Polycystic ovary syndrome detection using neural network.

by

Tahsin Istiyaq
19201111
Nusrat Jahan
19201071
Sifat-E-Sadakin
18201179
Rakib Ahmmed Diptho
19201118
Fairuz Anika
20301464

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Declaration

It is hereby declared that

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2. The thesis does not contain material previously published or written by a third party, except where this is appropriately cited through full and accurate referencing.
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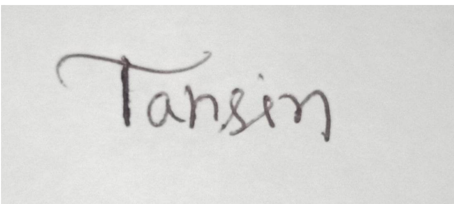
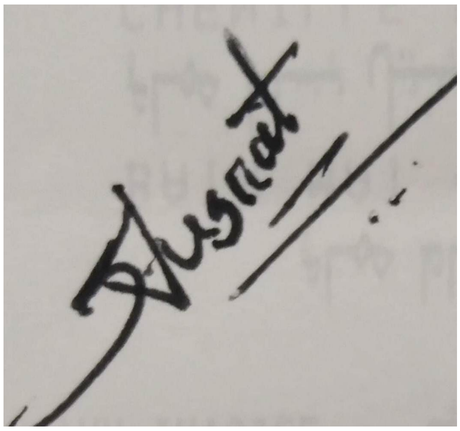
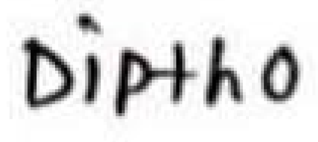


Tahsin Istiyaq
19201111

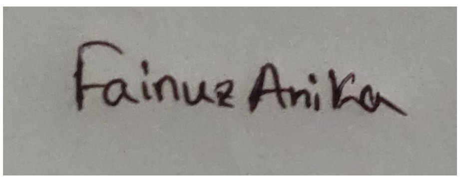


Nusrat Jahan
19201071

Sifat-E-Sadakin
18201179



Rakib Ahmmed Diptho
19201118



Rakib Ahmmed Diptho
19201118

Approval

The thesis/project titled "Polycystic ovary syndrome detection using neural network." submitted by

1. Tahsin Istiyaq (19201111)
2. Sifat-E-Sadakin (18201179)
3. Rakib Ahmmed Diptho (19201118)
4. Nusrat Jahan (19201071)
5. Fairuz Anika (20301464)

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Examining Committee:

Supervisor:
(Member)

Dr. Muhammad Iqbal Hossain
Associate Professor
CSE
Brac University

Head of Department:
(Chair)

Sadia Hamid Kazi
Chairperson
Department of Computer Science and Engineering
Brac University

Abstract

A fairly frequent endocrine abnormality among women of reproductive age is polycystic ovary syndrome (PCOS). In this disease, the ovaries produce abnormally high levels of androgens, which are male sex hormones that are typically present in women in trace amounts. The basic difference between PCOS and normal ovarian cysts is the substantial hormonal imbalance, which is not a general occurrence in ovarian cysts. A study says that among 15 percent of reproductive women, this disease is found, which is a major cause of women's infertility. Even though this is a very common and widely spread serious disease worldwide, it is hard to diagnose properly. So firstly, since this is a worldwide problem, a lot of people are thinking, but they cannot come to a conclusion. Secondly, detecting this disorder is very difficult since the symptoms of PCOS match those of other diseases, which makes detection difficult. For this reason, we became interested in this area.

Keywords: Otsu threshold; Machine Learning; Follicles; KNN Algorithm; Linear Regression Analysis; Androgens;

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Chapter 1

Introduction

Polycystic ovarian syndrome (PCOS) is a common endocrine disorder that affects women of reproductive age. It is characterized by hormonal imbalances that can result in a variety of symptoms, such as irregular menstrual cycles, acne, and excessive hair growth, in addition to the presence of cysts in the ovaries. Additionally, PCOS can raise your risk of contracting diseases such as diabetes and heart disease. The diagnosis of PCOS is presently made based on a combination of clinical and laboratory indicators, such as irregular menstrual periods, increased androgen hormone levels, and the presence of cystic ovaries on ultrasound. It has been established that ultrasound imaging, a popular, non-invasive technique for assessing the ovaries, is a helpful tool for detecting the distinct cystic abnormalities seen in PCOS. The purpose of this study is to look at how well ultrasound imaging can be used to diagnose PCOS. Certain traits connected to PCOS will be discovered through ovaries' ultrasound scanning. In order to enhance the diagnostic process and enable early treatment for those who are affected, the project's objective is to provide a more effective and accurate method of PCOS diagnosis utilizing ultrasound imaging. We'll also examine how to use sophisticated image processing methods, such as machine learning algorithms, to analyze ultrasound images and increase the precision of PCOS identification as part of this study. These methods have the potential to automate the process of finding the distinctive cystic abnormalities associated with PCOS since they can be trained to spot patterns that are challenging for human observers to notice. As a result of this research, new PCOS biomarkers that may be utilized to speed up diagnosis could be found. It is our goal to find distinguishing patterns or characteristics that are unique to PCOS and may be utilized to distinguish the illness from other disorders by examining ultrasound images of the ovaries in PCOS patients. The major goals of this study are to enhance PCOS detection effectiveness and accuracy and to show the potential of ultrasound imaging as a PCOS diagnostic tool. The results of this study might significantly alter how PCOS is handled and treated, which will ultimately improve the health of people who have it.

1.1 Problem Statement

A prevalent endocrine condition that commonly affects young women called polycystic ovarian syndrome (PCOS) is characterized by the presence of several small cysts in the ovaries. Ultrasound imaging is frequently used to diagnose PCOS, although the procedure may be time-consuming and complicated. To enhance the diagnosis process and subsequently improve patient outcomes, the issue is to create a computer-aided diagnostic system that can quickly and reliably diagnose PCOS using ultrasound pictures. The objective of this problem statement is to create an automated PCOS detection system utilizing ultrasound pictures. While taking into account additional elements like the size and form of the ovaries, the system should be able to analyze the pictures and detect the existence of cysts in the ovaries. Medical professionals with little to no specialized training in ultrasound imaging should be able to utilize the system with ease and deliver a diagnosis with a high degree of accuracy. To reduce patient wait times and increase the effectiveness of the diagnostic procedure, the system should also be able to process the pictures quickly. The ultimate purpose of this issue statement is to enhance PCOS diagnosis and treatment by giving medical practitioners a trustworthy and effective diagnostic tool to employ. The inter-observer variability problem, a frequent difficulty in the ultrasound-based diagnosis of PCOS, is also addressed in this problem statement. When interpreting ultrasound pictures, various practitioners may have varying degrees of experience and knowledge, which can result in an inconsistent or incorrect diagnosis. This is referred to as inter-observer variability. Regardless of how skilled the practitioner using the computer-aided diagnostic system is, the system must be capable of producing impartial and reliable results. This issue statement also takes the significance of patient confidentiality and data security into account. By following the necessary rules and regulations and taking the necessary precautions to secure the ultrasound pictures and patient data, the system should be created to preserve patient privacy. In order to enhance the diagnosis process, reduce inter-observer variability, protect patient privacy, and secure patient data, it is necessary to create a computer-aided diagnostic system that can rapidly and correctly identify PCOS using ultrasound pictures. In the long run, this will enhance patient outcomes and streamline the diagnosis procedure for medical personnel.

