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Automated prediction of endometriosis using deep learning

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Abstract

Endometriosis is the anomalous progress of cells at the outer part of the uterus. Generally, this endometrial tissue stripes the uterine cavity. The existence of endometriosis is identified through procedures known as Transvaginal Ultra Sound Scan (TVUS), Magnetic Resonance Imaging (MRI), Laparoscopic procedures, and Histopathological slides. Minimal Invasive Surgery (MIS) Laparoscopic images are recorded in a small camera. To assist the surgeon in identifying their presence of endometriosis, image quality (characteristics) was enhanced for more visual clarity. Deep learning has the ability in recognising the images for classification. The Convolutional Neural Networks (CNNs) perform classification of images on large datasets. The proposed system evaluates the performance by a novel approach that implements the transfer learning model on a well-known architecture called ResNet50. The proposed system train the model on ResNet50 architecture and yielded a training accuracy of 91%, validation accuracy of 90%, precision of 83%, and recall of 82%, which can be applied for larger datasets with better performance. The presented system yields higher Area Under Curve (AUC) of about 0.78. The proposed method yields better performance using ResNet50 compared to other transfer learning techniques.

Keywords: TVUS, MRI, Laparoscopic images Deep Learning, Convolution neural network (CNN), Transfer Learning, ResNet50.

1. Introduction

Endometriosis is a traumatic disorder occurring in the women of age between 12 to 40. The rise of endometrial tissue appears on the interior portion of the uterus and it sheds out during menstrual

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cycle. If the endometrial tissue appears at outer part of uterus, then it leads to the development of endometriosis. This tissue can also appear in other regions includes ovary, peritoneum, gall bladder etc. The endometrial tissue can also found in both anterior and posterior regions. If the endometrial tissue is found in the posterior region and affects many parts then it is called as "Deep infiltrating Endometriosis (DIE)".

Endometriosis are identified due to pelvic pain and hormonal imbalance. The identification of endometriosis can be done through various modes includes (a) Transvaginal Ultra sound(TVUS) (b) Magnetic Resonance Image(MRI) (c) Laparoscopic procedures etc.

In TVUS and MRI images, position of endometriosis can be identified only in anterior position. Through laparoscopic procedure images can be viewed with more visual clarity i.e. both posterior and anterior position images can be viewed for locating the exact position of endometriosis. Laparoscopic procedure is confirmed to get rid of pain and to remove infertility problem in women who are dealing with endometriosis [25]. The cause of endometriosis is still challenging task. The key factor is identified as "retrograde menstruation". The other causes are "immunologic abnormalities, endometrial disorders, and peritoneal dysfunction" [29].

The role of deep learning (DL) have the capability of learning from unsupervised data. The neural network prospers the contemporary metrics, when comparing the enactment of human. The "deep learning" itself derived as it contains more number of unknown layers i.e. around 100 to 150 layers. The DL consume the fact from "artificial intelligence" to recognise, predict the information applied in large areas for achieving accuracy [5].

The DL includes additional unknown layers to the networks model in-order to solve complex and large datasets. As a result, the researchers gained some attention to identify the best solution for image analysis [33]. In case of deep learning "feature extractions" are automated. The deep learning architecture behaves well i.e. performance are improved while handling large set of data. The Deep learning neural network are categorised into four types known as (a) Convolutional Neural Networks (CNNs) (b) Auto encoder and Sparse Coding, (c) Restricted Boltzmann Machines (RBMs). The CNN comprises of three different layers known as "(a) Convolution layer (b) Pooling layer (c) Fully Connected layer". The CNN consist of two stages for training includes forward and backward stage which is altogether known as epochs [40].

Convolutional neural networks (CNNs) is the most promising neural network model. The CNN can perform computational algorithms stimulated by the "biological neural networks" comprises of human brain like structure. The CNN model consist of single input layer proceeded by several unknown layer finally one output layer. The term "Black box" is referred in CNN which is used for the hidden layer since every process undergone in this layer only. The CNN model which are trained by any neural network algorithm has made incredible accomplishments in various extensive recognition tasks [14].

The CNN model can be used for attribute learning as well as for classifying or recognising the images [39]. By improving deep learning model, more accurate results are obtained. In-order to perform effectively in CNN, traditional CNN are added with additional features known as transfer learning. The transfer learning gathers a model that is trained on larger dataset and handover its knowledge to a smaller dataset. The transfer learning for image classification are classified as (a) VGG (b) Google Net (c) ResNet50.

Challenging problem is to classify images the traditional approach involves several steps and self-determined analysis steps. By implementing CNN based approach the prediction of components was found to be easier. The effective pre-trained model was implemented to distinguish various "cell morphologies" with more accuracy between "95% and 97% respectively [18].

