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Early Stage of Cervical Cancer Detection Using YOLOv5

Submitted by

Md. Zahid Hasan Ontor

ID: 181-35-289

Department of Software Engineering

Daffodil International University

Supervised by

S A M Matiur Rahman

Associate Professor

Department of Software Engineering

Daffodil International University

Co-supervised by

Ms. Syeda Sumbul Hossain

Lecturer,

Department of Software Engineering

Daffodil International University

A thesis submitted in partial fulfillment of the requirement for the degree of Bachelor of Science in Software Engineering.

APPROVAL

This **thesis** entitled on “**Early Stage of Cervical Cancer Detection Using YOLOv5**”, submitted by **Md. Zahid Hasan Ontor (ID: 181-35-289)** to the Department of Software Engineering, Daffodil International University has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of Bachelor of Science in Software Engineering and approval as to its style and contents.

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Daffodil International University



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Internal Examiner 1

S A M Matiur Rahman
Associate Professor
Department of Software Engineering
Daffodil International University

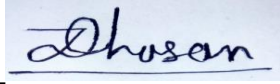


Internal Examiner 2

Syeda Sumbul Hossain
Lecturer (Senior Scale)
Department of Software Engineering
Daffodil International University

DECLARATION

It hereby declares that this thesis has been done by us under the supervision of **S A M Matiur Rahman**, Associate Professor and **Ms. Syeda Sumbul Hossain**, Lecturer, department of Software Engineering, Daffodil International University. It is also declared that neither this thesis nor any part of this has been submitted elsewhere for award of any degree.



Md. Zahid Hasan Ontor

Id: 181-35-289

Department of Software Engineering

Faculty of Science & Information Technology

Daffodil International University

Certified by:



S A M Matiur Rahman

Associate Professor

Department of Software Engineering

Faculty of Science & Information Technology

Daffodil International University



Ms. Syeda Sumbul Hossain

Lecturer

Department of Software Engineering

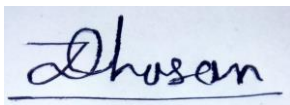
Faculty of Science & Information Technology

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Md. Zahid Hasan Ontor

Id: 181-35-289

Department of Software Engineering

Faculty of Science & Information Technology

Daffodil International University

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LIST OF NOMENCLATURE

Terms	Nomenclature
ML	Machine Learning
DL	Deep Learning
AP	Average Precision
gflops	Gigaflops
Exp	Experiment
Val	Validation
Cls	Class
Obj	Object
mAP	Mean Average Precision
HIV	Human Immunodeficiency Virus
HPV	Human Papilloma Virus
TP	True Positive
TN	True Negative
FP	False Positive
FN	False Negative

ABSTRACT

Cervical cancer is a very familiar disease all over the world. It is the tacit slayer. For this many women lose their life. Early detection of cancer cells can save many lives. To do this we have collected some cervical cancer pap-smear test image data. After preprocessing and labeling these data we applied a deep learning model called yolov5. The model has four versions, from these we have applied three versions. All of the model's variations performed admirably. We are the first authors who are working to detect cervical cancer cells by applying the yolov5 model, and we were able to detect cervical cancer cells with a pap-smear test data set both from image and video data. The model can effectively detect cervical cancer photos, according to the findings of the experiments. In the medical field, our study will be quite useful. It can be a good option for radiologists and help them make the best selections possible.

Keywords- Cervical Cancer, Pap-Smear, Deep Learning, Activation Function, YOLOv5.

CHAPTER 1

INTRODUCTION

1.1 Problem outline

Cancer is a disease in which the cells of the body grow out of control. Cancer is usually called after the area of the body where it originates, even if it spreads to other regions of the body. Cervical cancer is a form of cancer that starts in the cervix. The cervix connects the vaginal canal (birth canal) to the uterus' upper section. Cervical cancer is one of the malignant and critical cancer all over the world. Many life is falling down for this deadly disease. It develops in a woman's cervix. The main types of cervical cancers are squamous cell carcinoma and adenocarcinoma [6]. Basically, human papillomaviruses (HPV) are responsible for developing this disease. According the National Cancer Institute there are about 14 high-risk HPV types including HPV 16, 18, 31, 33, 35, 39, 45, 51, 52, 56, 58, 59, 66, and 68 present. Among these cancer is caused by type16 and type18 [7]. According to the world health organization, it is the fourth leading cause of death from cancer. Cervical cancer was diagnosed in an estimated 570 000 women worldwide in 2018, with 311 000 women dying from the disease [1]. Cervical cancer is distributed differently over the world, with more than 85 percent of deaths taking place in underdeveloped countries [2]. Cervical cancer is most common in Sub-Saharan Africa, accounting for more than 90% of all cases [3]. HIV-affected women must be aware of this cancer because these patients are more likely to get this cancer.

Since the affected women belong to lower or middle-class families for this reason they are not properly concerned about the disease. Even they do not have enough liquid for treatment

against cancer though the disease is very malignant. Treatment of this cancer is expensive and when a patient faces a very critical moment then doctors decide to uproot the cervix from the patient's body. If doctors easily identify the early stage of cancer then they treat the patients properly. Cervical cancer is a type of cancer that begins in the cervix and has no symptoms until it is advanced. When examined under a microscope, this cancer is divided into two forms. Squamous cell carcinoma is the first form, and it begins in the cells that line the bottom of the cervix. Adenocarcinoma is another type of cancer that originates in gland-related cells in the upper section of the cervix [8]. Cervical cancer has no symptoms in the early stages, although it can cause bleeding or discharge from the vaginal area that is not usual for you, such as bleeding after sex [4]. According to the Cancer.Net Editorial Board, there are some types of tests to observe cervical cancer, such as Pap test, HPV typing test, Colposcopy, Biopsy, Pelvic examination under anesthesia, X-ray, Computed tomography (CT or CAT) scan, Magnetic resonance imaging (MRI), Positron emission tomography (PET) or PET-CT scan, Molecular testing of the tumor, Cystoscopy and Sigmoidoscopy (also called a proctoscopy)[5]. All of the treatments are very costly and time-consuming for this reason lower class and middle-class families are unable to bear the cost of treatments. On the other hand, many lower-class countries don't have the facilities of that kind of treatment. It is very important to solve the problem to give a safe and beautiful life for our mother race.

A process in which cells are gently removed from the surface of the cervix and the surrounding area with a tiny brush in order to be examined under a microscope for cervical cancer or cell alterations that could lead to cervical cancer. Other problems, such as infections or inflammation, may be detected by a Pap smear. It's normally done in conjunction with a pelvic exam, but it can also be done in conjunction with a test for certain forms of human papillomavirus. In our task, we have worked with an image dataset. Sometimes face problems

in collecting datasets. Every medical image is very critical in labeling and annotating. Without the proper annotation, the dataset won't train appropriately. On the other hand, noise plays a bad impact in detecting disease clearly. Because the cervix is a small object, pinpointing the malignant site is difficult. Accuracy is the major fact in detecting the real-time object. When coming to less accuracy then we have to hyper-tuning our models, such as reducing and increasing batch size and epochs.

Earth is a place which is very amazing. From the beginning of civilization, the world has been developing day by day because human beings have created and discovered new and more advanced things and technologies. There is no doubt that old is gold but with the touch of new and advanced technologies, old people become useless day by day undoubtedly. Artificial intelligence (AI) is modern technology. Nowadays it has been used in various sectors. In the medical sector, it is performing a good job too. Machine learning and deep learning are parts of artificial intelligence (AI) [9]. Here we use a convolutional neural network (CNN) based model called YOLOv5 to perform our task. It is a very advanced model and it works very well than other models and algorithms. YOLOv5 is used for real-time object detection based on the data streams. We are the first authors who are working with this model to detect cervical cancer because there is no cervical cancer-related paper with the YOLOv5 model.

1.2 Motivation

The overall perspective of this research is to help the medical sector to detect cervical cancer cells in early stage within a short time and without any doubt. I hope that our contribution really very helpful for our mother race.

1.2.1 Elements of our study

We studied data analysis and data processing techniques, ML, DL YOLOv5 model workflow, evaluation matrix, activation function, loss function etc. to complete our whole task.

1.2.2 Interest behind our research

Because for a poor or middle class belonged woman's/girls who doesn't want to test their cervix scaring a high cost, our model will eradicate their cost fear because it is time efficient for this reason it will cost efficient.

1.3 Research Objectives

- To prevent this deadly disease.
- Recognize the early stage of this cancer by using some deep learning algorithms and models.
- Cost and time efficient diagnostics system.

