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Classification of Ultrasound PCOS Image using Deep Learning based Hybrid Models

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***Abstract*—Polycystic Ovary Syndrome or (PCOS) is one of the medical disorders that affect female pregnancy. High levels of androgens in women are the root cause of the symptoms that make up Polycystic Ovarian Syndrome (PCOS). According to recent studies, this illness affects roughly 20 of Indian women. Damaged ovaries were identified by a physician's manual review of ultrasound images, but they were unable to determine whether they were simple cysts, PCOS, or malignant cysts. 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. This paper proposes a method of prediction of PCOS using transfer learning techniques like Alexnet, Inception V3, Resnet50, VGG16 and Hybrid Models. Here, an attempt to offer a methodology in which Hybrid Models will be included in order to train models and improve accuracy. Finally, the test data set is used for the feature extraction procedure and using the performance coefficients, the results are 93 percentage accurate.**

Keywords— Polycystic Ovarian Syndrome, Deep learning, Transfer Learning, Hybrid Model, Ultrasound images

I. 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 5 in discovering hidden data opportunities, helping the medical business to operate more efficiently. It also helps doctors analyse 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 10 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 disorderthat affects female bodies. According to one research, one in every five women, or more than 20 of the population, has this condition [1]. Low levels of luteinizing hormone as well as follicle stimulating hormone and high levels of prolactin in PCOS-affected ovaries prevent follicles from growing and maturing, whereas in normal ovaries, a single follicle develops to a diameter of 20 mm, is fully developed, and is prepared for ovulation. The exact cause of PCOS is unknown, however 20 important factors include hormonal disturbance, having a body mass index more than 24, and irregular menstruation cycles [2]. 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 25 recognizing PCOS. One of the best techniques for spotting PCOS is the Rotterdam criteria. If the ovaries have a volume greater than or equal to 10 cm3 or if there are 10 or more follicles with diameters ranging from 2 to 9 mm, PCOS has most likely been diagnosed. 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. Figure 1 depicts an undamaged ovary, 35 whereas Figure 2 depicts numerous follicles afflicted by PCOS spread around the ovary's perimeter.

II. LITERATURE REVIEW

Polycystic ovarian syndrome (PCOS) is a significant area of research in medicine. Women with PCOS often have polycystic ovaries, which are characterized by a large number of small, unharmful cysts (less than 8 mm in diameter). For many women, infertility or irregular periods are the only symptoms. PCOS symptoms include irregular periods, infertility, excessive facial and chest hair growth, excess weight, hair thinning. Rachana et al, 2021[30] 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. Gopalakrishnan et al[32] recommended to use an automated ultrasound-based PCOS diagnostic and classification approach. A Gaussian low pass filter, multilayer thresholding for edge detection, the recommended GIST-MDR technique, and supervised machine learning algorithms for PCOS classification were used to pre-process the raw pictures. Bhosale et al[31], The authors propose DCNN based methods, write PCOS classification code in Python,

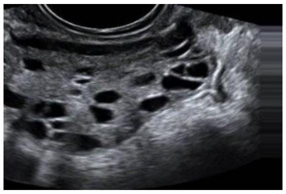

Fig. 1. PCOS Infected

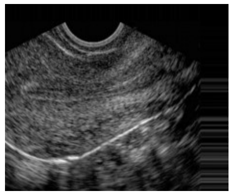

Fig. 2. PCOS not Infected.