ResNet50 Architecture is a transfer learning strategy used for effective implementation for image clas-

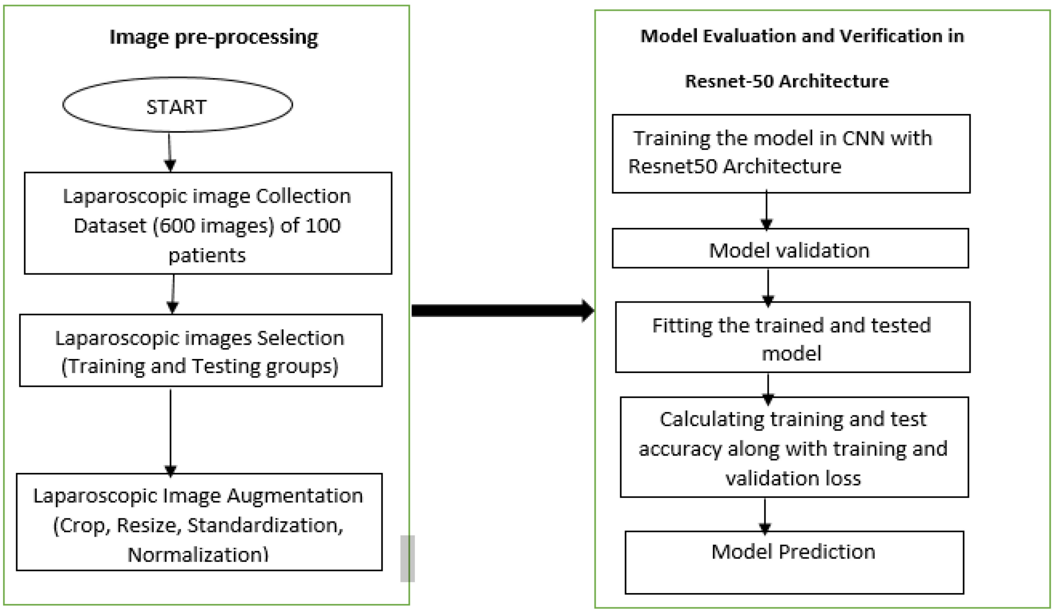

Figure 1: Workflow of Transfer Learning

sification. The ResNet50 contain 50 hidden layers so that the network has ample feature extractions from a large set of images. The ResNet50 architecture was implemented on "finger print recognition system" for enhanced prediction also incredible accuracy were achieved [28]. The ResNet50 model along with "Keras" was with "pre-trained weights", can identify up to 1500 "ImageNet objects" [35]. Laparoscopic images can enhance the quality of the images compared to scanning procedures. The laparoscopic images particularly can be used for recognising the deep infiltrating endometriosis (DIE). The laparoscopic procedure obtained images are trained in either machine learning or deep learning to categorise the presence/classify the form of endometriosis. Various deep learning approaches are available where Convolution neural network are found to be more prevalent for image classification. Deep learning algorithms were used to "anatomy and assess" laparoscopic images with high precision [27].

The transfer learning model known as ResNet50 architecture were implemented. The transfer learning can train the model with more amount of "hidden layers". For training the model in CNN the workflow is illustrated in figure 1 as follows. The model was pre-trained in ResNet50 architecture and fitting the model in the given architecture for running several number of epochs. The workflow of the paper is illustrated in figure 1.

The paper is divided into various sections: Section1 as Related study followed by section 2: methods to implement Transfer learning using ResNet50 in CNN for classifying endometriosis followed by Section 3: discussion on results obtained in the predicted model and section 4: Conclusions

2. Related Study

Yun Zheng Zhang in 2021 [32] Proposed a neural network model for classifying endometriosis. Convolution neural network architecture known as VGGNet-16 were implemented on 6478 histopathological images for training. The results obtained were compared to the results of radiologists. The accuracy yielded through "VGGNet16 was 80.8%. The performance of VGGNet16 was better than gynaecologist performance in classifying the five classes of endometriosis.

Huang in 2021 [17] Proposed a technique called "Robotic Single site surgery" for handling endometriosis of various stages. Patients of deep infiltrating endometriosis along with other features known as post-operative difficulties, loss of blood, age group were considered for this technique. This method was found to be more effective for treating various stages of endometriosis.

Sabrina Madad Zadeh [26] developed a solution called "Deep learning based Semantic segmentation" i.e. to find the location of endometriosis from laparoscopic images. "Mask R-CNN" deep learning method was implemented on 461 laparoscopic images. The training accuracy obtained for annotated images are "84.5% for uterus, 29.6% for ovaries and 54.5% for surgical tools". The validation accuracy was "97% for uterus, 24% for ovaries and 86% for surgical tools". The Limitation of this method was applied to a very smaller database.