1.4 Research Schedule

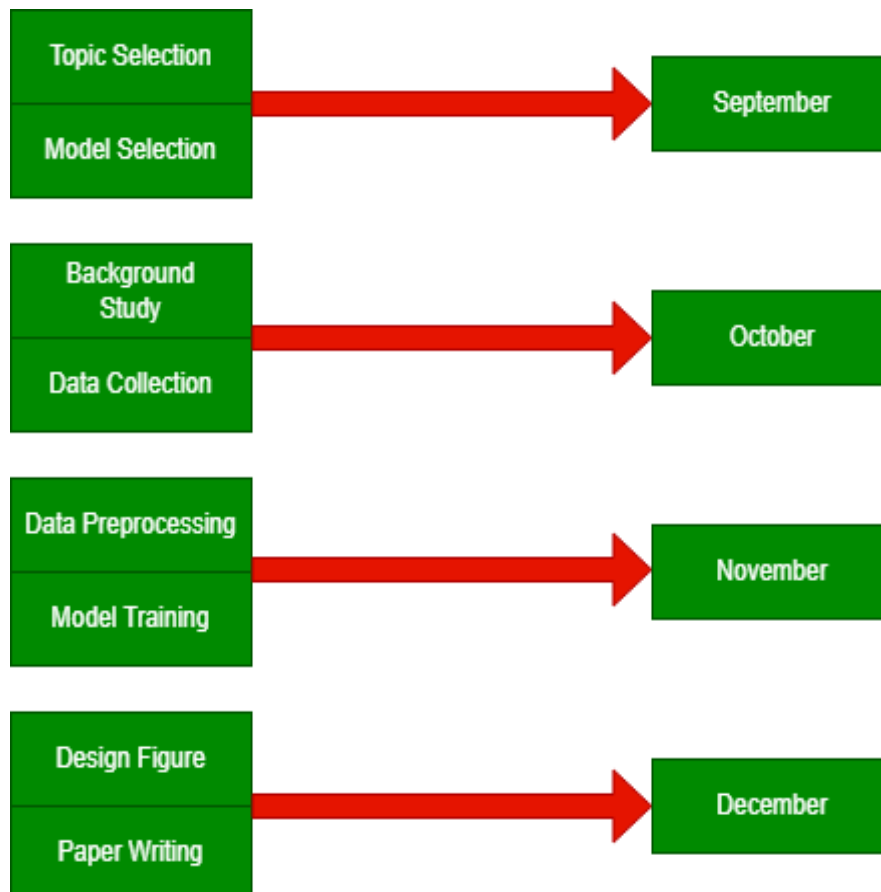


FIGURE 1. 4: RESEARCH SCHEDULE

CHAPTER 2

BACKGROUND

2.1 Research 1

A novel automation-assisted cervical cancer reading method based on convolutional neural network (2020)

Xiang [10] worked with deep learning algorithms especially Convolutional Neural Network (CNN). A baseline model was used called YOLOv3. YOLO uses features learned by a deep convolutional neural network to detect an object. In that paper the authors showed the detection process of the yolov3 model. Evaluation metrics used by the PASCAL VOC object detection. In that paper, the authors used AP at a single intersection over union (IoU) threshold of 0.5.

2.2 Research 2

Comparison of machine and deep learning for the classification of cervical cancer based on cervicography images (2021)

ML and DL techniques via the classification of cervicography images performed by Park [11]. He also pre-processed his image data by using some methods. In linear regression, 10 out of 300 characteristics from pre-processed photos were selected using 1984 negative images and 2135 positive images, for a total of 4119 cervicography images. All tests were validated by five-fold cross-validation and Receiver operating characteristics (ROC). Used ResNet-50 model and XGB, SVM, and RF algorithms to fully fill the approach.

2.3 Research 3

Automatic Classification of Cervical Cells Using Deep Learning Method (2021)

YU [12] distinguished between normal cells and abnormal cells. Four classification models were used for this task. The first one is a 10-layer convolutional neural network (CNN). The second is spatial pyramid pooling (SPP) + (CNN). Third is (CNN + Inception) and fourth is (CNN + Inception + SPP). Using the identical testing data and assessment index, the four models' performances are calculated and compared.

2.4 Research 4

Diagnosis of Cervical Cancer based on Ensemble Deep Learning Network using Colposcopy Images (2021)

A deep learning approach has been expressed by Chandran [13]. Colposcopy images used as data and convolutional neural network (CNN) models used to classify cervical cancer by using deep learning. There are two kinds of CNN architectures to detect cervical cancer using colposcopy images. One is VGG19 which is adopted as a transfer learning and another is Colposcopy Ensemble Network (CYENET) to classify cervical cancers.

2.5 Research 5

Classification of cervical cancer using Deep Learning Algorithm (2021)

Tripathi [14] showed that the most popular and favored due to the low cost and pain-free diagnosis method is the Pap-smear test. Applied RESNET-50 and RESNET-152 for using a huge number of image data for the train. Also, express VGG-16 and VGG-19 which are other architectures of convolution neural networks. These approaches obtained 94.89\% accuracy.

2.6 Research 6

Machine Learning Approach for Prediction of Cervical Cancer (2021)

Machine Learning and Deep learning approaches with classification techniques applied Priyanka [15] in her contribution. A pap-smear test has been used for cervical screening. Convolution Neural Networks (CNN's) ResNet50 was used for the pre-trained model for the prediction of cancerous cells. This paper discusses the types of the HPV virus. Seeing microscope cervical cancer is two types, one is Carcinoma and another is Adenocarcinoma. The proposed method is used for a dataset of pap-smear screening images with three classes of normal and four classes of abnormal.

2.7 Research 7

Single and Clustered Cervical Cell Classification with Ensemble and Deep Learning Methods (2020)

Kuko [16] showed machine vision, ensemble learning, and deep learning methods. Bethesda system for classification and cell clusters for reporting cervical cytology. Automated Pap smear screening test with five-fold cross-validation. The authors used the Cell Extraction method and Cell Segmentation. The initial step in this procedure is to split the cell slides into smaller pieces.

2.8 Research 8

DCAVN: Cervical cancer prediction and classification using deep convolutional and variational autoencoder network (2020)

Image regeneration and data classification using a variational convolutional autoencoder network performed by Khamparia [17]. The multilayer perceptron is very helpful for image classification and regeneration. In 2D and 3D input images used convolution layers for compute feature maps and perform complex convolutions tasks. Max pooling is used to diminish bugs in images. For generated latent codes and resembled the input used variational autoencoders.

2.9 Research 9

Prediction of Cervical Cancer Diagnosis Using Deep Neural Networks (2019)

Alkhawaldeh [18] expressed some machine learning and deep learning algorithms and approaches. Applied data preprocessing for handling missing values. The deep Neural Network model was designed for providing risk scores for cervical cancer. There also applied Feature Selection technique. It's the method of identifying the most consistent, non-redundant, and important characteristics to employ in model creation. The primary purpose of feature selection is to increase the predictive model's performance while lowering the modeling cost.

2.10 Research 10

CytoBrain: Cervical Cancer Screening System Based on Deep Learning Technology (2020)

Chen [19] applied a cervical cell segmentation module for extracting cell images. Cyto Brain is used to automatically screen abnormal cervical cells. The visual geometry group (VGG) classified the cell and visualized a human-aided diagnosis module for automatically diagnosing the whole slide images (WSI).

2.11 Research 11

An optimized deep learning model using Mutation-based Atom Search Optimization algorithm for cervical cancer detection (2021)

A pap smear is very useful to detect early cervical cancer. DenseNet 121 architecture is optimized by the Mutation-based Atom Search Optimization (MASO) algorithm. Chitra [20] applied different kinds of augmentation techniques inherent in the DenseNet-121 architecture. Various types of performance metrics and confusion matrices used to evaluate the performance of MASO-optimized DenseNet 121 architecture for cervical cancer detection.

2.12 Research 12

Imaging based cervical cancer diagnostics using small object detection - generative adversarial networks (2021)

Elakkiya [21] Used Small-Object Detection (SOD), Generative Adversarial Networks (GAN) with Fine-tuned Stacked Auto encoder (F-SAE), and multivariate heterogeneous data. Also used Region-based Convolutional Neural Network (RCNN) to generate and discriminate against the SOD-GAN.

2.13 Research 13

A Machine Learning Tool to Predict the Response to Neoadjuvant Chemotherapy in Patients with Locally Advanced Cervical Cancer

Neoadjuvant therapy, progression-free survival by using machine learning approaches used the task of Arezzo [22]. To predict cancer from the data set, 10-fold cross-validation was used to train and verify Logistic Regression (LR), Random Forest (RFF), and K-nearest neighbors (KNN). Data from 92 individuals was utilized to calculate progression-free survival (PFS).

CHAPTER 3

METHODOLOGY

In this section, we discuss all of the tasks, actions, and experiments. We all analyze our model outcomes and results. The **Fig 03** shows our overall methodology workflow.

