IMPROVING PATIENT OUTCOMES THROUGH EARLY AND ACCURATE OVARIAN CYST DIAGNOSIS: COMPARATIVE PERFORMANCE OF DEEP LEARNING ARCHITECTURES

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ABSTRACT

Ovarian cysts, fluid-filled sacs that form within or on the ovaries, pose diagnostic challenges due to their varied presentation. Simple cysts are often benign, while complex cysts may indicate malignancy and demand timely intervention. Conventional imaging techniques such as ultrasound and Magnetic Resonance Imaging (MRI) rely heavily on radiologist interpretation, which can be subjective and error-prone, particularly in resource-limited healthcare settings. This highlights the need for reliable, automated diagnostic tools. This study aimed to improve patient outcomes through early and accurate ovarian cyst diagnosis by comparing the performance of three deep learning architectures: Convolutional Neural Networks (CNNs), Residual Networks (ResNet-50), and the Visual Geometry Group Network (VGG19). A comparative experimental design was employed using 577 ultrasound images (313 simple cysts, 264 complex cysts) obtained from Kaggle and validated by radiologists. Images were preprocessed through resizing, normalization, and augmentation. Models were implemented in Python (TensorFlow/Keras) on Google Colab, trained with binary cross-entropy loss, and evaluated using accuracy, precision, recall, and F1-score. Transfer learning was applied to ResNet-50 and VGG19 to enhance performance on the limited dataset. Results showed that ResNet-50 achieved the most reliable classification performance, supported by higher precision, recall, and F1-score, despite not recording the highest raw accuracy. This robustness is mathematically linked to its residual learning framework, which improves feature extraction and mitigates vanishing gradient issues. CNN performed adequately but was constrained by its shallow depth, while VGG19, although reaching 85% accuracy, overfit to the small dataset. In conclusion, deep learning particularly ResNet-50 demonstrates statistically balanced and mathematically justified potential for early and accurate ovarian cyst classification. Its integration into clinical workflows could reduce diagnostic errors and support better patient outcomes.

Keywords: Ovarian Cysts, Deep Learning, Medical Imaging, Convolutional Neural Networks, ResNet, VGG19, Early Diagnosis, Ultrasound Classification.

1. INTRODUCTION

One on each side of the uterus, located beneath the fallopian tubes are the ovaries, the female reproductive organs which is contained in the pelvic cavity. The ovaries are almond-sized and have an oval form. Each ovary has many follicles in its outer zone, or cortex which contain female reproductive cells or oocytes (Ovum). Every month, around the middle of the menstrual cycle, a follicle grows and releases an ovum; after that, the ovum is sent to the fallopian tube where a sperm may fertilize it. Subsequently, if the egg is fertilized it moves into the uterus, implants in the endometrium that is growing and develops into a fetus; otherwise, the ovum then shrinks and the endometrium breaks off and discharges as menstruation. The ovaries also secrete female hormones like progesterone and estrogen (MedPark Hospital, 2024). All these are natural functions of an ovary and the overall process is called Ovulation, a natural process that happens during the menstrual cycle of a woman and is the leading cause of a disease called ***Ovarian Cysts.*** Ovarian cysts are fluid filled sacs that develop within or on the ovaries. It is a common experience that affects women of all ages. Classifying these cysts into simple or complex is important for proper medical treatment. Simple cysts are often benign (non-cancerous) and cause little or no harm and go away on their own while complex cysts are characterized by being Malignant (cancerous) and can lead to complications such as rupture, twisting including infertility; in order to curtail this, early detection of ovarian cysts is paramount for improving patient outcomes, as delayed diagnoses often lead to advanced-stage disease with limited treatment options. When women find out they have an ovarian cyst, they may feel surprised or afraid. Although, contrary to the popular belief, this fluid filled sacs that form on or inside a woman's ovaries are much more common and usually do not need any concern (Pelham, 2022). One of the most common gynecologic conditions seen in outpatient clinics and gynecologic surgeries is Ovarian Cysts (Vejthani Hospital, 2020). According to (Cleveland Clinic, 2016) the bulk of the materials state that between 8% and 18% of premenopausal and postmenopausal women have ovarian cysts, although estimates of the prevalence of these conditions vary greatly. The vast of postmenopausal cysts last for several years. Advanced Research has shown that 10 out of 100 women have ovarian cysts and they are usually benign (non-cancerous) and most often do no cause any harm therefore they don't need to be treated. Surgery is also very rarely needed (U.S. National Library of Medicine, 2022).