Takahashi Y in 2021 [36] Presented how computer vision helps in detecting the regions exposed to endometriosis from laparoscopic images. Along with deep learning neural network method, continuous analysis was implemented to achieve higher prediction rates. The yielded accuracy through continuity analysis was 90.29%.

Praiss AM in 2020 [31] Developed predictive method through machine learning. This system was used for endometrial cancer. "Ensemble Algorithm for clustering cancer data" was involved with "endometrial cancer dataset". The prognostic structure was made grounded on parameters includes tumour staging, corresponding grades and patient age. C-index was calculated as 0.8313 with the help of eight prognostic groups. The limitations in this system are as follows, (a) Minimum of 100 patients' data needed for Ensemble algorithm. (b) Performance was not analysed based on node arrangements (c) "Adjuvant therapy" was not comprehended for this predictive examination.

Chen X in 2020 [8] Predicted the endometrial cancer with the help of T2 weighted MRI images using deep learning model. Lesion area was identified using T2W Magnetic Resonance Image. YOLO v3 detection algorithm was used for tracing the lesions. The evaluation done in identifying the depth of myometrial Invasion was calculated as "Accuracy of 84.78%, Sensitivity of 66.67%, Specificity of 87.50%, positive predictive value of 44.44%, and negative predictive value of 96.3%". The limitations are: (a) only T2Weighted Magnetic Resonance Image dataset were only considered as input, (b) "T1WI,DWI" were not considered.

Dong HC in 2020 [12] Proposed the purpose of AI and deep learning techniques. Magnetic Resonance Images (MRI) as input along with DL, can be used for diagnosing endometrial cancer in the initial stages. The CNN along with "U-Net architecture "used for MR images segmentation. The limitation are that this model provide lower accuracy when compared radiologists results.

Runyu Hong in 2020 [16] Identified that by implementing deep learning along with histopathological subtypes, gene mutations can also be performed. This model yields an AUC curve rate of "0.934 to 0.958".

Ewa J in 2020 [20] Proposed that endometriosis recognition was done by using various Artificial Intelligence techniques. "Logistic regression and Extreme Gradient Boosting (XGB)" algorithms were implemented on patient dataset containing infertility problem details.

Tianyi Liu in 2019 [24] Analysed that convolution neural network for recognising the facial expression. It takes longer time to train in traditional approach as computational time is higher. For effective processing cloud platform were used.

Ahmed M in 2018 [1] Recognized "Magnetic resonance Imaging (MRI)" as input set of images to forecast the harshness of endometrial cancer. "sagittal T2W1 and sagittal T1W1" helps in assessing the "Signal Intensity (SI)" of tumours. Logistic Regression compare the values obtained on MRI with findings of several features includes depth of "Myometrial invasion, tumour grade and subtype, lymph vascular invasion, and microsatellite Stability status" etc. The limitations of this study was category of tumour and grade of tumour were not related with outcomes of Magnetic Resonance Images.

J. Bouaziz in 2018 [6] Identified the endometriosis through genes by implementing natural language processing. Endometriosis. Gene set were filtered and text mining were applied to evaluate the growth of endometriosis. Genes were used as biomarkers for treating endometriosis.
S. Akter in 2018 [2] Analysed endometriosis based on gene structure and RNA samples obtained from various endometriotic patients. Normalization techniques and decision tree algorithm were applied to classify endometriotic and non endometriotic patients.
J. Avaneesh in 2020 [4] Identified Yolo v3 algorithm was effectively used for detecting images. The processing of image was found to be faster through Yolo which results in higher precision rate and lower accuracy.
A. Rohini in 2020 [34] Identified unsupervised learning can recognise the influence between nodes. Also find the strong and weak links. Attributes are comments, post, share, tag etc.
Saba L in 2012 [33] Evaluated MRI images namely T1 and T2 MRI parts and analysed (a) ovary, (b) uterus (c) vaginal fornix (d) Rectum through McNemar test. The three analysis was done on the dataset around 2 years.
Coutinho A Jr in 2011 [11] Presented that deep endometriosis will intrude around $5mm$ to the layer. Traditionally surgery was found to be finest treatment for treating endometriosis. Magnetic Resonance Imaging (MRI) was found to be more powerful in identifying the lesions by the radiologists.

3. Transfer learning using ResNet50 for classifying endometriosis

This study has examined data gained from standardised Laparoscopic images from GLENDA: Gynaecologic Laparoscopy Endometriosis Dataset [22]. These images are obtained from video stream of Laparoscopic surgery procedure. Patients with both pathological and non-pathological category is considered for evaluation. An overall of 6000 laparoscopic data were taken as input. It was split as training, testing and validation groups respectively. The training group contains 60% of the laparoscopic images of both the classes and summarise the trainable and non-trainable parameters. To evaluate the enactment of the model, dataset taken was different from training group images was validated by fitting the model in the trained environment.

