THE POLYCYSTIC OVARIAN SYNDROME(PCOS) CLASSIFICATION BY USING DEEP LEARNING ALGORITHM

Deepika.k,Student,Dr.S.K.Manikandan,Professor,Dr.M.Nisha Angeline,Professor, Department of Biomedical Engineering, VelalarCollege of Engineering and Tehnology, Erode, India

ABSTRACT- Deep learning is enhancing the medical industry by enabling academics and healthcare practitioners find opportunities concealed in data. In addition, it helps physicians accurately diagnose any type of illness and improve patient medication, leading to better medical decisions. Medical conditions like Polycystic Ovarian Syndrome (PCOS) need appropriate diagnosis and treatment other options. It is a common endocrine condition that triggers ovarian cysts to form in women who are trying to conceive, which leads to in infertility. Deep learning techniques using the VGG 16 convolution neural network design can be used to aid in the diagnosis of PCOS. These techniques yield effective solutions in problems involving picture classification. The current study compares the accuracy and other performance measures of previously described deep learning techniques and discusses the issue of over-fitting and the accuracy was achieved in this proposed work was 94% [1].

INDEX WORDS: polycystic ovarian syndrome (PCOS), Deep learning, VGG 16, convolution neural network.

INTRODUCTION

The complicated disorder known as polycystic ovarian syndrome (PCOS) is typified by high testosterone levels, irregular menstruation, and/or tiny cysts on either or both of your ovaries. The condition may be primarily biochemical (hyperandrogenemia) or morphological (polycystic ovaries). One of the clinical features of PCOS is hyperandrogenism, which can lead to anovulation, microcysts in the ovaries, follicular development suppression, and menstrual abnormalities [2]. A diverse condition, PCOS impacts at least 7% of adult females. The Office of Disease Prevention at the National Institutes of Health estimates that 5 million American women who are of childbearing age suffer from PCOS. The discovery and treatment of PCOS costs the American healthcare system about $4 billion annually. Studies indicate that PCOS affects 5% to 10% of females between the ages of 18 and 44, making it possibly the most prevalent endocrine condition among reproductive-age women in the United States. A PCOS diagnosis is frequently given to women who seek medical attention for problems with obesity, acne, amenorrhea, abnormal hair growth, and infertility as Endometrial cancer, cardiovascular disease, dyslipidemia, and type 2 diabetes mellitus are more prevalent in women with PCOS. The pharmacotherapeutic approach to PCOS is studied in this article.

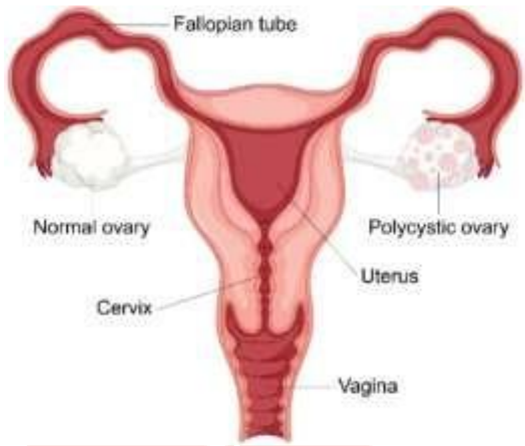

Fig 1.1 ovarian structure

Types of PCOS

1. Insulin resistance PCOS

The dietitian claims that in 70% of cases, it happens. This kind of PCOS can be brought on by an illness known as insulinoma, which develops when cells lose their ability to react to the adverse effects of insulin. Treatment for this can involve regular mobility and exercise. Choose for a balanced diet instead of foods heavy in sugar. To control insulin levels, minimize stress and get enough sleep. Magnesium, chromium, NAC, and inositol supplements can be advantageous.

2. Adrenal PCOS

This happens in the midst of a very stressful time. High cortisol and DHEA levels are marked markers. Practice yoga, meditate, and get enough sleep to lower your stress levels [3]. Steer clear of intense activity. The neurological system and adrenal glands can be supplied with magnesium, vitamin B5, and vitamin C[4].