1.2 Research Objective

In order to improve patient outcomes through early identification and treatment, research on polycystic ovarian syndrome (PCOS) detection would probably aim to create or enhance methods for correctly detecting and diagnosing the illness in people. This may entail researching PCOS-related biomarkers, symptoms, and risk factors as well as assessing the efficacy of various diagnostic methods and tools. The ultimate objective would be to create a PCOS detection approach that is simple to use in clinical settings and both effective and trustworthy. The underlying causes of PCOS, a complicated and poorly known illness, might potentially be the subject of research. This can entail researching possible illness processes as well as the genetic and environmental variables that influence PCOS development. The creation of novel PCOS treatment options might be a crucial field of study, given the effectiveness of certain present treatments can be poor and they can have serious adverse effects. This might entail looking into the use of lifestyle treatments, such food and exercise, to control PCOS symptoms, as well as looking into the development of novel drugs or therapies that target certain disease-related pathways. Lastly, the main goal of PCOS detection research is to develop a more accurate and efficient method of identifying and diagnosing PCOS as well as new ways of treating the condition to improve the quality of life of people with PCOS.

Chapter 2

Previous Work and Models

2.1 Detailed literature review

This paper [7] has depicted the process of detecting PCOS using Deep Neural Network via image segmentation. In this research, CNN (Convolutional Neural Network) is adopted which can attain 76.36 performance in the testing phase. This can detect the disease more precisely and accurately as it works in layers. At first ultrasound image of two ovaries is given as input in JPG format ,whose intensity and quality is improved via histogram equalization. Then through image enhancement, its brightness level is adjusted. Follicles form is achieved by comparison of two threshold methods : Global Basic and Otsu threshold. After the binarization and image cleaning phase , region based image segmentation is adopted to detect follicles and watershed image segmentation is introduced to separate foreground and background of the image. Finally , the disease is classified based on it's severity into mild, moderate or high level using KNN algorithm,which has an accuracy of 78.81. It's a time saving approach which will be more beneficial to doctors.

This paper[6] describes the identification of Polycystic Ovary Syndrome (PCOS) by analyzing ultrasound images of ovaries using various image processing techniques after collecting basic information about size , position and ovarian follicle count. At first an ultrasound image is transformed into a gray-scale image using RGB-GrayScale conversion. Then the image is divided into a forefront and foundation using image thresholding. After that speckle noise in ultrasound images are undermined with dot clamor using Speckle Noise Elimination. The edge of the follicles is found using the Canny edge detection method. Finally, the SIFT (Scale- Invariant Feature Transform) algorithm is adopted to identify the presence of the syndrome. For training and classification of analyzed data SVM (Support Vector Machine) is adopted as it has highest accuracy of 94.40 , while other two ML algorithms named Naive Bayes and Decision tree have accuracy of 88.25 and 87.54 respectively. Thus, PCOS is detected accurately using above machine learning methods and algorithms.

In this paper[5], researchers want to detect polycystic ovary syndrome (PCOS) by using image segmentation of ultrasound images of ovaries using AI techniques. Firstly, a grayscale colored ultrasound image is given as input. Then, threshold methods Global Basic threshold and Otsu threshold are applied. Background and foreground images are separated. Also Convolution Neural Network (CNN) is used to differentiate the images into PCOS and nonPCOS classes. CNN method, K-means algorithm, Gaussian edge operator has also been used. Using Bayesian and Logistic Regression (LR) classifiers, vector features are classified. The accuracy of the Bayesian classifier is 93.93 whereas it is 91.04 in LR. In differentiating normal and polycystic ovary, Linear discriminant, K Nearest Neighbour (KNN), Support Vector Machine (SVM) were used with the accuracy of 92.86, 91.43 and 91.43 respectively. It is very tough to recognise this disease through traditional methods but with the help of AI method PCOS can be diagnosed easily with higher accuracy.

The paper[9] represents automated methods for identifying follicles for PCOS diagnosis. Here in this automated method, follicles are detected using image processing techniques which consist of preprocessing of images, segmentation, extracting of features and finally with the help of classifiers. Among which segmentation is very crucial for that reason these methods are being present in this paper with their accuracy rate. Watershed segmentation method is used for image enhancement in pre-processing of ultrasound images. Region growing method is used with a recognition rate of around 78. A modified version of this method is also here with more efficiency. Edge based method is also applied and found to be more efficient than manual detection. Active contour method is another method without edge based that shows less number of false acceptance and false rejections which is indicating the accuracy of the proposed method. The Threshold method has 90 accuracy. C-means and K-means clustering algorithms are also used. Here, K-means performs with a higher accuracy of 96. Using these methods obstructions can be overcome in finding follicles.

The paper [3] describes how determining the number and size of ovarian follicles by manually interpreting ultrasonographic images is currently the only way to diagnose PCOS. However, the variability, reproducibility, and efficiency of this approach may be low. The paper suggests employing an automated system to segment the follicles and identify geometric components quantitatively using stereology and Euclidean distance approaches in order to get over these issues. The suggested approach is designed to help physicians accurately analyze PCO and identify PCOS using ultrasonographic pictures.

In this paper [16] An automated deep learning technique is suggested in this paper for the supplementary identification of PCOS. Scleral alterations are used by the algorithm as potential PCOS diagnostic signals. The method was used on a dataset of 721 Chinese women's full-eye pictures, 388 of whom had PCOS. An enhanced U-Net is used in the algorithm to separate scleral images from full-eye images, and a Resnet model is used to extract deep features. For classification, a multi-instance model is next applied. The algorithm's average AUC is 0.979 and its classification accuracy is 0.929, showing that deep learning has a chance to diagnose PCOS.

In this paper [14] a method is proposed by which Polycystic ovary syndrome (PCOS) can be determined saving doctor's time by using image processing of ultrasound images. This method takes an ultrasound image with gray-scale colored data in JPG format as input. Then the image is enhanced and partitioned using OSTU thresholding. Image binarization is also done then segmentation, features extraction and lastly classification helps to diagnose the disease. This is a detailed diagnosis method using the information of the number of detected follicles, texture and geometric parameters. This automated method works with higher accuracy with KNN classifiers. Using this method can help to diagnose this disease with up to 97 accuracy.

In this paper [13] using ultrasound images as dataset researchers identified polycystic ovary syndrome with follicle recognition. Important information about the ovary is obtained through ultrasound imaging of the follicles, including the type of cyst, the wide variety of follicles, and the size of the follicles' response to hormonal imbalance. Data gathering is the initial phase in their procedure. Dataset includes USG images with PCOS status along with values for BMI, cycle length, postmenstrual LH, and FSH levels. Patients with conditions like hypercortisolism or thyroid issues are not eligible for this study.To improve the effectiveness of the images obtained, preprocessing techniques like Gray scaling and Histogram equalization are used. Feature extraction, a multi scale morphological approach is used to extract the dark or bright properties from the source image. Then comes the segmentation part by which images are extracted from source images. Using thresholding, edge detection and binarization follicles are detected . In this paper they used SVM ,KNN and Logistic regression and they got accuracy over 90.