Ovarian cysts come in different forms, majority of which are benign (non-cancerous), and malignant (cancerous). Symptoms of ovarian cysts are not always visible except if discovered coincidentally during a pelvic exam or pelvic ultrasound (Cleveland Clinic, 2024). Throughout their reproductive years, women have two ovaries each of which contains a large number of eggs that are produced in monthly cycles; without medical intervention, ovarian cysts practically go away on their own but it becomes a problem if it does not disappear, enlarge or produce any symptoms (Vejthani Hospital, 2020). It has been discovered that most cysts often measure up to two (2) – three (3) millimeters and in rare cases, they may reach a maximum size of 30 centimeters. Although when they are large enough, they tend to affect a woman's bladder and colon leading to pressure and edema (Pelham, 2022). Ovarian cysts are usually asymptomatic but in case of symptoms, according to (Vejthani Hospital, 2020, U.S. National Library of Medicine, 2022) may include the following: Pelvic pain, this is a dull pain in the lower abdomen on the side where the cyst is located; Irregular menstrual cycle such as heavy or irregular periods, spotting (abnormal vaginal bleeding between periods). This problem occurs if the cyst generates sex hormones that cause the lining of the womb to expand more. And, the bladder or bowel may be pressed against by very big cysts. This may lead to constipation, pain when urinating, a swollen stomach, a sense of fullness and pressure. A cyst rupture may cause abrupt pain and nothing else after that but it can become twisted due to the weight of the cyst pulling on it. This causes a fast pulse rate, nausea, vomiting and sudden intense cramping pain on the afflicted side of the lower abdomen.

Deep learning is a subset of machine learning that uses artificial neural networks to learn from data. The structure and operation of the human brain serve as inspiration for neural networks which can recognize patterns and connections in data. Deep learning is a potent machine learning method that has produced remarkable outcomes in a wide range of tasks, including language translation, image recognition and text comprehension and generation (Mariam Kili Bechir, 2023). One of the key technologies of the current Fourth Industrial Revolution (4IR or Industry 4.0) is deep learning (DL), a subfield of machine learning (ML) and artificial intelligence (AI). Owing to its capacity to learn from data, deep learning (DL) technology, which evolved from artificial neural networks (ANN), has gained popularity in the computing community and is used extensively in a wide range of fields, including healthcare, cybersecurity, text analytics, and visual identification, among many others (Sarker, 2021). Deep learning models use several layers to learn features ranging from simple to complicated and it eliminates the requirement for manual or human feature engineering by allowing raw data to be trained directly on them. It also works well with large datasets and robust computer resources.

Earlier studies on the use of traditional methods for detecting ovarian cysts were quite helpful but not a 100% efficient as the normal diagnostic method of detecting these cysts Ultrasound, MRI (Magnetic Resonance Imaging) and TVUS (Trans-vaginal Ultrasound) rely solely on manual interpretation by the radiologists which often times may not be accurate and can lead to misdiagnoses and other related consequences. Over the years, there has been new developments in Artificial Intelligence (AI) specifically Deep Learning models like CNNs (Convolutional Neural Networks), ResNet and VGG19 to mention but a few. These presents interesting ways for enhancing accurate diagnoses and reduce personal opinions thereby improving patient's health and outcome. Greenlee et al. (2010) characterized the epidemiology of simple ovarian cysts in older women particularly through serial TVU screenings. They also measured the prevalence and incidence rate of common simple ovarian cysts in postmenopausal women and found that 14% of women during their first screening were detected to have simple ovarian cyst with an incidence rate of 1-year for new simple cysts to be found among 8% of women who had no cysts earlier. This study only focused on simple cyst and TVUS as a method of screening for ovarian cysts detection. It was noted however that one septation may be present in simple cyst; The daughter cysts sign, which is tiny, spherical, anechoic object inside a cyst is said to be **"Pathognomonic for an ovarian cyst".** Complex ovarian cysts may have heterogeneous echogenicity and thick walls. According to histologic research and postnatal surgical specimens, primitive gonadal dysgenesis brought on by vascular compromise may give rise to complicated ovarian cysts. Furthermore, there have been reports of complicated cysts that resemble hemorrhagic or ovarian teratomas. Additional ultrasonographic abnormalities include fetal ascites or polyhydramnios, which can be caused by cyst rupture or transudate; this study conducted by Yvonne et al. (2021) found out that simple cysts often resolve spontaneously; complex cyst may cause torsion and require intervention; and the diagnosis relies on ultrasound features.

According to The Society of Maternal-Fetal Medicine [SMFM] (2021), fetal ovarian cysts which are often identified through prenatal ultrasound, need to be monitored in order to differentiate between simple and complex cysts by emphasizing the value of serial ultrasound evaluations but the subjective nature of the evaluation is still a limitation. (Vaden-Brink et al., 2020) in their study to assess the follicle numbers and classify Polycystic ovarian morphology (PCOM) employed the use of ultrasonographic techniques by comparing 2D and 3D ultrasound procedures. There were significant differences between the 2D and 3D results indicating the need for more reliable and consistent tools for diagnoses. However, a deep learning method for ovarian cyst identification using the fuzzy convolutional neural network (OCD-FCNN) declared an accuracy of 98.37% on a set of datasets (Ravishankar et al., 2023). This finding shows how AI may enhance diagnostic results.

Irrespective of these developments, a thorough comparison of several deep learning models for the classification of ovarian cysts is still essential. By comparing the effectiveness of CNN, ResNet and VGG19 in the identification and classification of ovarian cysts, learning from the successful use of deep learning in recognizing the need for improved screening and treatment strategies, this study aims to close the gap and help improve better patient's outcome and also, the study seeks to address the urgent need for improved early detection and management methods by comparing these three different Deep Learning models to see which can accurately predict and classify the cysts into either simple or complex while utilizing the ability of AI to enhance the current approaches and improve patient's health and outcome.