3.1. Deep Learning Neural Network

The Deep learning (DL) techniques resembles the biological neurons, so called as Artificial Neural networks [9]. DL comprises of 2 parts. The first part known as training. Here the system got trained from a large dataset. The second part known as the prediction or validation phase. Here the system predicts the data from new dataset provided.
Here we use a deep neutral network architecture named "Resnet50". The CNN model with more number of hidden layers are able to solve complex datasets which can have the ability for extracting influential features [3]. The architecture of CNN based on certain categories includes feature-map, channel allocation, boosting etc [19].
Algorithm Transfer Learning for Endometriosis Localisation (TLEL)
Input: Data as "$X = \{X_1, X_2, X_3, ..., X_n\}$"
Methodology:

1. Split the dataset as training and test image data set as
   $X\_train = \{X\_t_1, X\_t_2...\}$
   Test/validation as
   $X\_val = \{X\_v_1, X\_v_2...\}$ in the ratio of $70 : 20 : 10$.
2. Assign the label value as 0 –Non-pathology,1-Pathology

3. Pre-process the data and if necessary perform data augmentation includes scaling, rotation, sheering etc...
4. Train the model in Resnet50 neural network architecture with the following specifications.
$model\_res50 = Sequential()$
$model\_res50.add(ResNet50(include_top) = False, pooling =' avg', Weights =' ImageNet')$
5. The trained model need to be optimised as
The loss function and metrics are used to predict the loss and accuracy of each model.
$model\_res50.compile(optimizer =' adam', loss =' binary\_crossentrophy', metrics = ['accuracy'])$
6. Model is summarised as Trainable and Non-trainable parameters
7. Summarised compile model is fit to Resnet50 architecture with parameters known as epochs and verbose.
$model\_res50.fit(x\_train, y\_train, epochs = 60, verbose = 1, validationdata = (x\_val, y\_val))$
8. Repeat step 7 with more number of epoch's in-order to achieve the best accuracy.
Model is predicted by comparing validation with tested images

3.2. Image Analysis

The pre-processing of image is a significant work for classifying the images. Real time images obtained from various source are found to be raw format. There are various pre-processing techniques includes image augmentation, image enrichment, grey to binary conversion and binary to grey conversion, masking etc.
"Texture based feature extraction techniques" are used for brain MRI images to categorise and segment the surrounding tissue of the brain [15]. Image Pre- processing for medical images includes processing such as image pre-processing, histogram equalization, image enhancement, smoothening, image augmentation, erosion, and dilation [38].
"Mid-level feature extractor" were implemented for improving efficiency in larger datasets. Clearer feature extraction method was used for "fine tuning "of x-ray images [21]. "Visual processing algorithm" were used for identifying the part of injured cells in the brain. The OpenCv method includes "morphology operation and watershed algorithm "were implemented for pre-processing the image [23].
Medical images are in raw format i.e. irrelevant parts are associated with the images. Image quality is enhanced by implementing various filtering process, noise removal etc [30]. Medical images guide doctor for making any decision. Image classifiers were implemented to extract and classify brain MRI images. Efficient extraction can be done with exact attributes [13].

3.3. ResNet50 Architecture

For effective prediction, neural network can be implemented efficiently with the help of various architectures namely "VGG16, InceptionV3, ResNet50, Xception, InceptionResNetV2, ResNet50". ResNet50 provides a break-through for efficient image classification and recognition since more number of deep layers solve complex tasks with higher accuracy and throughputs [10].
A total of forty-eight convolutions, one Max-Pooling and one Average-Pooling layers formed in "ResNet50". The ResNet50 comprises *C_layer* with 64 kernels of 7*7 as first layer; Next *C_Layer* consists of three sets of 64 kernels as 1*1 followed by another 64 kernels as 3*3 and 256 kernel as 1*1 of three times repeated which gives a total of nine sub layers at the second layer; Next layer contains a 128 kernels as 1*1 followed by another 128 kernels of 3*3 and finally 512 kernels as 1*1 which is repeated for four times for a total of twelve layers. Next layer consist of 256 kernels as 1*1 added with two more kernels of 256 as 1*1 with another set of two kernels of 256 as 3*3 and 1024 as 1*1