This paper [15] is dedicated to detect polycystic ovary syndrome using ovarian ultrasound images through convolutional neural network and pretrained convolutional neural network where a convolutional machine leaning architecture PCONet has been developed using five convolutional layer to detect PCOs with highest precision. Besides, an image recognition model called fine-tuned Inception V3 which contains 42 layers has also been applied for the classification of ultrasound images achieved from different kind of ovaries. In this work, 2 data sets have been use where 1st dataset was dedicated to train and validate the models where training images have been augmented to overcome the image limitations. On the other hand, 2nd dataset has ensured an impartial performance evaluation of the models. Here, both 1st and 2nd dataset included photos of varying dimensions where all the photos have been rescaled to 224 $\times$ 224 pixels. Henceforth, ImageDataGenerator has been used to normalize the image data. Eventually PCONet has been admired since it has proved its superiority and came up with the precision of of 98.12, whereas fine-tuned inception V3 demonstarted the accuracy of 96.56 accuracy.

This paper [12] introduced an automated detection and classification system for Polycystic Ovary Syndrome using machine learning algorithm where ultrasound images have been used to detect PCOS by scrutinizing affected and unaffected cases. According to this paper, multiple ultrasound images differing one from another had been collected and preprocessed using Gaussian low pass filter where images have been equally cropped with the sizes of 256*256. Gaussian low pass filter is a superior technique to annihilate noise since ultrasound images generate strenuous noise. To accomplish the experiment, 90 normal images, 25 cystic images and 35 PCOS cases had been taken where GE LOGIQ ultrasound imaging system has been embedded to get the highest precision. While preprocessing images, ultrasound images get transformed to gray scale from RGB where ROI gets evicted from grey scale. Henceforth, GIST-MDR technique has been used for feature extraction after completing image

segmentation through multilevel thresh holding process. This GIST-MDR technique would eventually enhance the accuracy of classification. Thus, this proposed method came up with the highest precision of 93.82 comparing with other techniques.
In this [8], a polycystic ovary syndrome (PCOS) diagnosis system has been proposed using several machine learning algorithms on a dataset. A dataset of 541 patients has been used here. At first, the best features for predicting PCOS are found by applying a univariate feature selection algorithm. All 10 attributes have been proven to be the best to predict the disease in the dataset. It also showed that we can find the disease with greater accuracy in a short time if we use these 10 attributes. Different classifiers have also been used for these selective features. Gradient boosting, logistic regression (LR), random forest, and RFLR showed good accuracy with a good recall value. The accuracy is 91.01, and the recall value is 90% with RFLR. Detection is done based on only 10 features, which is the good side of this paper because it takes less time.
This paper [2] proposes a polycystic ovary syndrome (PCOS) detection method where detection is done based on some markers. Clinical and metabolic parameters are taken care of in this process. According to these parameters, this disease's detection started primarily These clinical and metabolic characteristics are used by the algorithm to create a feature vector. Based on two sample t-tests, the most important traits were picked. These characteristics are classified using classifiers based on Bayesian and Logistic Regression (LR). A system will function automatically as a supplemental tool to help the clinician quickly identify PCOS concerns. This research shows the accuracy rates for Bayesian and Logistic Regression rates are 93.93% and 91.04%, respectively. That means a Bayesian classifier performs better than LR here. In this current world where PCOS has become a very common disease among women of reproductive age, this innovative method may speed up the early diagnosis of this condition.
This paper [1] suggests an automated process for predicting polycystic ovary syndrome (PCOS). Ultrasound images are used in this process. With the help of an adaptive morphological filter, these ultrasound images are filtered for the watershed algorithm to extract those images. In this research on detecting this disease, follicular cysts are detected. And this happens due to the application of the clustering method, finally. This is an endocrine disorder among women that can result in infertility. As a serious disease, early determination is necessary, which is not possible for doctors with manual determination. whereas this automated process gives 84% accuracy with less time and more efficiency.
This article [10] discusses the prevalent endocrine condition of polycystic ovarian syndrome (PCOS). Anovulation, an overabundance of androgens, and polycystic ovaries are its defining features. Menstrual cycle irregularities, ultrasound evidence of polycystic ovaries, and hyperandrogenic symptoms are all PCOS diagnostic criteria. Prior to starting oral contraceptive treatment, it is advised that teenagers with irregular cycles who have been menstruating for one year or more evaluate their menstrual patterns and examine if they are clinically and biochemically hyperandrogenic. The most clinically effective way to diagnose PCOS is through biochemical hyperandrogenism, which may be detected using a variety of androgens, including testosterone, LH, FSH, and DHEAS. Androgens are measured using hormonal assays such as LC-MS/MS, GCMS, RIA, CLIA, and ELISA in the diagnosis of PCOS. Mild-to-moderate androgen excess symptoms, such as hirsutism, alopecia, and acne,

are indicative of clinical hyperandrogenism.Ultrasound measurements of stromal-to-ovarian size ratio, antral follicle count, follicle number per ovary, ovarian area, and ovarian blood flow may be used to assess PCOS. According to the Rotterdam criteria, ovarian size (OV), which has a threshold of OV >10mL, is a key determinant in the diagnosis of PCOS. Numerous threshold ranges have been found in various studies using AMH as a diagnostic marker for PCOS. Adolescent "irregular cycles" need to be defined, clinical hyperandrogenism has to be assessed, and the best way to measure androgens needs to be found.
The concerns underlying the PCOS diagnosis are covered in this article [4]. Its diagnosis is debatable, with several medical associations proposing differing criteria. The Androgen Excess Society (AES) accepted the original NIH standards from the 1990s. According to studies, there are relationships between androgens, hirsutism, and PCOS ultrasonography characteristics. PCOS may be indicated by hirsutism, baldness, and other symptoms of clinical hyperandrogenism. Antral follicles are an ultrasound characteristic that may help in diagnosis. For counting antral follicles, the Lujan grid system approach showed high sensitivity and specificity. Using a cut-off of 20 or more follicles in one or both ovaries, or an ovarian volume of more than 10 mL was recommended by the ESHRE PCOS guideline committee in 2018. Comparatively speaking, manual 2D scans were less accurate than 3D scans. Due to conflicting findings, the value of serum AMH concentrations as a PCOS marker is yet unknown.
The article [11] identifies Polycystic Ovarian Syndrome (PCOS), a challenging medical illness that affects women of reproductive age, using a range of machine-learning approaches. These techniques include CART, Naive Bayes (NB) classification, Random Forest, Support Vector Machine (SVM), and Logistic Regression. In women in reproductive age range, PCOS, which is characterized by hormonal abnormalities and metabolic issues, affects 5–10% of them. 42 independent variables associated with PCOS symptoms were included in the study's data collection from 10 hospitals in Kerala, India, which were made accessible on Kaggle. On samples of this data chosen at random, the algorithms were trained and assessed. Through the use of criteria like accuracy, precision, recall, F-statistics, and Kappa Coefficient, the study compares the performance of different methods. Key details include variables utilized for PCOS diagnosis, such as age, weight, height, BMI, pulse rate, hormone levels, and various symptoms associated with the disorder. The study finds that Random Forest exhibits the best performance, achieving 96% accuracy, followed by SVM with 95% accuracy. The research also employs visualizations, such as R-box and whisker plots and parallel plots, to compare the algorithms and evaluate their effectiveness. Ultimately, the paper suggests future directions, including the exploration of different or larger datasets for disease diagnosis.

