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DEEP LEARNING FOR POLYCYSTIC OVARIAN SYNDROME CLASSIFICATION USING CONVOLUTIONAL NEURAL NETWORK

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Abstract—*Polycystic Ovarian Syndrome (PCOS) is the main cause of infertility in women. This condition results in abnormal hormone levels. Women who experience this syndrome will have irregular hormone levels and experience irregular menstrual cycles as well, thereby affecting the reproductive system. Symptoms that arise as a result of the increase in these hormones can be seen from the growth of hair on the legs, weight gain which results in not being ideal, irregular menstruation, unusual acne growth, and oily skin. The problem of Polycystic Ovarian Syndrome can cause disturbances in ovulation and cause infertility in women. Urgency This research requires a classification that has good accuracy in diagnosing early to minimize the rate of pregnancy failure. The aim of the research is to be able to model early detection of Polycystic Ovarian Syndrome with high accuracy so that it can help the health team in detecting Polycystic Ovarian Syndrome or not having Polycystic Ovarian Syndrome. The research stage has 3 stages including the first stage of identifying problems and collecting datasets from Telkom University dataverse in the form of images and literature reviews of various sources. The second stage is Pre Processing of image data, Data Training, modeling design by managing image data and classifying using the Convolutional Neural Network Algorithm deep learning model and testing. The third stage is evaluating the test results and discussing the results of accuracy in determining the status of Normal Polycystic Ovarian Syndrome or PCOS. The results of training and validation on the ovarian xray image dataset using the CNN architecture that has been made, 40 iterations (epochs), and 4 step_per_epochs show an accuracy value of 0.8947 or 89.47% and a loss value of 0.2684.*

Keywords: *convolutional neural network, hormones, reproduction, polycystic ovarian syndrome, pregnancy.*

Intisari—*Polycystic Ovarian Syndrome* (PCOS) merupakan penyebab utama *infertilitas* pada wanita. Kondisi ini mengakibatkan kadar hormon yang tidak normal. Wanita yang mengalami sindrom ini akan memiliki tingkat hormon yang tidak teratur dan mengalami siklus menstruasi tidak teratur juga, sehingga mempengaruhi sistem reproduksi. Gejala yang timbul akibat peningkatan hormon tersebut terlihat dari tumbuhnya rambut bagian kaki, penambahan berat badan yang mengakibatkan tidak ideal, menstruasi tidak teratur, tumbuh jerawat yang tidak wajar, serta kulit berminyak. Permasalahan *Polycystic Ovarian Syndrome* dapat menyebabkan gangguan pada ovulasi dan menyebabkan ketidaksuburan pada wanita. Urgensi penelitian ini diperlukan klasifikasi yang memiliki akurasi yang baik dalam mendiagnosa secara dini meminimalisir tingkat gagal hamil. Tujuan penelitian untuk dapat memodelkan dalam deteksi dini penyakit *Polycystic Ovarian Syndrome* dengan memiliki akurasi yang tinggi sehingga dapat membantu tim kesehatan dalam deteksi *Polycystic Ovarian Syndrome* atau tidak memiliki *Polycystic Ovarian Syndrome* ini. Tahapan penelitian memiliki 3 tahapan diantaranya yaitu tahap pertama identifikasi masalah dan pengumpulan dataset bersumber *Dataverse Telkom University* dalam bentuk *image* serta *literatur review* berbagai sumber. Tahap kedua *pre procesing* data *image*, *data training*, desain *modelling* dengan mengelola data *image* serta melakukan klasifikasi dengan menggunakan model *deep learning* algoritma *Convolutional Neural Network* dan pengujian. Tahap ketiga evaluasi hasil pengujian dan pembahasan hasil akurasi dalam menentukan status *Polycystic Ovarian Syndrome* Normal atau PCOS. Hasil *training* dan uji coba (*validation*) pada dataset citra *ovarium xray* dengan menggunakan arsitektur CNN yang telah dibuat, iterasi (*epoch*) sebanyak 40 kali, serta *step_per_epoch* sebanyak 4 menunjukkan nilai akurasi sebesar 0.8947 atau 89,47% dan nilai *loss* sebesar 0.2684.

Kata Kunci *: convolutional neural network*, hormon, reproduksi, *polycystic ovarian syndrome*, hamil.

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INTRODUCTION

Polycystic Ovary Syndrome (PCOS) is an endocrine disorder that affects women of reproductive age. The main symptoms of PCOS include increased levels of androgens (male hormones) in the body, which can result in hormonal disturbances and menstruation [1], [2]. In addition, PCOS can also cause other signs such as increased insulin production, acne, obesity, and excessive hair growth on the face and body [3].