and use ultrasound pictures to assess whether they are filled with blood or fluid. DCNN-based image classification is used in this study to categorize PCOS in the dataset. In [24], It is proposed to use an SVM linear kernel combined with Logistic Regression features in a novel hybrid and optimal 65 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. Azil et al [25], analyzed 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. Tiwari et al [25], applied machine learning algorithm to find PCOS instead of using non invasive method.. Priya and jeevitha [26], The regularised CNN technique is used to categorize ovarian cysts. Furthermore, the classification method' thinking was improved by employing the data augmentation technique and several additional droplet layer strategies for greater accuracy. Kumari and Sweta[31], Another development in computer vision was made by utilizing a simple GAN model to create artificial images to make up for a lack of dataset, then augmenting the data with resized and reprocessed ultrasonic images, and then training the models. Djenouri et al [33] investigated the connections between diverse biological data sets using several deep learning architectures (VGG16, RESNET, and DenseNet) using ensemble learning and attention methods in order to detect and diagnose illnesses. Xue et al[34] TL structuresbased on Inception-V3, Xception, VGG-16, and Resnet-50 were created. The proposed methodology is then evaluated using a dataset of 307 pictures stained with three immuno-histochemical techniques (AQP, HIF, and VEGF). Individually, AQP staining pictures had the overall highest accuracy of 97.03. Yan et al [35] For the Fourier transform near infrared (FT-NIR) spectra, several data pretreatment methods were used, and the modeling outcomes of partial least squares discrimination analysis (PLS-DA), support vector machines (SVM), and residual neural network (ResNet) was compared. Aravind and Raja [36] The findings of six pre-trained Convolutional Neural Networks (CNNs)—AlexNet, Visual Geometry Group 16 (VGG16), Visual Geometry Group 19, GoogLe Net, ResNet, and DenseNet used in this study were examined. These thorough testing show that the proposed approach has a 92.31% accuracy rate.

III. Methodology

CNN based learning algorithm's play a important role, especially when it comes to image analysis. All these advantages make it a prominent part of the medical image analysis. This paper 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 modelling uncertainty that mixes several types of deep neural networks with statistical techniques. However, by applying data augmentation before training the ensemble model gives satisfactory results. Hybrid modeling techniques have the ability to mitigate the negative impacts of over- parameterization, save computing time, and potentially in-crease accuracy. The ultrasound PCOS image is classified using classifier such as Alexnet, VGG16 and later by hybrid models. The validation accuracy, validation loss, precision, Recall and FScore is calculated for evaluating the performance of the applied classifier on the PCOS image.

A. Feature Selection

Feature selection refers to the process of picking a few helpful and relevant characteristics from a large number of op-tions. 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]. The over fitting can be decreased and accuracy can be improved by using feature selection. A filtering-based uni variate 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. The significant features in this study were identified, and the score was generated by using the uni variate method of feature selection [8].

B. Image Pre processing

The categorization of the picture must first go through pre-processing. This procedure aims to distort the picture database[13]. Since each dimension of an image file might have a particular feature connection, it is possible for each picture to be independent of the others. As a result, a straight-forward 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]. The data base considered for analysis taken from Kaggle database[38]. 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 understand- able. This is the process of modifying images to provide betterexamples, such as rotating images, turning them horizontally, or increasing brightness [29].

C. Evaluation Metrics

The following metrics are used to assess our model's perfor- mance: 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 NO- 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. Accuracy = T P + T N /T P + F P + T N + F N. The Evaluation parameters such as precision, Recall, Sensivity Specificity and F1 score are calculated for evaluating the classifier applied on the PCOS images.

D. Alexnet

Alexnet has eight learn-able levels. With the exception of the output layer, which employs max pooling and is followed by three fully connected layers, each of the model's five levels utilizes relu activation. That the very Initial layer of AlexNet is utilized for the input of a filtered picture with dimensions of 227, 227, and 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]. AlexNet can instantaneously generate a 4096- dimensional feature vector for each input picture that contains the hidden layer activations. There are 650,000 neurons with 60 million parameters[3,4]. The model was tested on 150,000 test images from the ImageNet data sets after being trained on around 1.2 million training images. The final entirely linked layer, commonly called as the output layer, includes 2 neurons since the data set has 2 classifications. The activation function used at this layer is called Softmax. With the aid of sustaining dropout and data replenishment, this model is quite effective at decreasing the overfitting issue [11]. The architecture of Alexnet is shown in figure 3. AlexNet failed to show how 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 pre-trained 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 categorized.

