

CLASSIFICATION AND CHARACTERIZATION OF PCOS USING HYBRID MODELS

A Project Report Phase-II

Submitted in partial fulfillment of the requirements for the award of
Bachelor of Engineering Degree in Electronics and Communication Engineering

by

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BONAFIDE CERTIFICATE

This is to certify that this Final Year Project Report is the bonafide work of **Jagadeesh Mandala (Reg No. 39130276)**, who have done the project work entitled "**CLASSIFICATION AND CHARACTERIZATION OF PCOS USING HYBRID MODELS**" under my supervision from November 2022 to April 2023.

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ABSTRACT

Polycystic Ovary Syndrome or (PCOS) is one of a medical disorder that affects female pregnancy. High levels of androgens in women are the root cause of the symptoms that make up polycystic ovarian syndrome (PCOS). Every 21 days or more frequently, according to PCOS-afflicted women, menstruation occurs. Periods can occasionally be less frequent (fewer than eight in a year), or women with PCOS may stop getting their period altogether. This may result in ovarian cyst formation and infertility. Menstrual irregularities, weight gain, and acne are all signs of PCOS. PCOS is caused by a mix of hereditary and environmental factors, which is also characterized by persistent infertility and is frequently accompanied by clinical symptoms including, hirsutism, acne, and hyper androgenism. According to recent studies, this illness affects roughly 20% of Indian women.. The majority of imaging characteristics are utilized to diagnose the illness. Ultrasound imaging has become an essential diagnostic technique for PCOS. Because it is essentially an experience-based operation, the typical look of the picture becomes progressively challenging due to overlapping follicles, intrinsic noise of the equipment, and a lack of operator comprehension, making the diagnosis method time consuming. A method of prediction of PCOS using transfer learning techniques like VGG16, INCEPTION V3, ALEXNET and Hybrid Models. In previous research, feature extraction using Convolution Neural Networks has been suggested manually. Here, an attempt to offer a methodology in which Hybrid Models will be included in order to train model and improve accuracy. Finally, the test data set is used for the feature extraction procedure and using the performance coefficients, the results are 93% accurate.

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LIST OF ABBREVIATIONS

PCOS: POLYCYSTIC OVARY SYNDROME

CNN: CONVOLUTIONAL NEURAL NETWORK

VGG16: VISUAL GEOMETRY GROUP

KNN: K NEAREST NEIGHBOUR

SVM : SUPPORT VECTOR MACHINE

PCOM: POLYCYSTIC OVARY SYNDROME MORPHOLOGY

CHAPTER 1

1.1 INTRODUCTION

Deep Learning is a rapidly emerging technology that has the potential to solve problems in a multitude of industries. Deep learning is assisting healthcare practitioners and academics in discovering hidden data opportunities, helping the medical business to operate more efficiently. It also helps doctors analyze illnesses more correctly and effectively medicate patients, resulting in better medical decisions. In recent years, PCOS in women has been one of the most prevalent but undertreated diseases. Polycystic ovarian syndrome is one of the primary causes of impotence in women (PCOS). Multiple sacs form in the ovaries as a result of a disorder that affects female bodies. According to one research, one in every five women, or more than 20% of the population, has this condition [1]. Follicles fail to grow and mature in PCOS-affected ovaries due to low levels of follicle stimulating hormone and luteinizing hormone and high levels of prolactin, whereas in normal ovaries, a single follicle grows to a diameter of 20 mm, is totally matured, and is ready for ovulation. The exact cause of PCOS is unknown, however important factors include hormonal disturbance, having a body mass index more than 24, and irregular menstruation cycles [2]. Polycystic Ovarian Syndrome (PCOS) is a significant medical research issue. Polycystic ovaries are characterized by the presence of a high number of cysts that aren't harmful and aren't more than a centimeter in diameter PCOS is a condition that affects women in the eighth millimeter. Many women's only symptom is infertility or inability to conceive. Issues with menstruation PCOS is characterized by a number of symptoms. The reproductive system is one of the most important organs for women. According to the research, it can also cause cancers such as breast and uterine cancer in women of reproductive age. Because of these different criteria, physicians continue to struggle recognizing PCOS. The Rotterdam criterion is one of the most appropriate methods for detecting PCOS. The main principle behind identifying PCOS is to see if the ovaries have a volume more than or equal to 10 cm³ or if there are 10 or more follicles with diameters ranging from 2 to 9 mm. An attempt to categorize the ultrasonic picture based on several feature extraction criteria by using the Hybrid Models. The method begins with the addition of picture data, followed by preprocessing and segmentation to eliminate unnecessary data and diagnose the disease with high accuracy.

around 6–10% of premenopausal women. Distorted hormone ratios, chronic anovulation, which leads to irregular menstrual cycles, insulin resistance, elevated androgen levels, and the appearance of polycystic ovarian morphology on ultrasound imaging are all typical symptoms of PCOS. These women are more likely to experience reproductive abnormalities as well as diabetes type II, , and coronary artery disease (CVD), with subclinical signs appearing earlier in life. Although the exact aetiology of the condition is uncertain, several researchers theorise that the primary issue is excessive androgen synthesis in ovarian theca cells [69-70]. The most common imaging technique used in the clinical examination of a patient with ovarian pathology is ultrasound. Compared to medical imaging techniques like computed tomography (CT) and magnetic resonance imaging, ultrasound provides a number of benefits. The rationale for this is because ultrasonography is inexpensive, easily accessible, safer, and yields findings immediately. This imaging technology provides a fantastic chance to create a deep learning model for autonomous analysis, which improves the objectivity and diagnostic accuracy of the test. Deep learning is a potent technique used in image analysis and computer vision. Automatic PCOS classification in the early stages based on ultrasound pictures and clinical data aids in illness detection.

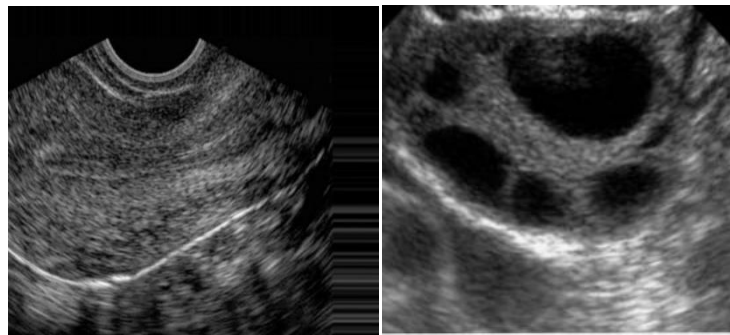


Figure 1.1 (a)

Figure 1.2(b)

Figure 1.1(a) Polycystic ovary syndrome un-effected

Figure 1.2 (b) Polycystic ovary syndrome effected

1.2 PROBLEM STATEMENT

PCOS is caused by a mix of hereditary and environmental factors, which is also characterized by persistent infertility and is frequently accompanied by clinical symptoms including, hirsutism, acne, and hyper androgenism. To detect PCOS infected ovaries from MRI images. This paper proposes a method of prediction of PCOS using transfer learning techniques like VGG16 and Hybrid Models

1.3 OBJECTIVE

The diagnosis of PCOS is one of the most critical issues in the field of women's healthcare. According to the clinical characteristics, PCOS is classified into different phenotypes. However, there is a controversy in the criterion of PCOS diagnosis. Among the criteria offered by various groups, the argument appears to affect the prevalence rates of PCOS. To ensure the accuracy of the initial diagnosis of PCOS, patients are supposed to have undergone ovarian ultrasonography. The exclusion criteria were fractures, tumors, infection, or spine implants. The training was performed using k-fold cross-validation ($k=10$), and performance was evaluated using the dice similarity coefficient (DSC) and cross-sectional area error (CSA error).

CHAPTER 2

2.1 LITERATURE REVIEW

This chapter deals with all the infernces from the literature survey ,polycystic ovarian syndrome (PCOS) is a significant area of research in medicine. Women with PCOS often have polycystic ovaries, which are characterised by a large number of small, unharful cysts (less than 8 mm in diameter.

Rachana et al, [2021] The real time spent manually tracing follicles and assessing the geometric characteristics of each follicle would be reduced with the use of an automatic PCOS diagnosis tool. KNN classifier will increase the accuracy and speed of PCOS diagnosis, decreasing the chance of the potentially catastrophic consequences that might result from a delayed diagnosis. [46]

Gopalakrishnan et al[2021]An ultrasound-based automated PCOS diagnosis and categorization method is suggested. The input photos were pre-processed using a Gaussian low pass filter, multilayer thresholding for edge detection, the suggested GIST-MDR approach, and supervised machine learning algorithms for PCOS classification.[18]

Bhosale and Joshi[2022], The authors propose DCNN-based methods, write PCOS classification code in Python, and use ultrasound pictures to assess whether they are filled with blood or fluid. DCNN-based image classification is used in this study to categorise PCOS in the dataset. [7]

Dua et al [2021] It is proposed to use an SVM linear kernel combined with Logistic Regression features in a novel hybrid and optimal technique. This model's output is sent to the RMSprop optimizer. Optimization will train the model iteratively to enhance its output. For this study, 1600 datasets were collected from the top hospital in Bangalore's urban region. [16]

Azli [2022]analyses the picture quality of an ovarian segment using a segmentation approach for follicle detection in the ovaries. A segmented picture of an ovary is effectively created and examined using the watershed approach, edge enhancement method, and Kirsch's template. [5]

Tiwari et al [2022]This research is focused on diagnosis using a clinical dataset provided by Kottarathil and accessible through its Kaggle repository. Non-invasive screening criteria are

used to assess a variety of machine learning algorithms for screening patients without invasive diagnostics. [54]

Priya and jeevitha [2022] The ovarian cyst categorization is carried out utilising the regularised CNN approach. Furthermore, using the data augmentation strategy and many more droplet layer tactics for improved accuracy, the classification process's reasoning enhanced. [45]

Kumari et al [2021] Another advancement in computer vision has been accomplished by using a basic GAN model to produce synthetic pictures to overcome a shortage of dataset, followed by data augmentation on re-processed ultrasonic images with resizing, and lastly training the models. [28]

Raghavendra et al [2020] a Image processing techniques which deal with the shape of features in an image is described by Morphological image processing The four morphological operations that is dilation, erosion, opening and closing and 2 basic algorithms that is boundary extraction and region filling were proposed using MATLAB program with user interface [34].

Sakshi, Patel et al [2020] proposed a comparative study of different his- togram equalization methods were performed using histogram processing. The major role of these methods is to enhance the brightness and contrast of the input image. However, the image should not lose its features while implementing image enhancement techniques. Hence, they concluded that those methods can be used for the enhancement of medical images for better diagnosis [42].

Kiruthiaka et al [2020] proposed an algorithm that uses machine learn- ing in ovarian detection and classification in this study. Use of machine learning algorithm has enhanced the precision of ovarian detection and classification.. The intelligent automatic system by simplifying the probability of misconfiguration and enabling diagnosis and treatment were the major take away in the paper [56].

Neetha et al [2019] studied to predict occurrence PCOS before get- ting worse. The proposed system was novel hybrid structure to deter- mine chances of PCOS that combine navies bayes and artificial neural network algorithm to produce the best result. In order to find best model to predict the chance of occurring PCOS a real data set with various at- tributes were used. Data partitioning procedure was divided as 70% of training and 30% of testing data [40].

Pim and Jelmer [2019] was carried out the deep learning research on multitasking segmentation of medical images with multiple methods .The CNN network was trained to divide

six tissues on the MRI image of the brain, the pectoral muscle in MR breast image, and the coronary artery in CTA of the heart. The results show that for training the CNNs, a single CNN structure can be used that can obtain accurate results for images from different methods and show different anatomical structures. Furthermore, it is possible to train a single unit of CNN that cannot segment multiple tissue categories into a single anatomical structure, but also multiple structures. [39]

Joseph et al[2019], proposed a study on the application of a convolutional neural network (CNN) to segment medical X-rays suitable for small data sets .Its application provides an overall accuracy of 92%, F1 0.92, and AUC 0.98, bypassing traditional image processing techniques such as aggregation and entropy methods while preserving the existing neuron networks used for segmentation in non-medical environments. They developed a fully automatic method for segmenting medical radiograms using a small set of data. They have also presented a two-module decoding architecture as a compromise between a deep network for extracting high-level features and subtle details and a network that avoids excessive transformation into small data sets. [10]

Khazendar, et. Al [2021], a proposed automatic model which characterize the ultrasound ovarian tumors images using support vector machine and local binary pattern operator.. A Support Vector Machine (SVM) was used for training by using cross-validation with random sampling. This procedure was repeated 15 times and 100 images were randomly selected in each round. [10]

Jing Li et al [23] The BP neural network prediction with the addition of monthly moderators and the Based neural network based on the adaptive moment estimation optimization method (Adam-BP) (Month-Adam-BP). The experimental findings demonstrate that the Adam-BP model can boost prediction precision.

Miaomiao Liu et al [37] To address issues with the Adam optimization algorithm, such as slow convergence, the propensity to miss the global optimal solution, and the ineffectiveness of processing high-dimensional vectors, a better algorithm is proposed that combines adaptive coefficients as well as composite gradients based on randomised block coordinate descent.

Ming Xing Zhang and Xiao Ming Su [38] The Adam optimization method is used in the neural network model of deep learning instead of the conventional optimization algorithm to address the issue of declining accuracy and to increase prediction accuracy and stability. It is not hard to

infer from the end experimental results that the featured algorithm significantly increases accuracy rate under various sounds and decreases algorithm operation time consumption.