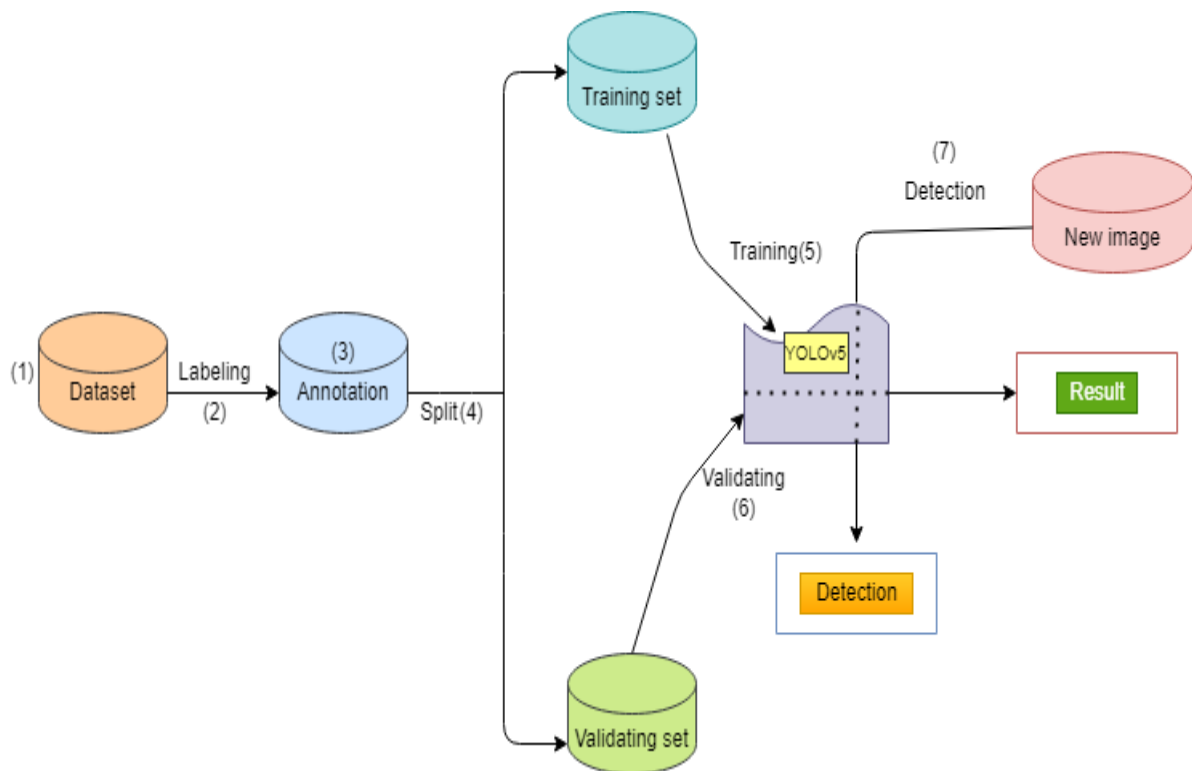


Fig 03: Workflow

Nowadays artificial intelligence is a part and parcel of our life. It makes our life easier day by day. Machine learning is a part of artificial intelligence. Machine learning is a subfield of computer science that allows computers to learn without having to be explicitly programmed. One of the most intriguing technologies that one has ever encountered is machine learning. It provides the computer with characteristics that make it more human-like. Machine learning is

currently in use, possibly in far more locations than one might imagine [23]. Deep learning algorithms are a complex evolution of machine learning algorithms. It was built by flowing human brain structure and works like the human brain. In recent times, object detection is an important figure in deep learning. Object detection, a subset of computer vision, is a method for automatically detecting interesting things in an image in relation to the background. It's a computer vision technique for finding things in photos or videos. To obtain meaningful results, most object detection systems use machine learning or deep learning. This is a problem that requires supervised machine learning. Object detection's purpose is to use a computer to imitate this intelligence. YOLO is a favorite algorithm of deep learning to detect real-time objects. It is a One-Stage Method algorithm. The latest version of YOLO is YOLOv5. It's a collection of compound-scaled object identification models trained on the COCO dataset, with easy capabilities for TTA, model assembly, hyperparameter development, and export to ONNX, CoreML, and TFLite. Model. It was also the first time a YOLO model was constructed entirely within PyTorch, allowing for quicker FP16 training and quantization-aware training (QAT). The new YOLOv5 features resulted in quicker and more accurate models on GPUs, but they also increased complexity to CPU deployments. It outperforms other yolo models, which achieve 90.8 percent recall and 7.8 percent FPR when paired with unique pre- and post-processing processes, and 9.1 percent recall and 10.0 percent FPR when not completed. It is the Leader in Real-time Object Detection. YOLO was the first object detection model to integrate bounding box prediction and object classification into a single end-to-end differentiable network. Darknet was used to write it and is still used to maintain it. YOLOv5 is initially implemented in PyTorch, and it benefits from the PyTorch ecosystem established to support and deploy, it is much more lightweight and easy to use. Iterating on YOLOv5 may also be easier for the broader research community, given it is a more well-known study

paradigm [25]. It can detect any object very fast and easily. To complete our task we have used this algorithm.

3.1 The versions of the YOLOv5 algorithm

It has 4 versions. In table number 01, we show the pre-trained checkpoints of versions of yolov5 model.

- i. yolov5-s which is a small version
- ii. yolov5-m which is a medium version
- iii. yolov5-l which is a large version
- iv. yolov5-x which is an extra-large version

We have used yolov5 small, medium, and large versions in our task.

Table 3.1: Pre-trained Checkpoints

Model	Size	APval	APtest	AP50	Speedv100	FPSv100	params	gflops
yolov5s	640	36.8	36.8	55.6	2.2ms	455	7.3M	17.0
yolov5m	640	44.5	44.5	63.1	2.9ms	345	21.4M	51.3
yolov5l	640	48.1	48.1	66.4	3.8ms	264	47.0M	115.4
yolov5x	640	50.1	50.1	68.7	6.0ms	167	87.7M	218.8

Table 3.1 show the Size, APval, Aptest, AP50, Speedv100, FPSv100, params and gflops of all versions of YOLOv5 model. For YOLOv5s Size, APval, Aptest, AP50, Speedv100, FPSv100, params and gflops respectively 640, 36.8, 36.8, 55.6, 2.2ms, 455, 7.3M, 17.0. 640, 44.5, 44.5, 63.1, 2.9ms, 345, 21.4M, 51.3 for YOLOv5m. Size, APval, Aptest, AP50, Speedv100, FPSv100, params and gflops respectively 640, 48.1, 48.1, 66.4, 3.8ms, 264, 47.0M and 115.4 for the YOLOv5l. And for X these are 640, 50.1, 50.1, 68.7, 6.0ms, 167, 87.7M and 218.8. Here we notice one thing that for every version of this model the same value for APval and Aptest.

3.2 Architectural block YOLOv5 algorithm

The whole structure of YOLOv5 [24] is shown in Fig 3.2.

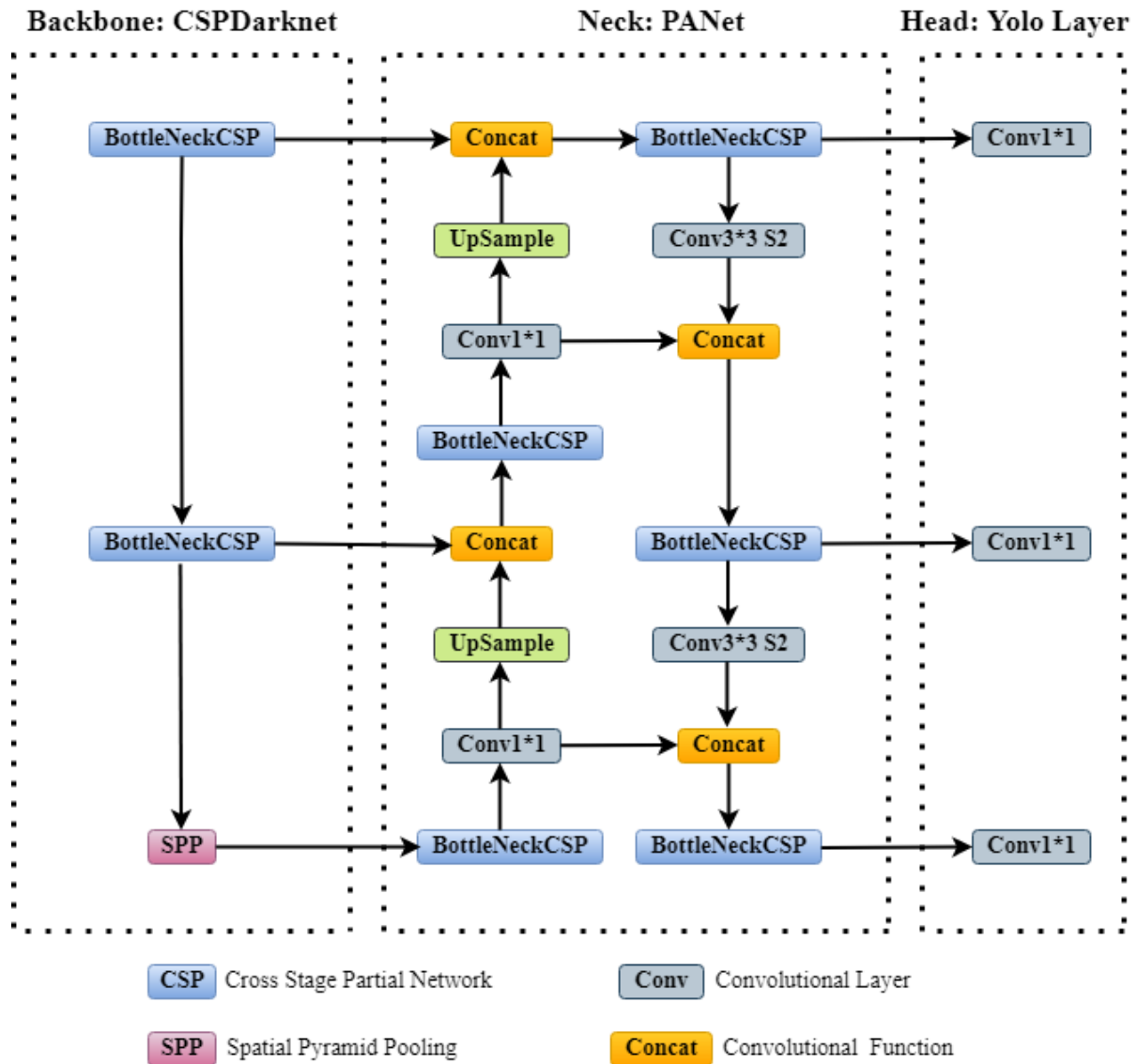


Fig 3.2: Structure of yolov5 [24]

It has three main architectural blocks: Backbone, Neck, and Head.