3. Inflammatory PCOS

The cause of this kind of PCOS is persistent inflammation. PCOS is brought on by high testosterone levels, which are raised by an unhealthy diet and way of life. Symptoms include headaches, unexplained fatigue, high C reactive protein. By repairing leaky gut tissue, enhancing digestive enzymes, and maintaining a balance of gut flora, you can maintain optimal gut health. Steer clear of foods that cause inflammation. Use antioxidants like NAC, curcumin, and omega 3 fatty acids as natural anti-inflammatories to help yourself [5].

4. Post-pill PCOS

This happens when you stop taking oral contraceptives. Pooja claims that stopping the artificial progesterone pills can result in a "party in the ovaries," which can lead to PCOS. Although taking the medication can temporarily halt the symptoms, stopping it later can make the issue worse .The specific kind of PCOS is transient and curable. Relaxation and sound sleep are beneficial. Zinc, magnesium, vitamin B6, and vitamin E are among the beneficial nutrients [11].

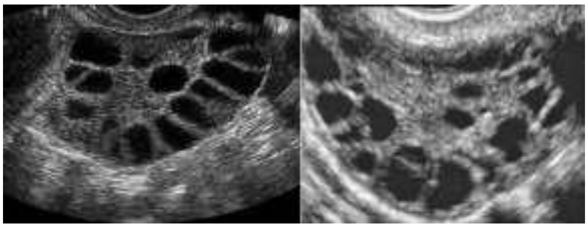

Fig 1.2 Ultrasonic Images of PCOS

PROPOSED METHOD

In this investigation, two convolutional neural network models were used. Using the transfer learning approach, we have optimized the VGG 16 convolutional neural network and tailored the model to meet the needs of our dataset. A summary of our work approach is shown in our dataset, which we have also constructed a lightweight convolutional neural network to detect ovarian cysts. A. Description of the Dataset Two distinct datasets—Dataset A and Dataset B— made up our database for this project. Our models were trained and validated using Dataset A. However, in order to evaluate the models objectively, we have employed a discrete dataset B rather than splitting a test set from dataset A.

1) Dataset A: We downloaded dataset A from Kaggle, which served as our first dataset and was used to train and evaluate both of our models. A training set of 1,924 images and a test set of 1,932 images were initially included in Dataset A. But the photos in this dataset's training and test sets were almost exactly the same. As a result, we have just used the training set and ignored the test set. The original training set from Dataset A has been further divided into two sets: the training set and the validation set. Ultrasound images of both healthy and cystic ovaries were included in both sets. The ultrasound images displaying infected cysts on the ovary were labeled as "infected," whilst the ultrasound images displaying a healthy ovary were labeled as ‘not infected’. Finally, we have come up with our final version of Dataset A which contained a total of 1,346 training photos in addition to validation images. Sample images of both cystic and healthy ovarian ultrasound images[7].

2)Dataset B: We have collected ultrasound images of both healthy and cystic ovarian tissues from multiple online sites for our test set, Dataset B. Two licensed medical professionals have advised us on how to properly categorize these images as either cystic or healthy. Images of cystic ovaries were classified as "infected," whereas ultrasound pictures of healthy ovaries were classified as "not infected." A total of 339 photographs made up Dataset B, 154 of which were ultrasound pictures of healthy ovaries and 185 of which showed images of ovarian cysts. To guarantee an objective assessment of our models' performance, this dataset was totally unrelated to dataset A. Examples of dataset B's ultrasound pictures showing both healthy and cystic ovarian tissue.

IMAGE PREPROCESSING

As previously indicated, dataset B was utilized for testing, whereas dataset A was used for training and verifying our models. The photographs in datasets A and B were different in size. We have resized all the images in both datasets to 224 x 224 pixels in order to give our models uniformly sized images. Each of our test, validation, and training sets contained sixteen batches. To normalize our image data, we used Keras' Image Data Generator. In addition, we have enhanced our training photos to get around dataset A's image restrictions. About 80% of dataset A has been used as the training set, and the remaining 20% has been used as the validation set. The test set was Dataset B.

MODEL DESCRIPTION

A deep learning model called a Convolutional Neural Network (CNN) architecture is used to interpret structured, grid-like data, including photographs. It is made up of several layers, such as fully connected, pooling, and convolutional layers. CNNs' hierarchical feature extraction capabilities make them very useful for tasks like object identification, picture segmentation, and image classification.