Yu Jiaping [21] This study intends to increase work efficiency, lessen the workload of human resource managers, and optimise the HRM process. A salary prediction model (SPM) is created using a backpropagation neural network (BPNN) based on AI digitising technology, and the model is then optimised using the Nesterov and Adaptive Moment Estimation (Nadam) methods. Finally, the content information of the resumes are utilised to forecast the hiring salary of the applicants and verify the model. The Nadam optimization algorithm's final expected result score is 0.75%, which is lower than that of other optimization methods, according to the results.

Zeng et al [62] Deep learning has made extensive use of the adaptive gradient method and its derivatives, including RMSProp, Adam, AMSGrad, etc. While being quicker during the initial training phase, these methods' generalisation performance is frequently worse than stochastic gradient descent (SGD). So, it makes theoretical and practical sense to use a trade-off mechanism to convert Adam to SGD after a specific number of iterations in order to benefit from both methods. In order to provide a seamless and reliable transition from Adam to SGD, a decreasing scaling transition method known as DSTAdam was developed. In an online convex scenario, the suggested DSTAdam's convergence is also demonstrated. Lastly, several datasets are used to verify the efficiency of the DSTAdam.

Dwaram and Madapuri [48] Using a long short term memory network with the Adam optimizer and Huber loss function, the normalised data are categorised. In contrast to existing classifiers, the proposed classifier has adaptable learning rates for different parameters by detecting the first and second-moment gradient estimation.

Venugopal et al [57] The prior machine learning architectures were primarily hampered by a variety of difficulties while processing the attack characteristics, including prolonged processing times, a high need for manual intervention, difficulty managing huge datasets, and poor prediction accuracy. This study suggests a revolutionary deep learning architecture for data forensics to address these problems. In order to increase the model's capacity for optimization, the limited generalisation capability of the neural network is addressed using the Hadoop clustering and convolution-based ADAM (CADAM) optimizer technique.

Hu et al [20] Convolutional neural networks were employed for classification, and the weights of the networks were updated using the Adam optimizer, which combined the momentum and exponentially weighted moving average gradients approaches. The prediction model divided the

data of each kind of patient into two groups, with 80% serving as the training group and the remaining 20% serving as the independent testing group.

Oyelade et al [41] Using a few benchmarked datasets, the research conducted a comparative analysis of the performance of the optimal configuration. The developed model was applied to publicly accessible benchmark datasets, specifically, the DDSM and MIAS datasets. Results from the experimentations demonstrated that hyperparameters with Adam optimization method exhibited supremacy by giving an accuracy of 1.0 utilising DDSM dataset, while SGD, RMSprop, Adam, and Adagrad generated an accuracy of 0.9375 using MIAS dataset. The results of this investigation have strengthened Adam optimizer's suitability even more, and a cutting-edge CNN model has also been created.

Hasan et al [19] Deep neural network (DNN) with Adam optimizer was utilised for the classification model. Five distinct performance measures, including the confusion matrix, classification accuracy, area under the receiver operating characteristic (AUC-ROC), F score, and Cohen's Kappa with four-fold cross-validations at various numbers of MFCCs, were used to evaluate the performances. Every performance parameter yielded the highest rating.[10]

Kim et al [26] Imaging genetic connections have often been found using the traditional method, such as canonical correlation analysis (CCA). To comprehend the intricate relationship between imaging and genetic measurements, a deep learning approach has recently been presented. To combine and recognise the intricate imaging genetic correlations in AD, suggested a graph convolutional neural network (GCN) with a CCA loss function.

Dai et al [13] The delayed convergence and oscillation of SGD optimization methods for deep learning are caused by inappropriate gradient update direction or learning rate selection. Adam algorithm still experiences the overshoot problem, which results in the waste of computational resources and poor convergence even if it is capable of adaptively adjusting the update direction and learning rate at the same time.

Rahaman et al [47] By back-propagating the cross-entropy loss calculated from the last layer's prediction and the subject's label, the Adam optimizer modifies the weights in the suggested DNN. To reduce overfitting, a dropout layer with $p = 0.2$ is placed after each FC layer.

Wang et al [60] To address the issues with rolling bearing defect diagnostics, a novel CNN model with 8 convolutional layers based on identity mapping and Adam optimizer is presented. Identity mapping enables the direct transfer of computed data from the shallow convolution layer

to the deep convolution layer without the need for extra parameters or increased processing complexity.

Salem et al [57] A multilayer perceptron-based artificial neural network can forecast and identify the effectiveness of planned water desalination that relies on solar thermal energy. The primary goal of the Adam optimizer is to determine the MLP's ideal parameters, such as the activation function, learning rate, and number of hidden layers and neurons.

Sharma et al [50] Eight neural network models and two time-series models utilising LSTM with various optimizers are compared to the proposed model. The forecasting accuracy is significantly improved by 30.56% over the autoregressive integrated moving average and by 47.48% over the seasonal autoregressive integrated moving average in the results produced using LSTM and Nadam optimizer.

Xie et al [61] The TCNNn (Transformer+CNN+nAdam) model put forward in this work is based on the enhanced Adam optimizer and the incorporation of the Transformer mechanism. The autocorrelation of each word in the text is determined by estimating the contribution size of input data using the attention mechanism. On the news text data set, a classification experiment is run.

Mishra and Pati[39] The Deep Convolution Neural Network (DCNN) ensemble with an optimizer-based ensemble and an on-the-fly data augmentation strategy is presented in this study for the identification of ASD. The method of assembling the same model by fusing the same DCNN model with several optimizers is novel in this study. There are 484 ASD and 491 Control participants who were taken into consideration for this study. Using a data division ratio of 70:30, 80:20, and 90:10, respectively, the suggested ensemble model of DCNN with Adam and Nadam optimizer has achieved accuracy of 77.58%, 77.66%, and 81.35%.

Pranata[61] The system was created by combining the CNN (Convolutional Neural Network) algorithm with the Efficient-Net architecture (Magnetic Resonance Imaging). The Kaggle Alzheimer's Dataset, which contains a total of 1600 photos, served as the input. With the aid of Adam, Adamax, Nadam, RMSprop, and SGD, the optimization is carried out. The Nadam optimizer delivered the best system performance, with a top accuracy value of 0.97.

Kousalya et al [27] In this study, the seven basic human emotions are used to instruct computers. Disgust, fear, fury, surprise, happiness, sadness, and neutrality are a few of the emotions. One of the most well-known and challenging issues that convolutional neural networks can tackle in fields like deep learning and computer vision is the recognition of facial

emotions. With each iteration, the accuracy will increase by fine-tuning crucial parameters including the unit count of the first thick layer, the rate of dropout in the dropout layer, and optimization strategies. A number of optimizers, including Adam, Adagrad, Stochastic Gradient Descent, and Nadam, were utilised to achieve the best accuracy.

Patokar et al [43] Three different optimizers Use of Adam, Nadam, and RMSProp with learning rates of 0.0001, 0.002, and 0.04 has been made. Data that was available to the public was used in all testing. Other data augmentation techniques include rotation, zooming, height shifting, width shifting, and others. As compared to Nadam and RMSProp optimizers and learning rates, Xception Architecture with Adam optimizer and Learning rate of 0.001 provides superior accuracy, recall, precision, and F-score values of 99% on average. These numbers are greater than any other learning rate and optimizer combination could have produced.

Said Aldemier[49] In this study, tested the impact of various loss functions and optimizers on these CTR models using two real-world datasets. Nearly all studies choose the Adam optimizer and binary cross-entropy loss while training the model for the CTR prediction issue. Experiment investigations, however, demonstrate that various optimizers and loss functions may considerably enhance the performance of CTR models. Particularly, offline findings show that the binary cross-entropy function in the CTR prediction issue may be replaced with a promising focal loss function that addresses the class-imbalance problem. Moreover, offline research shows that RMSprop and Nadam optimizers enhance the model's AUC performance.

Uddin et al [55] To predict hourly typhoon rainfall, the CNN model performed the best at learning rates of 0.1, 0.01, and 0.001. The CNN model using SGD, RMSprop, AdaGrad, AdaDelta, Adam, Adamax, and Nadam optimizers with learning rates of 0.1, 0.01, and 0.001 demonstrated more accurate forecasts than the previous models for long-lead-time forecasting (1-6 hr).

Kalaiselvi et al [66] Artificial neural networks (ANNs), or deep learning, are a subset of AI that can learn characteristics without human assistance. The choice of optimizers is important when describing deep neural networks. By changing the neural network's weight and learning rate properties, optimizers are utilised to reduce the loss function. common optimizers employed with artificial neural network systems in the proposed study, including SGD, adam, rmsprop, adagrad, adadelta, adamax, and nadam, have been examined.

2.2 Open problems in Existing System

Polycystic ovary syndrome (PCOS) is a complex endocrine disorder that affects many women of reproductive age. Deep learning models have shown great potential in detecting PCOS through various medical imaging modalities, such as ultrasound, magnetic resonance imaging (MRI), and computed tomography (CT) scans. However, there are several existing problems in detecting PCOS with deep learning models

Lack of standardization in data acquisition: The data used to train deep learning models are often collected from different sources, leading to variations in imaging protocols, equipment, and patient populations. This can result in inconsistencies and biases in the data, making it difficult for deep learning models to generalize to new data.

Limited availability of labeled data: PCOS is a relatively rare condition, and collecting large amounts of high-quality labeled data for deep learning models can be challenging. This can lead to overfitting and poor generalization performance.

Complex heterogeneity of PCOS: PCOS is a multifaceted disorder with a range of clinical presentations and underlying pathophysiology. This heterogeneity can make it difficult for deep learning models to accurately capture the full complexity of the condition and lead to false positives or false negatives.

Lack of interpretability: Deep learning models are often criticized for their "black box" nature, making it difficult to interpret the results and understand the underlying features that contribute to the diagnosis. This can limit the clinical utility of deep learning models in PCOS diagnosis and management.

Ethical and legal considerations: There are ethical and legal considerations surrounding the use of deep learning models in healthcare, including issues of patient privacy, bias, and discrimination. These concerns must be carefully considered and addressed before deploying deep learning models for PCOS diagnosis.

CHAPTER 3

REQUIREMENTS ANALYSIS

3.1 Feasibility Studies/Risk Analysis of the Project

Before jumping right into your new modeling task, consider performing a feasibility study. A feasibility study of a predictive model will answer key questions that can help in detecting problems if the modeling task is likely to succeed. Feasibility studies are common across industries and disciplines. They are an important project planning tool that can help identify points of failure in a project before any money or time gets invested.

Feasibility studies are particularly useful for machine learning projects because ML projects are generally experimental in nature. They can fail for many reasons, some of which can be identified upfront with a feasibility study.

Feasibility and risk analysis are important aspects of any technology deployment, including deep learning models. Here are some key considerations for feasibility and risk analysis of deep learning models:

Data Availability: The availability of high-quality data is essential for training and validating deep learning models. Feasibility analysis should consider whether the required data is available and can be accessed in a timely and cost-effective manner.

Hardware and Software: Deep learning models require significant computing resources such as TensorFlow and PyTorch. Feasibility analysis should consider whether the required hardware and software resources are available or can be acquired within the project budget.

Expertise: Deep learning models require specialized knowledge and skills to develop and deploy. Feasibility analysis should consider whether the required expertise is available within the project team or can be acquired through partnerships or training programs.

Deployment Environment: Deep learning models must be deployed in an appropriate environment that meets performance and security requirements. Feasibility analysis

should consider whether the deployment environment is available or can be established within the project budget.

Performance: Deep learning models may not always perform as expected, leading to inaccurate results or even harm to patients. Risk analysis should consider the potential risks associated with inaccurate or unreliable deep learning models and establish appropriate risk mitigation strategies.

Security: Deep learning models may be vulnerable to security threats, including data breaches, hacking, and unauthorized access. Risk analysis should consider the potential security risks associated with deep learning models and establish appropriate security measures.

Bias: Deep learning models may perpetuate or even amplify biases in the data used to train them. Risk analysis should consider the potential biases associated with deep learning models and establish appropriate measures to address them.

Ethical and Legal Considerations: Deep learning models may raise ethical and legal considerations, including issues of patient privacy, autonomy, and fairness. Risk analysis should consider these ethical and legal considerations and establish appropriate measures to address them.

3.2 Software Requirements Specification Document

- **Base software:** ENVI 5.6.3 and the ENVI Deep Learning 2.0 module
- **Operating systems:**
 - Windows 10 and 11 (Intel/AMD 64-bit) or
 - Linux (Intel/AMD 64-bit, kernel 3.10.0 or higher, glibc 2.17 or higher)
- **Hardware:**
 - Online Google Colab
 - A CPU with the Advanced Vector Extensions (AVX) instruction set. In general, any CPU after 2011 will contain this instruction set.
 - Intel CPUs are recommended, though not required. They have an optimized Intel Machine Learning library that offers performance gains for certain Machine Learning algorithms.

3.3 System Use case



Figure:-3.1 System Use Case

3.3.1 Data Collection:

A research was done on a public dataset published in Kaggle repository by praseon kottarathil named as Polycystic ovary syndrome (PCOS) 1 . In this dataset, the data publisher has changed the patients file number for privacy issues. Dataset has 45 attributes based on clinical and metabolic parameters which will help us to detect the PCOS. Data is collected from 10 different hospitals in Kerala, India. The dataset has important attributes like Follicle-stimulating hormone(FSH), Luteinizing hormone(LH), Cycle Length, Cycle, Endometrium, Follicle Number, BMI etc. Because of the 45 attributes the challenge here is to select top 10 highest ranking attribute for the early detection of PCOS.

3.3.2 Data Preparation

The data obtained in data collection is in csv format which will be used in python. For this, anaconda distribution packages, Jupiter notebook, Scikit-learn library, Matplotlib, are used in the python development. In data preparation, it was important to check the missing values first then removal of unwanted columns which don't needed in modelling phase.