2. MATERIAL AND METHODS

2.1. Research Design

The research design employed in this study is the experimental design, specifically a comparative experimental study. This approach was chosen to systematically evaluate and compare the performance of three distinct deep learning models CNNs, ResNet, and VGG19 in the task of classifying ovarian cysts into simple and complex categories based on ultrasound images.

2.2. Data Source and Data Characteristics

The success of any deep learning model, particularly in medical image classification tasks, depends heavily on the quality and quantity of the dataset used. For this study, the data was specifically curated to ensure that it accurately represents the problem of ovarian cyst classification. The Ultrasound images dataset utilized for this research was obtained from Acharya et al. (2018), obtained via Kaggle. All images were verified by certified radiologists to ensure accurate labeling into two classes: Simple Cyst and Complex Cyst. The data characteristics comprises of a total of 577 ultrasound images in which 313 images were labeled as "Simple Cyst" and 264 images labeled as "Complex Cyst". The image format is JPEG (Joint Photographic Experts Group) and PNG (Portable Network Graphics). The image resolution varied initially but was standardized to 224 x 224 pixels during preprocessing for model compatibility.

2.3. Data Labeling and Data Quantity Consideration

Class 0: Simple cyst and Class 1: Complex cyst

This binary classification approach simplifies the model's task to distinguishing between benign (simple) and potentially risky (complex) ovarian cysts. Given the size of the dataset is relatively small, the following techniques: Data Preprocessing, Image Resizing, Image Normalization, Data Augmentation and Dataset splitting were implemented to artificially increase the diversity and quantity of the training data. This helps prevent overfitting and improves model generalization on unseen images.

2.4. Model Architectures

2.4.1. Convolutional Neural Network (CNN)

The CNN architecture designed for this study consists of the following components:

The input layer accepts 224 x 224 x 3 image; the convolutional layers extract low- to high-level features from the input image using a set of learnable filters. **Activation Functions**: ReLU (Rectified Linear Unit) is applied after each convolution to introduce non-linearity. **Pooling Layers**: Max Pooling is used to progressively reduce the spatial dimensions of the feature maps, reducing computational complexity. **Fully** Connected **Layers**: After flattening, dense layers are used to perform classification based on the extracted features and **Output Layer**: A single neuron with a sigmoid activation function for binary classification (simple vs complex cyst).

2.4.2. Residual Network (ResNet)

For this study, a **ResNet-50** variant was employed through transfer learning. The main components include: **Input Layer:** Accepts standardized 224 × 224 × 3 images, **Initial Convolution and Pooling**: A large kernel size convolution followed by max pooling, **Residual Blocks**: Each block contains convolutional layers with shortcut connections that bypass one or more layers, allowing gradients to flow directly through the network, **Global Average Pooling Layer**: Reduces the feature maps to a 1D vector by taking the average of each feature map. **Fully Connected Layers**: Dense layers for final classification and **Output Layer: A sigmoid-activated neuron for binary classification.**

2.4.3. Visual Geometry Group Network (VGG19)

This model consists of the following architectures: Input Layer: Accepts 224 × 224 × 3 images, **Convolutional Blocks**: Multiple blocks, each containing two to four convolutional layers followed by a max-pooling layer, **Activation Functions**: ReLU activations used after every convolutional operation, **Fully Connected Layers**: Three dense layers, with the first two using ReLU activations and a dropout layer for regularizations, **Output Layer**: A dense layer with a sigmoid activation for binary classification.

2.4.4. Training Parameters

The key training parameters used are detailed below:

- Optimizer: Adam Optimizer was used for all models.
- Learning Rate:
- Loss Function: Binary Cross-Entropy Loss was used, as the task is a binary classification (simple cyst vs complex cyst).
- Batch Size: Batch Size: 32
- Number of Epochs: 50. Early Stopping was applied with a patience of 7 epochs (training stops if validation loss does not improve for 7 consecutive epochs).

2.4.5. Hardware and Software Environment

Hardware:
GPU: NVIDIA Tesla T4
RAM: 16GB
Software: Google Colab
Package: Python 3.10
Libraries: TensorFlow 2.x, Keras, OpenCV, Scikit-learn

2.4.6. Evaluation Metrics

The following metrics were used:

Accuracy: Accuracy is the proportion of correctly classified instances (both simple and complex cysts) among the total instances. It gives a general idea of overall model performance.

Precision: Precision measures the proportion of correctly predicted positive instances out of all instances predicted as positive. In this context, it reflects how many cysts identified as complex are truly complex. High precision indicates a low false positive rate.

Recall (Sensitivity): Recall quantifies the ability of the model to correctly identify all relevant instances (complex cysts). It is especially important in medical diagnostics where missing a complex cyst can have serious consequences

F1-Score: The F1-Score is the harmonic mean of precision and recall. It balances the two metrics, offering a more reliable measure when the dataset is imbalanced.