VGG-16

A convolutional neural network (CNN) architecture called the VGG-16 model was put forth by the University of Oxford's Visual Geometry Group (VGG). With 16 layers total—13 convolutional layers and 3 fully linked layers—it is distinguished by its depth. VGG-16 is well known for its efficiency and simplicity, as well as for its ability to perform well on a variety of computer vision tasks, such as object recognition and image categorization. The design of the model consists of a stack of progressively deeper max-pooling layers after a series of convolutional layers. Because of its design, the model can learn complex hierarchical representations of visual data, which results in predictions that are reliable and accurate. For many deep learning applications, VGG-16 is still a popular choice despite being simpler than more modern architectures due to its versatility and excellent performance.

Teams compete on computer vision tasks such as object localization and picture classification in the annual ImageNet Large Scale Visual Recognition Challenge (ILSVRC). Top rankings were attained by VGG16, which was introduced by Karen Simonyan and Andrew Zisserman in 2014[10]. It was able to identify items from 200 classes and categorize photos into 1000 groups [8].

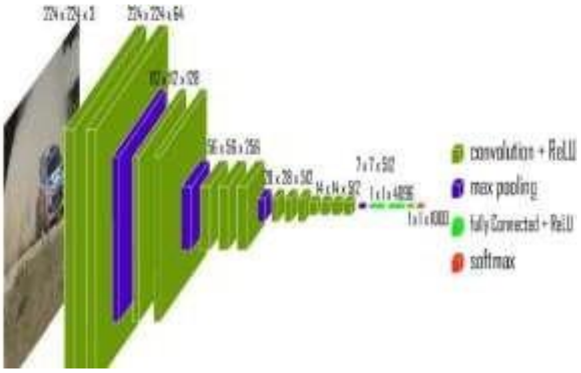

Fig 1.3 VGG 16 Architecture

VGG Architecture:

A deep convolutional neural network (CNN) with the VGG-16 architecture is intended for image categorization applications. The University of Oxford's Visual Geometry Group introduced it. VGG-16 is easy to comprehend and apply because of its uniform architecture and simplicity. Typically, the VGG-16 design has 16 layers: 3 fully linked layers and 13 convolutional layers. These layers are arranged into blocks, with a max-pooling layer for down sampling coming after each block that contains several convolutional layers[19].

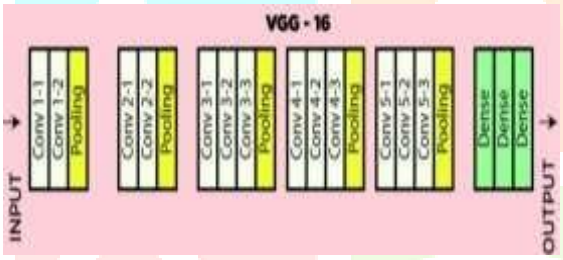

Fig 1.4 VGG 16 Layer

Here's a breakdown of the VGG-16 architecture based on the provided details:

Input Layer: Input dimensions: (224, 224, 3) **Convolutional Layers (64 filters, 3×3filters, samepadding):** This model consists of two convolutional layersthat follow each other, each having 64 filters and a 3×3 filtersize. The spatial dimensions are maintained by applying thesame padding [12].

Convolutional Layers (128 filters, 3×3 filters, same padding): Two consecutive convolutional layers with 128 filters each and a filter size o

Convolutional Layers (512 filters, 3×3 filters, same padding): Two sets of three consecutive convolutional layers with 512 filters each and a filter size of 3×3.
Max Pooling Layer (2×2, stride 2): Max-pooling layer with a pool size of 2×2 and a stride of 2.

Stack of Convolutional Layers and Max Pooling: Two additional convolutional layers after the previous stack. connected layer to produce probabilities for 1000 classes, in accordance with the parameters[23].

Flattening: Flatten the output feature map (7x7x512) into a vector of size 25088

Fully Connected Layers: ReLU activated in three fully connected layers.4096 output size and 25088 input size make up the first layer.4096-sized input and 4096-sized output make up the second layer. The third layer, which corresponds to the 1000 classes in the ILSVRC challenge, has input size 4096 and output size 1000. The third completely linked layer's output is subjected to Softmax activation for categorization.