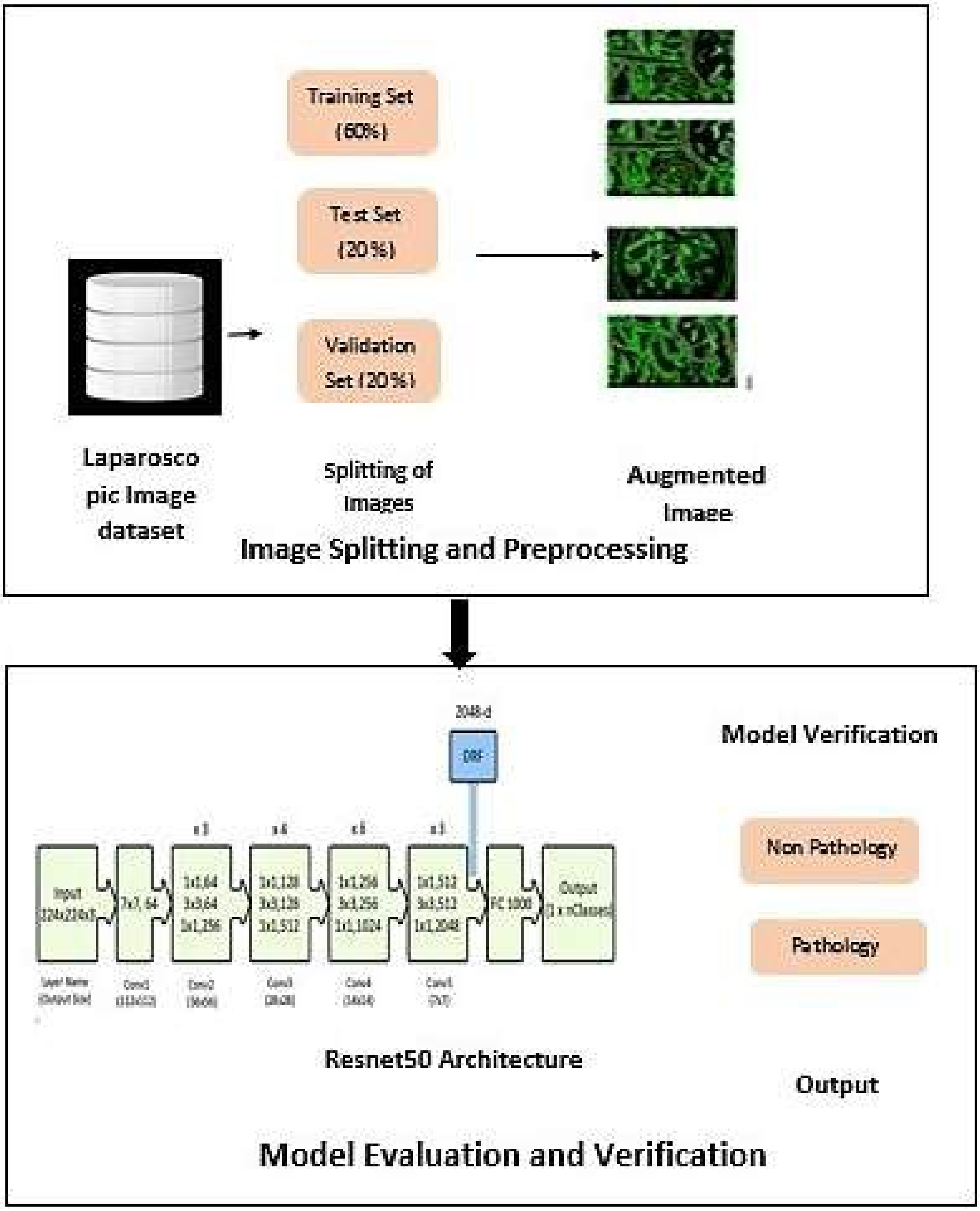

Figure 2: System Architecture of Transfer Learning using CNN for Endometriosis classification