3. RESULTS AND DISCUSSION

3.1. CNN

A brief summary of the model's architecture, the first image predicted, training history and multiple images predicted upon was achieved after the dataset was properly labelled. The model's performance metrics on Test Accuracy and Loss was also determined. This model was able to predict successfully the first image in which the actual was **Simple Cyst** and the predicted label was **Simple Cysts.** Two graphs were plotted in the training history having two components each namely: "Training and Validation Loss" and" Training and Validation Accuracy", results show for the "Training and Validation Loss" that the model is learning effectively and the consistent downward trend suggests no overfitting for the training loss, the movement of the trend of the validation loss indicates that the model is generalizing well with the data and there maybe little or no overfitting. The Training and Validation accuracy movement indicates a 23% relative accuracy gain from 0.52 against Epoch 0 to 0.64 against Epoch 20 confirming positive learning and no fluctuations or plateau in the later epochs meaning the model hasn't saturated. It successfully predicted on multiple images showing the Actual label and Predicted label alongside Confidence Score. The model achieved a Test accuracy of 56.72% and a Test Loss of 67.90% under 2seconds.

3.2. RESNET50V2

The brief summary of this model's architecture, first image predicted successfully, training history, multiple images predicted upon and the model's performance metrics on Test Accuracy and Loss will be discussed in this section.

A brief summary showing the layer type, output shape and parameters characterized as a part of the model was installed. The first image predicted upon had an actual label of **Simple Cyst** and in less than a second, its predicted label was **Simple Cyst.** The training history had two graphs with two components each plotted namely: "Training and Validation Loss" and" Training and Validation Accuracy". The training loss starts above 1.2 on the *y-axis* and decreases as the epochs increases but it has fluctuations. This indicates that the model is learning and making little mistakes on the training data as training progresses though the improvement is not smooth. The Validation loss remains low and almost flat from 0.67 loss on the *y-axis* throughout the epochs. The above training loss suggests that the validation set is easier or less diverse than the training set or there could be data split issue or leakage as it is unusual for the validation loss to be consistently lower than the training loss and that of the Validation loss suggests the model is not generalizing better on unseen data in-spite some learning on the training set.

The Training and Validation Accuracy graph: it is noted that the training accuracy fluctuates between 0.47 and 0.54 with no clear upward trend, indicating the model is not consistently improving in correctly classifying the training data. The validation accuracy stays flat at about 0.62 even as the epoch increased, showing no improvement and suggesting the model is not learning features that help it generalize to the validation set. From this report, we can conclude that the validation data is not representative or is much easier than the training data there could be an issue with how the data is split or labeled.

It achieved a test accuracy of 53.75% and a test loss of 70.10% in less than a second.

3.3. VGG19

In this section, the brief summary of this model's architecture, first image predicted successfully, training history, multiple images predicted upon and the model's performance metrics on Test Accuracy and Loss will be discussed.

The Training and Validation loss with Loss on the *y-axis and Epoch on the x-axis* and Training and Validation accuracy with Accuracy on the *y-axis and Epoch on the x-axis* VGG19 model. The loss starts at 0.0 for epoch; this is unusual as it normally starts higher though it rises at an early epoch to 0.5, there is slight fluctuations, and the trend finally drops to 0.0. the validation loss shows a downward trend as it drops to o.0 as the epoch increases.

The Training and Validation Accuracy in which the accuracy starts at an expected point for untrained model of 0.0, rising steadily to 50% or 0.5 accuracy, shows little fluctuations after that. The validation accuracy begins at 0.6 against epoch 0.0 having few downward spikes and later maintains a rising trend as the epochs increased.

The low loss and high accuracy are important but as the loss drops to 0.0 it suggests the model might be overfitting and as accuracy fluctuates at 50%, it suggests that the model is not learning effectively after epoch 5. A Test Accuracy of 85.00% and Test Loss of 78.02% in 0.043 seconds was achieved by this model.

4. CONCLUSION

The comparison of these models in detecting, predicting, and classifying ovarian cysts into simple or complex has shown that model performance depends not only on accuracy but also on reliability, robustness, and generalizability. The CNN model, though achieving a higher accuracy than the ResNet50v2 model, could not consistently predict and classify more than 50% of the images into either simple or complex categories. This limitation can be traced to its shallow architecture and limited feature extraction capacity. The ResNet50v2, despite having the lowest test accuracy of 53.75% among the three models, demonstrated the most reliable prediction and classification by correctly categorizing more than 50% of the test images. This strength is attributed to its robust residual architecture, which enhances feature learning and reduces errors. VGG19, on the other hand, attained the highest test accuracy of 85.00% but performed poorly in prediction on multiple images due to its tendency to overfit on the small dataset.

From these findings, the best model is selected not solely based on accuracy but on a combination of criteria: prediction reliability, classification consistency, architectural robustness, and resistance to overfitting. By these measures, ResNet50v2 emerges as the most effective model for ovarian cyst classification in this study. Accuracy being the basis of this comparison brings us to understand that there is a higher chance of VGG19 performing better than ResNet50v2 in the early detection, prediction and classification of the disease ovarian cysts into either simple or complex. This research had the issue of getting localized dataset causing the data to be biased as it had to work on dataset gotten from a very far region. For future studies, we recommend that the model be finetuned for better improved results, the dataset can be localized to solve biasedness, a webapp can be designed for the models to be properly understood and accessed, clinicians should be trained to interpret and encouraged to accept this aspect of technology for the achieving of better results and other DL models can be compared too especially with larger dataset in order to diversify the result and achieve better result. This will help improve clinical conclusion by radiologists and patient health and outcome.