2.2 Neural network models

Long Short-Term Memory (LSTM):
A deep learning architecture called a recurrent neural network (RNN) has three layers: an input layer, a hidden layer, and an output layer. Although it is frequently employed for sequence-based learning, the vanishing gradient problem makes it less successful at handling long-term dependencies. Long ShortTerm Memory (LSTM) RNNs were developed by Sepp Hochreiter and Jurgen Schmidhuber in order to

overcome this restriction. The vanishing gradient problem is successfully solved by LSTM, which is critical for capturing long-term dependencies. An input gate, forget gate, and output gate are the three gates that make up an LSTM cell, which is a memory block combined with each of these gates. When a piece of information or data is fed into the LSTM network, this memory block can assess its significance and preserve just the pertinent material. To better capture long-term dependencies, the LSTM network may effectively learn what information to remember and what to forget during the training phase. An LSTM memory block is depicted in diagram form in Figure n.

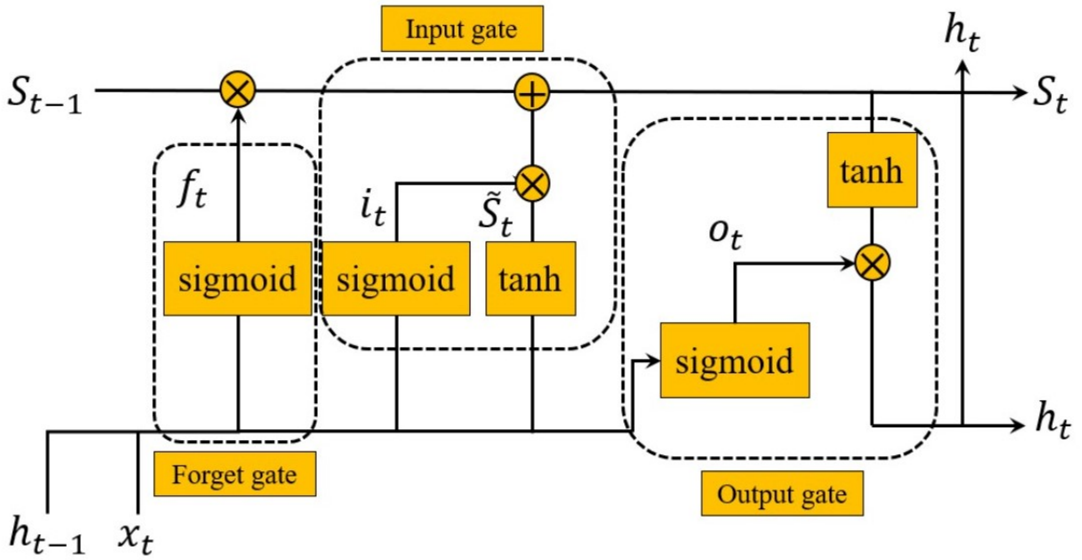


Figure 2.1: Structure of a LSTM memory block

Forget get: This gate is utilized to determine which input information of the previous node should be dropped from the memory block. The input of this gate are determined as and that denotes the output as follows:

$$f_t = sigmoid(W_f.[h_t - 1 - x_t] + b_f)..........1$$
$$here, W_f = weights, b_f = bias.$$

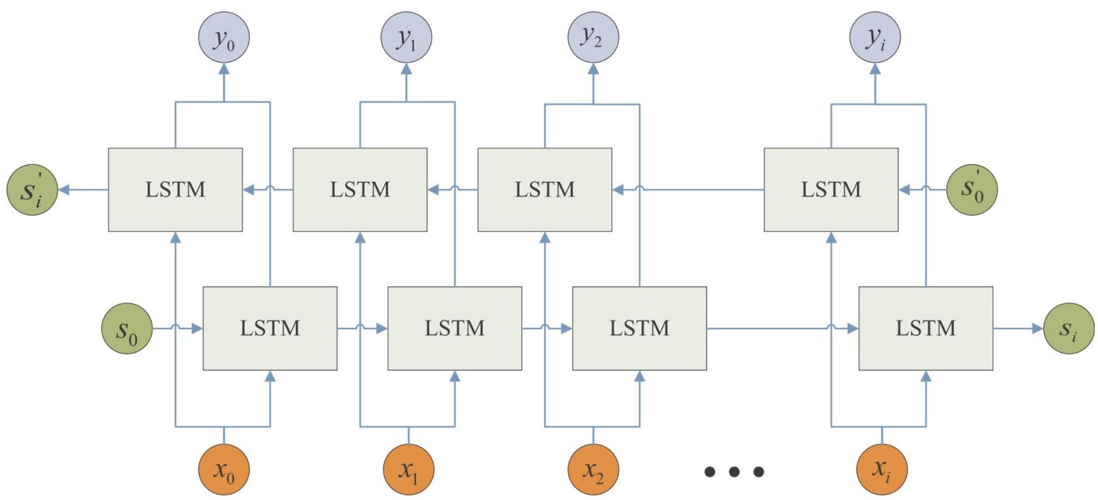
Input gate: This gate is utilized to which information should be stored in the memory block and update the old state to new state . This get consist of two parts: initially, the layer decide the value that needs to be updated, then the layer is responsible for creating a new candidate value vector . The statues of the memory block can be updated as following equation: Where is the weights and is the bias. In equation m, and are multiplied to determine the information that needs to be forgotten, * are added to get the latest status.

$$i_t = sigmoid(W_i.[h_t - 1 - x_t] + b_i)...........2$$
$$S_t = tanh(W_c.[h_t - 1 - x_t] + b_c)..................3$$
$$S_t = f_t * S_t - 1 + i_t * S_t...............................4$$
$$here, Wi, Wc = weights, bi, bc = bias.$$
$$Inequationm, ftandS_{t-1}aremultipliedtodeterminetheinformation$$
$$thatneedstobeforgotten, i_t * S_tareaddedtogetthelateststatus.$$

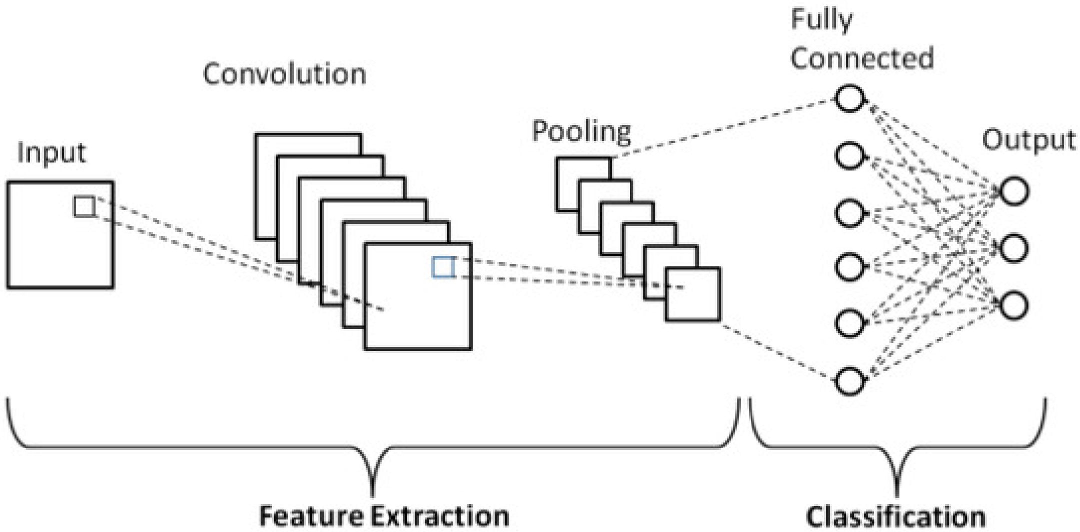
Output gate: This gate is utilized to determine which output will be taken as a current state, and it is also combined with two parts. Initially, a layer determines which parts from the cell state will be output. Then use tanh to process the cell state and multiplied it with the output of the gate to obtain the final output result. This process can be defined as follows: Where is the weights and is the bias, and is the final output result.

