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Classification of PCOS/PCOD Using Transfer Learning and GAN Architectures to Generate Pseudo Ultrasound Images

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Abstract

Polycystic Ovarian Syndrome(PCOS) is one of the most worrying concerns for women in the 21st century.Undiagnosed and treatable for long periods of time can be fatal.As deep learning is a rapidly emerging technology in medical diagnosis and various neural network have produced promising results in image classification and detection.However, classifying Polycystic ovarian syndrome in ovary ultrasonic images automatically was motive as implemented in other diagnosis such as X-Rays, MRI, CT Scan etc using CNN and other neural networks.Another progress in computation vision has been made by implementing a simple GAN model to generate synthetic images in order to overcome the lack of dataset then also data augmentation on re-processed ultrasonic images with resizing and finally trained the models. Among all the implemented model namely VGG-19, DenseNet-121, ResNet-50 and Inception V3 and model stacking, highest accuracy with better sensitivity and specificity is achieved by VGG-19 i.e.approximately 70%.
Keywords— *Deep learning, Medical Diagnosis, Polycystic ovarian syndrome(PCOS), transfer learning, GAN, data augmentation*

Contents

1 Introduction

1.1 Background & Motivation

There are several diseases that put women's health at risk in the 21st century but the most common and prevalent is PCOS/PCOD (Polycystic Ovarian Syndrome) occurs in reproductive age (18-44).It can cause permanent infertility or ovarian cancer if untreated can also induce other diseases like diabetes and hypertension in young age. Worldwide, infertility is on the rise side, with more losses occurring owing to hormonal shifts, and 25 percent of infertility cases being caused by disordered ovulation as per journal[1].As stated by Soni and Vashisht PCOS affects 18% of Indian girls, according to a study that examined the risk factors and symptoms of this syndrome.In India, urban women are more likely than rural women to have PCOS, according to a cross-sectional survey mentioned in Bharathi et al. (2017).The lifestyle and stress could be a contributing factor according to this estimate.This illness has already affected about 120 million women or 4.4% of all women in the world, according to 2012 statistics from the World Health Organization.In India based on Ramamoorthy et al. (2021), 10 percent of young girls dealing with the curse from this illness, which is associated with a high cases of miscarriages in the first trimester and a large number of infertility cases.

Polycystic Ovarian Syndrome also known as Stein–Leventhal syndrome which is endocrine condition where ovaries develops multiple fluid-filled sacs, preventing them from ovulating normally.Before undergoing an ovarian ultrasound, some of the key indicators of PCOS are irregular menstruation, painful acne owing to hormonal imbalance, metabolic problems, thyroid, and hypertension.In the event of the long-term effects of this syndrome chances of getting uterine cancer make this illness life-threatening.But at this time, no cure has been found for the disease.Metformin, anti-androgens, and other birth control drugs[2] prescribed by doctors which has its own side effects.Besides hormonal therapy (such as estrogen-progestin contraceptive pills), surgery and lifestyle changes (such as exercise, yoga, and a well-balanced diet) many women witnessed success with home remedies.Completely effective treatment options are very limited and despite the severity of the cyst ailment and gravity of medication available, awareness is the key to curb the numbers and catch the disease at initial stage.

Based on Rotterdam conference & criteria[3], ovulation abnormalities, higher levels of androgen hormone, and polycystic ovaries in ultrasonic images are the three key signs that indicate PCOS in a woman. An international consensus guideline(2018) states that patients with this condition have an average of 12-20 FNPOs (Follicle No Per Ovary) with a diameter between 2 and 9 millimetres, or an average size of 10 centimetres in ultrasonography.This process performed manually by radiologist and consumes more time for accurate results.In accordance with the author's Mehrotra et al. research, machine learning applied to certain physical and hormonal level characteristics aids in the detection of cysts, but only until cyst presence is confirmed by ovarian ultrasound.Hence emergence of Image classification, segmentation, assessment and enhancement occurred in detection of cyst eventually and helped to automated the detection.

Artificial intelligence in medical diagnostics's is growing very rapidly lately specially in image classification and segmentation using neural networks and helping decision making

[1] https://fertilitynj.com/infertility/female-infertility/ovulation-disorders/

[2] https://en.wikipedia.org/wiki/Polycystic_ovary_syndrome

[3] https://www.fertstert.org/article/S0015-0282(03)02853-X/fulltext

in clinicals.With the advent of technology, robotics in healthcare is producing excellent results in predicting medical history of patients, drug discoveries and other foresee potentials and improving the system with healthcare.Considering the scenario of PCOS detection where manual identification of cyst in ovary images confirms the disease by doctors but with automated detection mechanism life will be much easier for radiologists.Convolutional neural network pre-trained modelling has improved significantly in recent years, particularly in image classification.Transfer learning have many feather of achievements in classifying diseases on varied types of images namely, X-Ray, Ultrasonic,Magnetic resonance imaging (MRI).Here Chang et al. also used pre-trained model i.e. Google's Inception v3 for classification of breast cancer in histopathological images achieving impressive accuracy than using state-of-art CNN model in computation vision.

After ANN employed in neural network, with more hidden layer i/o and activation functions and brought the Transfer Learning method which is re-usability of ANNs models trained on large databases (Imagenet [4],Coco[5] etc.) and applied on different image classification problems with tweaking some layers in the model based on the relationship of problem.As a result, for the research activity, transfer learning was used, but another issue in the medical area is a tiny dataset and fragmented images.Data augmentation has helped to some extent with tiny datasets, but another novel method of data augmentation for generating fake images is Generative Adversarial Networks(GANs), which have performed well in many studies and paper work discussed with two types of generative and discriminative models.Various types of GAN models existed like Deep Convolutional GANs (DCGANs),Conditional GANs (cGANs) etc and mostly employed ones so far are image-to-image technique.Hence utilizing the approach of pre-trained model with GAN data augmentation is proposed.

1.2 Research Goal

Adding pre-trained learning techniques to medical diagnostics is a major objective of my study specially in detection of Polycystic ovarian syndrome which is rise threat globally to females.With this research project also want to provide more weight to existing research with CNN on detection and classifications done on pre-trained architecture (VGG-16, VGG-19, DenseNet, ResNet-50, AlexNet etc) in medical diagnostics particular to ultrasound images.As PCOS/PCOD is a serious concern around the world and can only be diagnosed by ultrasound, researchers became interested in combining the problem with existing solutions, as seen in the Literature review below.

Since dataset is very small applying Generative Adversarial Networks (GANs)[6] which was introduced in 2014 by Ian Goodfellow which has shown promising outputs in relation to generating artificial images and proved a breakthrough in computation vision using them could open doors for other medical diagnosis as well.

1.3 Research Question

To what extent can a pretrained model utilizing GAN architecture provide better sensitivity and specificity to detect PCOS/PCOD from ultrasound images.

[4] `https://https://www.image-net.org/`

[5] `https://cocodataset.org`

[6] `https://en.wikipedia.org/wiki/Generative_adversarial_network`

1.4 Report Structure

Continuing further, in section 2 I have reviewed related work and its conclusions in the field of medical imaging, as well as the evolution of technology over the years.In section 3 after exhibiting previous work, detailed information on methodology implemented is covered.Coming to section 4 which provides additional details on the approach used, as well as a complete description of the technique's architecture and design.The next section 5 will go over everything from data preparation to the implementation of the applied algorithm, following with the outcomes and evaluation methods in section 6.Finally in section 7, obstructions, conclusion and scope of future work will be covered respectively.