- i. YOLOv5 Backbone: The basic purpose of Model Backbone is to extract key features from a given input image. Cross Stage Partial Networks (CSP) are employed as a backbone in YOLO v5 to extract rich in useful characteristics from an input image. CSPNet overcomes the problem of repeating network optimization gradient information in the backbone network. The base layer's feature map is replicated by the backbone network, which then employs a dense block to send the copied feature map to the next level, separating the base layer's feature map.
- ii. YOLOv5 Neck: The most common application of Model Neck is to create feature pyramids. Feature pyramids assist models in achieving good object scaling generalization. It makes it easier to recognize the same item in different sizes and scales. The neck was created to optimize the benefits of the backbone's characteristics. It is frequently made up of a number of bottom-up and top-down routes. The usage of an up and down sampling block is the earliest neck. It reprocesses and uses the feature maps extracted by Backbone at various stages in a reasonable manner. The usage of an up and down sampling block is the earliest neck. The target detection architecture relies heavily on the neck. This approach differs from SSD [29] in that it does not use a feature layer aggregation process.
- iii. YOLOv5 Head: The model Head is mostly in charge of the final detection procedure. After anchor boxes are applied to features, it generates final output vectors with class probabilities, objectness scores, and bounding boxes. The head is responsible for determining the object's location and category using characteristics maps collected from the backbone. There are two types of heads: one-stage object detectors and two-stage object detectors. The RCNN series is the most representative of two-stage detectors, which have long been the dominating method in the field of object detection.

The head model in the YOLOv5 model is the same as in the YOLOv3 and YOLOv4 models, and it is mostly utilized in the final inspection stage. After applying anchor boxes to the feature map, it generates a final output vector comprising class probabilities, object scores, and bounding boxes. Choosing an activation function for deep learning networks is crucial, according to YOLOv5.

3.3 Activation Function

An artificial neural network's activation function calculates a weighted sum and then adds bias to it to determine whether a neuron should be activated or not. The goal of this function is to add non-linearity to the output of a neuron. Based on the output error, we may adjust the weights and biases of the neurons in a neural network. Back-propagation is the term for this procedure, the reason for gradients are supplied simultaneously with the error to update the weights and biases, activation functions enable back-propagation. Without an activation function, a neural network is just a linear regression model. The activation function transforms the input in a non-linear way, allowing it to learn and accomplish more complicated tasks. There are many kinds of activation functions. The choice of activation functions is the most crucial part of any deep neural network. Activation features such as Leaky ReLU, Sigmoid, mish, swish, and others have recently been implemented. YOLOv5 uses Leaky Relu and Sigmoid activation functions.

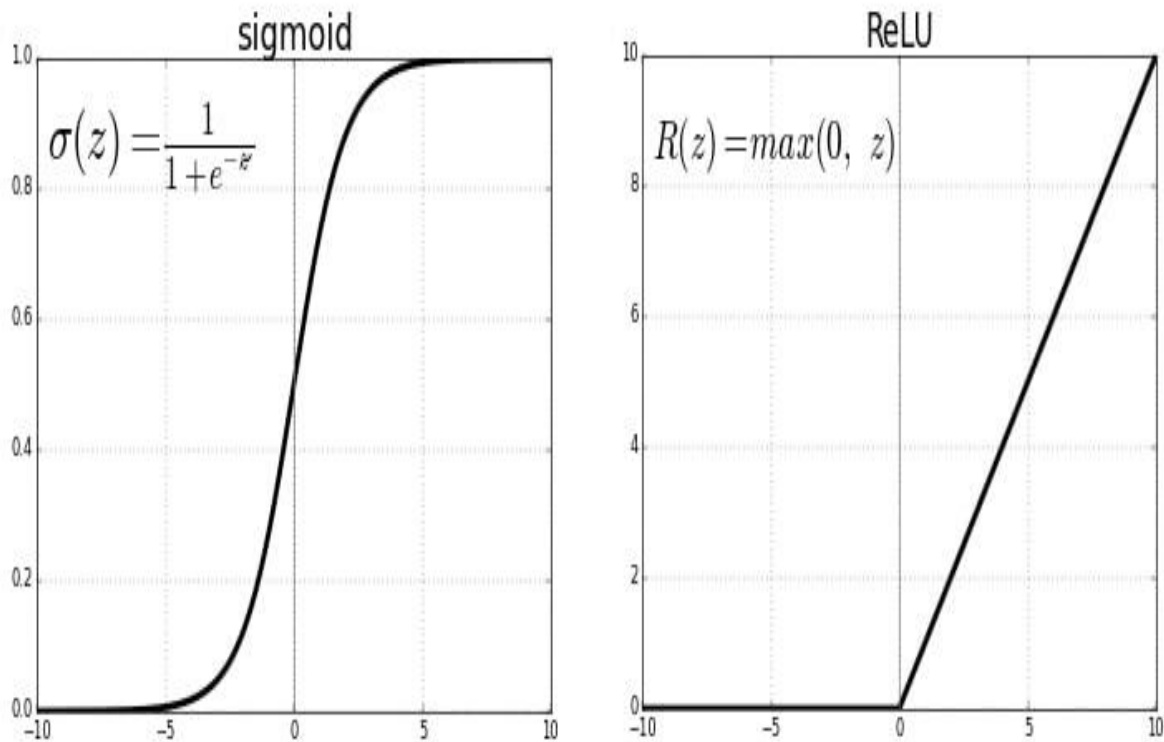


Fig 3.3: Leaky ReLU & Sigmoid

- i. **Leaky ReLU:** It's a form of activation function based on a ReLU, but instead of a flat slope, it has a slight slope for negative values. This form of activation function is widely used in applications involving sparse gradients, such as training generative adversarial networks. Leaky ReLUs are one solution to the "dying ReLU" problem. Instead of being zero when $x = 0$, a leaky ReLU's function will have a little positive slope (of 0.01, or so). The Leaky ReLU activation function is employed in the middle/hidden layers of YOLO v5.
- ii. **Sigmoid:** A sigmoid function is a real function that is bounded, differentiable, and has a non-negative derivative at each point and precisely one inflection point that is determined for all real input values. It's a sigmoid curve, which is a mathematical function with a "S"-shaped curve. It's commonly referred to as the logistic function, and it's been a popular neural network activation function for a long time. The input to the

function is changed to an integer between 0.0 and 1.0. The function's shape is an S-shape from zero to 1.0 for all conceivable inputs. It is used to add non-linearity in a machine learning model, in simple words it decides which value to pass as output and what not to pass. In YOLO v5 the sigmoid activation function is used in the final detection layer

The loss function is a crucial metric for determining a model's generalization capacity. We trained this model by computing the difference between the predicted and real data values. The final objective of the model optimization was to lower the loss value as much as feasible while avoiding fitting.

3.4 Boundary Loss Function

It is expressed as a distance metric on the space of contours or forms, rather than on the space of regions. In severely uneven settings, it may be simply paired with typical regional losses to solve the segmentation job. Furthermore, the suggested term may be used to solve any N-D segmentation problem in any current deep network architecture. The intersection over union (IoU) [32] is a typical target detection indicator whose major role is to determine the positive and negative samples as well as to calculate the distance between the output box and the proper label. IoU is scale-invariant, which means it is unaffected by changes in scale. Because it employs integrals across the border (interface) between regions instead of unbalanced integrals over regions, it helps alleviate the issues of regional losses in the setting of extremely unbalanced segmentation problems. The loss function of the Bounding box in YOLOv5 is GIOU Loss, which is as follows.

$$IoU = \frac{|A \cap B|}{|A \cup B|} \dots\dots\dots (1)$$

$$GIoU = IoU - \frac{|C \setminus (A \cup B)|}{|C|} \dots\dots\dots (2)$$

$$GIoU_{Loss} = 1 - GIoU \dots\dots\dots (3)$$

3.5 Cost Function or Loss Function

The Loss Function is one of the most important aspects of Neural Networks. Loss is nothing more than a prediction mistake in a Neural Network. The Loss Function is a method of calculating loss. To put it another way, the Loss is used to compute the gradients. Gradients are also used to update the weights of the Neural Net. It's a function that estimates the difference between the present and predicted outputs of an algorithm. It's a measure of how effectively your algorithm represents the data. The cost function boils down all of the positive and negative features of a potentially complex system to a single value. They offer more than simply a static depiction of your model's performance. YOLOv5 has Binary Cross-Entropy with Logits Loss function but instead it sometimes uses Focal Loss function. Binary Cross-Entropy with Logits Loss: In the YOLO family, a compound loss is produced using the objectness score, class probability score, and bounding box regression score. For the loss computation of class probability and object score, Ultralytics employed PyTorch's Binary Cross-Entropy with Logits Loss function. Binary cross entropy finds a simile for every of the predicted probabilities to real class output which can be either 0 or 1. A sigmoid layer and the BCELoss are integrated into a single class in this loss. This method is quantitatively more stable than using a simple Sigmoid and then a BCELoss because we use the log-sum-exp method for numerical stability by merging the operations into one layer.