$$o_t = sigmoid(W_o.[h_t - 1 - x_t] + b_0).....................5$$
$$h_t = tanh(S_t)...6$$
$$here, W_o = weights, b_o = bias, h_t = finaloutputresult.$$

Bi-directional Long Short-Term Memory(Bi-LSTM):
LSTM can only process sequential information in the forward direction, which sometimes can not provide better results. However, there is an advanced variant of LSTM called bi-directional LSTM (Bi-LSTM) that can process sequential information in both forward and backward directions. It also provides improved classification results compared to LSTM, as it can learn from past and future information during training. A bi-LSTM network typically employs two LSTM layers, one for forward processing and another for backward processing. The internal memory block architectures of LSTM and Bi-LSTM are the same. Figure n shows the visual representation of Bi-LSTM.



Convolutional Neural Network:
A convolutional neural network (CNN) is a deep learning model that is widely utilized for processing image and video data [ref-aps]. CNN is inspired by neuroscience and designed based on the human brain, which is connected, functions with the help of neurons, and acts like the human brain. CNN architecture has two special aspects, i.e., local connections and shared connections. In CNN, certain connections between neurons are duplicated over the entire layer and share the same weights and biases. This architectural design, especially local connections and shared weights, often enhances generalization in different computer vision tasks. A complete CNN is a highly layered structural neural network that is combined with convolutional layers, pooling layers, and a classification layer. In a CNN model, the convolution layers initially break down images into low-level features and then combine these features to create more complex, high-level image representations. Pooling layers are employed to downsize the feature maps immediately after convolution. Dense layers, also known as fully connected layers, are responsible for making classification predictions based on these extracted features. A CNN can perform both feature extraction and classification tasks, thus dividing its functionality into two parts: a feature extraction and classification. A visual representation of a CNN is provided in Figure n.



Feature extraction takes place in the convolution and pooling layers, while the classification layer is responsible for making predictions. In the initial stages, the input image undergoes convolution using shared weights and multiple learned kernels. The number of feature maps in a convolutional layer is determined by the architecture, and a deep CNN consists of a stack of these convolutional layers. These layers apply various filters to the raw image data, extracting essential features that are subsequently used for classification. Mathematically, we can gain insight into how 2D convolution operates. The value of a neuron or node at position of the feature map in the layer is denoted as follows:

where m indexes the feature map in the layer connected to the current feature map, is the weight of position connected to the mth feature map, and are the height and the width of the spatial convolution kernel, and is the bias of the feature map in the layer.

$$v_{ij}^{xy} = g(b_{ij} + \sum_{m} \sum_{p=0}^{P_i-1} \sum_{1=0}^{Q_i-1} w_{ijm}^{pq} v_{(i-1)m}^{(x+p)(y+q)}) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad 7$$

$$F(x) = max(0, x)\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 8$$

Typically, a nonlinear layer is applied immediately after the convolution layer. Sigmoid or tanh also can be applied as a nonlinear function. Researchers have found that the Rectifier Linear unit (ReLU) works far better because it allows the network to train faster. ReLU layer function can be written as follows:

Where feature value after convolution. ReLU has been employed as an activation function in our custom CNN model.

Pooling layers can provide invariance by reducing the feature map's resolution. Each pooling layer correlates to the previous convolutional layer. The convolutional layer and pooling layer compose the feature extraction part. Afterwards, the feature maps are flattened into a 1-D vector and passed through the fully connected layers, which perform final classification on the extracted features by the convolutional layers and the pooling layers. Fully connected layers (FC) are combined with one or more hidden layers and an output layer that provides the predicted class. Initially, FC layer takes the flattened vector as input and passed through the hidden layer , mathematically it can be defined as follows:

$$h_i(x) = w_i.x + b_i\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 9$$

Where is the weight and is the bias. This hidden layer output then passed through an activation function (i.e., ReLU, sigmoid, tanh etc.). Mathematically it can be defined as follows:

$$a_i = activation(h_i(x))\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 10$$

The output of this FC layer can then be passed through additional hidden layers if needed. Ultimately, it serves asinput to the output layer, which provides the predicted class probabilities. For binary classification, a single neuron in the output layer with a sigmoid activation function is typically used. For multi-class classification, a softmax activation function is commonly employed. This output is then utilized to calculate the training loss during the training process. Various optimizers can be adopted to update the model's weights during training time to facilitate model generalization.

Convolutional Neural Network with LSTM:
CNN can capture spatial information, effectively extract features from an input image, and classify these features through fully connected layers. It automatically extracts features from images by detecting edges, corners, and complex patterns. Manually extracted features or reshaping can lead to a poor feature extraction process. However, CNN can be utilized for both feature extraction and classification tasks simultaneously; thus, we can use the feature extraction part of a CNN as a feature extractor. In recent years, researchers have been using CNN for feature extraction with tremendous success . LSTM provides compatible results on sequential data. From this investigation, we were inspired to develop a deep learning model combining CNN with LSTM layers.

Convolutional Neural Network with Bi-LSTM:

LSTM is unidirectional and can only process information in the forward direction. The pattern of an image is quite complex, and a pixel's intensity often depends on the intensities of its neighboring pixels. Therefore, processing pixel intensity information or feature map information in both the forward and backward directions might be more effective than using a unidirectional LSTM. Bi-LSTM can process information in both directions, so we designed another deep learning model by combining a CNN and a Bi-LSTM layer.The primary goal of designing the CNN+BiLSTM model architecture is to assess the impact of Bi-LSTM when integrated with

Chapter 3

Data set Description

3.1 Data Description

Basically, we are working on image based data for our research which was taken from Kaggle. Our dataset in this work was made up of two distinct datasets, A and B. We tested our models using discrete dataset B after training and verifying them on dataset A. This allowed for an unbiased evaluation of the models' performance. Initially, Dataset A had a test, a training set of 1,924 photos, and a batch of 1,932 images. A total of 339 pictures made up Dataset B, some of which were contaminated and some of which were not.