2 Related Work

In Medical Imaging field, Polycystic Ovarian Syndrome detection has been challenge in early screening due to growing cases.Many studies and researches are being conducted in order to find the exact cause of the disease which is yet unanswered.Using deep learning techniques to detect diseases in patients specially in medical diagnostics has shown promising results in recent years, with fine tuning and other enhancement approaches on numerous unsupervised or supervised methods.Hence, Image processing (classification, segmentation etc.), transfer learning (deep learning) and other renowned traditional machine-learning methods used in automatic medical diagnostics with their evaluations and results are discussed in following sections.

This research paper review is divided into several sections, which are listed below in chronological order to show how various medical imaging classification has evolved and performed:

2.1 Transfer Learning Techniques Used in Medical Diagnostics

2.1.1 VGG-16 & VGG-19

State-of-the-art convolutional neural network plays a crucial role in image classification, particularly in medical diagnosis, with its growing breakthroughs methodologies and advancements.Due to sensitive privacy regulations, mostly researchers able to obtain fewer images, which posed a difficulty for our training model.Hence it is becoming more popular to use various transfer learning techniques.Abbas et al. (2020) proposed DCNN - Deep Convolution Neural Network one of the best approach in DeTrac (Decompose, Transfer and composition) which is on decomposition of class to enhance image classification using pre-trained models and it was validated on various dataset comprises, X-ray of chest, colorectal and mammogram images for processing. This DeTrac model could achieve high accuracies upto 99.80% fitting ResNet model on X-ray images then VGG-16 could achieve accuracy of 98.5% and GoogleNet with little enhancement of shallow tuning could achieve 99.7%.Clearly, it illustrates robustness in sensitivity, accuracy and also specificity using transfer learning techniques.

Using the same type of data set as mine, another transfer learning experiment was conducted on the detection of malignant breast tumours using ultrasound images.

Hijab et al. (2019) used various approaches, starting with CNN model then training dataset using transfer learning VGG-16 pre-trained model and finally tuned the model on parameters to overcome over-fitting.After 50 iterations on tuning process, the final convolutional layers were frozen and the network weights on the dataset were modified with stochastic gradients.In a nutshell the approach was aimed to get better with each experiment.To attain accuracy of up to 97% and AUC values of up to 98%, the researcher began with data augmentation before fitting the model based on VGG19 pre-requisites such height, width, and rotation shifts before tweaking on factors. Another approach of automatic classification applied on brain MRI images by

Kaur and Gandhi (2019) using VGG-16 which has shown better results on comparing with traditional CNN networks in image detection.By using mechanism of tenth-fold cross validation, the image was received by a convolution layer with 224X224 pixel scaling, then propagated to various layers with a field of 3X3, and the convolution stride was taken as 1 pixel.On 2X2 window max pooling was performed in connecting 3 layer with different size in channels.As VGG-16 worked efficiently among others was considered for this research.Just tweaking final soft-max layers and reLu (rectification layer) enabled to encapsulate hidden layers.By tuning the final layers let the researcher to achieve accuracy upto 95% in classifying the disease. With growing outperforming results of VGG-16 upgraded to VGG-19 brought by K.Simonyon and another renowned person A. Zisserman from Oxford University achieving 92.7% in ImageNet Database in Image classification specifically.Impressed by VGG-19 Abuared et al. (2020) author implemented VGG-19 in prediction of skin cancer and resizing of image to 64X64 and on output layers changes the softmax activation function.Motive of the research was to categorizes the images unto carcinogenic and non carcinogenic automatically and performed research and kept eyes on loss and accuracy.This experiment on testing model produced accuracy of 97.5% and loss value upto 11.9% whereas training the data even performed as well with accuracy of 98.5% and loss upto 9.9% with epocs between 60-70 gave satisfactory results.

Sharma (2019) utilized traffic images of signs and classified them into 10 discrete classes applying VGG-19 pre-trained model architecture and shown upto 76% test accuracy.Even though images gathered in dataset were blurred and shifted, for such accuracy of 53% still shown up.Hence transfer learning has also worked well in other domain too not only medical.

2.1.2 DenseNet-121/169 & ResNet Architecture

Deep networking comes with its own pros and cons as compared to existed pre-trained architecture and except DenseNet all other has once issue of vanishing gradient.Going further I could find LeNet at max 5 layers and VG- 19 inclusive of 19 layers and ResNet upto 100 but DenseNet has unique feature of connecting pattern that just compounded or concatenate feature map with almost same space and resolution and add them to next layer like a *dense block*.Author Chowkkar (2020) made an attempt of using DenseNet in image classfication of histopathological images for detecting breast cancer.Take away of the research work was to notice resolution 100x and 200x both suits better and adding histogram -normalization, data augmentation to generate images and tuning the overfitting helps the model to achieve 88.3% accuracy.Much better than CNN performance and faster as it was tuned well.

High efficiency of DenseNet model has attracted many authors in the classification of images specially in medical field.Even here paperwork Jain (2020) has added another better performance results of DenseNet-169 among other four proposed models using machine learning, deep learning and two pre-trained model namely, Inception V3 and DenseNet-169. Among all DenseNet-169 performed best to showcase accuracy of 99.66%

much better than state-of-art approach i.e. CNN (98.80%). Evaluation of results done by f1 score but computation time of transfer learning too longer than CNN.To add another noted work by Xu et al. (2018) and implications of fine tuning in densely connected convolutional network to overcome gradient problem.These changes in tuning helped the researcher to get effective results in feature propagation's with accuracy upto 86%.

2.1.3 Inception V3 model Architecture

Digital Radiography (DR) has also modernised over the period of time in medical domain like low radiation exposure with fast results as compared to old methods.Many hospitals adopting this new tools in diagnosis as its more efficient and produce high resolution images but classification gets complicated.Alsabahi et al. (2018) made an attempt in classifying lung X-ray from DR using Inception V3 model for classification with same wights used in ImageNet dataset.Inception V3 model is made by Google and worked very well with ImageNet dataset.Manual labelling of images done for Normal(0) and abnormal(1), with tweaking the model last layer in back-propagation to give rise to cost function by also adjusting few parameters as well.The results shown nice figures in terms of accuracy like for tested dataset it has achieved 83.3%.Since, the images were less hence results could have come much better but achieving 83% with small dataset is an impressive attempt.

Another work used same approach Chang et al. (2017) but to classify breast cancer in histopathology images.As like other Inception V3 model performed really well on the dataset and gave 93% AUC value, it was just an attempt to see how useful the pertained model could be in detection but it opened doors for other medical diagnostics.As the dataset was provided less in number usage of data augmentation performed to generate more images in order to get better results.Less image dataset has always concern in many papers and using data augmentation help researchers to flip, rotate, or mirrored the images to increase the numbers.Preferred was rotating the image in various angles such as 90°, 180°, 270° along with flipping and labeled them into malign and benign for evaluation author used cross entropy and ROC, as a result this research witnessed final accuracy upto 98%.As I have found more asymmetric classification in the cost and high cases of FN than FP, optimizing demands on cut-off value method in the asymmetric classification.Finally, ROC curve showed cut-off upto 0.4 AUC for for both dataset of malign and gave fruitful results of classification of benign class to 83% and malignant class to 89%.