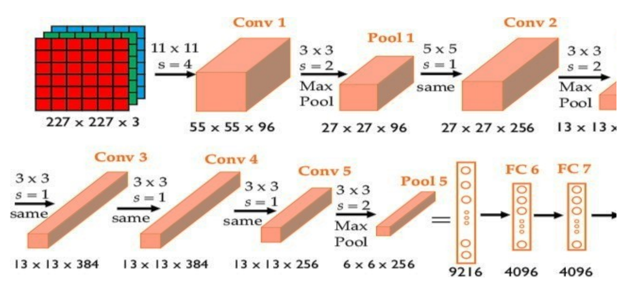

Fig. 3. Architecture of Alexnet.

According to the new input photographs, these parameters may only need a little update. These settings are ideal for training a brand-new class ofdatasets since they have a very small impact on the whole CNN training process [12]. Using Relu instead tanh activationfunction increased accuracy from 55% to 88%.

E. 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 is carried out. Each convolution layer is followed by a ReLU operation to improve the channel's nonlinear properties [17]. The Convolutional Neural Network is the most often utilized deep learning algorithm (CNN). The most noteworthy advantage CNN has over its competitors is its capacity to recognise important traits and qualities [18]. To increase the accuracy and decrease the computational complexity in detection of PCOS images. Softmax activation function is used instead of sigmoid functionin the output layer and achieved a accuracy of 75%. The architecture of Inception V3 is shown in figure 4. The performance of the inception V3 classifier applied on the PCOS image is also

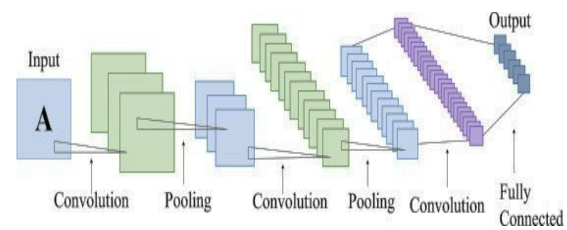

Fig. 4. Architecture of Inception V3.

evaluated using validation accuracy and validation loss which is shown in figure 10. From the graph it was found that loss decreases with increase in epoch.

F. VGG16

There are several hyper parameters in the VGG16 model. The first layer's input picture has a 224x224 RGB dimension. The image is processed using a stack of convolutional layers with the exact padding and max-pooling layer being usedto the 3x3 filter size and stride 1, 2x2 filter and stride 2,and 3x3 filter and stride 3, respectively [20]. Convolutional, ReLU, and max pool layers make up this architecture's layers. ReLU encourages rapid learning and reduces the possibility of vanishing gradient problems, making it more computationally

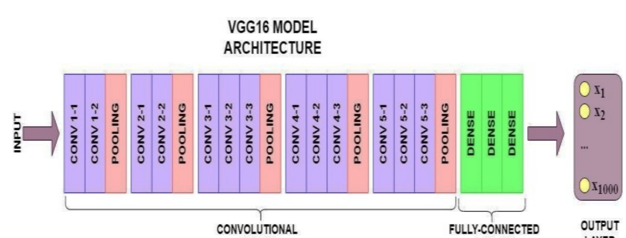

Fig. 5. Architecture of VGG-16

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 and to categorize pictures by feeding the result to a new classifier. Accuracy was raised to 90% from 83% by adding a few dropout layers with 0.5 before output layers. The architecture of VGG-16 is shown in figure 5.

G. Resnet50

The idea of residual blocks is used in this design to get around the vanishing/exploding gradient issue. This network used a technique called" skip connections." Layer activations are connected to following levels via the skip link, which skips certain intermediate layers. A residual block is created as a result of this. Renets are created by stacking these extra bricks. This network enables the networks to fit the residual mapping rather than layers learning the underlying mapping. The advantage of using this kind of skip con- nection is that regularization will skip any layers whose performance compromises the architecture. As a consequence, vanishing/exploding gradient problems may be avoided while training an exceedingly deep neural network.

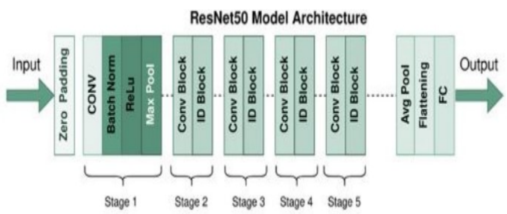

Fig. 6. The architecture of Resnet 50.