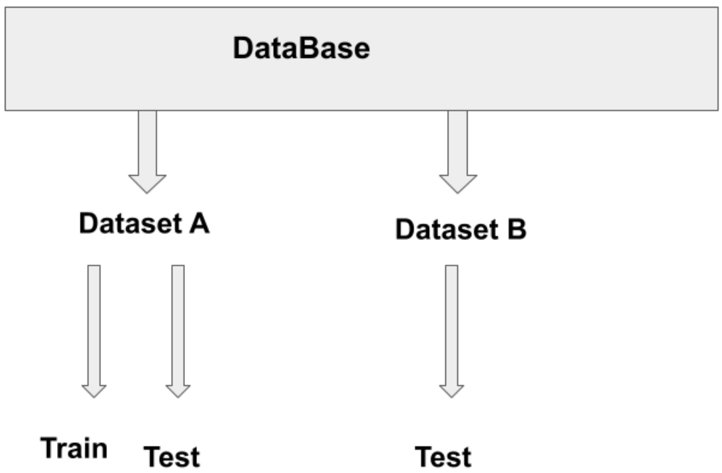


Figure 3.1: Overview of whole database

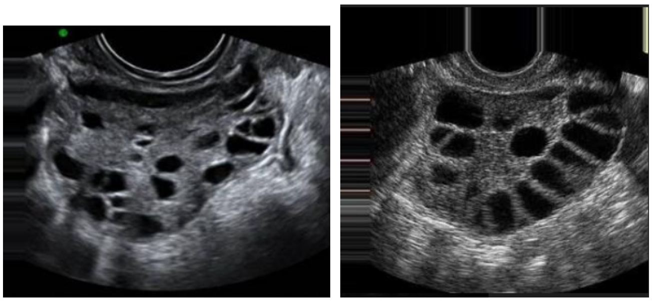


Figure 3.2: Infected data

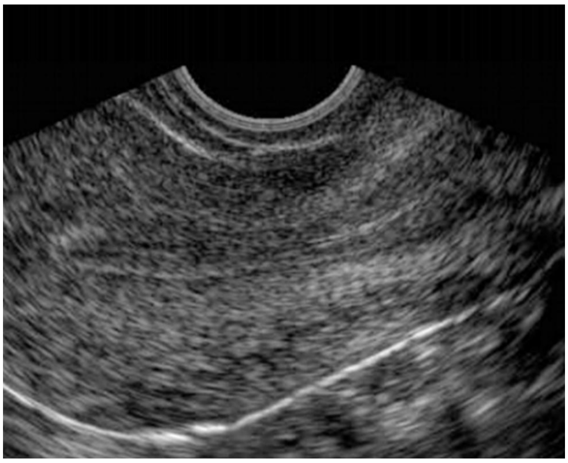


Figure 3.3: Not infected data

3.2 Data Preprocessing

As we know, we have different sets of images in datasets A and B, and the dimensions of the photos vary. So, to run our model, we need to preprocess the data by resizing and rescaling it. We used ImageDataGenerator from Keras and also augmented our training images. As a result, we got the same size images to overcome some limitations.

In our experiments, we initially encountered variations in the shapes of our input RGB images. To standardize our dataset, we resized all input images to a uniform size of 224 x 224 x 3. Additionally, we applied rescaling to all input images, dividing each pixel value by 255. This rescaling operation converts pixel values into the [0-1] range, enables the model for faster convergence and improves optimization during training. To introduce diversity in our training data and enhance our model's ability to generalize, we employed data augmentation techniques. We applied different data augmentation techniques including horizontal flips,vertical flips, random zooming (with a probability of 0.2), shearing transformations (with a probability of 0.2), and random rotations of up to 30 degrees as part of our data augmentation strategy. Data augmentation helps to reduce overfitting, enhancing regularization during training, and ultimately yielding an optimal classification model.

Before training with our model, we divided our dataset into two subsets: a training set and a validation set,with a ratio of 70:30. Notably, we applied data augmentation exclusively to the training set. The validation set was utilized to evaluate the performance and generalization of our trained model.

Chapter 4

Methodology

4.1 Model Selection

Model selection is a crucial step to addressing any real-world classification problem using deep learning methods, as we are not certain whether a specific deep learning model will work perfectly in a specific dataset or not. Therefore, we have explored five different deep learning methods to classify PCOS as infected or non-infected to determine the best one. In our research, we used long short-term memory (LSTM), bi-directional long short-term memory (Bi-LSTM), convolutional neural network (CNN), CNN combined with LSTM, and CNN combined with Bi-LSTM. We carefully assess many methods in an effort to identify the methodology that produces the highest classification performance. We can choose the ideal deep learning architecture for the PCOS classification task using this process. .

4.1.1 Long Short-Term Memory (LSTM)

To implement the LSTM model in our study, we first used a reshape layer to convert our input image into a sequence of features, as LSTM takes input as a sequence. The resized image with a size of 224x224x3 is converted into 224x672, which is treated as a sequence of length 224, with each ”time step” having 672 features. Following that, we have added 2 LSTM layers and 3 dense layers. A categorical cross-entropy loss has been employed as a loss function in our LSTM model architecture. We have employed the Adam optimizer with a learning rate of 0.001, beta1 = 0.9, beta2 = 0.999, and epsilon = 1e-07 to optimize our defined model. The overall summary of our implemented LSTM model is shown in Table n,

Layer (type)	Output Shape	Parameters
reshape (Reshape)	(None, 224, 672)	0
lstm (LSTM)	(None, 224, 64)	188672
lstm_1 (LSTM)	(None, 32)	12416
dense (Dense)	(None, 32)	1056
dense_1 (Dense)	(None, 16)	528
dense_2 (Dense)	(None, 2)	34
Total parameters	202706	
Trainable Parameters	202706	
Non-trainable parameters	0	

Figure 4.1: Summary of the LSTM model

4.1.2 Bi-directional Long Short-Term Memory(Bi-LSTM)

As the Bi-LSTM layer also takes sequence based inputs like the LSTM layer, therefore, we have added a reshape layer to convert our input image as a sequence of features in Bi-LSTM model architecture. After the reshaping layer, we have added 2 Bi-directional LSTM layers, and 3 dense layers in our Bi-LSTM model. Softmax has been utilized as an activation function of the last dense layer for final output. For loss function, categorical cross entropy has been employed in our model architecture. We have employed Adam optimizer with a learning rate of 0.001, beta1 = 0.9, beta2 = 0.999, and epsilon = 1e-07 to optimize our defined model. The summary of our Bi-LSTM model is shown Table-2:

Layer (type)	**Output Shape**	**Parameters**
reshape (Reshape)	(None, 224, 672)	0
bidirectional (Bidirectional)	(None, 224, 128)	377344
bidirectional_1 (Bidirectional)	(None, 64)	41216
dense (Dense)	(None, 32)	2080
dense_1 (Dense)	(None, 16)	528
dense_2 (Dense)	(None, 2)	34
Total parameters	421202	
Trainable Parameters	421202	
Non-trainable parameters	0	

Table-2: Summary of the Bi-LSTM model

4.1.3 Convolutional Neural Network

In our experiment, we have used a customized CNN that is combined with 3 convolution and pooling layers and a FC layer. We have adopted Adam as our optimizer with a learning rate of 0.001, beta1=0.9, beta2=0.999, and epsilon=1e-07. Categorical cross entropy loss has been employed as a loss function in our CNN model. We have passed our training set in the CNN model and trained for 5 epochs. The summary of our custom CNN model is shown in Table-3:

Layer (type)	Output Shape	Parameters
conv2d (Conv2D)	(None, 220, 220, 12)	912
max_pooling2d (MaxPooling2D)	(None, 55, 55, 12)	0
conv2d_1 (Conv2D)	(None, 51, 51, 10)	3010
max_pooling2d_2 (MaxPooling2D)	(None, 12, 12, 10)	0
conv2d_2 (Conv2D)	(None, 10, 10, 8)	728
max_pooling2d_2 (MaxPooling2D)	(None, 2)	34
flatten (Flatten)	(None, 72)	0
dense (Dense)	(None, 2)	146
Total parameters	4796	
Trainable Parameters	4796	
Non-trainable parameters	0	