Next noted work was done by Fradi et al. (2020) in classification on USCT i.e. Ultrasonic computed tomography images and applied various transfer learning models namely, MobileNet (NasNet), Amoebanet, Inception V3 to classify into three sections - healthy, fractured and osteoporosis.For pre-processing data augmentation was used and on output side it outperformed and provided 100% train accuracy and 96% test in short span of time.Data gathered by researcher was 30 which made upto 250 by augmentation and worked wonder in providing fruitful results.In transfer learning resizing of image based on model is key factor hence 256X256 made based on model applied like Inception V3 model, also using graphic interface processor another good strategy applied to achieve results in short time.Comparing all the applied model in the project it was was found Inception V3 (91.7%) and AmoebaNet(96%) performed best.

2.2 Traditional Methods for Various Medical Diagnosis

Convolution neural network is proven traditional method applied by researchers specially in image classification in all the respective domains. Cahyono et al. (2017) used same methodology to predict the presence of PCOS in ultrasound images with bringing the hyper parameter layer for optimization produce better performance and minimized the drop-out to 1%.This tuning helped the author to achieve f1-score upto 73.36 % which seems to be efficient.

Bandeira Diniz et al. (2018) used image segmentation and registration along with classification to detect mass region in breast tissue over mammogram images.In training and testing stages FP reduction was applied then implication of segmented region testified.Whereas in testing phase secondary reduction in FP applied and helped to provide the accuracy upto 95.6% and sensitivity upto 90.4%.

With more advancement R-CNN introduced in computation vision and brings new norms in image classification.One of such example is research Kido et al. (2018) who tried to classify lung abnormalities in malignant and benign on X-Ray images by implementing R-CNN i.e.region based convolutional neural network CNN has been implemented not only PCOS/PCOD detection but also many other computer-aided medical diagnosis and estimated R-CNN outperformed the traditional CNN by 7%.

With coming years more focuses shifts towards image pixels as it directly effects the performance as work done by Maheswari et al. (2021) highlighted the importance and did more work on image size, feature selection and classification factor by object recognizing parameter followed with filtered to eradicate the noises in the images using histogram equalisation method. This model segmented the follicles in ovary image and identified better with firefly algorithm.Passing through the chosen images from usable classifiers such as ANN and NB significantly impacted the accuracy.Overall accuracy reached till 98.63% with 100% specificity which is must in medical domain and F-measure value reaches till 68.76% with recall value of 55%.This model was processed for smaller dataset and can be called as one of the best approach compared to others.

Another breakthrough was combination of various data mining techniques and procedural methods applied by Soni and Vashisht (2018) with initialised research focused on feature analysis and feature extraction later trained them on Naiive bayes classifier, decision tree and SCM(support vector machine) for aiming better accuracy.Here Apriori algorithm and clustering later by partitioning wise, density and hierarchical clustering and also statistical involvement helped in outlier detection.Hence, the approach with using statistical help and feature selection and extraction helped the detection of PCOS.

Further Sitheswaran and Malarkhodi (2014) applied the automated feature of bifurcating the PCOD in ultrasound images provided into two i.e PCO and NON PCO.Here author firstly divide the whole method into two section, initially in pre-processing performed with speckle noise reduction and media filter which helps in extraction of follicle features and identification using watershed algorithm for smooth segmentation.Such modelling follicles treated as object and detection occurs with spatial connectivity which results better performance compare to others by showing shows better F1 scores at $\beta = 6$.Hence modifications with pooling layers and resizing with enabling noise reduction in images helps to classify better and more efficiently.

2.3 Medical Image Enhancement & Augmentation Using GAN Architecture

Major issues in medical image classification is image dataset which is mostly less and fragmented and makes detection challening specially in CNNs. With the debut of Generative Adversarial Networks (GANs), which can produce artificial real images and load in training photos, has demonstrated substantial improvement in detection.As implemented in Han et al. (2019) GAN produces MRI images which were realistic and diverse and added to fill the lack in dataset for training the model.With implication of noise-to-image and image-to image boosted the performance by proposing PGGANS -Progressive growing GANs for high resolution images and secondly SimGAN (with MUNIT - Multimodal Unsupervised Image-to-image Translation on merging with AutoEncoders Variation) focuses more on loss part and with more refining process ab to achieve better images.Post data processing with GANS, feeded images modeled on ResNET-50 pre-trained model and improves much better with sensitivity from 93.67 percent to 97.48 percent.Hence, combining two-step GAN data augmentation outperforms single and also improves overall accuracy and sensitivity in brain tumor detection.

Another tested experiment performed on ultrasound ovary images in Liang et al. (2020) here motive was to compare GAN types and which model performs best as it can be helping hand in other anatomical image detection.Here adopted method is on US image synthesis with sketch generative adversarial networks (Sgan) this will introduce sketch and perform object mask in cGAN.More sketch cues, Sgan able to synthesize realistic images but effective is still hard to achieve.Further PGSgan introduced to work on high resolution hence results the promising efficacy after PGSgan

Traditional method of DA(data augmentation) with synthetic images GAN bringing diversity and enlarging of imaged has performed by Frid-Adar et al. (2018) to compare the effectiveness of which model performs better.Deep Convolutional GAN(DCGAN) could upscale the sensitivity and specificity upto 7% using as compared to classical DA method on liver Computed tomography 2D images.I can deduce synthetic generated images can bring up efficacy than original images augmentation. In generative network another approach was implemented by Lou et al. (2020) termed as U-net and for discriminator Fully Convolutional Networks(FCN).This augmentation applied on MM-WHS 2017 dataset of cardiac images and able to achieve dice score upto 86.32%, which has never attempted by anyone in segmentation and outperformed with other existed model.Results were evaluated on 5 different dataset and maximum of score reached till 93.64% with better generated images and scores.

Table 1: Literature Review Summary

Research Topic	Methodology Applied	Results	Limitations
Alsabahi et al.	Inception V3 Model	accuracy reached 83.3%	Labeled dataset was less hence scope for performance with more images.
Chang et al.	Inception V3 Model with data augmentation	For benign classification in accuracy reached till 83 % for benign class and other shown upto 89% for malignant.	Imae quality was not that great as it was lowest of magnifying factors (40X) as well as less dataset
Chang et al.	DenseNet-121, CNN	With hyper-parameter tuning accuracy for the CNN, the model achieved 90.9% whereas the transfer learning model resulted in 88.03 %.	From CNN feature extraction to be add before trasnfer learning model for better results.
Abuared et al.	VGG-19	accuracy achieved 97.5% with loss value of 11.9%	Image quality was bad, with good quality of images and more epocs run could be good approach
Kaur and Gandhi	DCNN VGG-16 model with 10th fold cross validation	100% recognisition rate	comparing computation complexity on various pre-trained model as training time was very high
Han et al.	Progressive Growing of GANs (PGGANs) on MR images	Senstivity spikes from 93.67% to 97.48%	Avoiding single step data augmentation with GANs
Liang et al.	cGAN,Sgan and PGSgan on Ultrasound images	cGAN, KID accuracy upto 83 % and Sgan upto 79.25	generating high resolutio is still difficult
Frid-Adar et al.	DCGAN and classic Data augmentation on CT images	With traditional data augmentation gives 88.4% specificity 78.6% sensitivity . After implementing DCGAN it gave 92.4% specificity and 85.7% sensitivity	Not limited upto 3D images.
Lou et al.	U-Net Generator and FCN as discriminator	MSE avg dice scorereached 86.32% and highest for another dataset 93.64%	performance declines with low contrast data and applicable to 2D images
Xu et al.	Enhance Framework GAN(EF-GAN), ResNET-50 and VGG-16 for evaluation	ResNtr average precision increased upto 84.1% and VGG-16 upto 38.7%	EF-GANs performs weak in generting artificial images for EM with clustered multi EM.