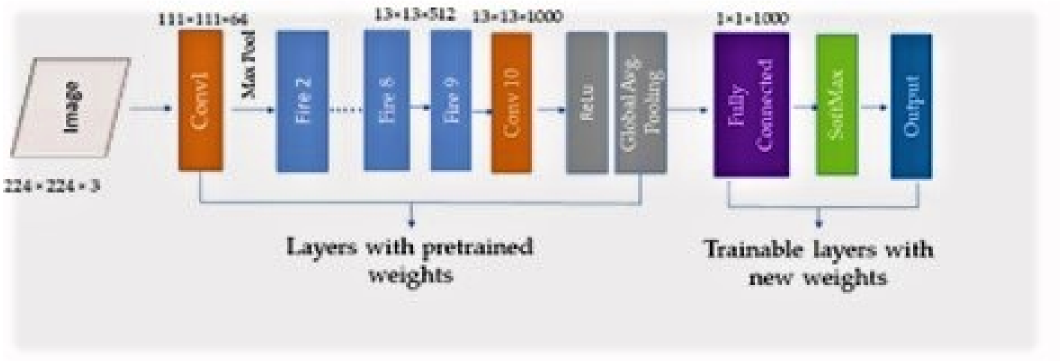

Figure 3: ResNet50 Architecture

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Downloading data from https://storage.googleapis.com/tensorflow/keras-
applications/resnet/resnet50_weights_tf_dim_ordering_tf_kernels_notop.h
5
94773248/94765736 [==============================] - 1s 0us/step
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
resnet50 (Functional)        (None, 2048)              23587712
_________________________________________________________________
dense (Dense)                (None, 1)                 2049
=================================================================
Total params: 23,589,761
Trainable params: 2,049
Non-trainable params: 23,587,712
```

Figure 4: Screen Shot of Training Model

where repeated for 6 times which results in eighteen layers; Subsequent layer comprise of 512 kernel as 1*1 added with another layer of 512 kernel as 1 * 1, with 2 layers of 512 kernel as 3*3 and another kernel of 2048 as 1 * 1 where it was repeated for thrice gives a total of 9 layers; An average pool along through FC layer with 1000 nodes and sigmoid function was considered as 1 layer. Totally, it has "$1 + 9 + 12 + 18 + 9 + 1 = 50$ layers" illustrated in the figure 3.

The model was implemented using Keras in google colab pro environment. Model was trained in Google colab pro environment with high utilising GPU of 25 GB virtual RAM and 108 GB of virtual disk space. Keras-CNN were used for computational research for bio-image analyst [4]. Trained and tested model was compiled, summarised and fitted in the ResNet50 environment. Trained model contains 23,589,761 parameters was illustrated in figure 4. Based on the accuracy obtained, model was validated and predicted.

4. Results and Discussion

The trained model was verified based on the input images used and then model was used to classify the category as pathological and non-pathological images. The architecture of neural network model was designed where input consist of laparoscopic images are split as training, test and validation group independent of each other. The obtained image is in BGR format which once again converted into RGB format i.e. images are annotated and then converted into Numpy array format [7].
The training and test image dataset in array format are split as features and labels. Since it is binary class, only two labels are mentioned in the model. The trained and tested accuracy were found to

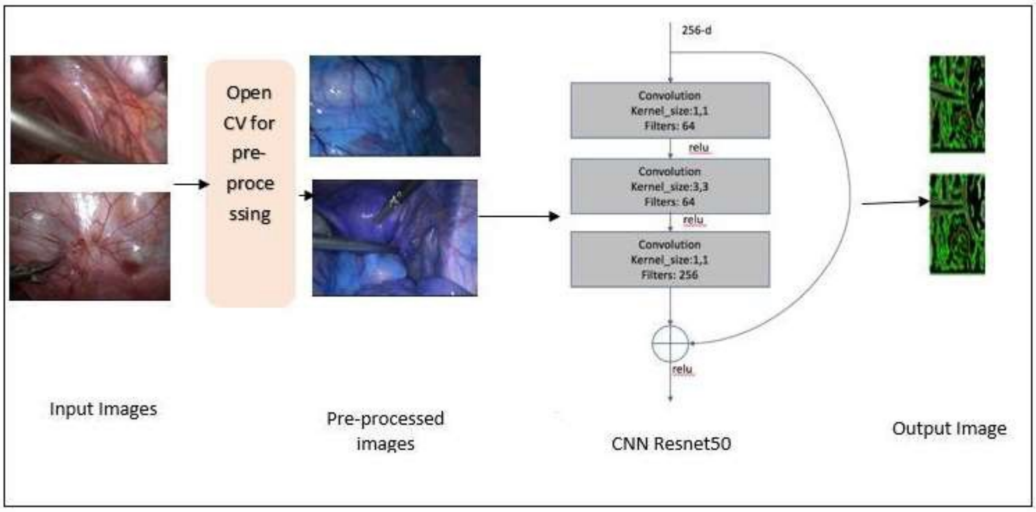

Figure 5: Workflow for Laparoscopic image recognition under ResNet50 Architecture