Table-3: Summary of the custom CNN model

4.1.4 Convolutional Neural Network with LSTM

We have utilized a scratched CNN model as our feature extractor that generates 11 x 11 x 256 feature maps after 3 convolution and 2 pooling layers. We converted these features into a 1-D vector by flattening and reshaping a size of 2 x 15488 as a sequence. After that, we added an LSTM layer with 128 units to capture the sequential information of those extracted features. Finally, we added three dense layers for classifying those features as output. Our defined CNN+LSTM model is combined with a total of 11 layers, including an input layer, 3 convolutional layers, 2 pooling layers, 1 flatten layer, 1 reshape layer, and 3 dense layers. Stochastic Gradient Descent (SGD) with a learning rate of 0.05 and momentum of 0.07 has been employed as an optimizer in our implemented model. We have used categorical cross-entropy loss as a loss function in our model. The summary of our CNN+LSTM model is shown in Table 4.

Layer (type)	Output Shape	Parameters
conv2d (Conv2D)	(None, 220, 220, 12)	912
max_pooling2d (MaxPooling2D)	(None, 55, 55, 12)	0
conv2d_1 (Conv2D)	(None, 51, 51, 128)	38528
conv2d_2 (Conv2D)	(None, 47, 47, 256)	819456
max_pooling2d_1 (MaxPooling2D)	(None, 11, 11, 256)	0
flatten (Flatten)	(None, 30976)	0
reshape (Reshape)	(None, 2, 15488)	0
lstm (LSTM)	(None, 128)	7995904
dense (Dense)	(None, 128)	16512
dense_1 (Dense)	(None, 64)	8256
dense_2 (Dense)	(None, 2)	130
Total parameters	8879698	
Trainable Parameters	8879698	
Non-trainable parameters	0	

Figure 4.2: Summary of the CNN+LSTM model

4.1.5 Convolutional Neural Network with Bi-LSTM

We designed a CNN+LSTM model architecture in Section 3.3.4. Bi-LSTM can process information in both directions, so we designed another deep learning model by combining a CNN and a Bi-LSTM layer.The primary goal of designing the CNN+BiLSTM model architecture is to assess the impact of Bi-LSTM when integrated with CNN. We kept the CNN portion identical to the CNN+LSTM model and aimed to investigate whether CNN+BiLSTM outperforms CNN+LSTM. Our proposed CNN+BiLSTM model comprises a total of 11 layers, including an input layer, 3 convolution layers, 2 pooling layers, 1 flatten layer, 1 reshape layer, 1 BiLSTM layer with 128 hidden units, and 3 dense layers. We utilized categorical cross-entropy loss as the loss function in our model. For optimization, we employed SGD with a learning rate of 0.08 and a momentum of 0.7.The overall summary of the CNN+Bi-LSTM model is presented in Table 5.

Layer (type)	Output Shape	Parameters
conv2d (Conv2D)	(None, 220, 220, 12)	912
max_pooling2d (MaxPooling2D)	(None, 55, 55, 12)	0
conv2d_1 (Conv2D)	(None, 51, 51, 128)	38528
conv2d_2 (Conv2D)	(None, 47, 47, 256)	819456
max_pooling2d_1 (MaxPooling2D)	(None, 11, 11, 256)	0
flatten (Flatten)	(None, 30976)	0
reshape (Reshape)	(None, 2, 15488)	0
bidirectional (Bidirectional)	((None, 256)	15991808
dense (Dense)	(None, 128)	32896
dense_1 (Dense)	(None, 64)	8256
dense_2 (Dense)	(None, 2)	130
Total parameters	16891986	
Trainable Parameters	16891986	
Non-trainable parameters	0	

Figure 4.3: Summary of the CNN+LSTM model

Chapter 5

Experiment and Result Analysis

5.1 Experimental Results

The tests were carried out using the NVIDIA Tesla T4 graphics card, 12.68 GB of RAM, and 107.72 GB of disk space in the Google Colaboratory environment. We used the Python 3.8.3 programming language along with the Tensorflow, Keras, Scikit-learn, and several libraries like Numpy, Pandas, Matplotlib, etc. to perform various deep learning techniques.

5.1.1 Evaluation

The main objective of our proposed model was to classify the PCOS images into one of the two phases (infected and non infected) as mentioned in the earlier section. In this study, we employed various performance metrics to evaluate our implemented models. We consider accuracy, AUC score, precision, F1

$$Accuracy = \frac{(TP + TN)}{(TP + TN + FP + FN)} * 100\% \quad \ldots\ldots 11$$

$$Recall = \frac{TP}{(TP + FN)} \quad \ldots\ldots 12$$

$$Precision = \frac{TP}{(TP + FP)} \quad \ldots\ldots 13$$

$$F1\,Score = \frac{2 * (Precision * Recall)}{Precision + Recall} \quad \ldots\ldots 14$$

score, and recall to evaluate each model. All these evaluation metrics can be written as follows: Here, true positive denotes a value that was accurately predicted as positive, true negative denotes a value that was accurately predicted as negative, false positive denotes a value that was incorrectly predicted as positive, and false negative denotes a value that was incorrectly predicted as negative.

5.1.2 Result Comparison and Selecting the Optimal Model

Using a variety of evaluation variables from our study, we have undertaken an analysis in this section to determine how well the deep learning models performed. For the categorization of the PCOS dataset in our experiment, we used five distinct

Model	Accuracy (%)	AUC	Precision	Recall	F1 Score
LSTM	87.32	0.9275	0.8704	0.8704	0.8704
Bi-LSTM	88.71	0.9510	0.8879	0.8879	0.8879
CNN	**97.74**	**0.9980**	**0.9774**	**0.9774**	**0.9774**
CNN + LSTM	69.79	0.7867	0.6989	0.6989	0.6989
CNN + Bi-LSTM	81.25	0.9004	0.8136	0.8136	0.8136

Figure 5.1: Classification performance of different deep learning models on PCOS dataset

deep learning models: LSTM, Bi-LSTM, CNN, CNN+LSTM, and CNN+Bi-LSTM. The main objective of this experiment and inquiry isto choose the model that performs the best and produces the best classification results out of all of them. The experimental findings from the validation set are displayed in Table 6.
As shown in Table 6, the CNN model obtained the highest accuracy of 97.74%, which is 10.4%, 9.03%, 27.95%, and 16.49% higher than LSTM, Bi-LSTM, CNN+LSTM, and CNN+Bi-LSTM, respectively. CNN has also reported the highest classification results in terms of AUC score, precision, recall, and f1 score, which outperformed all of the other employed models. This model obtained an AUC score, precision, recall, and f1 score with values of 99.8%, 97.74%, 97.74%, and 97.74%, respectively. The second-highest classification result is reported by the Bi-LSTM model with an accuracy of 88.71%. The CNN+LSTM model reported the lowest score among all of the models in terms of all evaluation metrics, and this model obtained an accuracy of 69.79%. Moreover, the CNN model has also reported 12.78%, 8.52%, 12.76%, 12.76%, and 12.76% higher scores than the average accuracy, AUC score, precision, recall, and f1 score, respectively. We also represented a group bar plot to visually compare our employed models that is illustrated in Figure n.