3 Methodology

To classify Polycystic ovarian syndrome in ultrasonic images, this study used a variety of pre-trained models such as VGG-19, DenseNet-121, Inception V3 and others.Because the dataset is so limited, the GAN (Generative Adversarial Network) architecture was used to produce artificial images for better performance.As read[7], CRISP-DM and the underlying data mining paradigm are still relevant for today's vast array of data science initiatives because of systematic approach and assisting in providing solution to business problems.CRISP-DM (CRoss-Industry Standard Process for Data Mining) approach is followed to continue the study work as it covers everything required to accomplish research work, all the stages are can be seen in Fig16a.

3.1 Business Understanding

Detection of PCOS/PCOD from ultrasound images is pretty common method performed manually but precisely finding the results is the crux especially when number of cases are in growing side.The manual check process consumes time to give precision results by experienced radiologist and doctors, therefore this research was considered to add help in

[7] https://ec.europa.eu/jrc/communities/en/file/6364/download?token=uXsDAsn5

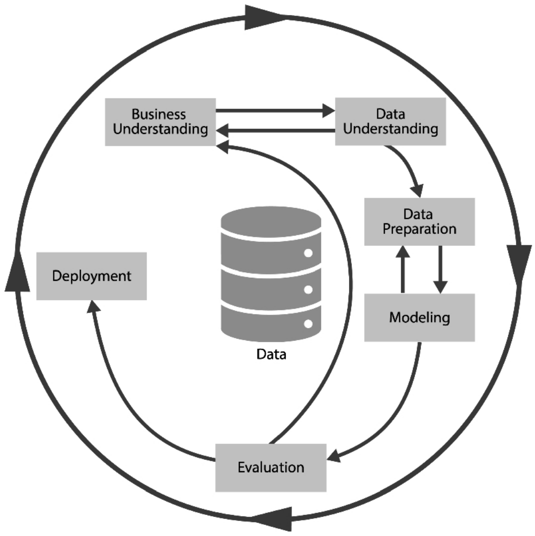


Figure 1: CRISP-DM Methodology

medical science.As mentioned and highlighted related work summary, there has been past work done to classify PCOD/PCOS using CNN but no attempt to check the efficiency of transfer learning on the same using GAN architecture(to overcome issue of insufficient images) which is latest technology added in deep learning lately.Here major focus is to check effectiveness of transfer learning in classifying the disease with GAN.Hence, this research work will help multiple doctors across region in order to detect disease in short span of time.

3.2 Data Understanding

To proceed further for this research data gathering was major issue as, here for this research dataset was made from various sources due to limited images available in each source.Startied from kaggle[8] dataset, but due to very less ultrasonic images in dataset I have referred few other websites to make dataset stronger such as Medpix[9], RadiologyKey[10], Radiological Society of North America (RSNA)[11] and open access book on Advancements and Breakthroughs in Ultrasound Imaging[12] all these were publically available and accessible websites hiding with anonymised data information of patient for complying medical ethics.These referral links not only helped in terms of providing images but also provide good insight on better understanding on disease.It is impossible to do medical diagnostic research without the guidance of a medical specialist, especially if the dataset is unlabeled.As a consequence, using a doctor's advice to label the dataset was ethical in medical science and produced accurate results.A total of 94 photos could be collected, of which 50 were PCOS images and 44 were non-PCOS ultrasonic images.

[8] https://www.kaggle.com/kerneler/starter-stein-leventhal-syndrome-pcos-6f4f243b-1
[9] https://medpix.nlm.nih.gov/search?allen=true&allt=true&alli=true&query=pcos
[10] https://radiologykey.com/the-ovary-and-polycystic-ovary-syndrome/
[11] https://pubs.rsna.org/doi/10.1148/rg.326125503
[12] https://www.intechopen.com/chapters/45102

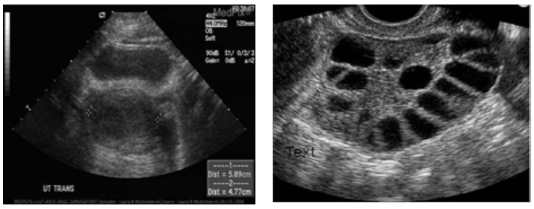


Figure 2: Normal Ovary & PCOS Ovary Image

3.3 Data Preparation

As there were very less images, suggested technique was using GAN to generate synthetic images for both the labelled class i.e. PCOS and NON PCOS.GAN Architecture majorly comprises of two key component in model *generator:* generates the images and *discriminator:* returns the loss percentage as how much it is different from fake and real images.On training the generator model which converts random points into images per class after performing image resizing and clipping process.For this research work 100 images were generated per class (100 generated images each for PCOS and NON PCOS) using binary_crossentropy optimizer.Below Fig: 3 represents the output of epoch generated during run of the model for both classes. Secondly, implementation of data augmentation was

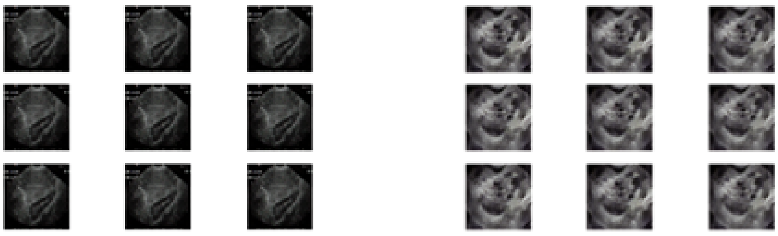


Figure 3: Generated Images by GAN

proposed before training the model to create even more synthetic sample to increase the data corpus and help the model to work better.As I know data augmentation doesn't create any new image but create replica of original images with some few tweaks namely, rotation, flipping, zoom, shear, dark, saturation etc and increases the number and set the image size to 122X128 with RGB format before fit into the model.Hence, synthetic image generator along with data augmentation both are different but does play imperative role in increasing the size of dataset and effects the performance and efficiency of model as dataset plays the pivotal role in any machine learning model.Below Fig: 4 is showing the augmented images with original images.

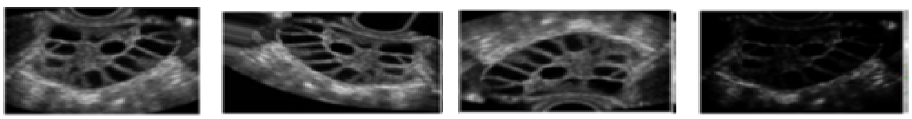


Figure 4: Data Augmentation on PCOS Images

3.4 Modeling

As research title states here I have used GAN architecture(building generator and discriminator) and train the dataset gathered on GAN model to generate synthetic images then follow with data augmentation method which increase the amount and diversity on data and created new data; more like transforming the existing data.Implementing augmentation, neural network can be exceptions from learning not relevant patterns and overall performance gets boosted.