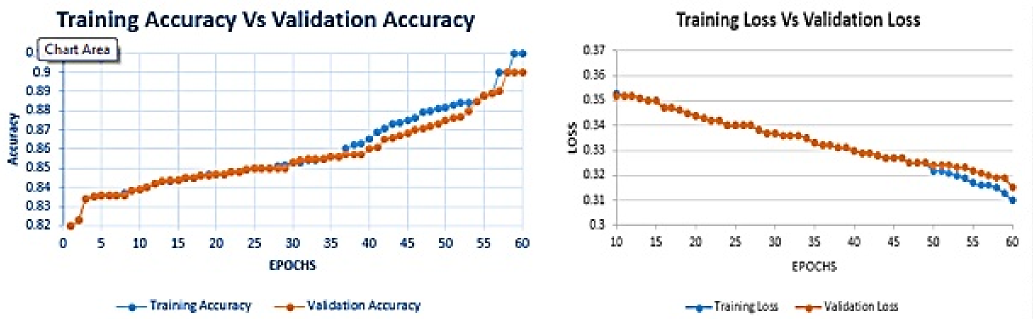

Figure 6: a) Training and Validation Accuracy b) Training and Validation Loss

be 91% and 90% respectively. There is no significant difference between training and test set. The workflow of laparoscopic image recognition is illustrated in figure 5.

The proposed model identifies the endometriosis by providing the laparoscopic images alone as parameters for recognising the presence. Here we proposed an effective and efficient approach of using OpenCV for pre-processing the data and ResNet50 based architecture for training and testing the model of large datasets with raw laparoscopic images. The prognostic model yields high accuracy and throughputs as laparoscopic images were given as input.

$$Accuracy = \frac{Correctly\ predicted\ value}{Overall\ Predicted\ value} \tag{4.1}$$

Accuracy is the quantity to measure the unambiguous value [37]. The accuracy and loss were calculated by fitting the model in the architecture. The trained and tested model yielded an accuracy of 92% and 90% respectively. The predicted model yielded an accuracy of 90%. The training and testing accuracy obtained in the model is illustrated in the figure 6.
To achieve effectiveness, the training was implemented for several times with epoch value of 60. Both training and test accuracy increases with epoch value as a result a positive correlation is achieved in the graph for tainting and validation accuracy. Simultaneously the graph shows there is decrease of training and validation loss representing negative correlation.

Table 1: Classification Report

Metrics	**Precision**	**Recall**	**f1-score**	**Accuracy**
Values Attained	83%	82%	82%	90%

Table 2: The Performance of Different Transfer learning for Endometriosis detection

Transfer Learning	**Sensitivity** (%)	**Specificity**(%)	**Accuracy**(%)
ResNet50	82	72	91
VGG16	76	70	80
Inception V3	80	75	84
Xception	78	71	83.5
Inception ResNetV2	75	70	88

The predicted model performance was evaluated through the classification report includes precision, recall, F1 Score, Specificity, Sensitivity, Positive predicate value, Negative predicate value, respectively.

$$\vartheta = \frac{\Delta P}{\Delta p + \nabla P} \tag{4.2}$$

Precision is represented as ϑ is calculated as the percentage of ΔP divided by the summation of $\Delta p + \nabla P$. The predicted model yields precision value of 0.83. The recall or sensitivity can be defined as number of true positive made out all of true positives including missed values. The recall value for the predicted model seems to be 0.82.