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APPENDIX

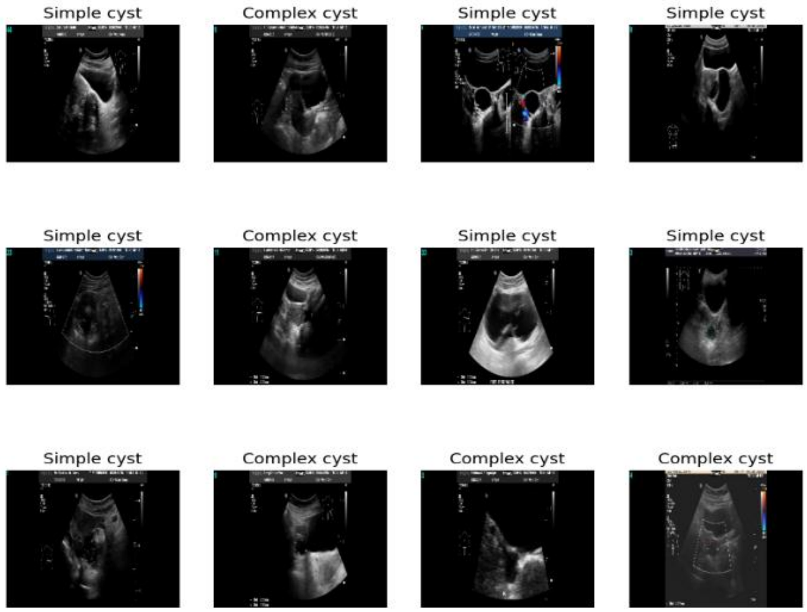


Figure 1: Showing Labeled Dataset With Class Names

Table 1: Showing Summary of the CNN Model
Model: "sequential_2"

Layer (type)	Output Shape	Param #
sequential (Sequential)	(None, 256, 256, 3)	0
Sequential_1 (Sequential)	(None, 256, 256, 3)	0
Conv2d (Conv2D)	(None, 254, 254, 32)	896
Max_pooling2d (MaxPooling2D)	(None, 127, 127, 32)	0
Conv2d_1 (Conv2D)	(None, 125, 125, 64)	18,496
Max_pooling2d_1 (MxPooling2D)	(None, 62, 62, 64)	0
Conv2d_2 (Conv2D)	(None, 60, 60, 128)	73, 856
Max_pooling2d_2 (MaxPooling2d)	(None, 30, 30, 128)	0
Flatten (Flatten)	(None, 115200)	0
Dense (Dense)	(None, 256)	29, 491, 456
Dense_1 (Dense)	(None, 128)	32,896
Dense_2 (Dense)	(None, 64)	8,256
Dense_3 (Dense)	(None, 2)	130

Total params: 29,625,986 (113.01 MB)
Trainable params: 29,625,986 (113.01 MB)
Non-trainable params: 0 (0.00 B)

First Image to Predict:
Actual label: Simple cyst

1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 246ms/step

Predicted label Simple cyst

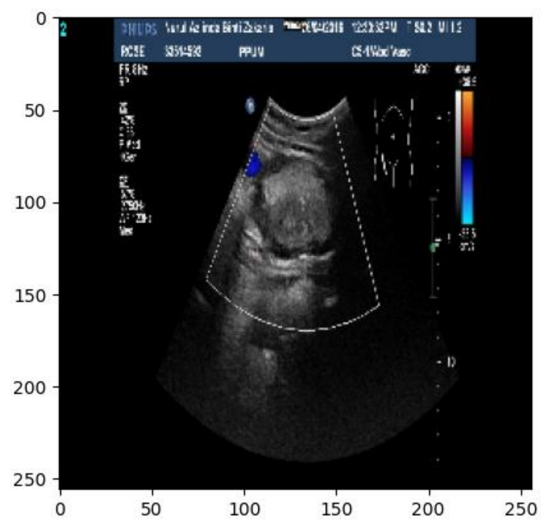
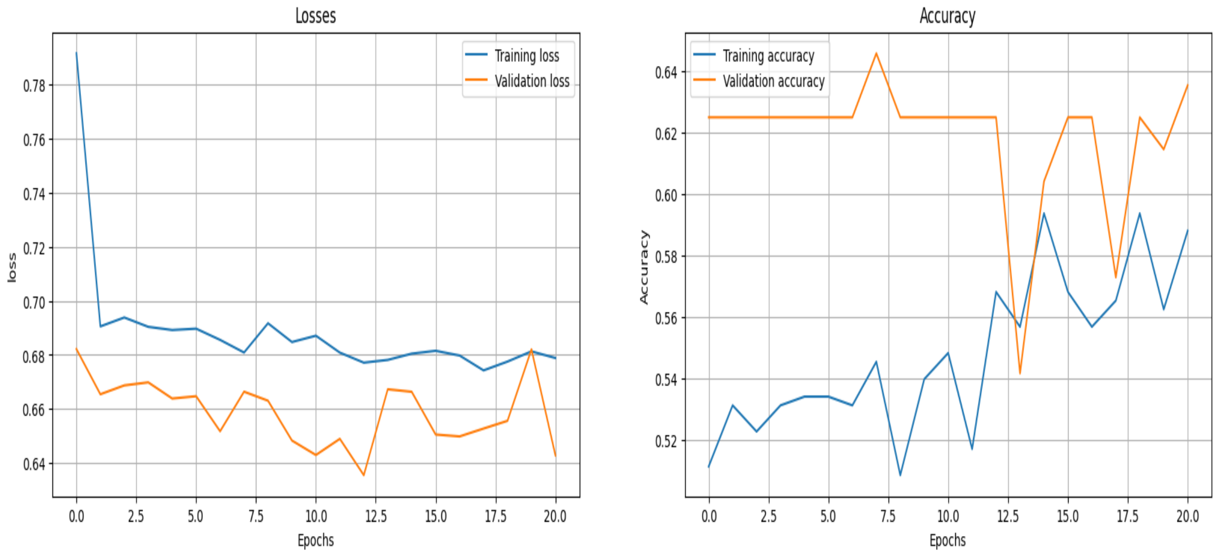