After increasing dataset various pre-trained architectures(explained in detail in 4 those are already trained on imagenet database will be used on each of these I have defined dense architecture as our standard model and merge them both and train the model which is illustrated in 5. I are considering 4 pre-trained model named as follow: VGG-19, Inception V3, ResNet-50, DenseNet and finally performing model stacking as stacking classifiers to classify PCOS and NON PCOS images and finally compare the performance in 6 with detailed information highlighting loss, accuracy, Precision, Recall and measuring F1-score to evaluate the performance of suggested model for this research.

Fig:5 shows the workflow diagram of entire approach at one glance for reference and layout of the entire research experiment covered for this work.

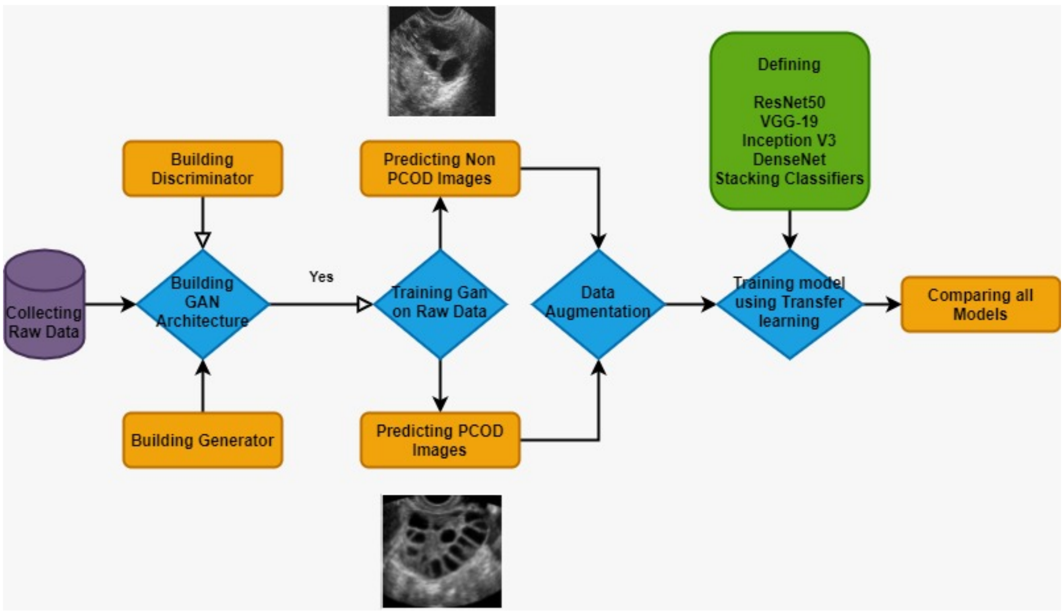


Figure 5: Workflow Diagram

4 Design Specification

As well illustrated the entire workflow diagram in Fig: 5 below is the subsections of design model covering key area from the start:

4.1 Basic GAN Model

Lately there has been revolution in machine learning in generative algorithm because of dataset issue, among few the renown one is Generative Adversarial Networks(or GANs). With unexpected invention by researcher Ian Goodfellow, this method is most fascinating notion in machine learning in the last ten years stated by Yann Lecun(director of AI research in Facebook). Below is the model architecture of GAN [13] having two key components plays crucial role namely:*Discriminator*(to identify fake and real sample data) and *Generator*(for noise to image generator) both are are convolution network applied up-sampling and down-sampling with sigmoid and LeakyRelu activation functions covered in implementation 5 in detail.

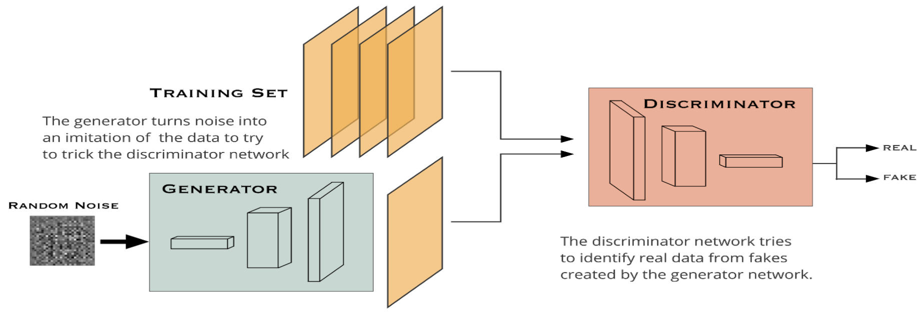


Figure 6: Model Architecture : GAN

4.2 Standard Model

Using 4 pre-trained architecture as mentioned with ights trained on imagenet database then have defined dense architecture which will be used for predicting images.After this, I have concatenated pretrained architecture and dense architecture labels can also termed as appending model.Then Pre-trained model will be frozen hence I can say it will be(non-trainable) where as dense architecture layer will be allowed to train and update it's weights and finally training images with batch size of 4 and storing all model metrics performance for evaluation.Below Fig:7 for illustration of standard model applied for all pre-trained models:

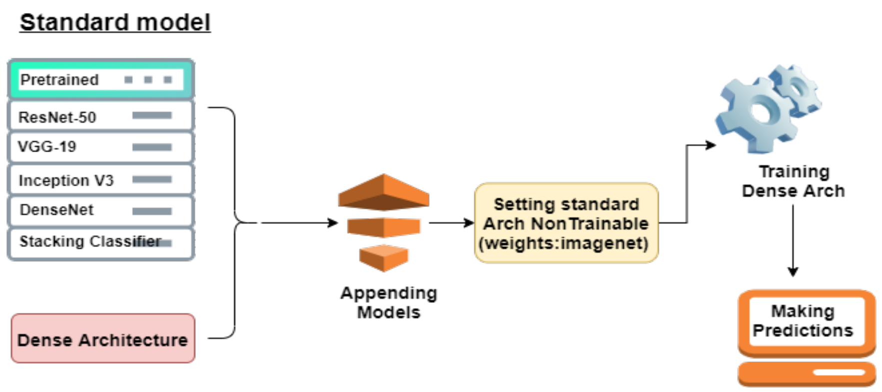


Figure 7: Standard Model Diagram

[13] https://towardsdatascience.com/image-generation-in-10-minutes-with-generative-adversarial-networks-c2afc56bfa3b

4.2.1 VGG-19

Transfer learning[14] is known method in deep learning and open source[15] where a pre-trained model will be re-used to complete particular task and tuned accordingly.Transfer Learning is mostly applied when there is an issue with insufficient dataset than original to train.There are two ways of using pre-trained model:

- Making a pre-trained model is used for feature extraction..
- By fine-tuning the transfer learning model.

VGG(Visual Geometry Group)is a CNN(convolutional neural network) which is comprises of 19 layers, which was built and trained in 2014 by Andrew Zisserman and another renown data scientist Karen Simonyan hails from university of Oxford.Information on very deep convolutions network for image recognition in large scale are also published in 2015.VGG-19 network was trained on millions of image fetched from ImageNet database with capacity of classifying upto 1000 objects.As its already trained its easy to import model with same ImageNet trained weights on 224X224 pixel of coloured images and passed through many convo layers along with applied ReLu for having non linearity along applied with convo filters and achieved accuracy upto 90%.As attempted by Abuared et al. in carcinogenic classification and gave accuracy upto 97.5%. Below is brief information about size and layers.