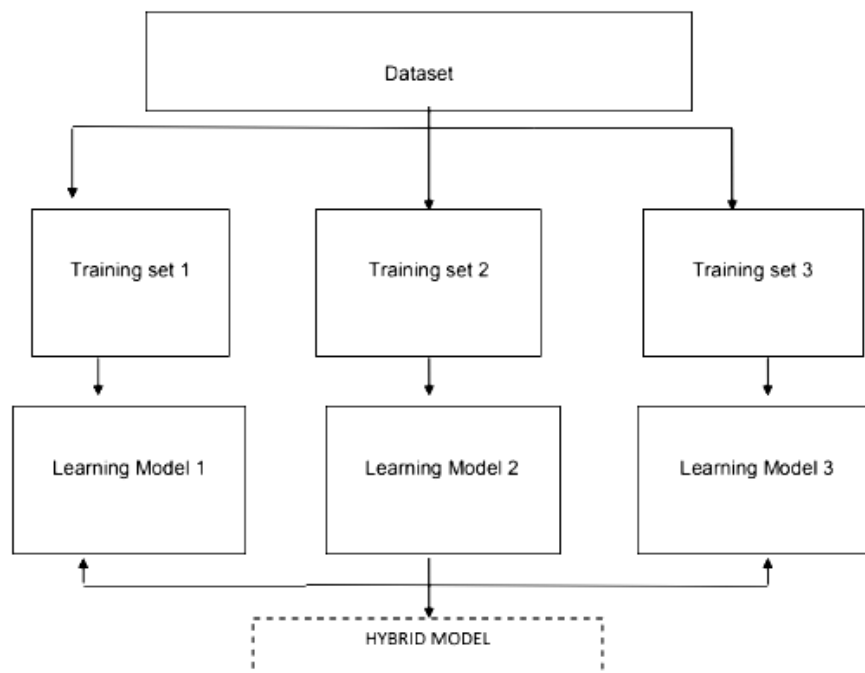
CHAPTER 4

DESCRIPTION OF PROPOSED SYSTEM

4.1 Selected Methodology of pre-trained networks

The training model deals with hybrid model approach by combining vgg16, alexnet, inception v3. All these three transfer learning techniques give less performance statistics on the dataset. A method for modeling uncertainty that mixes several types of deep neural networks with statistical techniques. However, by applying data augmentation before training ensemble model gives satisfactory results. Hybrid modeling techniques have the ability to mitigate the negative impacts of over-parameterization, save computing times, and potentially increase accuracy.

4.2 Architecture / Overall Design of Proposed System



4.1 System Architecture

4.3 Description of Libraries and Modules used

The Most Popular Deep Learning Software Tool

#1: Viso Suite Tool

#2: DeepLearningKit Tool

#3: H2O.ai Tool

#4: Microsoft Cognitive Toolkit Tool

#5: Torch Tool

#6: Keras Tool

#7: ConvNetJS Tool

#8: Deeplearning4j Tool

#9: Gensim Tool

#10: CAFFE Tool

#11: Neural Designer

For this project Keras and Tensorflow library is used.

Keras is a Python-based deep learning software tool that is popular for its simplicity and flexibility. This open-source library works as an interface for the machine learning platforms TensorFlow and Theano. The main advantage of deep learning with Keras is its exceptional speed – it allows to develop and train a neural network model using only a few lines of code. Hence, Keras often requires about 50% less code to define a model than native APIs of deep learning frameworks require. Here is an example of LeNet-5 trained on MNIST data in Keras – only 70 lines of code. Keras is one of the best deep learning software for beginners, as it makes running new experiments easier and faster. This also makes it popular to use for researchers who constantly train and deploy AI models. The user-friendly and easy-to-use interface makes it one of the most popular choices for students interested in gaining knowledge about deep learning with Python. Keras provides support for both convolutional and recurrent networks and a combination of both types.

- Evaluate model on test distribution; understand differences between train and test set distributions (how is “data in the wild” different than what trained on

4.4 Transition to Hybrid Model

Advantages of hierarchical data and knowledge representations have been known well before recent raise of DNN popularity. This concept is ubiquitous in natural sciences where hierarchical approach is common in both fundamental theoretical frameworks and in practical simulations of complex systems. For example, success of realistic simulations of multi-scale spatiotemporal dynamics in plasma and space physics critically depends on proper formulation and coupling of physical models describing processes on micro- and macro scales, since it is infeasible to model wide range of scales from first principles because of computational limitations and lack of detailed initial/boundary conditions.

The Graphs dashboard in TensorBoard is an effective tool for reviewing your TensorFlow model. Can rapidly study your model's structure and see if it matches your desired design by means of a conceptual graph of it. If want to see how TensorFlow interprets your program, may also inspect an op-level graph. The op-level graph can help understand how to modify your model.

A variety of computing solutions are available through Google Cloud for scaling up model deployment and training in TensorFlow. Deep Learning VMs (GA) and Deep Learning Containers (Beta) are features of TensorFlow Enterprise that make it simple to set up and scale. Both goods have been put through compatibility testing and had their performance enhanced for our broad selection of NVIDIA GPUs and our uniquely created AI processor, the Cloud TPU. Engineers and researchers can fully utilize TensorFlow's scalability and cross-platform features thanks to Keras. Can export your Keras models to run in the browser or on a mobile device, and can run Keras on TPU or on huge GPU clusters. It offers crucial building elements and abstractions for creating and delivering machine learning solutions quickly.

CHAPTER 5

IMPLEMENTATION DETAILS

5.1 Development and Deployment Setup

When deployed ML models, had to keep new data coming in all the time. Models need to adjust in the real world because of adding new categories, new levels and so on.

Deploying your model is the start, models often need to be retrained and checked for performance. The DL model needs to be trained with new data, so it's good to have a versioning system that will handle:

5.1.1 Model parameters

1. Model configuration
2. Feature pipeline
3. Training dataset
4. Validation dataset

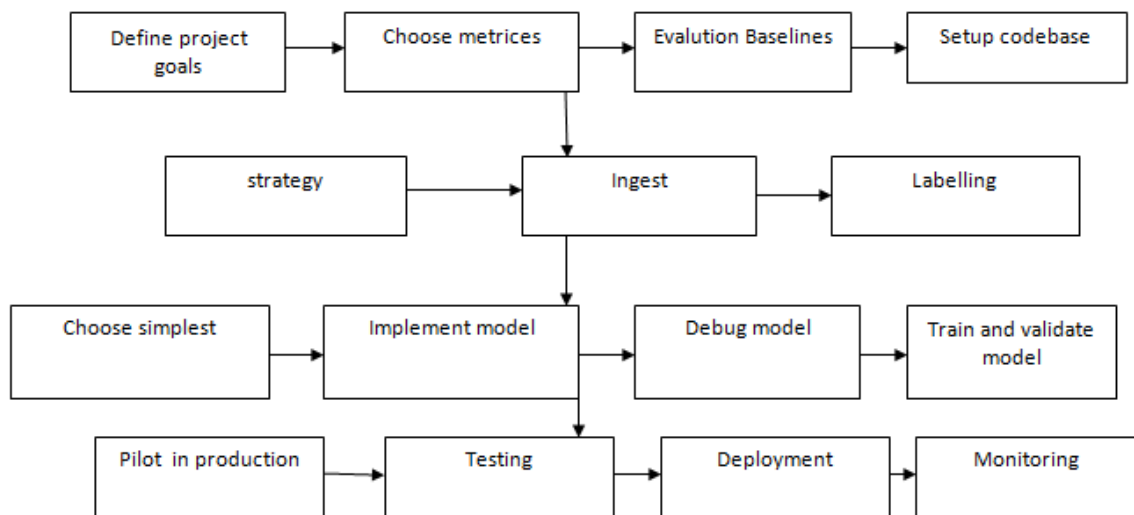


Figure 5.1 Development and Deployment Setup

The steps involved in the development and deployment of a deep learning model are as follows:

Data collection: The first step in developing a deep learning model is to collect the relevant data that will be used to train and test the model. The data should be

representative of the problem at hand, and it should be labeled or annotated if necessary.

Data preprocessing: Once the data is collected, it needs to be preprocessed. This involves cleaning the data, removing any irrelevant information, and transforming the data into a format that can be used by the deep learning model.

Model development: After the data is preprocessed, the next step is to develop the deep learning model. This involves selecting an appropriate architecture, defining the model parameters, and training the model using the preprocessed data.

Model evaluation: Once the model is trained, it needs to be evaluated to determine how well it performs on new, unseen data. This involves testing the model on a separate validation set and comparing the predicted outputs to the actual outputs.

Model optimization: Based on the evaluation results, the model can be optimized by adjusting the model architecture, changing the hyperparameters, or modifying the training data.

Model deployment: Once the model is optimized, it can be deployed for use. This involves integrating the model into an application or system, setting up the necessary infrastructure, and ensuring that the model works correctly in production.

Model monitoring and maintenance: After the model is deployed, it needs to be monitored and maintained to ensure that it continues to perform well. This involves tracking the model's performance metrics, addressing any issues that arise, and updating the model as necessary to keep up with changing requirements or data.

5.2 Algorithms:

5.2.1 Hybrid Model

To get rid of redundant classifiers that have a strong correlation with other basis classifiers after training the base classifiers. In addition to increasing the ensemble classifier's diversity, eliminating redundant classifiers also reduces the ensemble's temporal and spatial complexity[22]. In order to do this, correlation coefficients are computed using probabilistic outputs for pairs of classifiers. Each base classifier pair will have three coefficients, one for each

class. The correlations are aggregated across classes to provide a single measure of variety. This can be achieved by Deep Hybrid Learning, which is the resultant fusion network, which can be achieved by combining Deep Learning and Machine Learning. In this article, will learn how to use Deep Hybrid Learning, in which will use Deep Learning methods to generate or extract features from unstructured data and use classical Machine Learning approaches to build highly accurate classification models using the unstructured data. Thus, using Deep Hybrid Learning (DHL) — can take the benefits from both DL and ML and alleviate the drawbacks of both the techniques and provide more accurate and less computationally expensive solutions. In the suggested strategy, the redundant base classifiers are located via brute force search. The outputs of the remaining various classification algorithms should be fused after strongly correlated base CNNs have been eliminated. In the work that is being presented, the outputs of the base CNNs are combined. In this paper, first the three CNN's (Alexnet, Vgg16, Inception v3) are trained independently before merging into a single model. The final model (Merged) is giving more satisfactory results when compared to base or individual transfer learning techniques.

5.2.2 CNN:

CNN is the most widely used and efficient Deep Learning method in Image Processing. These are the most innovative techniques for deep learning [3]. CNNs have multiple applications due to parameter sharing and the ability to customize more powerfully than deep learning models. Biological text analysis, object recognition, and Detection and malware classification. CNN's features are used by researchers in a variety of ways. CNNs were inspired by the arrangement of animal vision cortex, which detects light in small patches that overlap over the visual field. The layers will then extract higher-level, more accurate information as they progress further into the network. It is well known that CNN models may build a link between the internal state of pixel values and the way those values are displayed in the shape of a two-dimensional matrix. Several convolution and pooling layers are often present, including one convolution layer linked to one pooling layer and alternating pooling layers coupled to convolution layers. Because each neuron in a convolution layer's output feature surface is locally linked to its input, sum and add the offset values of the local inputs using suitable connection weights [4]. As a consequence, the input data of neurons is gathered, and the approach is actually properly equated with the convolution process. CNN is a nonlinear mapping that produces output from input. In our CNN, first convolution layer contains 96 filters of size 11X11 with stride 4. The activation function used in this layer is relu. Following the first Maxpooling layer, which is a 3X3 layer with a stride of 2,

the next convolution operation is used. This time, the filter size is 5X5, and there are 256 of them. As the output spatial volume decreases, our number of learnt filters increases. Generally, a convolution is a mathematical operation on two functions that produces a third function expressing how the shape of one is modified by the other. It is an image processing operation that transforms an input image in order to show specific feature, e.g. edge detection, image sharpening, and image blurring. The input image can be altered by curling around the image and the matrix, called as filters or kernels. Deep learning has gained massive popularity in scientific computing, and its algorithms are widely used by industries that solve complex problems.

5.2.3 WORKING OF DEEP LEARNING

While deep learning algorithms feature self-learning representations, they depend upon ANNs that mirror the way the brain computes information. During the training process, algorithms use unknown elements in the input distribution to extract features, group objects, and discover useful data patterns. Much like training machines for self-learning, this occurs at multiple levels, using the algorithms to build the models. Deep learning models make use of several algorithms. While no one network is considered perfect, some algorithms are better suited to perform specific tasks. To choose the right ones, it's good to gain a solid understanding of all primary algorithms.

CNN's, also known as ConvNets, consist of multiple layers and are mainly used for image processing and object detection. Yann LeCun developed the first CNN in 1988 when it was called LeNet. It was used for recognizing characters like ZIP codes and digits.

CNN's are widely used to identify satellite images, process medical images, forecast time series, and detect anomalies.

CNNs Work

CNN's have multiple layers that process and extract features from data:

Convolution Layer

- CNN has a convolution layer that has several filters to perform the convolution operation.

Rectified Linear Unit (ReLU)

- CNN's have a ReLU layer to perform operations on elements. The output is a rectified feature map.

Pooling Layer

- The rectified feature map next feeds into a pooling layer. Pooling is a down-sampling operation that reduces the dimensions of the feature map.
- A fully connected layer forms when the flattened matrix from the pooling layer is fed as an input, which classifies and identifies the images.