Detecting PCOS is done to help identify this condition in women who show symptoms or are at risk of developing PCOS. Usually, the diagnosis of PCOS is based on the symptoms experienced by the patient as well as the results of a physical examination and laboratory tests, such as a blood test to measure hormone levels and a transvaginal ultrasound to check the condition of the ovaries [4], [5].

Early detection of PCOS using deep learning is a data and image processing method that is useful for identifying typical patterns and characteristics in ultrasound images of the ovaries taken from patients suspected of having PCOS. Deep learning techniques utilize machine learning algorithms that are able to recognize and learn special features on ultrasound images of the ovaries associated with PCOS, such as polycystic features of the ovaries or changes in ovarian size [6]–[8].

Women related to menstrual problems and cyst problems during pregnancy. Recently, ultrasound imaging and machine learning techniques have been used to detect ovarian cysts. Automatic ovarian cyst (OCD) detection and classification is implemented in this work using a fuzzy rule-based Convolutional Neural Network (FCNN). The proposed system (OCD-FCNN) has provided 98.37% accurate results when tested with a benchmark dataset [8], [9].

Polycystic ovary syndrome (PCOS) is the most common endocrinological anomaly in female reproduction that causes persistent disturbances of hormonal secretion, leading to the formation of multiple cysts within the ovaries and serious health complications. As a result, the proposed stacking ensemble technique significantly improves accuracy compared to other existing ML-based techniques if all kinds of feature sets are present. However, among the various models investigated to categorize PCOS and non-PCOS patients, the stacking ensemble model with the classifier 'Gradient Boosting' as a meta learner outperformed the others with 95.7% accuracy while making use of the top 25 features selected using Principal Component Analysis feature selection (PCA) [2], [10].

Exposure to chemicals in the past century has increased significantly in a variety of environments. There is no denying that these chemicals disrupt biological systems. Adverse effects of many chemicals have been recorded, both on humans and wild animals. The endocrine system in mammals, which is made up of various tissues that interact and regulate through hormones, has an important role in metabolism, growth, and development. More than fifty different hormones are produced by humans to control important functions in the body. However, a large number of internal and external chemical stressors have been identified as endocrine disruptors that can interfere with this vital function [1], [11].

The end products of advanced glycation reactions (AGEs), also known as Maillard products, are formed by non-enzymatic glycation reactions, the production of which increases with aging and under environmental stress. Processed foods are popular today because of their taste, convenience, and affordability. The process of making these foods often involves extreme temperatures, which can trigger the formation of AGEs. This can lead to increased oxidative stress, premature aging, diabetes, cancer and other degenerative diseases. What is interesting is the impact on hormonal disorders [12], [13].

PCOS, as a complex endocrine disorder, not only disturbs the physical, but also affects mental health. As many as 40% of women with PCOS experience depression, and this is closely related to psychoneuroimmunological factors. A search of the literature shows that the hypothalamic-pituitary-gonadal (HPG) axis plays an important role in delineating the relationship between depression and PCOS. In managing depression in PCOS, a comprehensive approach involving Consultation-Liaison Psychiatry (CLP) could be the main strategy to improve the prognosis in women with this condition [14].

Polycystic ovary syndrome (PCOS) is a hormonal disorder in women of reproductive age characterized by excessive androgen secretion from the ovaries. Symptoms include menstrual cycle irregularities, chronic anovulation, hyperandrogenism, and even infertility. K-Nearest Neighbors (KNN) method for data classification. As a result, after the feature selection process, KNN succeeded in achieving an accuracy level of 93%, precision 82%, recall 100%, and F1 Score 90%, showing the potential to detect PCOS with high accuracy based on the selected attributes [15].

PCOS, a condition affecting egg cell growth due to hormonal imbalances, impacts around 10-15% of women in their reproductive years globally. This study aimed to optimize PCOS detection by comparing algorithms. Specifically, it pitted random forest against logistic regression, analyzing a dataset with 40 features. Results indicated that the random forest algorithm outperformed logistic regression, boasting an impressive accuracy rate of 91% [16].

Based on a number of substantial and well-documented observations, this review examines the potential impact of diets containing AGEs on the endocrine system. The review highlights how such a diet can affect endocrine disorders through its mechanisms and participation. Economically and in terms of human well-being, the influence of AGEs could become a major burden for future societies. Therefore, this review aims to provide a new understanding of the role of AGEs in endocrine diseases and seeks to influence the views of the public and the scientific community on the impact of exposure to AGEs [17].