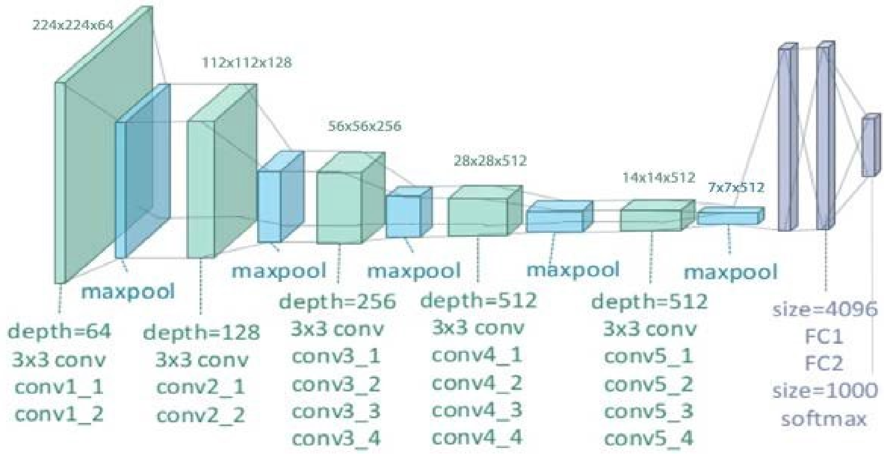


Figure 8: Model Architecture : VGG-19 (Zheng et al.; 2018)

4.2.2 DenseNet-121

Consider the DenseNet architecture, which consists of three Dense blocks with an intermediary layer of Convolution and pooling.VGG-16 shows a down-sampling issue that can be avoided by keeping the feature map size the same under dense blocks.The transition layer is a 1x1 convo layer followed by a 2x2 pooling layer.Jain has also applied and implemented DenseNet to perform classification and achieved better results.enseNet121, DenseNet169 etc are form of DenseNet but with varied number of convo layers.

[14] `https://en.wikipedia.org/wiki/Transfer_learning`

[15] `https://keras.io/guides/transfer_learning/`

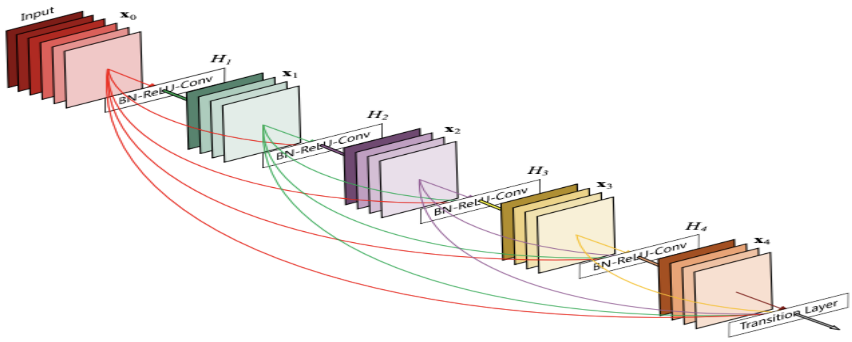


Figure 9: Model Architecture : DenseNet-121 (Huang et al.; 2016)

4.2.3 ResNet-50

Residual Networks is a classic neural network is major backbone under many models implemented for computer vision tasks.In year, 2015 this model was chose as winner as a result of ResNet which comes as breakthrough, I were able to train deep neural networks with 150+ layers.The problem of vanishing gradients made it difficult to train very deep neural networks before ResNet.Below model represents layering of this architecture with softmax activation function , maxpool, convolution etc.

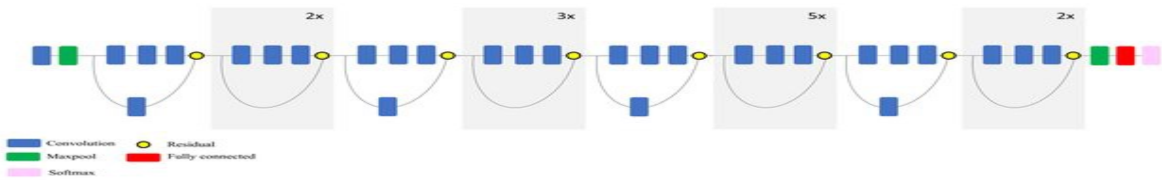


Figure 10: Model Architecture : ResNet-50 (Mahdianpari et al.; 2018)

4.2.4 Inception V3 Model

In the ImageNet dataset, this model has exhibited up to 78 percent accuracy, and its future version of GoogleNet as it's latest hence many researches yet to consider this approach.This model inclusive of both asymmetrical and symmetrical components.Having softmax layer for measuring loses and as also implemented by Chang et al. which has achieved 90% accuracy in detection of malignant breast cancer.

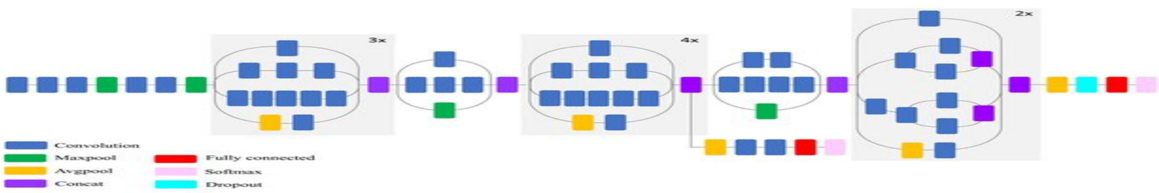


Figure 11: Model Architecture : Inception V3 (Mahdianpari et al.; 2018)

5 Implementation

5.1 Environment Setup

This section walk-through the technologies and setup requirement for the execution of model applied in this project.As this project dealt with deep learning such as GAN and transfer learning models took longer processing time, this carried on Dell Inspiron i5577 laptop with 16 GB RAM using Keras and Tensorflow.Dataset saved in local server.For visualisation MatplotLib is used and Keras for backend due it feature of lowering the load and helps in reliable and faster APIs and easily accessible.As Keras stays on Tensorflow architecture it open variety of option in implementing model such as CNN,VGG, ResNet etc and smoothly handles task such as feature extraction.Execution of code implemented on Jupyter notebook using python language and other libraries used such as numpy, pickle, sklearn etc.

5.2 Data Handling

All ultrasound images stored in local machine and bifurcated into train and validation for training and testing purpose.Both the data has two classes i.e PCOS and NON PCOS.Initially 94 images were used to generate pseudo images using GAN technology using keras model and layers produces upto 200 images.As dataset was still low data augmentation applied using imagegenerator class in keras and with the help of function *flow_from_directory()* splitting of data done with proper parameter and then used in model fit in 80:20 ratio as train and test.

5.3 Generative Adversarial Networks Architecture Implementation

With the crunch of dataset images GAN was suggested as state-of-art to generate synthetic images and help the dataset to grow.For this project basic GAN model was implemented comprises of *Generator* & *Discriminator*.Both of them are neural networks, generator role is to take noise images as input vector and synthesize as new set of image(128X128 pixel with RGB) and discriminator identify fake and real images in form of binary output.Both uses CNN, discriminator uses Conv2D where as generator uses Conv2DTranspose followed with pooling layer in second fully connected layer.In second and third layer for batch normalization usage of LeakyRelu as well sigmoid activation function used and finally compiled the model with binary_crossentropy optimizer with set number of epochs. Below Fig: 12 GAN model plotting taken from codes.