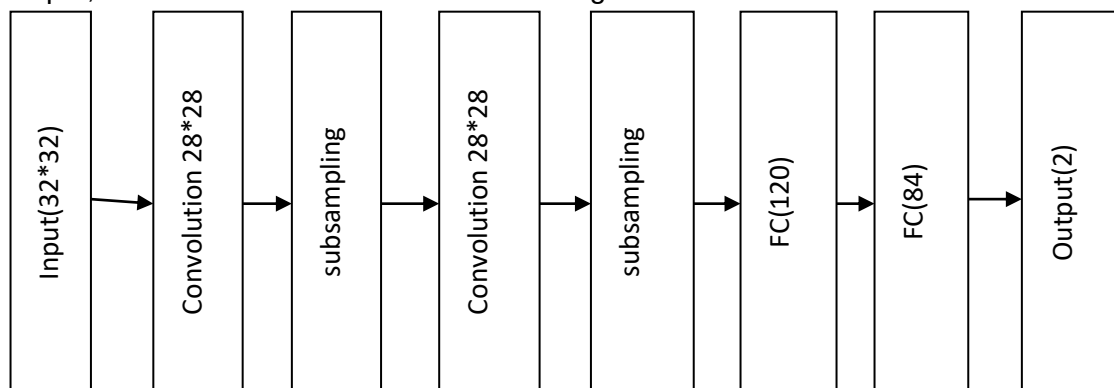


Figure 5.2 Architecture of CNN

5.2.3 FEATURE SELECTION:

Feature selection refers to the process of picking a few helpful and relevant characteristics from a large number of options. As a result, many classes may benefit from more precise pattern characterization. When irrelevant data characteristics are used, the performance of classification models might degrade [5]. Can decrease over fitting and improve accuracy by using feature selection. A filtering-based univariate attribute selection approach, which evaluates each feature individually in relation to the dependent variable, is one type of feature selection methodology [6-7]. Each feature is scored according to a set of criteria, and the features with the highest scores or ranks are chosen.

5.2.4 ALEXNET:

There are eight learnable levels in the Alexnet. Relu activation is used in each of the five levels of the model, with the exception of the output layer, which uses max pooling followed by three fully connected layers. That the very Initial layer of AlexNet is utilised for the input of a filtered picture with dimensions of 227, 227, 3 for width, height, and depth, respectively (red, green, blue)[9]. The last completely connected layer joins 1000 linked layers, and the remaining layers function as feature extractors [10]. Softmax is the activation function employed at this layer. With the aid of sustaining dropout and data replenishment, this model is quite effective at decreasing the overfitting issue [11]. AlexNet failed to show its excellent efficiency to classify and took time to train. Transfer learning is the technique of transferring the acquired knowledge into a new deep learning method without starting from scratch with a CNN model. The transferred network and the pretrained network were then separated from the structure. Millions of photos from ImageNet have been used to train the parameters in the pre-trained model, and the derived attributes have been effectively categorised. According on the new input photographs, these parameters may only need a little update. These settings are ideal for training a brand-new class of datasets since they have a very small impact on the whole CNN training process[12]. Our neural network architecture has 60 million parameters. Although the 1000 classes of ILSVRC make each training example impose 10 bits of constraint on the mapping from image to label, this turns out to be insufficient to learn so many parameters without considerable overfitting. Below, describe the two primary ways used to combat overfitting.

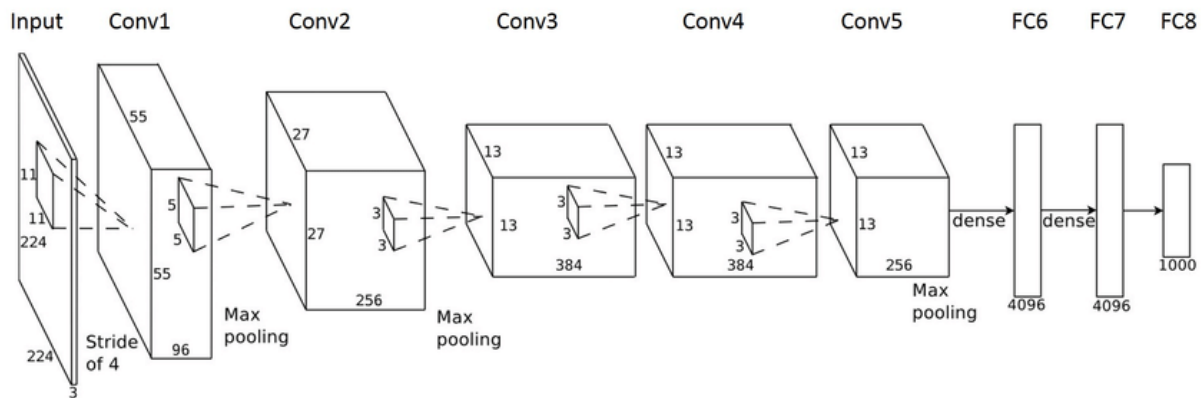


Figure 5.3 Architecture of Alexnet

5.2.5 IMAGE PREPROCESSING:

The categorization of the picture must first go through preprocessing. This procedure aims to distort the picture database[13]. Since each dimension of an image files might have a particular feature connection, it is possible for each picture to be independent of the others. As a result, a straightforward scaling method is initially applied to the image to generate an image vector that fits within an acceptable range. To scale a picture is simple to increase or decrease its original size while maintaining an identical aspect ratio. This procedure aims to more precisely detect picture characteristics before making an accurate analysis of the classification conclusion [14].

Feature Extraction- The process of extracting certain type of information from scanned input image is known as extraction. The features viz. area, boundary box, centroid, zoning density and line segment are extracted from the image. Centroid extracted to find out the weights of the component and it locates the centre of component.

Classification- In this part , neural networks are used as classifier. Neural Network are generally based on soft computing techniques. The architecture used in designing neural network is arranged in layers known as multilayer perceptron. It consist of three different layers including input layer, one or more layer of hidden nodes and a layer of outer nodes. This phase is dependent on the previous phases as the classification performance depends on good feature extraction.

Training and recognition- In this phase, all the digit collected from the data set are trained and the recognized for performing the further processes. Multilayer Perceptron Feed forward Back propagation neural network is used for recognition of handwritten mathematical symbols and recognition. However, severe data limitations and/or absence of relevant problem for transfer learning can drastically reduce advantages of DNN-based DL. For example, pure data-driven auto-encoders dealing with high-dimensional input data require large amount of data for effective operation. However, hierarchical data representations can be also implemented without NN

5.2.6 DESCRIPTION OF DATA:

The fertility PCOS dataset, which distinguishes between patients with and without PCOS, is utilised for experimental reasons. This dataset is selected since it serves as a baseline for several research studies on the PCOS issue. Later, applied data augmentation for getting better results by using hybrid models.

5.2.7 EVALUATION METRICS:

The following metrics are used to assess our model's performance:

TP(True PCOS): In the scenario where the patient has PCOS and the models predict the same.

FP(False PCOS): In the scenario where the patient has PCOS and the models predict it as PCOS infected.

TN(True NON-PCOS): In the scenario where the patient has NO-PCOS and the models predict the same.

FN(False NON-PCOS): In the scenario where the patient has PCOS and the models predict NO-PCOS.

$$\text{Accuracy} = \frac{T P + T N}{T P + F P + T N + F N}$$

The four terms listed above are then utilized to determine our model's recall, precision, and F1-score.

It is one of the widely used metrics and basically used for binary classification. A U C of a classifier is defined as the probability of a classifier that will rank a randomly chosen positive example higher than a negative example. Before going into A U C more, let me make comfortable with few basic terms. Dropout Combining the predictions of many different models is a very successful way to reduce test errors [1, 3], but it appears to be too expensive for big neural networks that already take several days to train. There is, however, a very efficient version of model combination that only costs about a factor of two during training. The recently-introduced technique, called “dropout” [10], consists of setting to zero the output of each hidden neuron with probability 0.5. The neurons which are “dropped out” in this way do not contribute to the forward pass and do not participate in back propagation. So every time an input is presented, the neural network samples a different architecture, but all these architectures share weights. This technique reduces complex co-adaptations of neurons, since a neuron cannot rely on the presence of particular other neurons. It is, therefore, forced to learn more robust features that are useful in conjunction with many different random subsets of the other neurons. At test time, used all the neurons but multiply their outputs by 0.5, which is a reasonable approximation to taking the geometric mean of the predictive distributions produced by the exponentially-many dropout networks.

True positive rate: Also called or termed as sensitivity. True Positive Rate is considered as a portion of positive data points which are correctly considered as positive, with respect to all data points those are positives.

True Negative Rate: Also called or termed as specificity. False Negative Rate is considered as a portion of negative data points which are correctly considered as negative, with respect to all data points those are negatives.

False-positive Rate: False Negative Rate is considered as a portion of negative data points which are mistakenly considered as negative, with respect to all data points those are negatives.

False Positive Rate and True Positive Rate both have values in the range $[0, 1]$. Now the thing is what is A U C then? So, A U C is a curve plotted between False Positive Rate Vs True Positive Rate at all different data points with a range of $[0, 1]$. Greater the value of AUC better the performance of the model.

5.2.8 INCEPTION V3:

Convolution (1×1 , 3×3 , 1×5) and the pooling operation (3×3), which are often used in CNN, are layered in this structure (the channel counts are raised, the convolution and pooling sizes are the same). This enhances the network's breadth while also improving its capacity to scale [15]. The network in the network convolution layer is capable of extracting every detail of the input, and the 5×5 filter may also cover the bulk of the receiving layer's input [16]. To lower the size of the space and overfitting, a pooling procedure may also be carried out. Each convolution layer above such levels should be followed by a ReLU operation to improve the channel's nonlinear properties [17]. The initial Inception version's 55 convolution kernel, however, took too much work and produced a large feature map. In order to avoid this, the feature diagram's width is decreased by inserting the 1×1 convolution kernel before the 3×3 , 5×5 , and after Max pooling [18]. Google then released the Inception-v2 architecture. The authors suggest many changes to increase accuracy and decrease computing complexity. This results in the network topology of Inception-v1 [19] as illustrated in the following picture. ReLUs have the desirable property that they do not require input normalization to prevent them from saturating. If at least some training examples produce a positive input to a ReLU, learning will happen in that neuron. However, still find that the following local normalization scheme aids generalization. Pooling layers in CNNs summarize the outputs of neighboring groups of neurons in the same kernel map. Traditionally, the neighborhoods summarized by adjacent pooling units do not overlap

(e.g., [17, 11, 4]). To be more precise, a pooling layer can be thought of as consisting of a grid of pooling units spaced s pixels apart, each summarizing a neighborhood of size $z \times z$ centered at the location of the pooling unit.

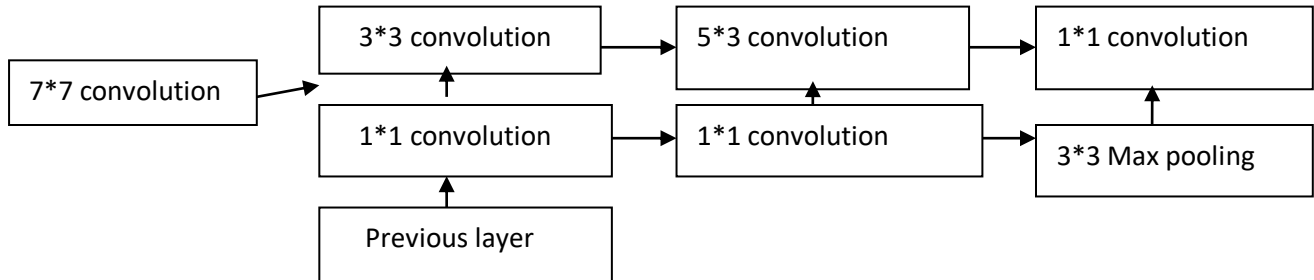


Figure 5.4 Architecture of Inception v3

5.2.9 VGG16:

There are several hyper parameters in the VGG16 model. The first layer's input picture has a 224x224 RGB dimension. The picture is passed through a stack of convolutional layers with the same padding and max-pooling layer being applied to both the 3x3 filter size and stride 1 and 2x2 filter and stride 2 filters, respectively [20]. ReLU encourages rapid learning and reduces the possibility of vanishing gradient problems, making it more computationally effective. A softmax for output follows two completely linked layers at the model's end [21]. Convolutional neural network model that has been trained to extract features while enhancing images. VGG-16 pre trained model will be used which is trained on image net weights to extract features, to categorize pictures by feeding the result to a new classifier.

During training, the input to our ConvNets is a fixed-size 224×224 RGB image. The only preprocessing do is subtracting the mean RGB value, computed on the training set, from each pixel. The image is passed through a stack of convolutional (conv.) layers, where use filters with a very small receptive field: 3×3 (which is the smallest size to capture the notion of left/right, up/down, center). In one of the configurations, also utilise 1×1 convolution filters, which can be seen as a linear transformation of the input channels (followed by non-linearity). The convolution stride is fixed to 1 pixel; the spatial padding of conv. layer input is such that the spatial resolution is preserved after convolution, i.e. the padding is 1 pixel for 3×3 conv. layers. Spatial pooling is carried out by five max-pooling layers, which follow some of the conv. layers (not all the conv. layers are followed by max-pooling). Max-pooling is performed over a 2×2 pixel window, with stride 2.