Figure 2: showing the first image predicted from the CNN test dataset



(a) (b)

Figure 3: Showing the Loss and Accuracy Line graph for CNN Model

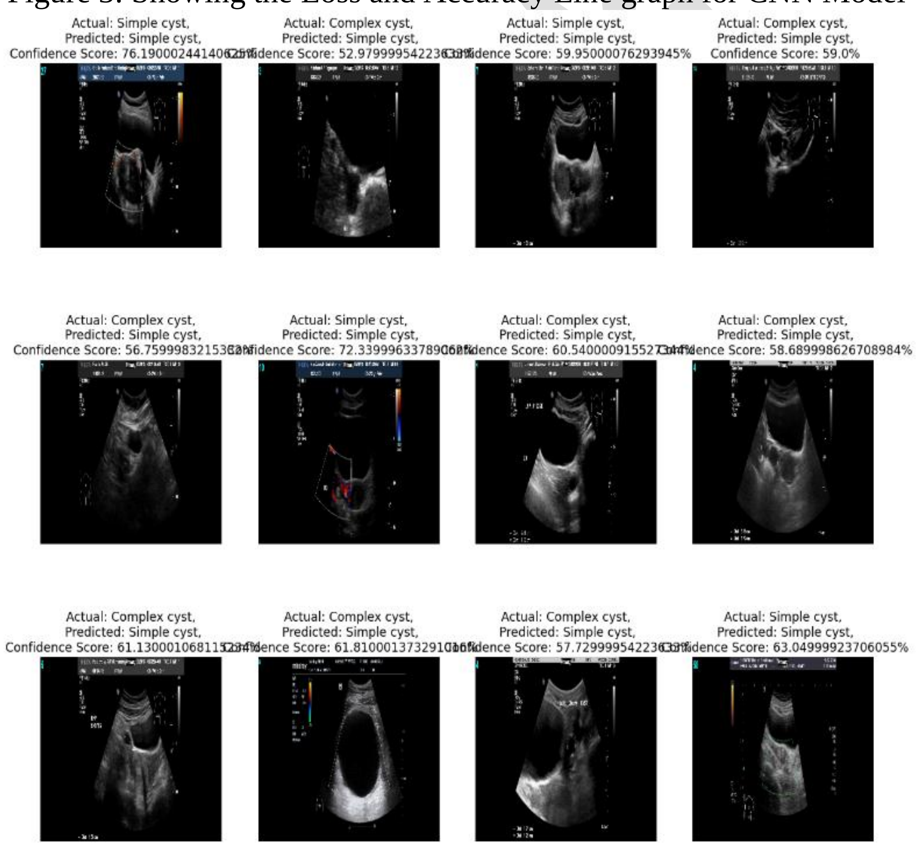


Figure 4: Showing Prediction of Multiple images and Confidence score from the Test Dataset

RESNET50V2

Table 2: Showing the summary of the ResNet 50 v2 Model
Model: “Sequential_3”

Layer (type)	Output Shape	Param #
Sequential (Sequential)	(None, 256, 256, 3)	0
Sequential_1 (Sequential)	(None, 256, 256, 3)	0
Conv2d_3 (Conv2D)	(None, 254, 254, 32)	896
Batch normalization (Batch Normalization)	(None, 254, 254, 32)	128
Max_pooling2d)6 (MaxPooling2D)	(None, 127, 127, 32)	0
Conv2d_4 (Conv2D)	(None, 125, 125, 64)	18,496
Batch_normalization_1 (Batch Normalization)	(None, 125, 125, 64)	256
Max_pooling2d_7 (MaxPooling2D)	(None, 62, 62, 64)	0
Conv2d_5 (Conv2D)	(None, 60, 60, 128)	73, 856
Batch_normalization_2 (Batch Normalization)	(None, 60, 60, 128)	512
Max_pooling2d_8 (MaxPooling2D)	(None, 30, 30, 128)	0
Flatten_1 (Flatten)	(None, 115200)	0
Dense_4 (Dense)	(None, 256)	29,491,456
Batch_normalization_3 (Batch Normalization)	(None, 256)	1,024
Dropout (Dropout)	(None, 256)	0
Dense_5 (Dense)	(None, 128)	32,896
Batch_normalization_4 (Batch Normalization)	(None, 128)	512
Droupout_1 (Dropout)	(None, 128)	0
Dense_6 (Dense)	(None, 64)	8,256
Batch_normalization_5 (Batch Normalization)	(None, 64)	256
Dropout_2 (Dropout)	(None, 64)	0
Dense_7 (Dense)	(None, 2)	130