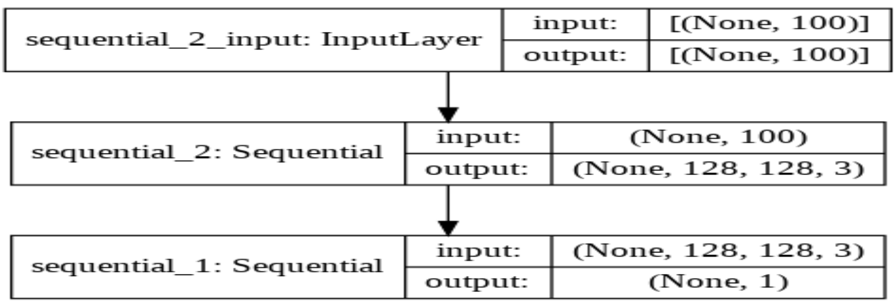


Figure 12: Model Architecture : GAN Model

5.4 Pre-Trained Networking Models Implementation

This research work follow base model style mentioned in below Figure: 13 implemented on ResNet-50 initially for all the rest pre-trained model such as Inception V3, VGG-19, DenseNet. As depicted in figure below model generated is sequential where top layer defines the pre-trained network, here it's resnet50 made it non trainable or I can also say it's frozen.I have flattened the layers and applied batch normalization with batch size of 4 keeping dropout value constant to 0.5 and then applied dense architecture finally having value 2 for binary result and used *softmax* activation function and Dense layer for 256 and 128 set with relu activation function for better performance.Based on hit and trial methods with various hyper-parameter tuning this setting worked best for all.Mechanism of appending ResNet with Dense is efficient to produce better images.And set the images into flips like vertically or horizontally,recalling zooming, rotation of image to 40 degrees other functionalities also taken care by this function.Each model was executed on 50 epochs initially.Finally, compiled the optimizer 'Adam' with 'categorical_crossentropy' value as loss function and primarily. For all the pre-trained model during model fit I need to set *include_top*=False, *weights*=”imagenet” as I have mentioned don't want to train Resnet layer just using the weight knowledge trained on imagenet with input image size as 224X224 passed into model.