$$\delta = \frac{\Delta P}{\Delta p + \nabla N} \tag{4.3}$$

F1 score known as "Harmonic mean of precision and recall" which in turn can be written as the proportion of ΔP distributed by half of ΔP and ∇N to the summation of ∇N The F1 Score calculated was 0.82.

$$F1Score = 2^{*}\frac{\vartheta * r\delta}{\vartheta + \delta} \tag{4.4}$$

Specificity can be defined as fraction of Δp divided by the total of ΔN and Δp. The specificity obtained is 0.32.

$$Specificity = \frac{\Delta N}{\Delta N + \nabla P} \tag{4.5}$$

where Δp represent acceptably forecast positive values, ΔN represent acceptably forecast negative values, ∇P represent wrongly forecast positive values and ∇N represent incorrectly forecast negative values. Performance metrics gained was illustrated in figure 7.
The table 1 presents the evaluation metrics. These metrics show the CNN based Models using ResNet50 architecture.

ROC is a graph for predicting probability of classes. The ROC can be implemented for assessing the "performance of a classification model". The "Area under Curve (AUC)" able to distinguish between classes where the AUC yields 0.78. The AUC value defines the probability of classes. If the AUC value is lesser than 0.5 then the model is predicting positive as negative classes and vice versa. If the AUC value is greater than 0.5 then the model prediction is found to be accurate [32].

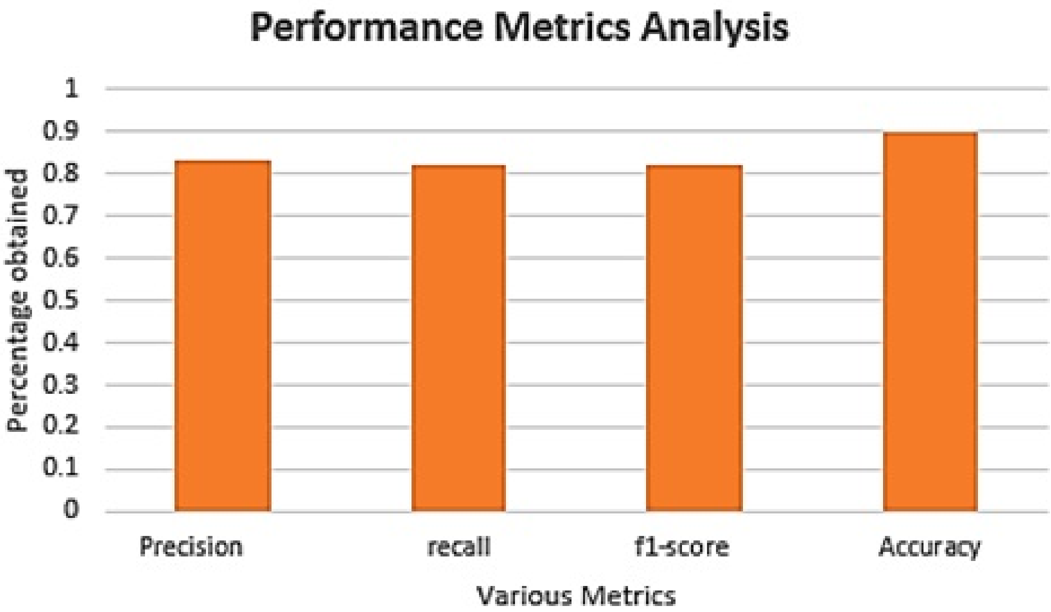

Figure 7: Performance Metrics for predicted model

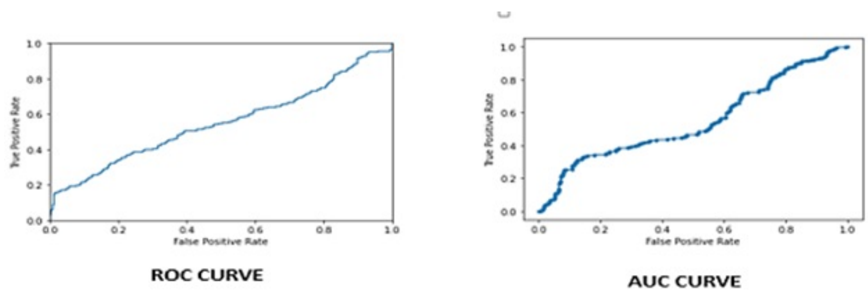

Figure 8: ROC and AUC Curve

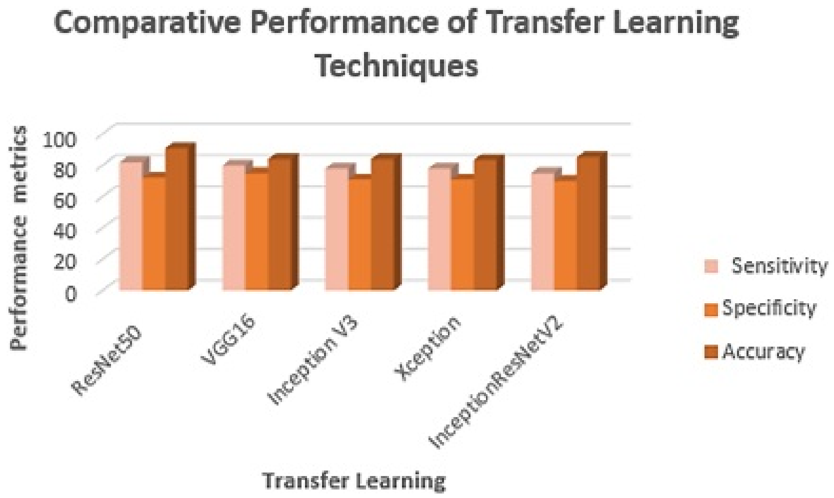

Figure 9: Comparison of Transfer Learning

The various transfer learning techniques include VGG16, Inception V3, ResNet50, Xception, and InceptionResNetV2 are executed and their accuracy, sensitivity, and specificity were compared in table 2. ResNet50 performs efficiently for the given dataset. The comparison was illustrated using the graph in figure 9.

5. Conclusion

This study aims to recognise endometriosis. It was achieved using transfer learning through Convolution neural network(CNN). The proposed CNN was capable of distinguishing two classes' namely non endometriotic and endometriotic tissues. The ResNet50 architecture in this study performed effectively in forecasting the incidence of endometriosis. The proposed system obtained an accuracy of 90% for predicted model. The model yields precision - 83%, recall - 82%, F1 score -82%, AUC - 0.78. The further enhancement is to identify the precise location of endometriosis through deep learning approach.

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