Total params: 29,628,674 (113.02 MB)
Trainable params: 29,627,330 (113.02 MB)
Non-trainable params: 1,344 (5.25 KB)

First Image to Predict:
Actual label: Simple cyst
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 252ms/step
Predicted label Simple cyst

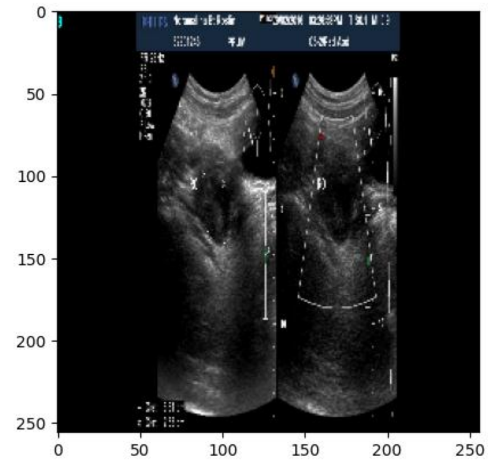
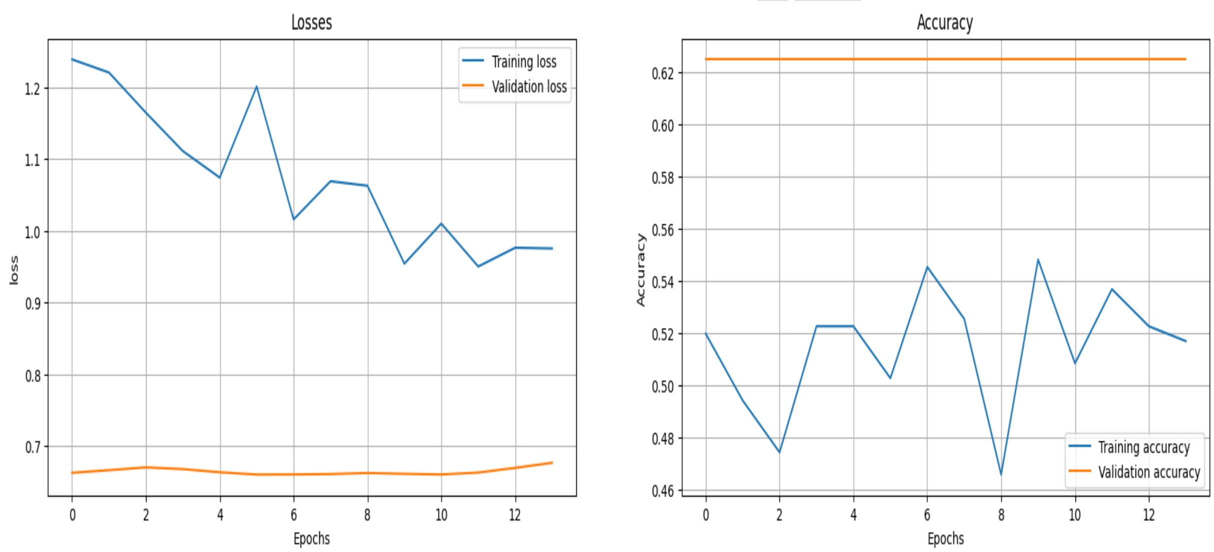


Figure 5: Showing The First Image Predicted On The Test Dataset By ResNet 50V2 Model



(a) (b)