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
resnet50 (Functional)        (None, 1000)              25636712
_________________________________________________________________
flatten (Flatten)            (None, 1000)              0
_________________________________________________________________
batch_normalization (BatchNo (None, 1000)              4000
_________________________________________________________________
dense (Dense)                (None, 256)               256256
_________________________________________________________________
dropout (Dropout)            (None, 256)               0
_________________________________________________________________
batch_normalization_1 (Batch (None, 256)               1024
_________________________________________________________________
dense_1 (Dense)              (None, 128)               32896
_________________________________________________________________
dropout_1 (Dropout)          (None, 128)               0
_________________________________________________________________
batch_normalization_2 (Batch (None, 128)               512
_________________________________________________________________
dense_2 (Dense)              (None, 2)                 258
=================================================================
Total params: 25,931,658
Trainable params: 292,178
Non-trainable params: 25,639,480
_________________________________________________________________
```

Figure 13: Standard Model Implementation Summary on ResNet-50

Finally, after implementing all models I have performed model stacking for better accuracy and performance where output of all the trained network will be taken and passed through logic regression and finally predict the output.As see in below Fig:14 for reference: Applied on code : stack_models = [model_resnet,model_vgg,model_ins,model_dense]

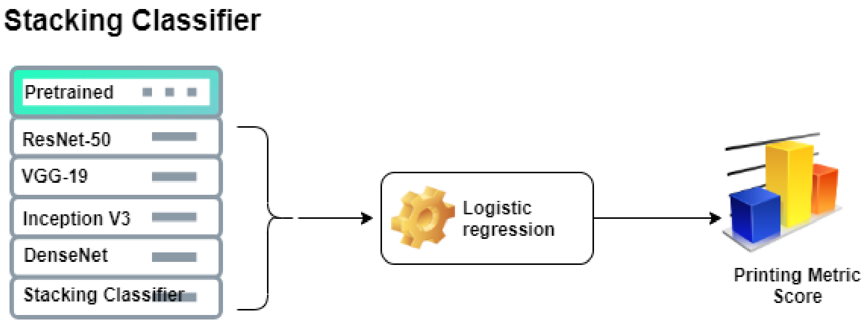


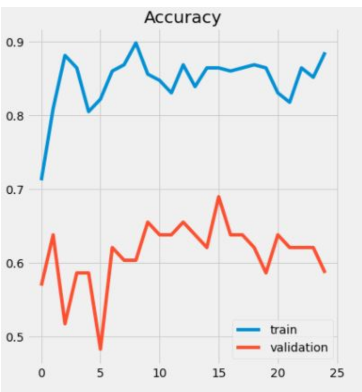
Figure 14: Stacking Classifier Model

Figures are the results for VGG-19 model, representing Accuracy, Loss and Precision:Referring first plot is constructed on epoch vs accuracy for both train and validation using command *plot(history_vgg,"VGG19")* likewise for every other four model.As seen in Fig: 16a accuracy of training dataset is reached upto 90% where as test accuracy reached upto 70%, the more higher the better model is hence I can say this model can be considered and might perform well with better dataset, for Fig: 16b showcasing about loss which is like penalty of wrong prediction the lower the value better for model.I can see for VGG-19 for training dataset its falling which is ideal same seen for validation i.e test class.

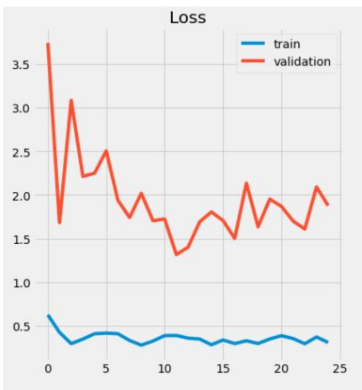
Finally, predicting precision which helps to quantify positive number classes prediction that actually belongs to positive class.For training model it has reaches upto 90% where as for validation it's coming 91% which is important feature in medical diagnosis.Running the same model with different Epoch value has shown significant change in value as I can see there is a difference between 50 Epoch run and 25 Epoch run.Hence, Epoch run does impact accuracy as illustrated below:

6 Evaluation

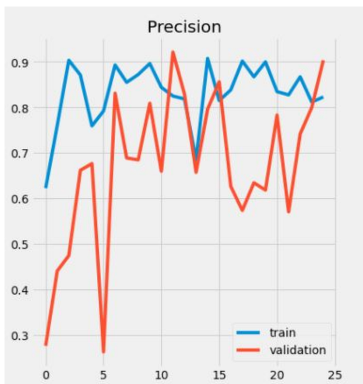
This section illustrates comprehensive analysis of firstly GAN followed with suggested pre-trained model with stacking and finally comparing the results to validate the ef-



(a) VGG-19 Accuracy Plot

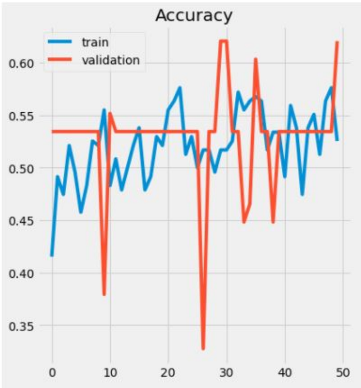


(b) VGG-19 Loss Plot

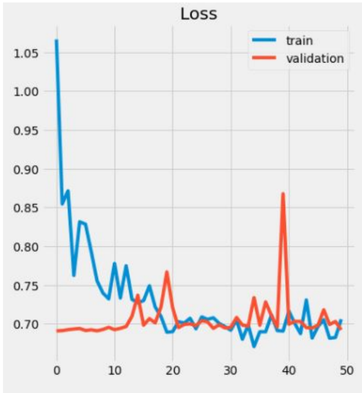


(c) VGG-19 Precision Plot

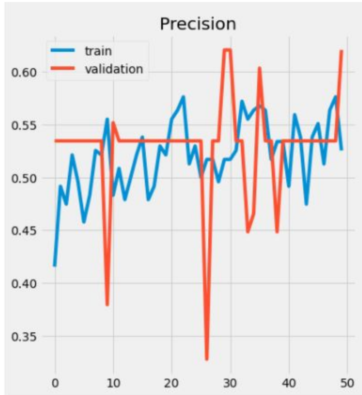
Figure 15: VGG-19 Model Evaluation Methods - 25 Epochs



(a) VGG-19 Accuracy Plot



(b) VGG-19 Loss Plot



(c) VGG-19 Precision Plot

Figure 16: VGG-19 Model Evaluation Methods - 50 Epochs

ficiency.Here I am evaluating models based on Accuracy, Loss, Precision, Recall and finally F1-Score plotted which is go to approach in image classification for both training validation and also test accuracy comparison for all applied models. As this research work dealt with medical science Precision(Specificity) is imperative function to check on.

6.1 Case Study 1:Generating Synthetic Image Using GAN Model Evaluation

6.1.1 Qualitative & Quantitative Evaluation

Below is the output from training model on 200 epocs for each class and I can see how images are generated, mostly first and last epocs set to generate image.Below image 17 reflects the output of synthetic images generated for epocs 10, 50, 150 and 190 and 190 epoch gives better output in terms of quality and precision.To perform quantitative evaluation key thing is to calculate loss generated by model and compare generator and discriminator performance.As dataset was very limited GAN could not perform very well and after epoch 200 it started overfitting showing loss value for discriminator as 0 which is not permissible led to stop the training.

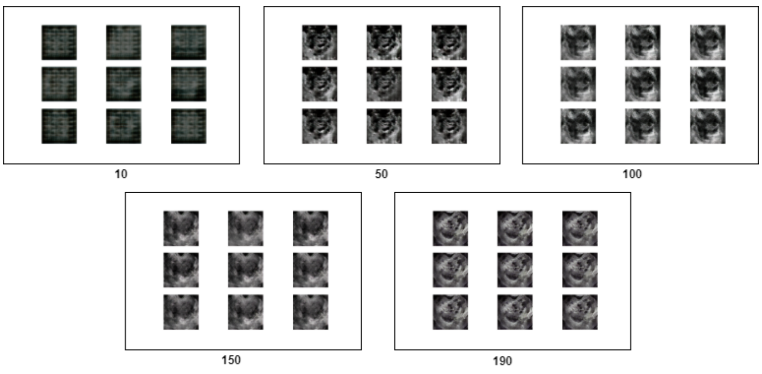


Figure 17: Generate Images by GAN for PCOS Class

6.2 Case Study 2:Four Pre-Trained Model Evaluation for Classification of PCOS

After implementation of all the four chosen pre-trained arch comparison of results taken place, based on observation I have concluded GAN is good approach in image classification and secondly, VGG-19 outperformed all other models even stack classifier by achieving test accuracy approximately upto 70% with less loss value which tell the model is better. Over-fitting issues were also on comparing test and train outputs for ResNet. As the model employed for implementation of transfer learning approach, here I have executed the model for 10 epochs and checked every 3rd epoch which resulted good accuracy in VGG-19 upto 75% and tested the model variance with 10-fold cross-validation.

Below table illustrates the each model applied in this research showing five different evaluation matrices values, namely Accuracy, Loss, Recall, Precision and F1-Score for final comparison and best two models in or research are VGG-19 and Inception V3 Model.

Table 2: Model Results based on Metrics

Model	Accuracy	Loss	Recall	Precision	F1 Score
ResNet-50	0.62	1.58	0.16	0.74	0.26
VGG-19	0.69	1.7	0.51	0.86	64
Inception V3	0.64	3.2	0.25	1	0.4
DenseNet	0.66	1.53	0.2	0.9	0.3
Stacking Classifiers	0.52	-	0.52	0.47	0.41

6.3 Discussion

From the beginning to carry this research work was challenge specially in data gathering which is chunk of information with more images in dataset, accuracy and performance of every model implemented could goes higher.Second challenge was GAN model implementation which is very tricky in order to balance both generator and discriminator is cumbersome. For this research work accuracy for GAN reached upto 93% after reaching epoch 200 it started performing poor reason is due to less corpus of data.Hyper-parameter tuning could fix this but the setting applied to this model performed bes compare to earlier hence recommended same.Similar work Xu et al. where VGG-19 accuracy came below 40% but for this model I have achieved the value upto 70% in a way better but overfitting of GAN and no tuning in our VGG-Model implementation made the model to suffer.But transfer learning in image classification used in VGG-19 by Abuared et al. provides 97% accuracy with 11.9% loss which is very good performance whereas lot of improvement can be implemented for this research work.Below Fig:18 representing all models accuracies:

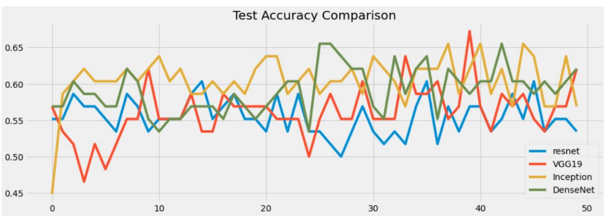


Figure 18: Test Accuracy Comparison Plot

7 Conclusion and Future Work

PCOS/PCOD classification lately is one of the active area in medical domain many past work has been performed but transfer learning with GAN for PCOS detection is novel approach tested in this research work.As the dataset was quite small compared to other studies, accuracy and specificity Ire severely harmed.Initially, this effort used GAN to solve insufficient data issues as Ill as data augmentation, but the data corpus was still much below what was necessary.It was found that hyper parameter tIaking may be used simultaneously with feature extraction in transfer learning and dataset plays a significant role.Here I have implemented overall 6 models starting from GAN, then VGG-19, DenseNet, ResNEt, Inception V3 and stacking classifier as a novel approach.In all models I have mostly found overfitting issue specially in transfer learning reason could be downsampling and loss of information during process.Despite data was less in number and poor quality images this approach still managed to achieved accuracy upto 70% and trained more than 90% in VGG-19 model, Inception V3 and DenseNet achieved around 64% and 66% respectively.

The future work will be more focused on data gathering using high resolution images or if possible 3D images as I'll which will help to predict exact efficiency of GAN with Transfer learning which is proposed for this research.Due to very less dataset and qualities of images of low resolutions results Ire compromised.As, this model can be state-of-art I can implement on other dataset as Ill with using oversampling and also downsampling technique.Most importantly introducing automatic hyper-parameter optimization techniques for pre-trained model on medical image using Bayesian Optimization or other techniques for better prediction rate.As seen lately, applying CapsuleNet can also be an additional help to check classification of images.

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