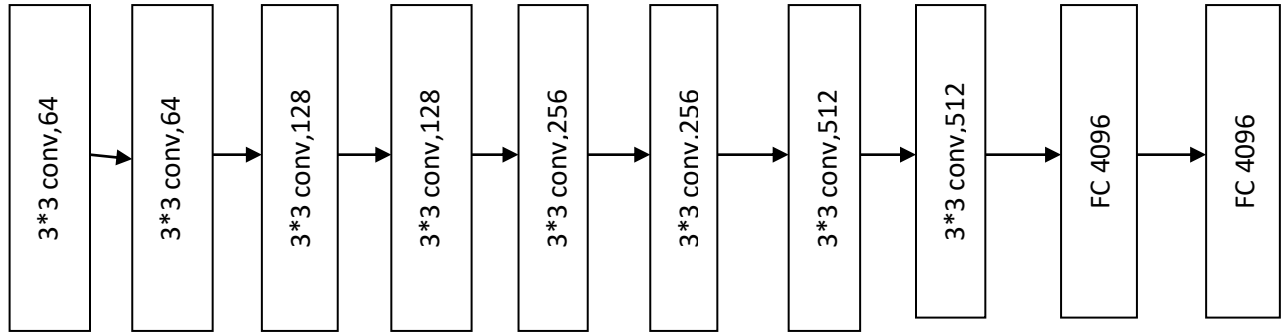


Figure 5.5 Architecture of VGG16

5.2.10 DATA AUGMENTATION:

A group of methods known as "data augmentation" use an existing dataset to produce artificial data. This synthetic data frequently consists of minute modifications to the original data, which should maintain the model's predictions[28]. Additionally, combinations of far-off samples that would be very challenging to deduce from natural data can be reflected in synthetic data. One of the most beneficial interfaces for affecting Deep Neural Network training is data augmentation. This is mostly because there is a window to see where the model is falling short and the improvements are understandable. This is the process of modifying images to provide better examples, such as rotating images, turning them horizontally, or increasing brightness[29]. The easiest and most common method to reduce overfitting on image data is to artificially enlarge the dataset using label-preserving . Employ two distinct forms of data augmentation, both of which allow transformed images to be produced from the original images with very little computation, so the transformed images do not need to be stored on disk. In our implementation, the transformed images are generated in Python code on the CPU while the GPU is training on the previous batch of images. So these data augmentation schemes are, in effect, computationally free. The first form of data augmentation consists of generating image translations and horizontal reflections. This by extracting random 224×224 patches (and their horizontal reflections) from the 256×256 images and training our network on these extracted patches⁴ . This increases the size of our training set by a factor of 2048, though the resulting training examples are, of course, highly interdependent. Without this scheme, our network suffers from substantial overfitting, which would have forced us to use much smaller networks. At test time, the network makes a prediction by extracting five 224×224 patches (the four corner patches and the center patch) as well as their horizontal reflections (hence ten patches in all), and averaging the predictions made by the network's softmax layer on the ten patches. The

second form of data augmentation consists of altering the intensities of the RGB channels in training images. Specifically, perform PCA on the set of RGB pixel values throughout the ImageNet training set. To each training image, add multiples of the found principal components.

The below figure shows how data augmentation works to create duplicate samples

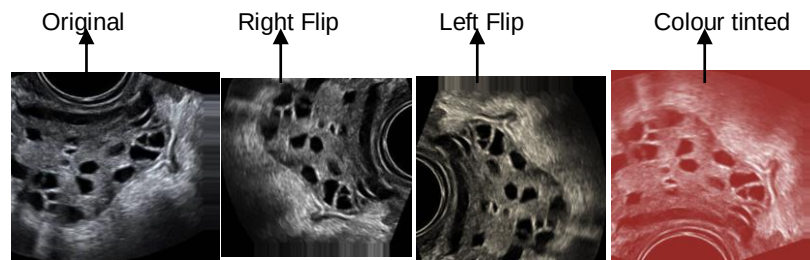


Figure 5.6 Data Augmentation

5.3 Testing

ML model evaluation focuses on the overall performance of the model. Such evaluations may consist of performance metrics and curves, and perhaps examples of incorrect predictions. This model evaluation is a great way to monitor your model's outcome between different versions. Remember that it does not tell us a lot about the reasons behind the failures and the specific model behaviors. All pre-trained networks have been tested and compared with all performance metrics and tabulated.

CHAPTER 6

6.1 RESULTS AND DISCUSSION:

The amount of time required is determined by various parameters, including the size of the dataset, the hidden layers, the hidden neurons per layer, the kind of model, the experiential surroundings, and so on. However, CNN would be the appropriate solution to decrease time-consuming since CNN can successfully handle the parameter expansion problem by enabling parameter sharing via each layer but fails to forecast the state of the ultrasound picture i.e. PCOS infected or not for a few image samples. The hybrid models require a long time to train, but the time decreases dramatically during testing and performs more efficiently than other base or individual networks. This section examines the outcomes of the approaches outlined in the Methodology. Results from the combination of Alexnet, vgg16, Inception v3, and other approaches are compared. Then, they are examined based on four criteria: accuracy, precision, recall, and F1 score. The findings of using the described experiment to identify polycystic ovary in ultrasound pictures are presented and discussed in this part. For feature capture and classification, the complete Deep Learning models are used. Four well-known CNN designs are used in the experiments: Alexnet, VGG16, Inception-v3, Resnet, and Hybrid model. The deep neural network architectures with adam and nadam optimizers' performance assessment on the test set is given. According to Figures [9,10,19,20,29,30,39,40], the Hybrid model used in the suggested model almost always produced accuracy levels of about 99%. In comparison to the results of cutting-edge studies that engage in detecting the PCOM using ultrasound images of the ovary, this model has produced excellent results. The accuracy rates for [32, 33] were 78.1% and 80.84%, respectively, whereas the findings of the present study are better. Additionally, they applied the conventional strategy by first applying a classification assignment using a CNN or Elman neural network and feature extraction using the Gabor wavelet technique. By employing the traditional methods and the Gabor wavelet as a feature generator and a modified backpropagation as a classifier, Abdullah et al. [34] achieved an accuracy of 93.02%. Additionally, the writers failed to mention the experiment's use of a specific amount of images, which is a vital and essential parameter. The confusion matrix for each model when using pre-trained architectures for this categorization assignment is shown in Figures[1–40]. This demonstrates the general classification rate and precision of the network. The diagonal cells display the number of occurrences that were properly classified, while the off-diagonal cells display the number of cases that were incorrectly classified. Using Adam optimizer with seed value=42 over sigmoid and softmax activation functions for pre-trained networks achieved

accuracy between 75 and 100. Here alexnet which shown an accuracy of 75% with sigmoid achieved 100% with softmax. With seed value=142 with adam optimizer for sigmoid activation shown more accuracy than seed value=42. Similarly for nadam optimizer was used with different activation functions and seed values and corresponding results was tabulated for comparison[Table1-8]. All validation graphs of models w.r.t the hyperparameters can be observed in figures[41-48].