From Figure 6.2, it is evident that CNN model outperformed all the employed models in terms of all evaluation criteria. From this investigation and experimental results it is clearly illustrated that our custom CNN is the best optimal model to classify the PCOS dataset.

We have observed robust performance in the custom CNN model compared to the other models in ourstudy. CNN is widely applied to image data because of its optimized architecture, which automatically detects and extracts spatial information using kernels. In the convolutional layers, it generates multiple feature maps from a single input image, while pooling layers select the most relevant features from these maps. The fully connected (FC) layer functions like a neural network, classifying these features into predicted classes. During the training time, the kernel weights in the convolutional and FC layers update concurrently with the help of an optimizer. As a result, CNN focuses on relevant information (features) that have a significant impact on the final classification.

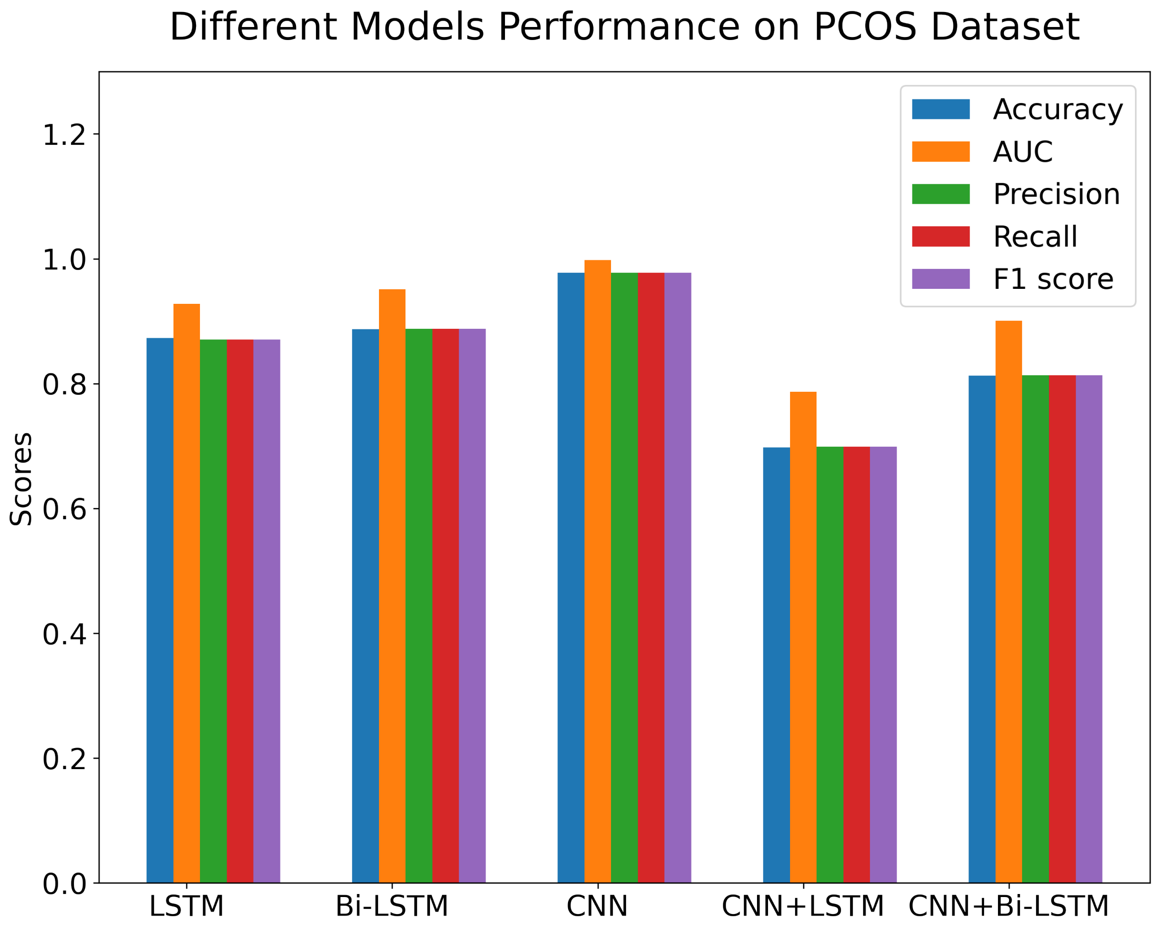


Figure 5.2: Comparison of different models based on accuracy, AUC score, precision, recall, and f1 score

On the other hand, LSTM and Bi-LSTM excel at handling sequential data, typically applied in natural language processing (NLP) tasks. In our study, Bi-LSTM yielded comparatively better results as it processes information in both forward and backward directions. However, using an image represented as a sequence to implement this model can be a drawback, potentially leading to suboptimal classification results, as images inherently contain spatial information.

When we attempted to combine CNN with LSTM and bi-LSTM, the classification results were notably poorer. We extracted features (spatial information) from input images through CNN and then converted these features into sequences for our models. The process of feature extraction using CNN inherently removes irrelevant features or information. This feature selection can lead to suboptimal sequences in terms of an LSTM layer. Our experimental results also reported poor classification outcomes with this approach.

Among all the models we implemented in ourstudy, CNN was found to be the best performer for classifying the PCOS dataset. Furthermore, the CNN model requires significantly fewer parameters compared to other models (shown in Section 3.3), resulting in lower computational costs. Therefore, we have selected the CNN model as the best choice for our classification task.

Chapter 6

Conclusion and Future work

In conclusion, the objective of our study was to evaluate the degree to which various deep-learning models classified data from the PCOS dataset, where five different deep learning models, including LSTM, Bi-LTSM, CNN, CNN+LSTM, and CNN+Bi-LSTM, were applied to find the model that would best perform this task. Our rigorous testing and analysis showed that the CNN model was the clear victor, outperforming the other models in terms of accuracy and performance. With a remarkable accuracy rate of 97.74%, CNN outperformed LSTM (87.34%), Bi-LSTM (88.71%), CNN+LSTM (69.79%), and CNN + Bi-LSTM (81.25%). Along with this exceptional accuracy, other important evaluation measures like the AUC score, precision, recall, and f1 score all had consistently high values that above 97%. In addition, as described in Section 3.3, the CNN model showed an advantage in terms of computing efficiency, requiring fewer parameters than the other models. We categorically advocate the CNN model as the best option for the classification of the PCOS dataset in light of these findings and the strong performance seen. It is a useful tool for the diagnosis and detection of Polycystic Ovary Syndrome because of its superior accuracy, efficiency, and feature extraction capabilities. This study advances the field of medical diagnostics while also highlighting how crucial it is to choose a deep learning architecture that is suited to the specifics of the dataset at hand.

Future Work: The accuracy and applicability of the model can be further improved by this work by pursuing a number of different directions. A more resilient model might result from a larger dataset including a bigger, more varied dataset that can contain additional medical characteristics like hormone levels, age, and lifestyle factors. Besides, new and latest models can be applied where TVS (transvaginal ultrasound) images can be used instead of using ultrasound images since the transducer is positioned closer to the ovaries during TVS than during conventional abdominal ultrasonography. In addition, studies in clinical experiments that confirm the model's efficacy can be carried out in conjunction with clinicians and researchers to produce better results.

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