The criteria experienced by PCOS sufferers can be seen from body changes, namely: first, PCOS sufferers often experience irregular menstrual cycles or perhaps even no menstruation at all (amenorrhea). Secondly, excess hair growth on parts of the body usually associated with men, such as the face, chest and back. Third, compaction of hair on the head, which can cause hair thinning or baldness in certain areas. All four PCOS can cause skin changes, including acne and oily skin. Fifth, many women with PCOS experience weight problems, especially fat accumulation in the stomach area.

PCOS detection involves a series of medical evaluation steps and tests. The following are the general steps used in the PCOS detection process: The doctor will take a complete medical history, including information about the menstrual cycle, symptoms such as excess hair growth, skin problems, and other related health problems. The doctor will perform a physical examination to look for physical signs of PCOS, such as hirsutism (excess hair growth), acne, and other skin problems. Blood tests can be used to check hormone levels in the body. This may include measurements of folliculostimulating hormone (FSH), luteinizing hormone (LH), testosterone hormone, and insulin hormone. Elevated androgen hormones and insulin resistance are hallmarks of PCOS. Transvaginal ultrasound examination is used to examine the ovaries. In PCOS, the ovaries may show many small, immature follicles.

Carrying out PCOS detection requires a fairly long series, and requires costs, so it is necessary to develop technology by developing detection from X-ray photos that can be diagnosed accurately.

This will have a quick and cost-effective impact on carrying out inspections, so this research really needs to be developed.

The contribution to this research is carrying out data tests using sampling of 90 and 10 so that it can be seen that the accuracy is more than 80%. The focus of this research is the impact of PCOS on ovulation which results in infertility problems in women. Therefore, it is important to carry out in-depth research with accurate classification in diagnosing early, with the aim of reducing the risk of difficulty getting pregnant.

MATERIALS AND METHODS

Dataset

Polycystic Ovary Syndrome data is sourced from the Telkom University Bandung database according to collaboration with numbers 056/Sam3/Kst/2022 and 013/MOU/STMIK-IKMI/III/2022 Concerning Tridarma Higher Education and Development of Institutional Resources with the data link https://dataverse telkom university.ac.id/. Polycystic Ovary Syndrome data is in the form of an image resulting from an ultrasound or ultrasound of the patient, the data will be preprocessed and then divided into two, namely training data of 90% and testing data of 10%.

Deep Learning

Deep Learning refers to the idea that it forms a sequence of layers of representation. Currently, in Deep Learning, there are usually a number of successive layers, reaching tens to hundreds, and these layers can automatically process the training data provided. In the context of Deep Learning, these representational layered structures are known as Neural Networks. Neural Networks have a tiered arrangement, so that one layer is placed on top of another[18]. The concept of Neural Networks is inspired by the field of neurobiology, taking inspiration from the human brain's ability to perceive information[19].

Although the main idea of Deep Learning comes from this inspiration, the Deep Learning model is not a replica of the human brain. This is due to a lack of evidence to support that the way the human brain operates is similar to current models of deep learning.

Convolutional Neural Network Algorithms

Convolutional Neural Networks are specifically designed to handle structured data such as images. This allows Convolutional Neural Networks to identify complex visual patterns that may be difficult or impossible to recognize by conventional analysis methods. Convolutional Neural Networks can be trained on image datasets of varying sizes and resolutions. can recognize patterns at various levels of detail, thereby enabling

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good adaptation to variations in data. Convolutional Neural Networks can be used to detect anomalies or abnormal conditions in medical images. In the case of PCOS, it can help identify the characteristic features of polycystic ovaries.

Convolutional Neural Networks, which are abbreviated as CNNs or ConvNets, are collections of neurons that have been placed in enhanced layers through a learning process. The function of CNN is to extract low-level features from the raw input data, and the deeper the input goes through the CNN layers, the more complex the features extracted from the data become[20].

Research Flow

The research methodology is divided 3 stages as shown in Figure 1.