Instead of Binary Cross-Entropy with Logits Loss focal loss is used in this YOLO model. Focal Loss is an upgraded variant of Cross-Entropy Loss that attempts to address the problem of class imbalance by giving harder or easily misclassified cases more weight and down-weighting simple examples. It can reduce the loss contribution from easy examples and increase the importance of correcting misclassified examples.

The next step was to use the model's loss value to optimize the model's parameters after calculating the loss value.

3.6 Optimization Function

Optimizers are strategies or approaches for reducing losses by adjusting the features of neural networks, such as weights and learning rate. The purpose of optimization is to create the "best" feasible design based on a set of prioritized criteria or restrictions. These include increased production, strength, reliability, lifespan, efficiency, and usage, among other things. YOLOv5 has two optimization functions and these are Stochastic Gradient Descent (SGD) & Adaptive Moment Estimation (Adam).

3.6.1 SGD

SGD (Stochastic Gradient Descent) is a fast and simple method for fitting linear classifiers and regressors to convex loss functions like (linear) Support Vector Machines and Logistic Regression. One of the most important characteristics of Stochastic Gradient Descent is its efficacy. Optimization methods based on stochastic gradient descent (SGD) are used in a variety of machine learning applications [26]. For cases with a high number of training examples, SGDs have the benefit of being simple to deploy and quick. In YOLOv5, it is the default optimization function for training.

3.6.2 Adam

It's a method for optimizing deep learning model training that substitutes stochastic gradient descent. Adam creates an optimization strategy for noisy problems with sparse gradients by combining the best elements of the AdaGrad and RMSProp techniques. It has the ability to modify neural network weights on a regular basis based on training data. It uses less memory and is better suited to issues with a lot of noise or sparse gradients [34]. The ADAM approach, which combines the GD and momentum methods with a change of the interval, is the most often used method. It works with first- and second-order momentums, as well as an exponentially decaying average of previous gradients [30].

CHAPTER 4

EXPERIMENTS

4.1 Data Collection

We have our data from kaggle [27]. These data are pap-smear test image data. Pap (cervical) smear testing is an excellent tool for identifying, preventing, and delaying cervical cancer progression [33]. The Papanicolaou test is a cervix and colon screening treatment that can detect precancerous and cancerous processes. Abnormal results are frequently followed by more sensitive diagnostic techniques and, if necessary, measures aimed at preventing cervical cancer development. From this dataset, we have selected 900 image data. All of the images of the dataset are very clear and real. These data are suitable for performing any deep learning task.

4.2 Data Processing

After collecting the dataset, we split these data into 3 parts. Five hundred for training, two hundred for validation, and two hundred for test data. There is a big difference between test datasets and validation datasets. The validation dataset is mostly used to illustrate how models are evaluated during hyperparameter tweaking and data preparation. On the other hand, the test dataset is mostly used to describe a final tuned model's evaluation when compared to other final models. After splitting the three parts we labeled and annotated the dataset. In **Fig 4.2** show split data.

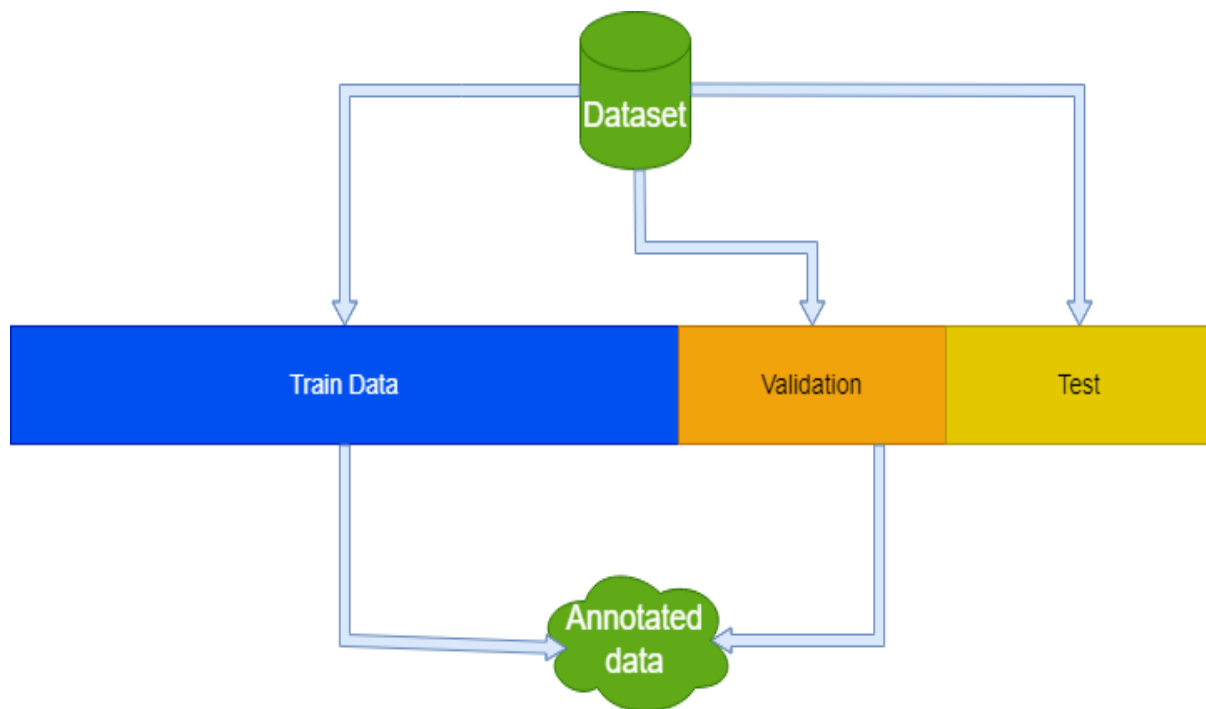


Fig 4.2: Split data

Data labeling is the process of identifying raw data and providing context by adding one or more relevant and useful labels. Because it's a vital technique that adds context to data before utilizing it in model training, it's necessary to pick the right strategy while keeping important criteria like quality and scalability in mind. It's an important part of the data prep and preprocessing process for AI development. It's the process of identifying and labeling data samples, which is especially important in supervised learning, where both data inputs and outputs are labeled to help an AI model train more effectively in the future. Data annotation is the process of labeling data so that machines may use it. It's particularly beneficial for supervised learning, in which the system uses labeled datasets to interpret, understand, and learn from input patterns in order to produce desired outputs. It happens before the data is supplied into a system. Without data labeling and annotation models can't identify objects properly so this step is very important. We labeled and annotated all of the train and validation data by using an online tool called makesense.ai [28].

4.3 Model & training

At first we load the YOLOv5 model. Then set our YAML file in the data folder which is located in the YOLOv5 model folder, this will be providing the path of training and testing data with its respective images and labels. We use Google Colab open-source GPU. We select input image size 640, and select the version YOLOv5 model. In our task, we have used 3 versions of YOLOv5 and the versions are YOLOv5s(small), YOLOv5m(medium), and YOLOv5L(large). In our fitting section, we perform 70 epochs with 16 batch sizes. After complete fitting, we test our model with some image data and videos. The **Fig 4.3** show clearly where we find our detected outputs and results.