Another issue with network deepening is degradation, which occurs when network performance deteriorates as depth grows. According to experience, the depth of the network is critical to the model's success. When the number of network layers is raised, the network may do more complicated feature pattern extraction, resulting in theoretically better outcomes when the model is deeper. The experiment, however, discovered thatthe deep network was deteriorating. The efficiency of the network tends to be diluted or even lowered as network depth increases.[34]. The architecture of Resnet 50 is shown in figure6.

H. 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 proba-bilistic outputs for pairs of classifiers. The correlations are aggregated across classes to provide a single measure of variety. Accordingly, couples with strong correlations are identified, and one of them is chosen at random to be kept [23]. 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 four CNNs (Alexnet, Vgg16, Inception v3, ResNet) are trained independently before merging into a single model. This study presented a hybrid CNN model that would include VGG- 16 and ResNet-50 characteristics to detect the probability of PCOS using an ultrasound image is shown in figure 7. Both CNN models were firstfed an input consisting of an MRI image. The final max pooling layer output from the VGG-16 architecture was then fed into a brand-new 1 × 1024 Fully Connected (FC) layer with a ReLU activation function. In parallel, we selected the output of the

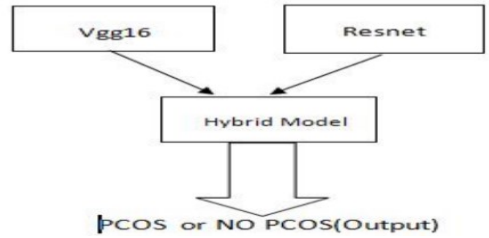

Fig 7. Flow diagram of hybrid model

last average pooling layer of the ResNet-50 architecture and sent it into a new 1×1024 FC layer with a ReLU activation function. used a further 1×512 FC layer to extract additional significant traits. Following that, a final

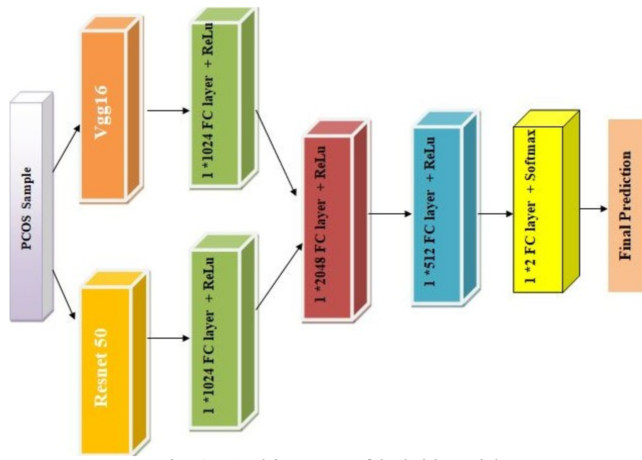

Fig. 8. Architecture of hybrid model

classification job was performed using the developed final 1×3 FC layer with Softmax activation function. The architecture ofhybrid model is shown in figure 8.

IV. Results and Discussions

The PCOS data considered for analysis is split randomly into Train, test and validation data. The data is fed into classifiers such as Alexnet, Inception V3, VGG16 and Resnet50. The evaluation parameters such as Accuracy, precision, Posi- tive Predictive Value (PPV), Negative Predictive Value (NPV), Sensitivity, Specificity and F1 score are calculated for each classifier. The values obtained for the evaluation parameters is shown in table 1. To improve further performance of classification of PCOS image the classifier Resnet50 and VGG-16 was combined to form a hybrid model. The accuracy of the developed hybrid model is giving a better accuracy of 95 percent. F1 Score combines the arithmetic mean of accuracy and precision. The F1 score of the

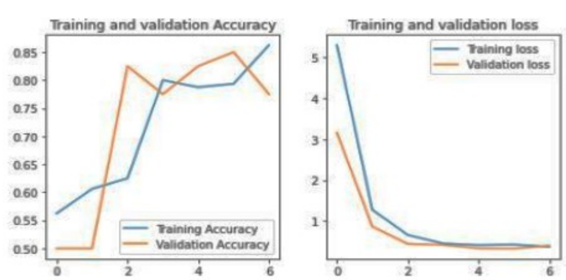

Fig 9: Accuracy and Validation graph of Alexnet

proposed hybrid model is giving 95%. This shows the prediction accuracy of the model compared to other model applied on the PCOS image.The training accuracy and validation loss is calculation for each classifiers and the graphs are shown in figure 9 to Figure 13. From the graph it was found that accuracy increases with increase in epoch and loss decreases.