CONFUSION MATRICES AND VALIDATION GRAPHS

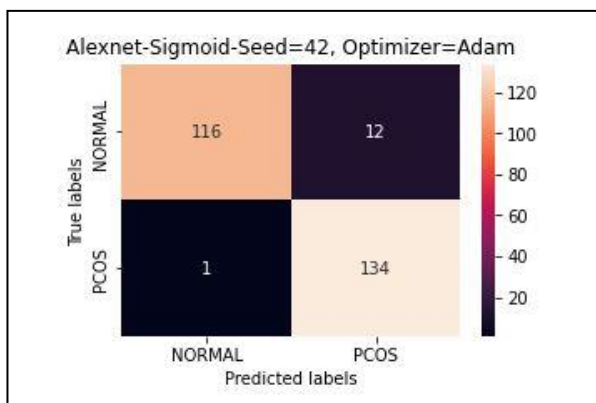


Figure-6.1 Confusion Matrice of Alexnet

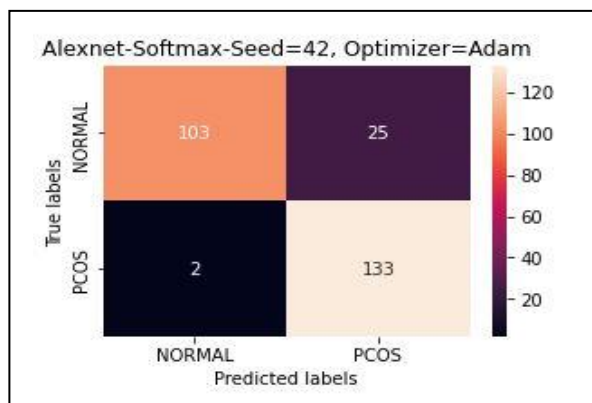


Figure-6.2 Confusion Matrice of Alexnet

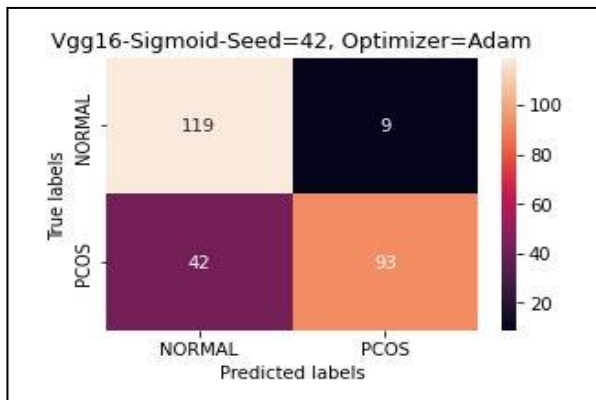


Figure-6.3 Confusion Matrice of vgg16

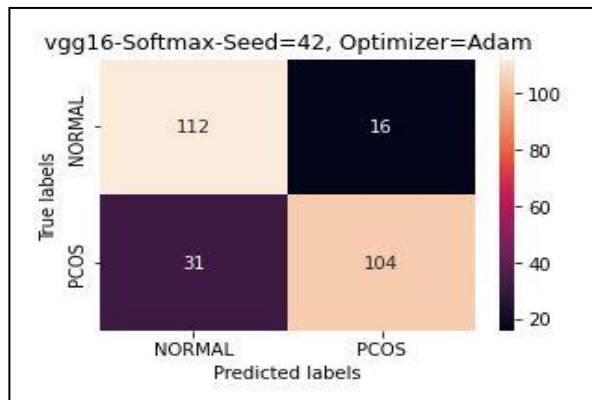


Figure-6.4 Confusion Matrice of vgg16

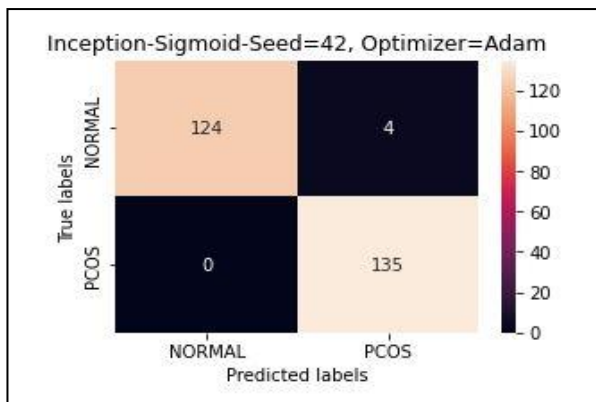


Figure-6.5 Confusion Matrice of Inception

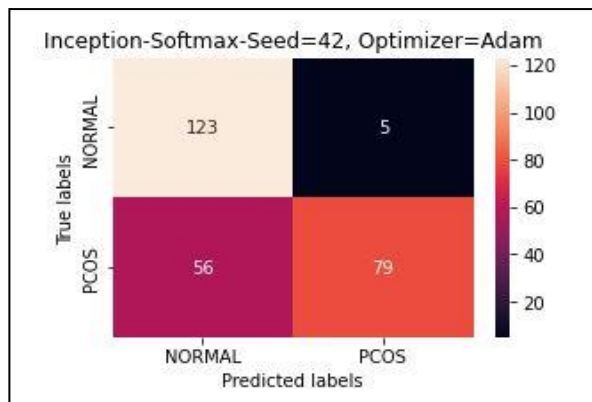


Figure-6.6 Confusion Matrice of Inception

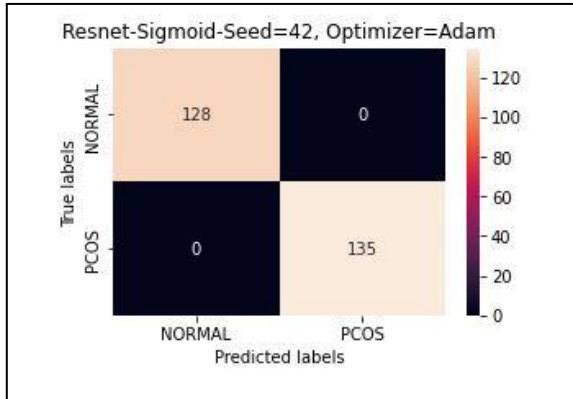


Figure-6.7 CM of Resnet with sigmoid

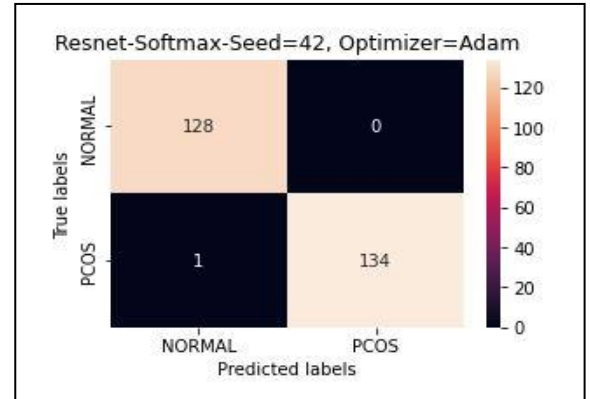


Figure-6.8 CM of Resnet with softmax

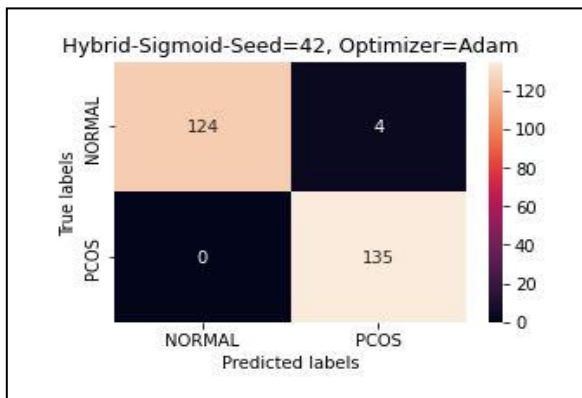


Figure-6.9 CM of Hybrid with sigmoid

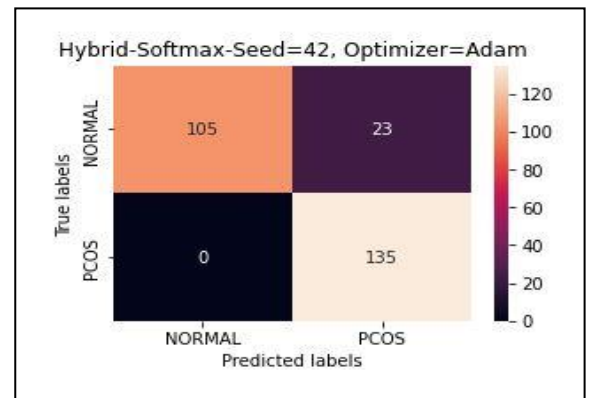


Figure-6.10 CM of Hybrid with softmax

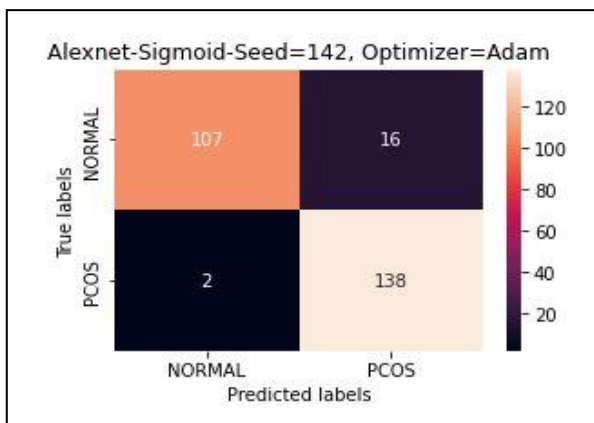


Figure-6.11 CM of Alexnet with sigmoid

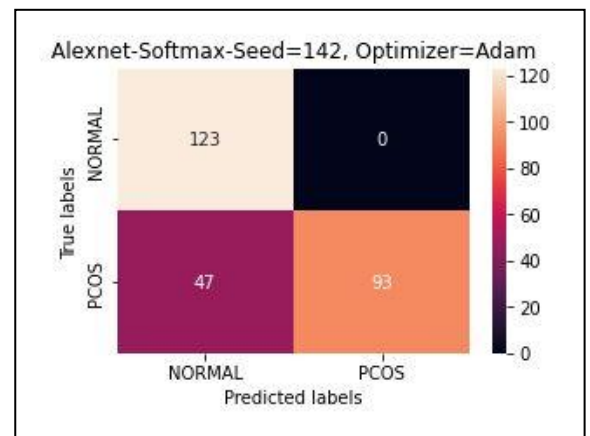


Figure-6.12 CM of Alexnet with softmax

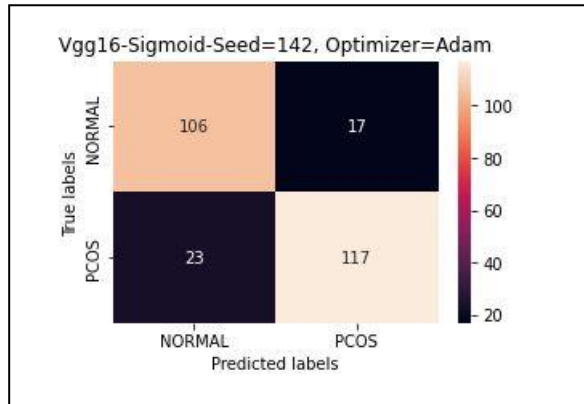


Figure-6.13 CM of vgg16 with sigmoid

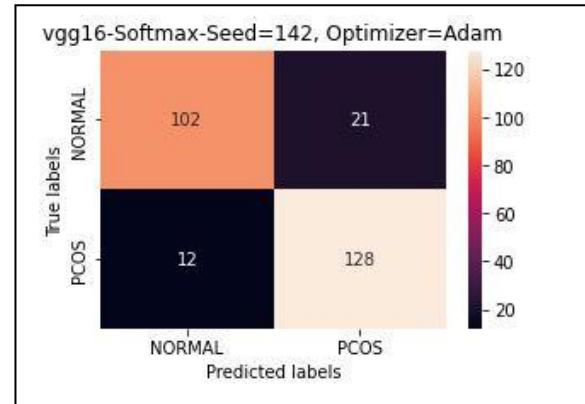


Figure-6.14 CM of vgg16 with softmax

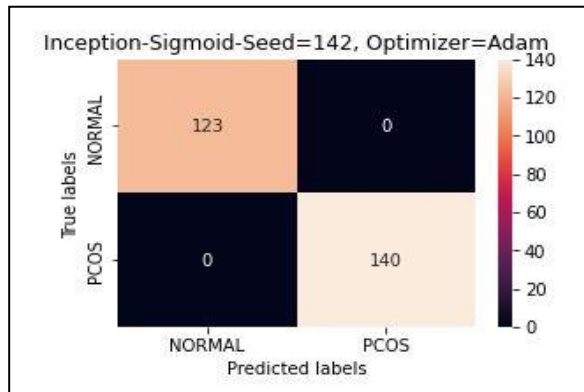


Figure-6.15 CM of Inception with sigmoid

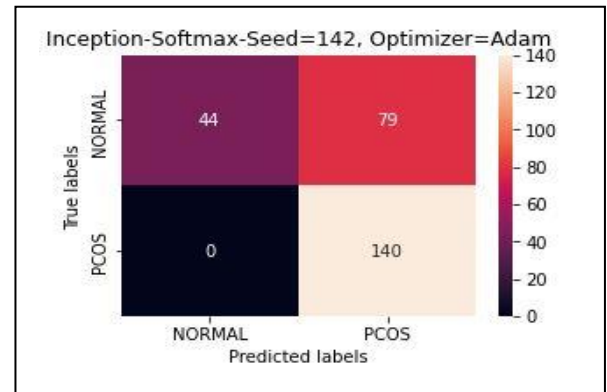


Figure-6.16 CM of Inception with softmax

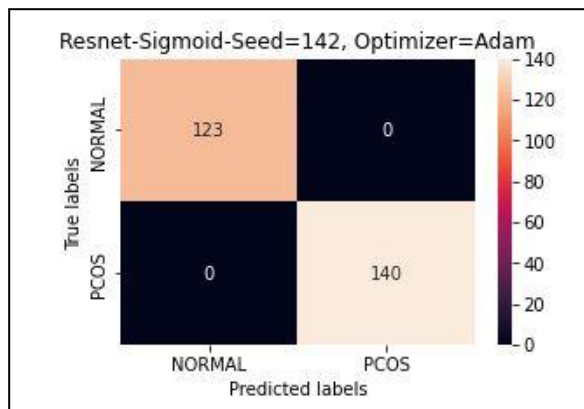


Figure-6.17 CM of Resnet with sigmoid

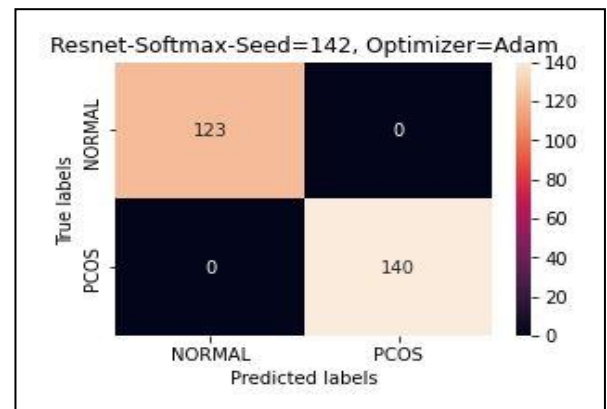


Figure-6.18 CM of Resnet with softmax

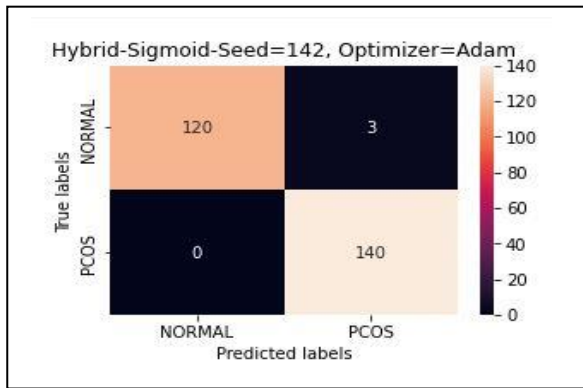


Figure-6.19 CM of Hybrid with sigmoid

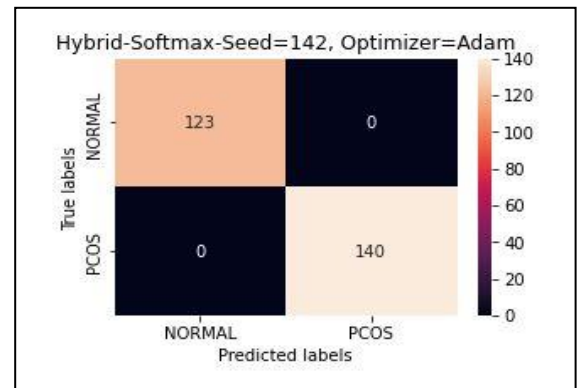


Figure-6.20 CM of Hybrid with softmax

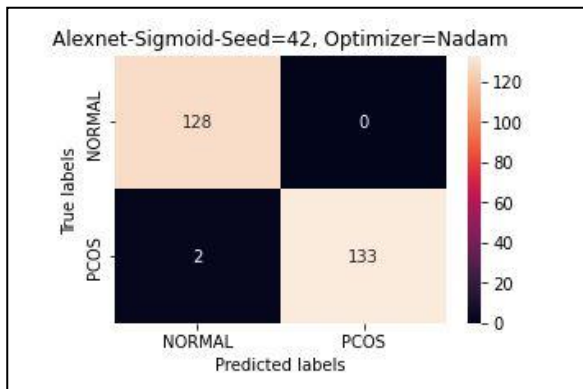


