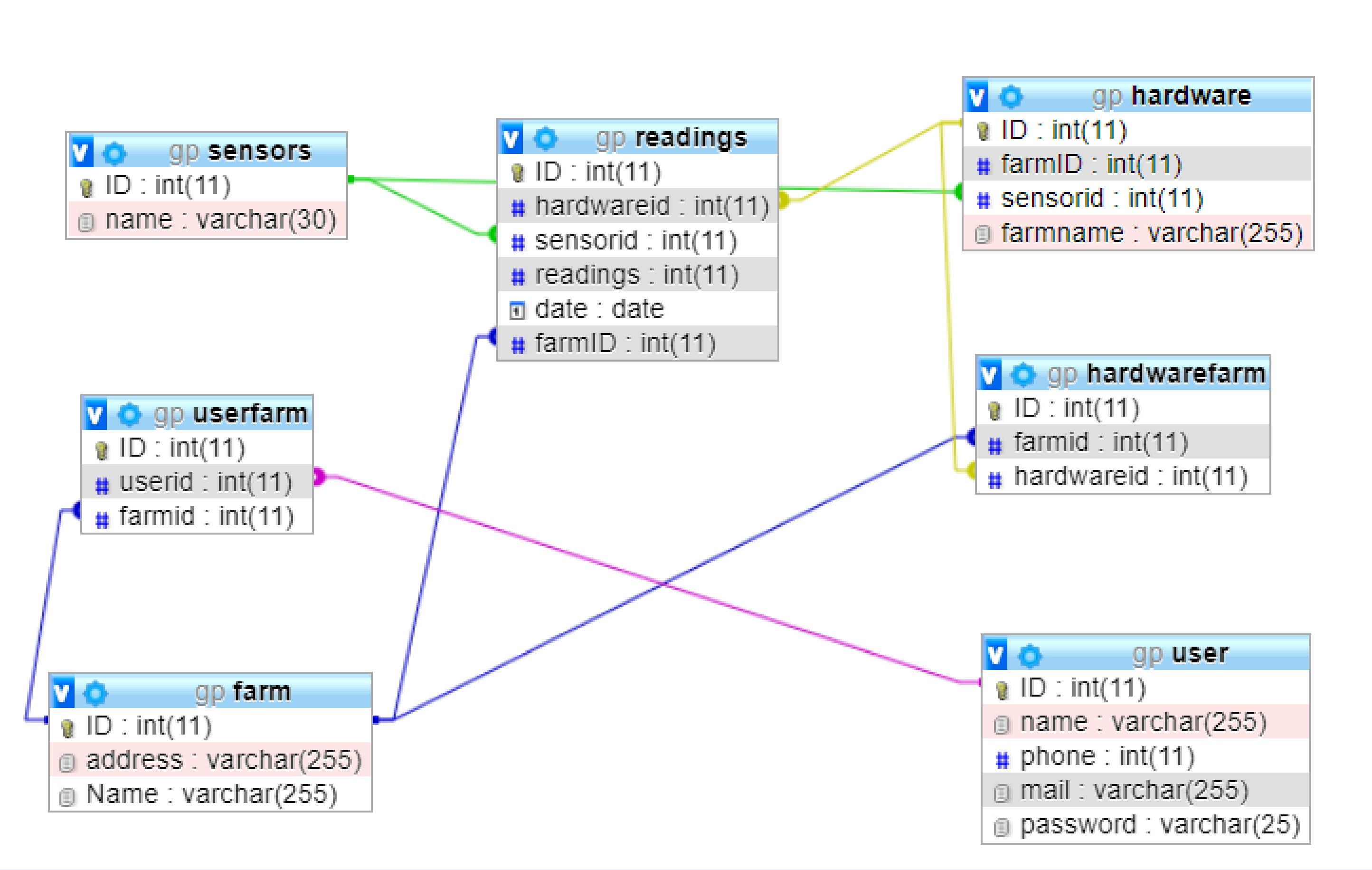
2



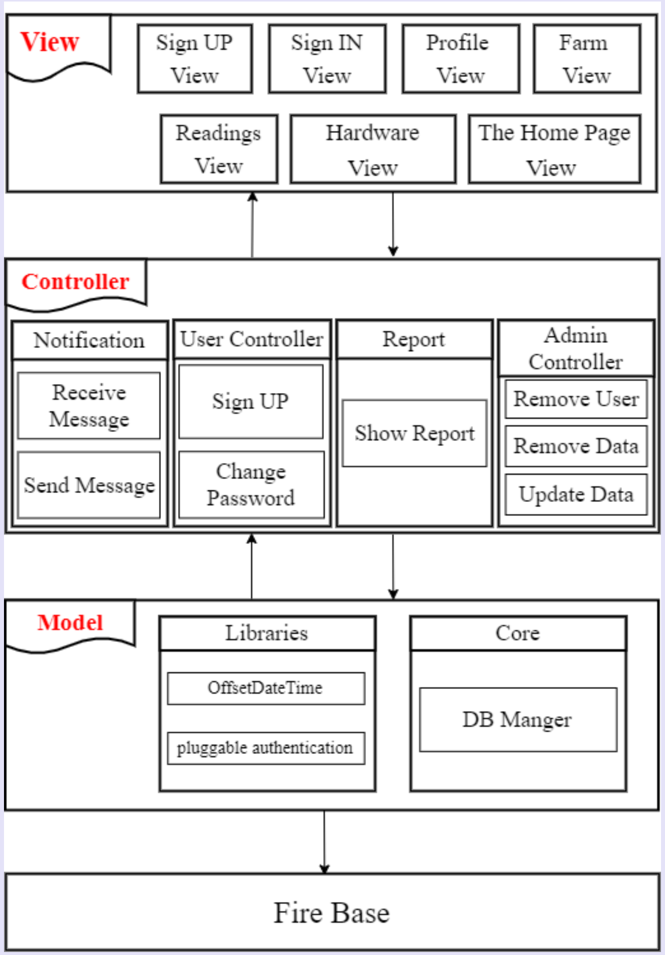
3



Database Shema



MVC Architecture



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