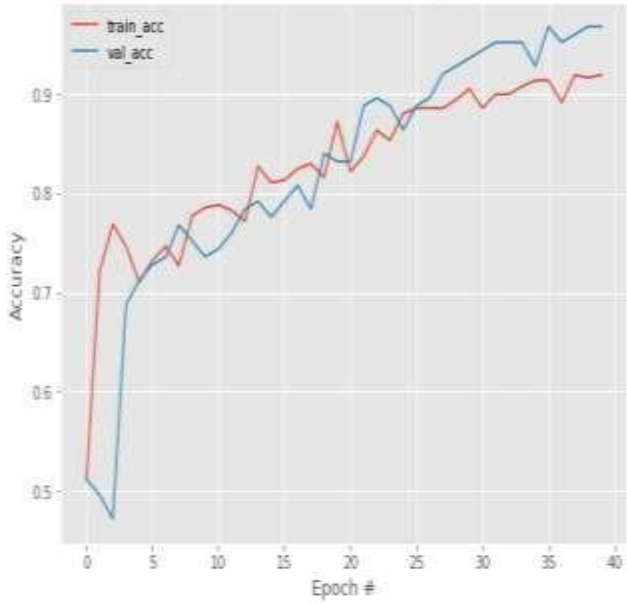

Fig 1.6 Training and validation accuracy graph

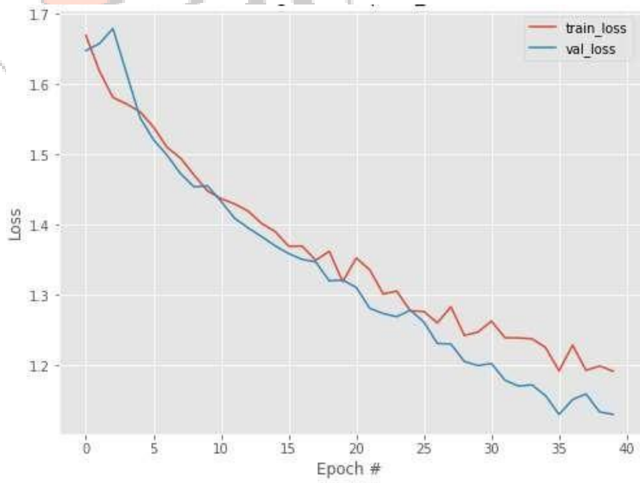

Fig 1.5 Training and validation loss graph

	precision	recall	f1-score	support
absence	0.91	0.97	0.94	61
presence	0.97	0.91	0.94	64
accuracy			0.94	125
macro avg	0.94	0.94	0.94	125
weighted avg	0.94	0.94	0.94	125

Table 1.2 Classification Table

RESULT AND DISCUSSION

In this paper, the detection of Polycystic Ovary Syndrome (PCOS) using deep learning, specifically with the VGG-16 model, is a cutting-edge approach that leverages convolutional neural networks (CNNs) for image classification tasks. In this study, a Convolutional Neural Network (CNN), to test machine learning models, it is necessary to obtain the features that best represent the images using feature extraction techniques from preprocessed images. In this study, values such as the diameter of the follicles, their distance from each other, and the number of follicles can be considered as features to be extracted from the ovary images. On the other hand, deep learning models have features that can be preferred in automatic diagnosis systems by classifying unsegmented or segmented images without the need for a feature extraction process. For this reason, the ovary images we obtained for this study were limited to deep learning models, although data augmentation techniques were also applied [7]. As a result, by using different deep learning architectures with more ovary images, the classification accuracy obtained in this study can be increased, and an automatic diagnosis system can be developed. The obtained accuracy of this paper is 94%

CONCLUSION

In this work, CNN is utilized as an image classifier. The dataset's cysts can be detected by the algorithm by segmentation and feature extraction techniques. For the purpose of to classify test data in the dataset and determine whether or not the ovary is impacted, this approach takes certain input ultrasound images as train data. Using deep learning algorithms, the project has successfully been executed to predict the early existence of PCOS from ultrasonic scanned images and to provide preventative actions (F.saleem). Algorithms like VGG16 are utilized to forecast whether an individual has PCOS disease according to the input image, while contrasting these results can improve system performance to anticipate the existence of illness. This ultimately shortens the time needed to diagnose PCOS and helps provide effective treatment in the least expensive manner. Since there are numerous methods for diagnosing conditions, there are numerous avenues for technological improvement.