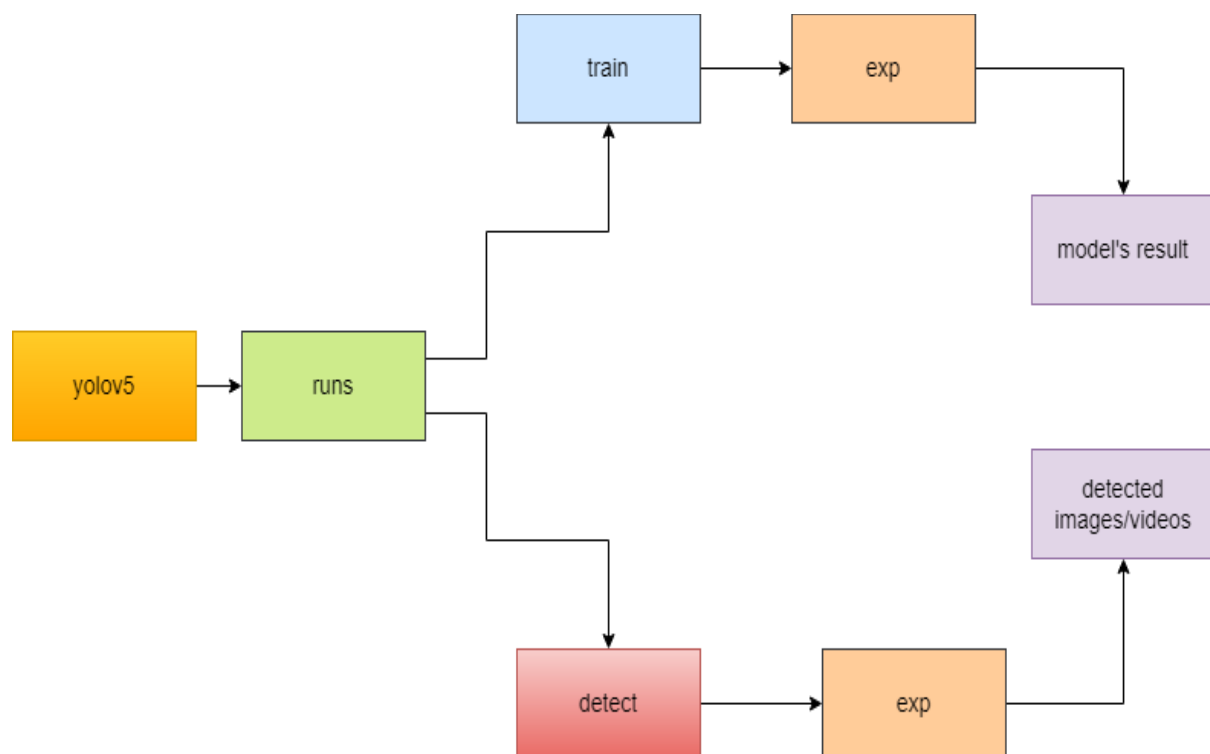


Fig 4.3: Path of Outcome

According to this **Fig** at first we have to go to the directory where we install our yolov5 model, then go to yolov5 folder. After that runs folder. For seeing result runs to train, train to recent exp and for detected photos or videos go to runs to detect, detect to recent exp.

4.4 Model Evaluation Exhibitor

Evaluation metrics are used to assess the quality of a statistical or machine learning model. A computer-aided design system [31] is what we call it. Any endeavor will necessitate a review of machine learning models or algorithms. A number of assessment measures may be employed to put a model to the test. Any endeavor will necessitate a review of machine learning models or algorithms. A number of assessment measures may be employed to put a model to the test. It is critical to evaluate your model using a variety of evaluation indicators. This is due to the fact that a model may perform well when using one measurement from one evaluation meter but poorly when using another measurement from a different evaluation metric. In order to ensure that your model is running correctly and optimally, you must use evaluation metrics. Here we describe Precision, Recall (Sensitivity) and Mean Average Precision (MAP). Before describing these we have to earn a good knowledge about TP, TN, FP, FN. **Fig 4.4** shows these.

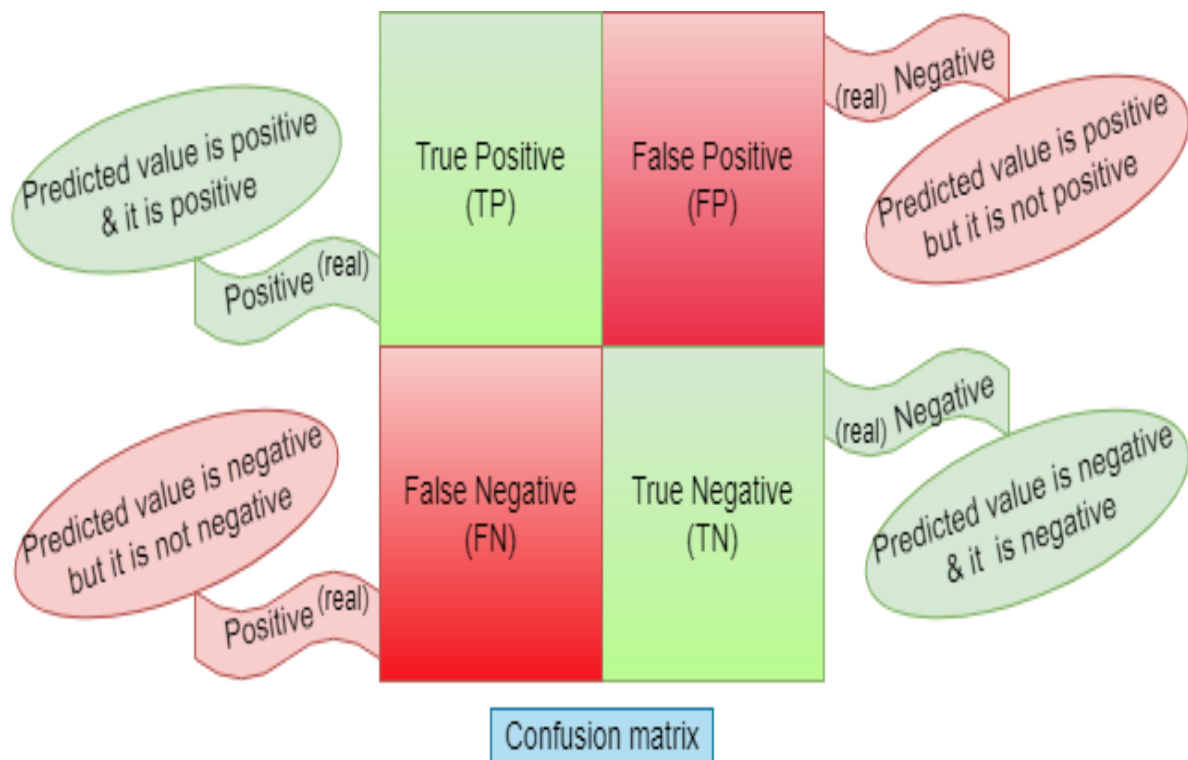


Fig 4.4: Confusion Matrix

True Positive (TP): Predicted value is positive and actually it is positive. For example, the predicted value is the patient has cancer and actually he/she is suffering from cancer.

True Negative (TN): Predicted value is negative and actually it is negative. For example, the predicted value is the patient hasn't cancer and actually he/she isn't suffering from cancer.

False Positive (FP): Predicted value is positive but actually it is negative. For example, the predicted value is the patient has cancer but actually he/she isn't suffering from cancer.

False Negative (FN): Predicted value is negative but actually it is positive. For example, the predicted value is the patient doesn't have cancer but actually he/she is suffering from cancer.

Precision: Precision is the property of being exact, and it relates to the distance between two or more measures, regardless of whether they are accurate or not. It denotes the proportion of

Predicted Positive cases that are correctly Real Positives and reflects how repeatable measurements are, even if they are far from the accepted value.

$$\begin{aligned}\text{Precision} &= \frac{TP}{TP + FP} \dots\dots\dots (4) \\ &= \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}}\end{aligned}$$

Recall: The fraction of Real Positive situations that are accurately Predicted Positive is known as recall (sensitivity). This metric indicates how well the projected positive rule covers the Real Positive situations. It has the advantage of reflecting how many relevant situations the expected positive rule picks up. It refers to the percentage of total relevant results that our system accurately classifies.

$$\begin{aligned}\text{Recall} &= \frac{TP}{TP + FN} \dots\dots\dots (5) \\ &= \frac{\text{True Positive}}{\text{True Positive} + \text{False Negative}}\end{aligned}$$

Average Precision: For ranked retrieval results, average precision is a statistic that combines recall and precision. The average precision for a particular information demand is the sum of the precision scores obtained after retrieving each relevant document. It shows whether your model can accurately identify all positive cases without mistakenly labeling too many negative ones as positive. It is a widely used metric for determining object detector accuracy, and it computes the average precision value for recall values ranging from 0 to 1.

$$AP = \sum (rn + 1 - rn)P \text{ interp } (rn + 1) \dots\dots\dots (6)$$

Mean Average Precision (MAP): It's the sum of the Average Precision (AP). It is a widely used object detection assessment metric. The mean average precision is used to evaluate the object detection models (MAP). By comparing the ground-truth bounding box to the detected box, the MAP derives a score. Depending on the multiple detecting challenges that exist, it is determined by calculating the mean AP across all courses and/or overall IoU thresholds.

$$mAP = \frac{1}{n} \sum_{n=1}^{k=n} AP_k \dots\dots\dots (7)$$

$$AP_k = \text{the AP of class k} \dots\dots\dots (8)$$

$$n = \text{the number of calsses} \dots\dots\dots (9)$$

CHAPTER 5

RESULT ANALYSIS

5.1 Result Analysis

Here we have used 3 versions of YOLOv5 and the versions are YOLOv5s (small), YOLOv5m (medium), and YOLOv5L (large). This research employs precision and recalls to assess the algorithm's efficacy in detecting cancer cells. The proportion of properly labeled cancer cells in all photos anticipated to be cancer cells is measured by precision, whereas the proportion of cancer cells discovered in all images is measured by the recall. Also exhibited were mAP, box loss, object loss, and cls loss. By comparing the ground-truth bounding box to the detected box, the mAP determines a score. The difference between the expected and ground truth bounding boxes is calculated using a loss function to forecast box loss. Using the object loss function, the true positive is calculated. Cls loss is a metric that assesses the accuracy of each anticipated bounding box's categorization. **Fig 5.1, 5.2, 5.3** consistently show the result of the YOLOv5s, YOLOv5m, and YOLOv5l models. We have applied the same image_size, batch_size, and epochs number for all of the versions. All of the applied versions image size = 640, batch_size = 16 and epoch was 70. Here we count epoch from 0 to 69.