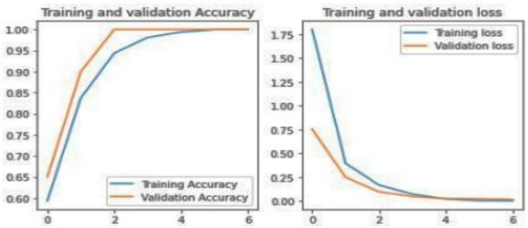

Fig 10: Accuracy and Validation graph of Inception V3

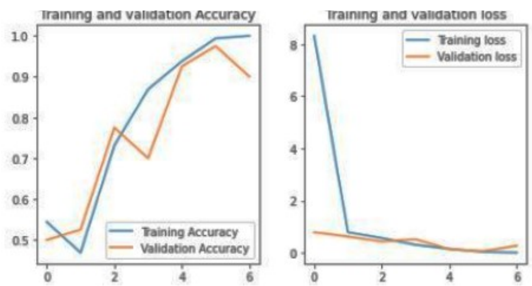

Fig 11: Accuracy and Validation graph of VGG-16

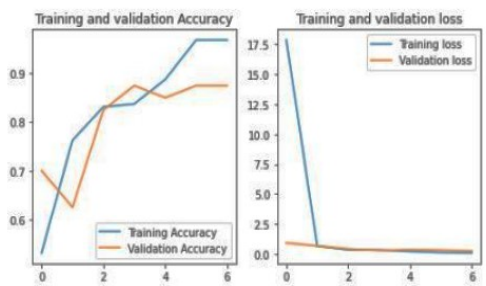

Fig 12: Accuracy and Validation graph of Resnet50

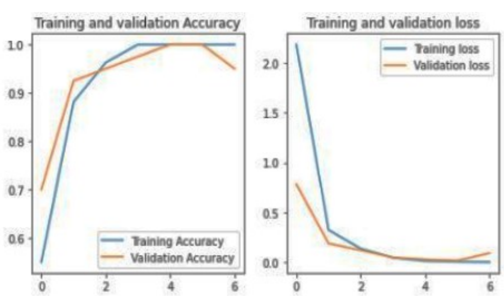

Figure 13: Accuracy and Validation graph of hybrid model

V. CONCLUSION

An automated technique for detecting PCOS using deep learning algorithms is suggested in this paper. 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, achieving an accuracy of 95%. If a result, as the number of pictures rises dramatically, the function of the architecture becomes less relevant. In this regard, gynecologists (who are not AI experts) might raise the number of samples in the training set to eliminate the need for selecting appropriate architecture and fine-tuning its hyperparameters. In the future, we hope to cre- ate a web service to collect more samples from gynecologists 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. 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 neural networks and their extensions such as CNN. 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. Another key constraint of the suggested identification method is that doctors must obtain an ultrasound image of a patient at an angle that clearly captures their ovaries. In rare cases, the livers in images can look like ovaries and might be found to be infected with PCOS. Finally, ensembles are more expensive to construct, train, and deploy. More complexity is often undesirable.

Table 1: Performance parameter comparison for different network

Classifiers	**Accuracy**	**Precision**	**Sensivity**	**Specificity**	**PPV**	**NPV**	**F1 Score**
Alexnet	0.78	0.87	0.72	86.66	0.9	0.65	0.74
Inception V3	0.73	0.73	0.77	0.72	0.70	0.80	0.76
VGG-16	0.90	1.00	0.83	100	100	0.80	0.89
Resnet50	0.88	0.80	0.90	0.85	0.85	0.89	0.98
Hybrid	0.95	0.91	100	0.90	0.90	100	0.95

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