Figure-6.21 CM of Alexnet with sigmoid

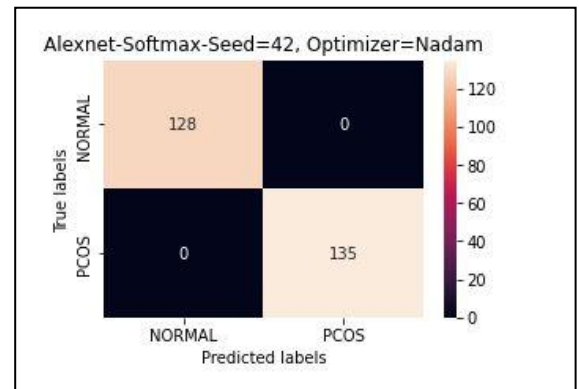


Figure-6.22 CM of Alexnet with softmax

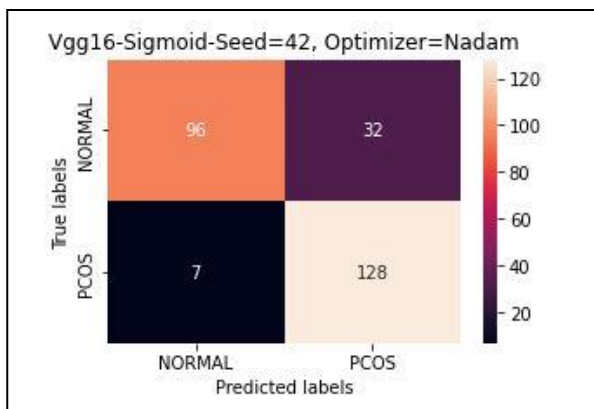


Figure-6.23 CM of vgg16 with sigmoid

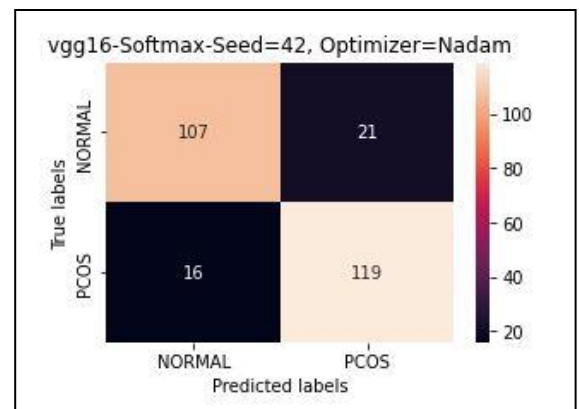


Figure-6.24 CM of vgg16 with softmax

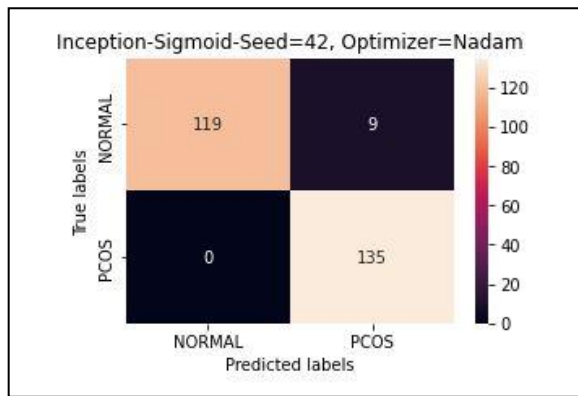


Figure-6.25 CM of Inception with sigmoid

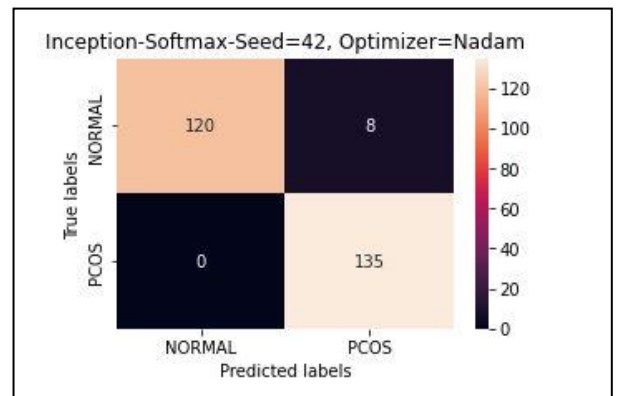


Figure-6.26 CM of Resnet with softmax

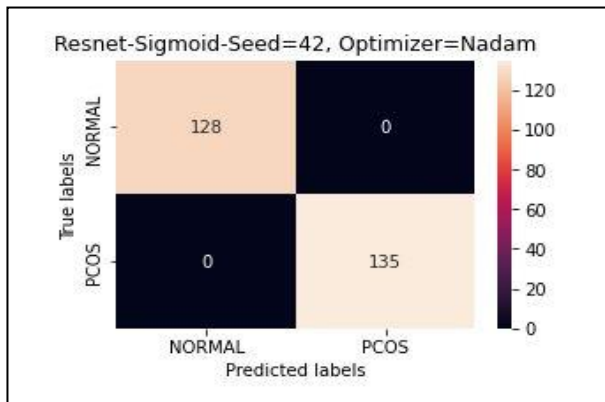


Figure-6.27 CM of Resnet with sigmoid

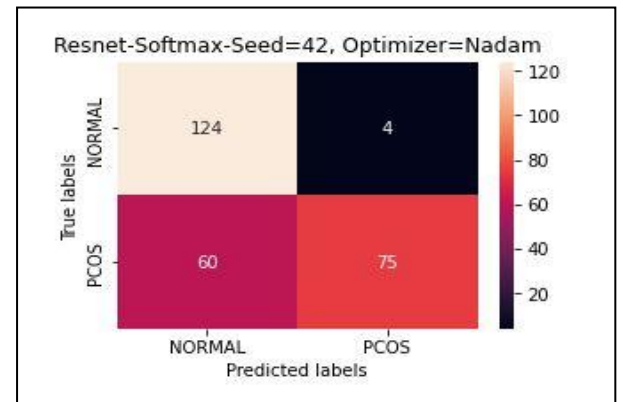


Figure-6.28 CM of Resnet with softmax

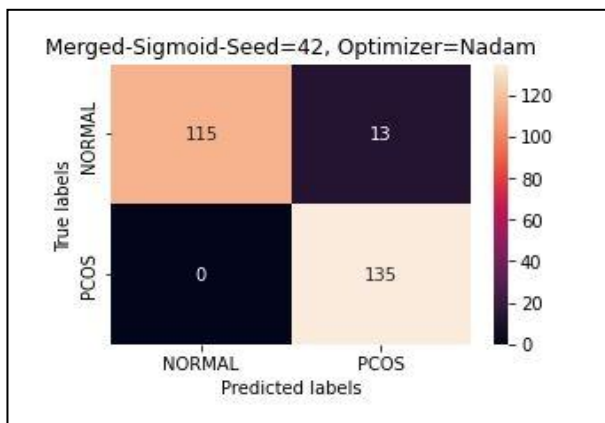


Figure-6.29 CM of Hybrid with sigmoid

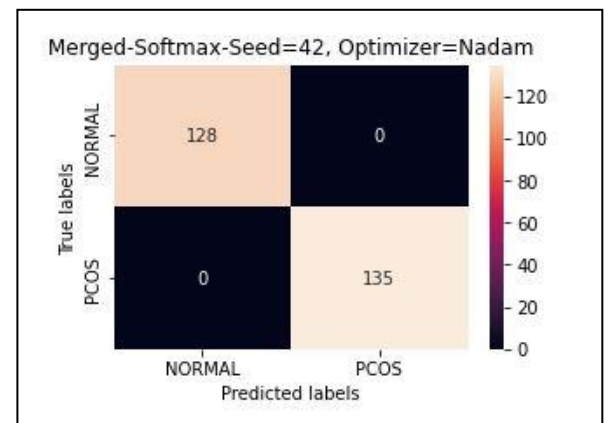


Figure-6.30 CM of Hybrid with softmax

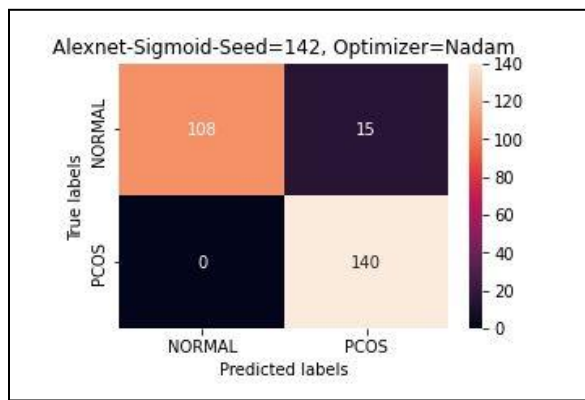


Figure-6.31 CM of Alexnet with sigmoid

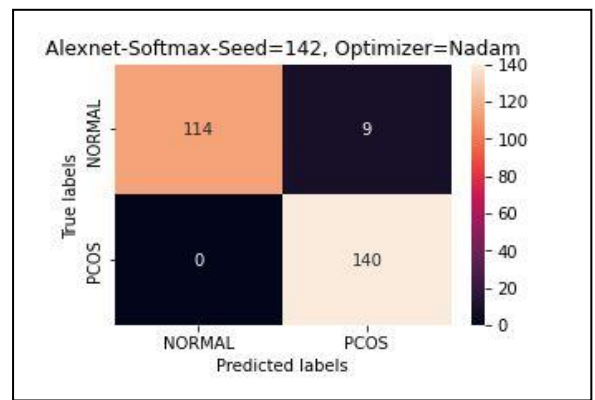


Figure-6.32 CM of Alexnet with softmax

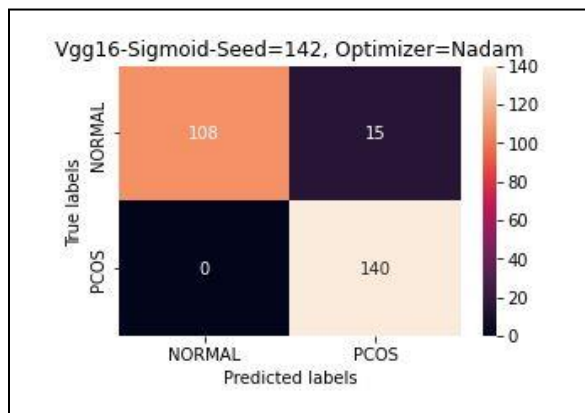


Figure-6.33 CM of vgg16 with sigmoid

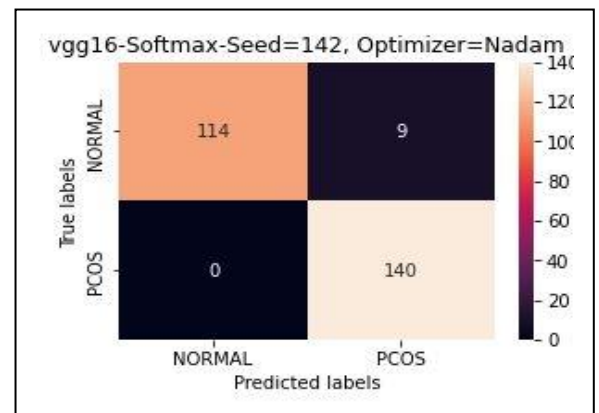


Figure-6.34 CM of vgg16 with softmax

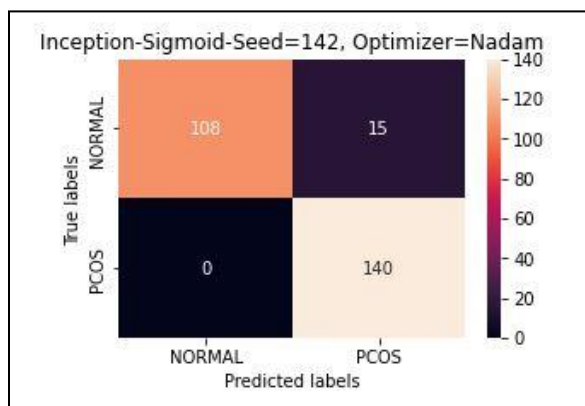


Figure-6.35 CM of Inception with sigmoid

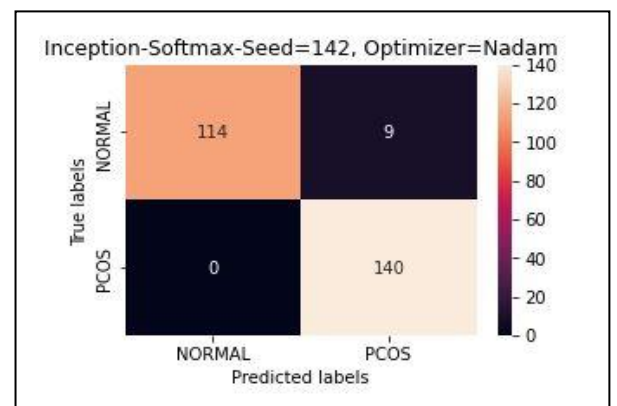


Figure-6.36 CM of Inception with softmax

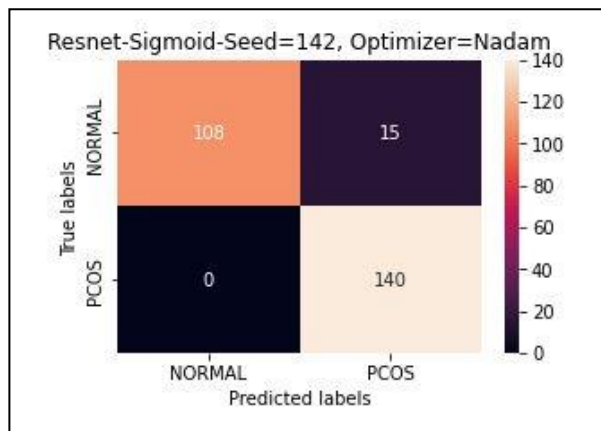


Figure-6.37 CM of Resnet with sigmoid

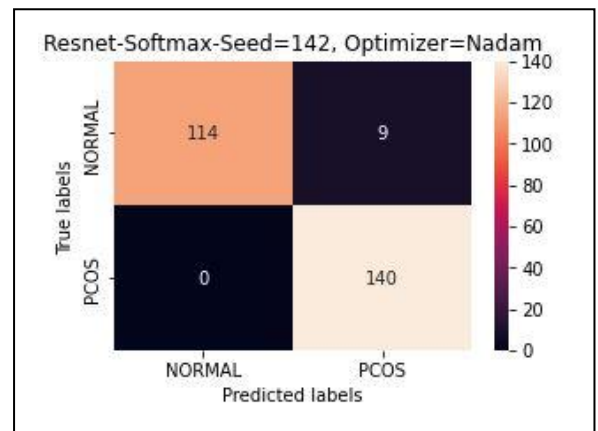


Figure-6.38 CM of Resnet with soft

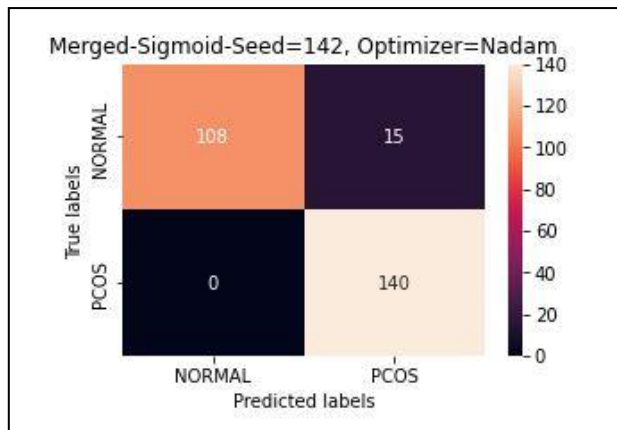


Figure-6.39 CM of Merged with sigmoid

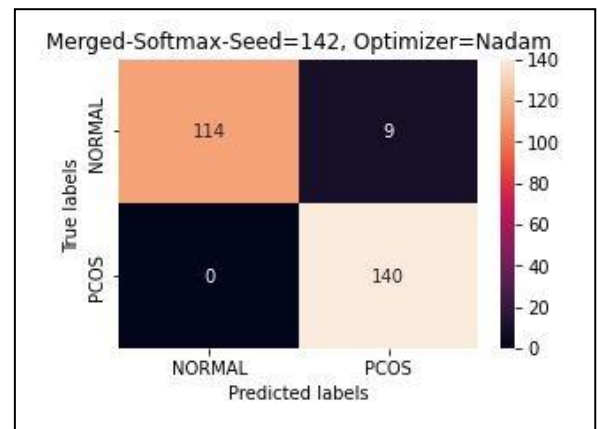


Figure-6.40 CM of Merged with softmax

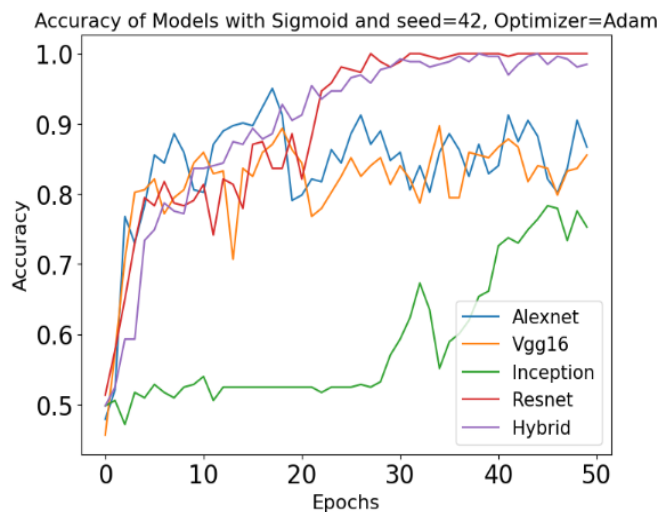


Figure :- 6.41 Accuracy of model with sigmoid and seed value of 42 with adam optimizer