Figure 6: Showing the Loss and Accuracy Line graph for the ResNet50V2 Model

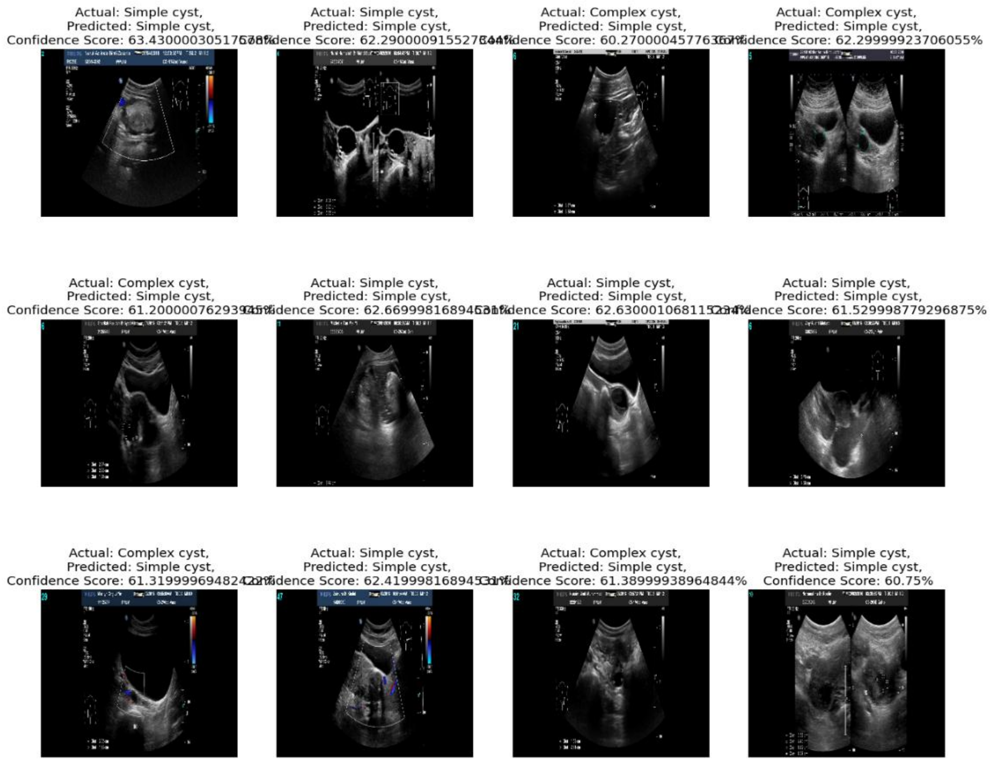


Figure 7: Showing Prediction of Multiple images and Confidence score from the Test Dataset VGG19

Table 3: Summary of the VGG-19 Model
Model: "Sequential_4"

Layer (type)	Output Shape	Param #
Vgg19 (functional)	(None, 8, 8, 512)	20,024, 304
Flatten_2 (Flatten)	(None, 32768)	0
Dense_8 (Dense)	(None, 512)	16, 777, 728
Dropout_3 (Dropout)	(None, 512)	0
Dense_9 (Dense)	(None, 256)	131, 328
Dropout_4 (Dropout)	(None, 256)	0
Dense_10 (Dense)	(None, 1)	257

Total params: 36,933,697 (140.89 MB)
Trainable params: 16,909,313 (64.50 MB)
Non-trainable params: 20,024,384 (76.39 MB)

First Image to Predict:
Actual label: Complex cyst
1/1 ━━━━━━━━━━━━━━━━━━━━ 1s 1s/step
Predicted label Complex cyst

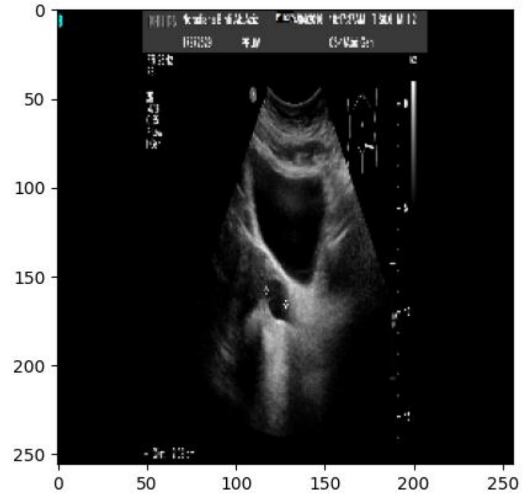
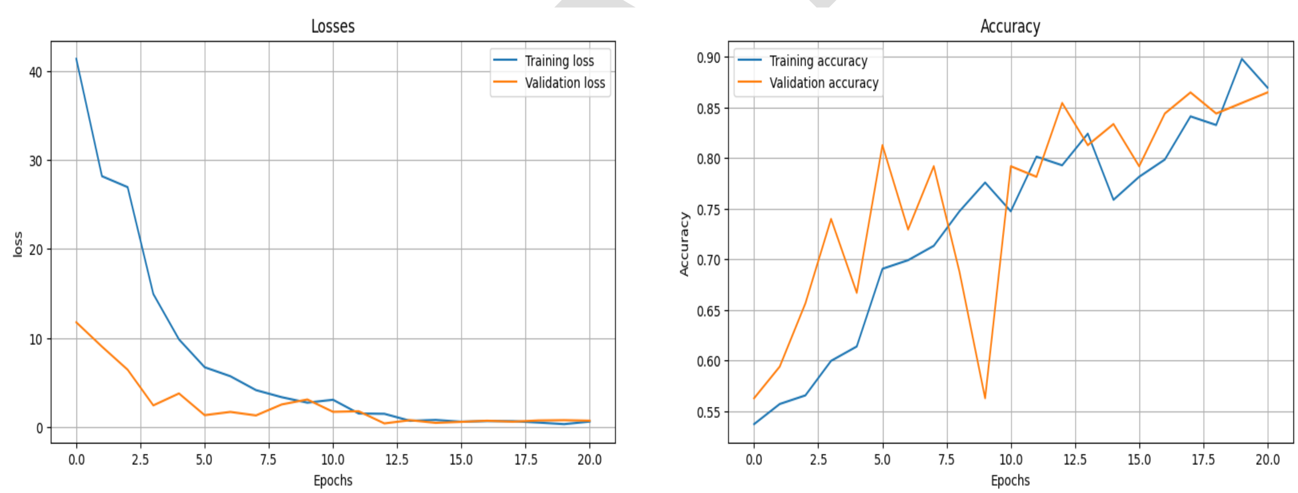


Figure 8: Showing the first image predicted on the test dataset by VGG19



(a) (b)

Figure 9: Showing the Loss and Accuracy Line graph for the VGG19 Model

Figure 10: Showing Prediction of Multiple images and Confidence score from the Test Dataset