FUTURE SCOPE

The majority of research on the identification of PCOS focused on machine learning; however, in this study, we employ a deep learning approach to identify polycystic ovarian syndrome. Future study aims to identify the different types of Polycystic ovarian syndrome using ultrasound images and to analyse the ovarian cyst. By comparing the outcomes of future models with real-time data, this interdisciplinary approach can result in the development of more clinically relevant models and solutions. Additionally, this research can be utilized to analyse gynaecologist ultrasound images in order to detect PCOS early on [13].

REFERENCES

[1] Kyrou, E. Karteris, T. Robbins, K. Chatha, F. Drenos, and H. S. Randeva, ‘‘Polycystic ovary syndrome (PCOS) and COVID-19: An overlooked female patient population at potentially higher risk during the COVID-19 pandemic,’’ BMC Med., vol. 18, no. 1, pp. 1–10, Jul. 2020.

[2] B. J. Sherman, N. L. Baker, K. T. Brady, J. E. Joseph, L. M. Nunn, and A. McRae-Clark, ‘‘The effect of oxytocin, gender, and ovarian hormones on stress reactivity in individuals with cocaine use disorder,’’ Psychopharmacology, vol. 237, no. 7, pp. 2031–2042, May 2020.

[3] X.-Z. Zhang, Y.-L. Pang, X. Wang, and Y.-H. Li, ‘‘Computational characterization and identification of human polycystic ovary syndrome genes,’’ Sci. Rep., vol. 8, no. 1, Dec. 2018, Art. no. 12949.

[4] E. Khashchenko, E. Uvarova, M. Vysokikh, T. Ivanets, L. Krechetova, N. Tarasova, I. Sukhanova, F. Mamedova, P. Borovikov, I. Balashov, and G. Sukhikh, ‘‘The relevant hormonal levels and diagnostic features of polycystic ovary syndrome in adolescents,’’ J. Clin. Med., vol. 9, no. 6, p. 1831, Jun. 2020.

[5] M. Woźniak, R. Krajewski, S. Makuch, and S. Agrawal, ‘‘Phytochemicals in gynaecological cancer prevention,’’ Int. J. Mol. Sci., vol. 22, no. 3, p. 1219, Jan. 2021.

[6] D. Dewailly, M. E. Lujan, E. Carmina, M. I. Cedars, J. Laven, R. J. Norman, and H. F. Escobar-Morreale, ‘‘Definition and significance of polycystic ovarian morphology: A task force report from the androgen excess and polycystic ovary syndrome society,’’ Hum. Reproduction Update, vol. 20, no. 3, pp. 334–352, 2014.

[7] S. Prapty and T. T. Shitu, ‘‘An efficient decision tree establishment and performance analysis with different machine learning approaches on polycystic ovary syndrome,’’ in Proc. ICCIT 23rd Int. Conf. Comput. Inf. Technol., Dec. 2020, pp. 1–5

[8] E. C. Costa, J. C. F. D. Sá, N. K. Stepto, I. B. B. Costa, L. F. Farias-Junior, S. D. N. T. Moreira, E. M. M. Soares, T. M. A. M. Lemos, R. A. V. Browne, and G. D. Azevedo, ‘‘Aerobic training improves quality of life in women with polycystic ovary syndrome,’’ Med. Sci. Sports Exerc., vol. 50, pp. 1357–1366, Jul. 2018.

[9] M. A. Karimzadeh and M. Javedani, ‘‘An assessment of lifestyle modification versus medical treatment with clomiphene citrate, metformin, and clomiphene citrate-metformin in patients with polycystic ovary syndrome,’’ Fertility Sterility, vol. 94, pp. 216–220, Jun. 2010.

[10] Almenning, A. Rieber-Mohn, K. M. Lundgren, T. S. Lovvik, K. K. Garnæs, and T. Moholdt, ‘‘Effects of high intensity interval training and strength training on metabolic, cardiovascular and hormonal outcomes in women with polycystic ovary syndrome: A pilot study,’’ PLoS ONE, vol. 10, Sep. 2015, Art. no. e0138793.