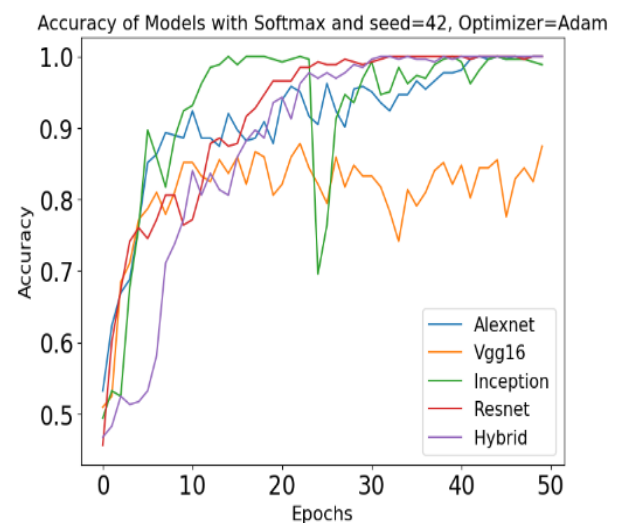


Figure :- 6.42 Accuracy of model with softmax and seed value of 42 with adam optimizer

Accuracy of Models with Sigmoid and seed=142, Optimizer=Nadam

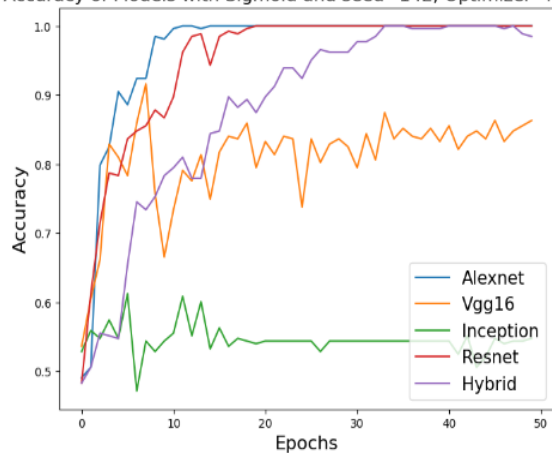


Figure :- 6.43 Accuracy of model with sigmoid and seed value of 142 with nadam optimizer

Accuracy of Models with Softmax and seed=142, Optimizer=Nadam

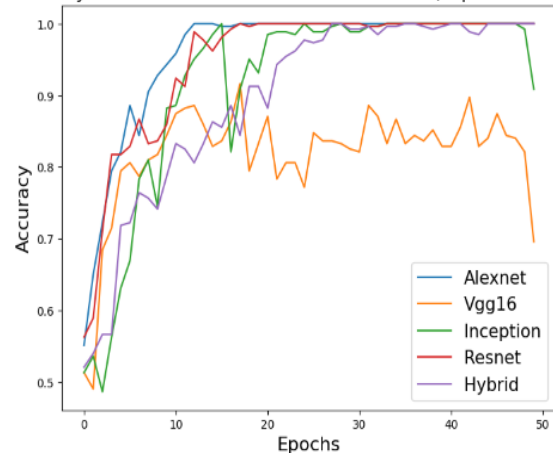


Figure :- 6.44 Accuracy of model with softmax and seed value of 142 with nadam optimizer

Accuracy of Models with Sigmoid and seed=42, Optimizer=Nadam

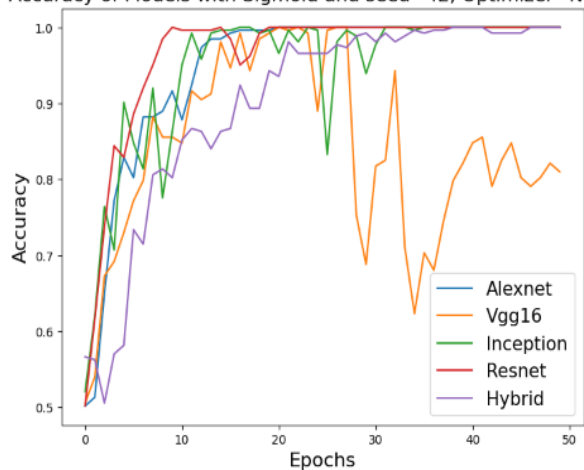


Figure :- 6.45 Accuracy of model with sigmoid and seed value of 42 with nadam optimizer

Accuracy of Models with Softmax and seed=42, Optimizer=Nadam

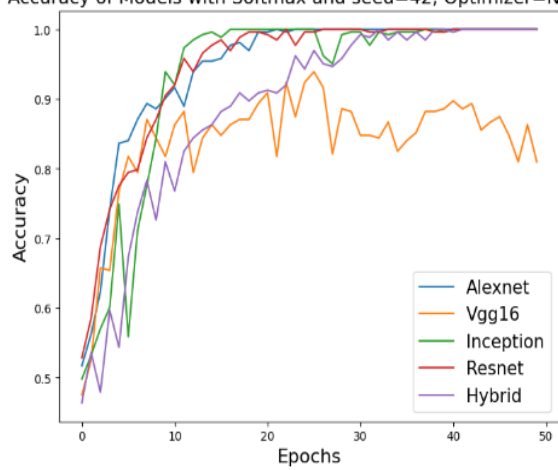


Figure :- 6.46 Accuracy of model with softmax and seed value of 142 with nadam optimizer

Accuracy of Models with Sigmoid and seed=142, Optimizer=adam

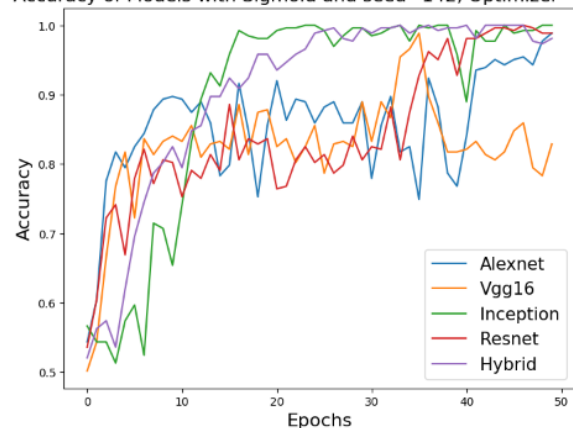


Figure :- 6.47 Accuracy of model with sigmoid and seed value of 142 with adam optimizer

Accuracy of Models with Softmax and seed=142, Optimizer=adam

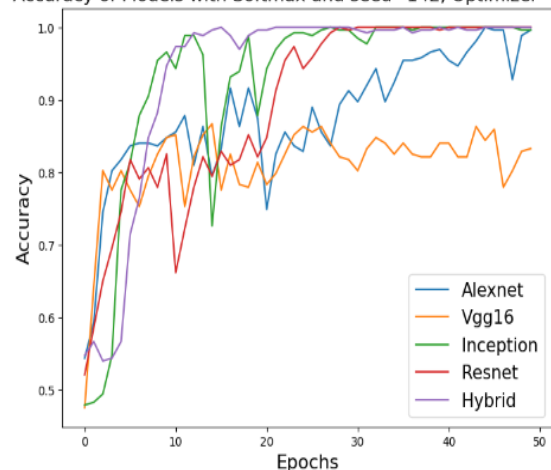


Figure :- 6.48 Accuracy of model with softmax and seed value of 142 with adam optimizer

Activation=Sigmoid,seed=42

Model	Precision		Recall	F1-score	Accuracy
Alexnet	0	0.69	1.00	0.81	0.78
	1	1.00	0.57	0.73	
Vgg16	0	0.89	0.59	0.71	0.77
	1	0.71	0.93	0.80	
Inception	0	0.88	0.77	0.82	0.84
	1	0.81	0.90	0.85	
Resnet	0	0.89	0.85	0.87	0.88
	1	0.86	0.90	0.88	
Merged	0	0.86	1.00	0.92	0.92
	1	1.00	0.85	0.92	

Table 6.1 Performance metrics with activation sigmoid and seed value of 42

Activation=Sigmoid,seed=142

Model	Precision		Recall	F1-score	Accuracy
Alexnet	0	1.00	0.35	0.52	0.66
	1	0.58	1.00	0.73	
Vgg16	0	0.83	0.86	0.85	0.83
	1	0.84	0.81	0.82	
Inception	0	0.89	0.99	0.93	0.93
	1	0.99	0.86	0.92	
Resnet	0	0.78	0.93	0.85	0.83
	1	0.90	0.71	0.80	
Merged	0	0.99	1.00	0.99	0.99
	1	1.00	0.99	0.99	

Table 6.2 Performance metrics with sigmoid and seed value of 142

Activation=softmax,seed=42

Model	Precision		Recall	F1-score	Accuracy
Alexnet	0	0.90	0.80	0.85	0.86
	1	0.83	0.92	0.87	
Vgg16	0	0.94	0.81	0.87	0.88
	1	0.84	0.95	0.89	
Inception	0	0.88	1.00	0.93	0.93
	1	1.00	0.87	0.93	
Resnet	0	0.69	0.97	0.81	0.77
	1	0.96	0.58	0.73	
Merged	0	1.00	0.87	0.93	0.94
	1	0.89	1.00	0.94	

Table 6.3 Performance metrics with softmax and seed value of 42

Activation=softmax,seed=142

Model		Precision	Recall	F1-score	Accuracy
Alexnet	0	0.94	0.76	0.84	0.85
	1	0.78	0.95	0.87	
Vgg16	0	0.72	0.87	0.79	0.75
	1	0.81	0.62	0.71	
Inception	0	0.96	1.00	0.98	0.98
	1	1.00	0.95	0.97	
Resnet	0	0.70	0.97	0.81	0.76
	1	0.93	0.53	0.68	
Merged	0	0.95	0.66	0.78	0.80
	1	0.72	0.96	0.82	

Table 6.4 Performance metrics with softmax and seed value of 42

CHAPTER 7

7.1 CONCLUSION AND FUTURE SCOPE

A automated technique to detecting PCOS using deep learning algorithms is suggested in this research. To that goal, well-known convolution neural network architectures have been integrated to determine whether or not a patient has pcos. The suggested ensemble technique with data augmentation beat other competing methods in the trials. Furthermore, the development of an intelligent solution for identifying PCOS online is planned. The proposed designs may simply be modified in the future to identify new types of PCOS. However, because other PCOS kinds are rare in certain settings, the produced dataset will be imbalanced, making the classification task difficult for unstable classifiers like as neural networks and its extensions such as CNNs. In a rare cases, the livers in images can look like ovaries and might be found to be infected with PCOS. The results of this trial showed that, when compared with various seed values and activation functions, the hybrid model consistently beat all other pre-trained techniques. In this trial, PCOM is only diagnosed using the ultrasound picture. Although pictures only enable for the correct identification of the polycystic morphology in PCOS, it is preferable to expand the model to include clinical characteristics.. As a result, the development of a strong CNN to imbalanced datasets of PCOS photos is anticipated . However, model ensembles are not necessarily superior. New findings can still be perplexing. other key constraints of the suggested identification method is that doctors must obtain an ultrasound image of a patient at an angle that clearly captures their ovaries.

7.2 FUTURE ENHANCEMENTS

In the future, hope to create a web service to collect more samples from gynaecologists in order to increase the accuracy of the proposed network. Furthermore, the development of an intelligent solution for identifying PCOS online is planned. The proposed designs may simply be modified in the future to identify new types of PCOS

Multi-modal data integration: Currently, PCOS detection using deep learning is mainly based on ultrasound images. In the future, integrating other modalities such as MRI, CT, or laboratory data may help improve the accuracy of PCOS detection.

Larger datasets: Deep learning models require large amounts of data to be trained effectively. Collecting larger and more diverse datasets may help improve the accuracy and generalizability of PCOS detection models.

Explainable AI: Deep learning models are often considered "black boxes," meaning that it is difficult to understand how they arrive at their predictions. Developing more explainable AI methods may help improve the interpretability and trustworthiness of PCOS detection models.

Personalized medicine: PCOS is a complex disorder with different clinical manifestations and underlying mechanisms. Developing personalized deep learning models that take into account individual characteristics such as age, body mass index, and hormone levels may help improve the accuracy of PCOS detection and diagnosis.

Clinical decision support: Deep learning models can be integrated into clinical decision support systems to assist physicians in making accurate diagnoses and treatment decisions. Such systems can provide personalized recommendations for patient care based on the patient's specific characteristics and medical history.

Real-time monitoring: Deep learning models can be used to monitor the progression of PCOS over time and detect early warning signs of complications. This can help improve patient outcomes and reduce the burden of PCOS on healthcare systems.

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