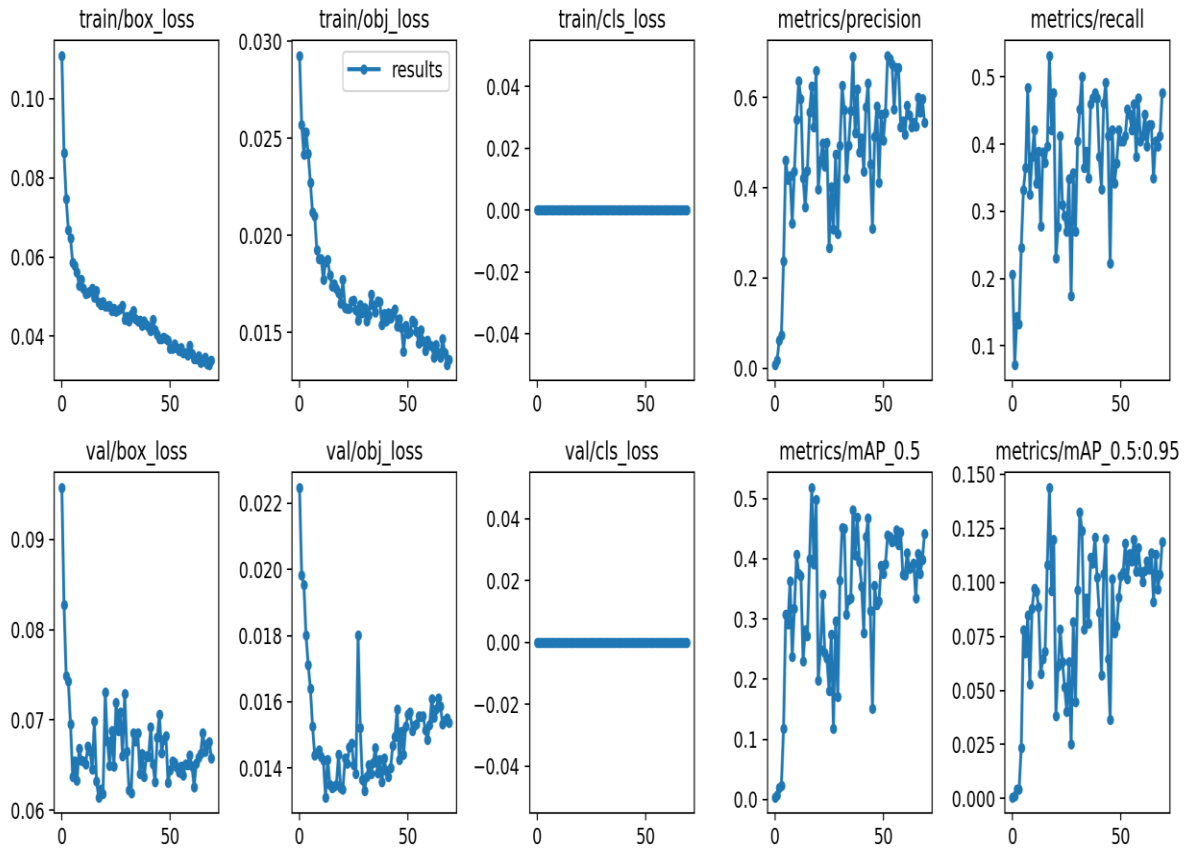


Fig 5.1: Result of yolov5s

Fig 5.1 expressing the results of yolov5s. Here minimum train/box loss is 0.032906 in 67 number epoch, train/obj loss is 0.01333 in 68 epoch, val/box loss is 0.061446 in 17 epoch and val/obj loss is same as bal/box loss but in 29 to 32 epoch it ups and downs tremendously. On the other hand the highest precision is 0.69328 in 52 number epoch, recall = 0.53175 in 17 epoch and mAP = 0.51795 in 17 epoch.

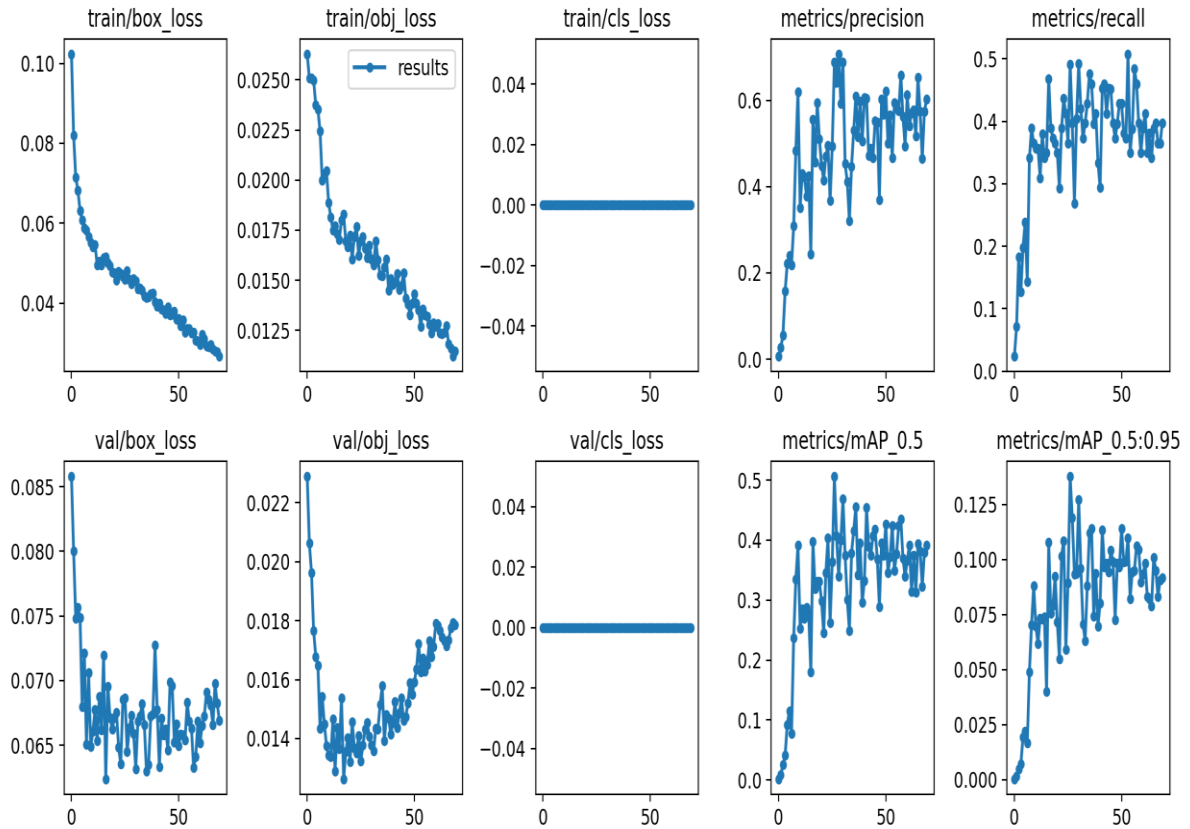


Fig 5.2: Result of yolov5m

Fig 5.2 show the results of yolov5m. Here the lowest train/box loss is 0.032906 in 69 number epoch, train/obj loss is 0.011206 in 68 epoch, val/box loss is 0.062389 in 16 epoch and val/obj loss is 0.01263 in 17 epoch. On the other hand the highest precision is 0.70764 in 28 number epoch, recall = 0.50794 in 53 epoch and mAP = 0.50608 in 26 epoch.