[11] D. Chizen, S. Serrao, J. Rooke, L. McBreairty, R. Pierson, P. Chilibeck, and G. Zello, ‘‘The ‘pulse’ diet & PCOS,’’ Fertility Sterility, vol. 102, p. e267,Sep. 2014.

[12] H. H. Mehrabani, S. Salehpour, B. J. Meyer, and F.

Tahbaz, ‘‘Beneficial effects of a high-protein, low-glycemic-load hypocaloric diet in over weight and obese women with polycystic ovary syndrome: A randomized controlled intervention study,’’ J. Amer. College Nutrition, vol. 31, pp. 117–125, Apr. 2012.

[13] F. Giallauria, S. Palomba, L. Maresca, L. Vuolo, D. Tafuri, G. Lombardi, A. Colao, C. Vigorito, and F. Orio, ‘‘Exercise training improves autonomic function and inflammatory pattern in women with polycystic ovary syndrome (PCOS),’’ Clin. Endocrinol., vol. 69, pp. 792–798, Nov. 2008.

[14] F. Saleem and S. W. Rizvi, ‘‘New therapeutic approaches in obesity and metabolic syndrome associated with polycystic ovary syndrome,’’ Cureus, vol. 9, pp. 1–12, Nov. 2017.

[15] Paul R, Hawkins S, Balagurunathan Y, Schabath M, Gillies R, Hall L, et al.. Deep Feature Transfer Learning in Combination With Traditional Features Predicts Survival Among Patients With Lung Adenocarcinoma. *Tomography* (2016) 2(4):388–95. doi: 10.18383/j.tom.2016.00211

[16] Raghavendra U, Fujita H, Bhandary SV, Gudigar A, Tan JH, Acharya UR. Deep Convolution Neural Network for Accurate Diagnosis of Glaucoma Using Digital Fundus Images. *Inform Sci* (2018) 441:41–9. doi: 10.1016/j.ins.2018.01.051

[17] He K, Zhang X, Ren S, Sun J. Deep Residual Learning for Image Recognition. In: 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR). Las Vegas, NV, USA: IEEE; (2016). pp. 770–8. doi: 10.1109/CVPR.2016.90

[18] Ilse M, Tomczak JM, Welling M. Attention-Based Deep Multiple Instance Learning. arXiv preprint (2014).

[19] Simonyan K, Zisserman A. Very Deep Convolutional Networks for Large-Scale Visual Recognition. *arXiv* (2014) 1409.1556.

[20] Christian Szegedy VVSI. Rethinking the Inception Architecture for Computer Vision. Proc IEEE Comput Soc Conf Comput. Vis Pattern Recognit (2016) 2818–26. doi: 10.1109/CVPR.2016.308

[21] Alkassar S, Woo WL, Dlay SS, Chambers JA. Robust Sclera Recognition System With Novel Sclera Segmentation and Validation Techniques. *IEEE Trans Systems Man Cybernetics: Syst* (2017) 47(3):474–86. doi: 10.1109/TSMC.2015.2505649

[22] Das A, Pal U, Ferrer Ballester MA, Blumenstein M. A New Efficient and Adaptive Sclera Recognition System. In: 2014 IEEE Symposium on Computational Intelligence in Biometrics and Identity Management (CIBIM). Orlando, FL, USA: IEEE; (2014). doi: 10.1109/CIBIM.2014.7015436

[23] Zhou Z, Du EY, Thomas NL, Delp EJ. A New Human Identification Method: Sclera Recognition. In: IEEE Transactions on Systems, Man, and Cybernetics - Part A: Systems and Humans, Vol. 42. IEEE; (2012). pp. 571–83. doi: 10.1109/TSMCA.2011.2170416

[24] Selvaraju RR, Cogswell M, Das A, Vedantam R, Parikh D, Batra D. Grad-CAM: Visual Explanations From Deep Networks *via* Gradient-Based Localization. In: 2017 IEEE International Conference on Computer Vision (ICCV). Venice, Italy: IEEE; (2017). doi: 10.1109/ICCV.2017.74