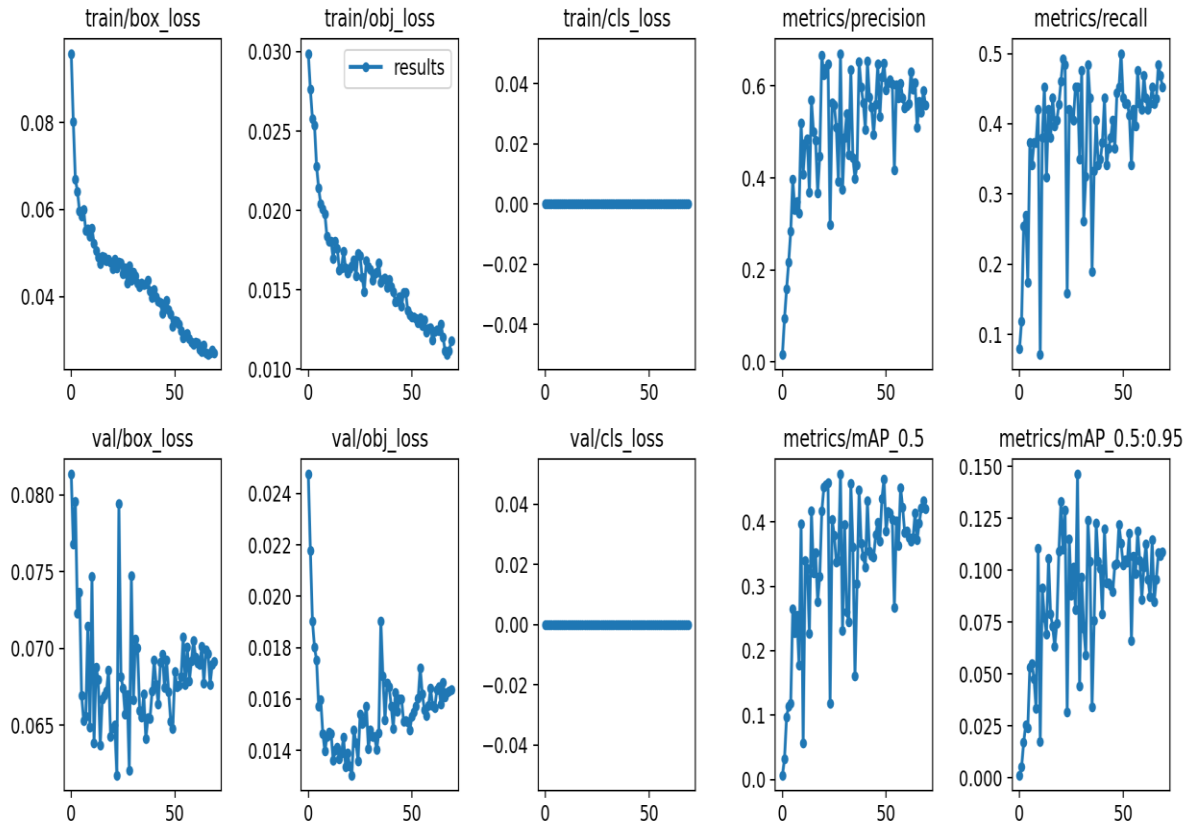


Fig 5.3: Result of yolov5l

Fig 5.3 show the results of yolov5l. Here the lowest train/box loss is 0.026642 in 66 number epoch, train/obj loss is 0.061743 in 22 epoch, val/box loss is 0.010918 in 67 epoch and val/obj loss is 0.013033 in 21 epoch. Besides the highest precision is 0.67039 in 28 number epoch, recall = 0.49997 in 49 epoch and mAP = 0.47374 in 28 epoch.

All of the above results figures we have noticed one thing that for all of the yolov5 versions cls_loss's are zero (0) for every epoch. This happened because here we have only one class and our applied model detect this very well.

Table 5.1: Minimum training and validation performance loss.

yolov5	train/box loss	Val/box loss	train/obj loss	Val/obj loss	train/cls loss	Val/cls loss
s	0.032906 (67epo)	0.061446 (17epo)	0.01333 (68epo)	0.061446 (17epo)	0 (every_epo)	0 (every_epo)
m	0.026675 (69)	0.062389 (16epo)	0.011206 (68epo)	0.01263 (17epo)	0 (every_ep)	0 (every_ep)
l	0.026642 (66epo)	0.010918 (67epo)	0.061743 (22epo)	0.013033 (21epo)	0 (every_ep)	0 (every_ep)

Table 5.1 show the minimum box, object and class loss of train and validation with epoch-size for yolov5 (s, m and l) version. Here we see that for yolov5s train/box loss is 0.032906 in 67 epoch, val/box loss is 0.061446 in 17 epoch, train/obj loss is 0.01333 in 68 epoch, Val/obj loss in 17 epoch, train and val/cls loss is 0. Similarly the **Table 5.1** show the above things for yolov5m and yolov5l.

Table 5.2: Maximum number of precision, recall, and mAP rate

yolov5	precision (maximum)	recall (maximum)	mAP (maximum)
s	0.69328 (52epo)	0.53175 (17epo)	0.51795 (17epo)
m	0.70764 (28epo)	0.50794 (53epo)	0.50608 (26epo)
l	0.67039 (28epo)	0.49997 (49epo)	0.47374 (28epo)

Table 5.2 show the maximum precision, recall and mAP for yolov5 (s, m and l) version. For the yolov5s precision is 0.69328 in 52 epoch, recall is 0.53175 in 17 epoch and mAP is 0.51795 in 17 number epoch. Likewise the **Table 5.2** sight the above things for yolov5m and yolov5l.

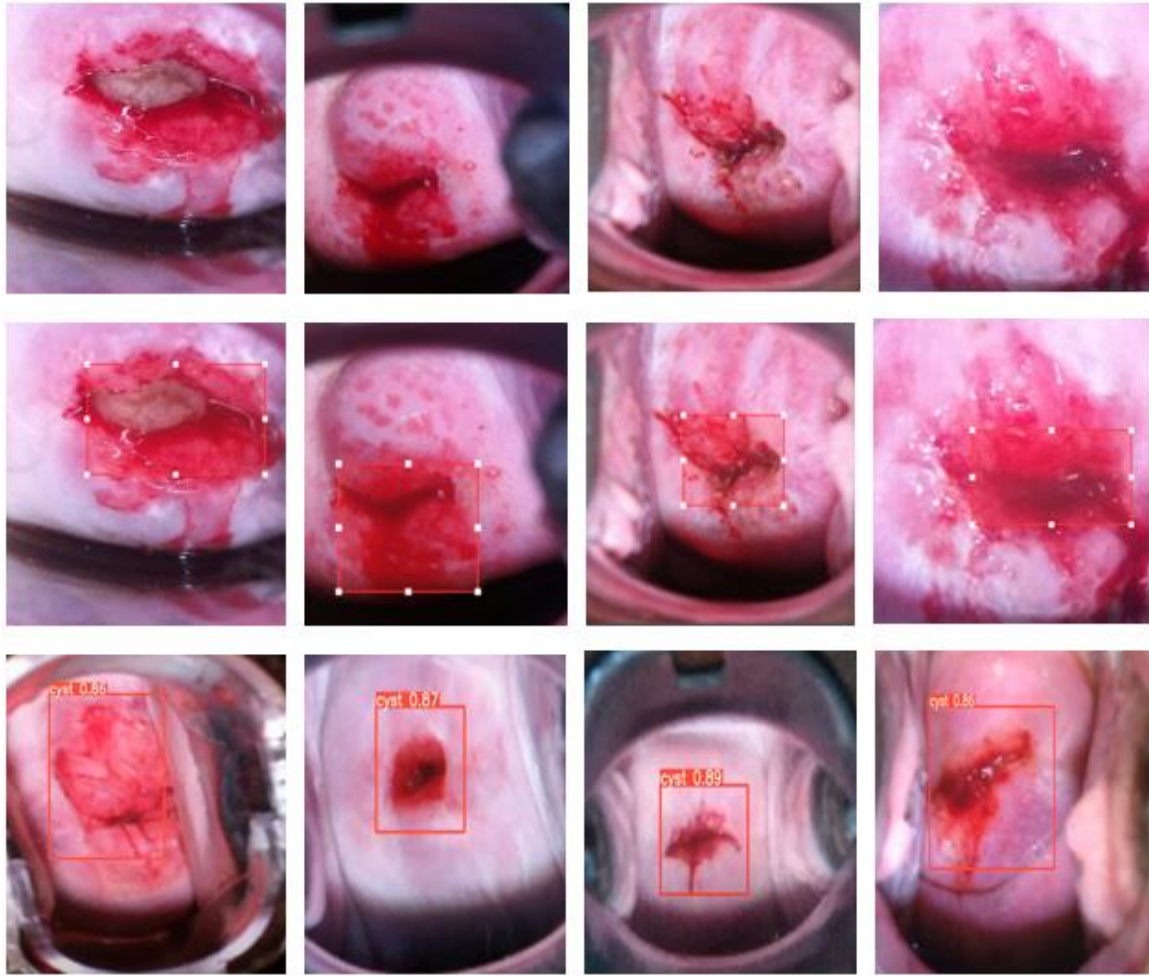


Fig 5.4: Detected image

The first row of **Fig 5.4** show the sample of raw image data those we have selected for our model. Second row show the processed image sample that we have labeled and annotated. And the last row of the above figure show the detected image sample that we have got after testing.

CHAPTER 6

CONCLUSION

6.1 Our Contribution

The goal of our task is to build a system to automatically detect cervical cancer cells using a deep learning model. Our contribution can support doctors to improve their diagnosis and make a faster decision in a very short time without any kind of hesitation. In the beginning of the introduction part, we have discussed the problem that we have to detect. Then we have covered the importance of solving the problem and the risks/ difficulties of the problem. At the ending of the introduction section, we have proposed our method. We have applied an object detection-based method called YOLOv5. In our task, we have applied three (3) versions of that model. In the methodology section, we have discussed the versions and the architectural structure of our applied model. In this section, we have explained the basic functionalities of our model, such as activation function, optimization function, etc. In the experiments & results analysis section, first, we introduced our dataset and also discussed how to process our dataset. Then we explained our whole work procedure and evaluation part. After that, we discussed our model result with figures and tables.

6.2 Future Works

In the future, we will collect a large number of real-time and clean data set from a valid source. We will support a GPU and machine so that we can apply more epochs than the present.

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Appendix A

Dataset Link:

<https://www.kaggle.com/ofrihare/224-224-cervical-cancer-screening>

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