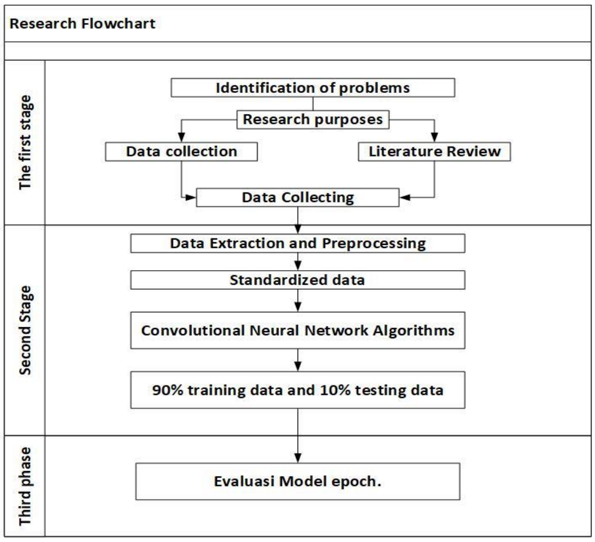

Figure 1. Research Flow[21]

The first stage

Problem Identification, namely at this stage determining the problem of Polycystic Ovary Syndrome. The purpose of this study is to be able to model early detection of Polycystic Ovarian Syndrome with high accuracy so that it can assist the health team in detecting Polycystic Ovarian Syndrome or not having Polycystic Ovarian Syndrome.

Data collection for Polycystic Ovary Syndrome is sourced from the Telkom University Bandung database according to collaboration with numbers 056/Sam3/Kst/2022 and 013/MOU/STMIK-IKMI/III/2022 Concerning Tridarma Higher Education and Development of Institutional Resources with data link https://dataverse.telkomuniversity.ac.id/ . Polycystic Ovary Syndrome data is in the form of an image resulting from an ultrasound or ultrasound of the patient, the data will be preprocessed and then divided into two, namely training data of 90% and testing data of 10%.

Second Stage

Egg cells (or ovum) are female reproductive cells. Normal and abnormal egg cells have significant differences in structure and quality, which can affect the egg's ability to be fertilized and develop into a healthy embryo. Following are the main differences between normal and abnormal egg cells :

1) Size and Shape:
    a. Normal Egg Cell: Usually has a comparable size and is round. The structure of a normal egg cell allows it to interact with sperm and initiate the fertilization process.
    b. Abnormal Egg Cells: May have an unusual size or odd shape. For example, abnormal egg cells may be too large or too small, or have defects in the cell membrane.
2) Chromosomes:
    a) Normal Egg Cell: Contains the complete set of chromosomes (23 single chromosomes).
    b) Abnormal Egg Cells: Can contain an abnormal number of chromosomes, such as too many or too few chromosomes. This condition is called aneuploidy.
3) Genetic Integrity:
    a) Normal Egg Cell: Has a balanced genetic structure and is properly integrated.
    b) Abnormal Egg Cells: Can experience mutations or genetic damage, which can cause genetic disorders in the embryo if fertilization occurs.
4) Reproductive Viability:
    a) Normal Egg Cell: More likely to be successfully fertilized and develop into a healthy embryo.
    b) Abnormal Eggs: More difficult to fertilize, and if fertilization occurs, there is a high risk of miscarriage or the birth of a baby with a genetic abnormality.

Data preprocessing at this stage prepares data before processing it by rescaling/resizing, converting to grayscale, normalizing, cropping, and filtering.

Training and testing data, namely in the training and testing stage, the dataset used is divided into two parts with the proportion of 90% training and 10% testing. The testing stage is carried out to validate the model that has been formed at the training stage. Testing is carried out at each cross validation for the Convolutional neural network algorithm[22]

Convolutional neural network algorithm model The configuration parameters used in the Convolutional neural network algorithm are the number of epochs, the convolution model, the type of activation function, the number of dense layers, and the number of batch sizes [23].

Third phase

At this stage it will be carried out by analyzing the results of data processing that has been done with the Convolutional neural network model.

RESULTS AND DISCUSSION

Research using Convolutional Neural Networks (CNN) in Python generally involves a series of stages, according to Knowledge Discovery in Databases.

The first stage

Polycystic Ovary Syndrome data is in the form of an image resulting from an ultrasound or ultrasound of the patient. This data is in the form of image data regarding the xray ovary. The data has 2 categories, namely PCO (polycystic ovaries) and normal. Ovary xray which belongs to the PCO category is 50 images and which belongs to the normal category is 200 images. Figure 2 is an x-ray image of a normal ovary and figure 3 is an x-ray image of an ovary in the Polycystic Ovary Syndrome category.

Figure 2. Normal Hormones

Figure 3. Abnormal Hormones (PCOS)

```
[4] # Menentukan direktori isi bahan
    normal_dir = os.path.join(bahan_dir, 'normal/')
    pco_dir = os.path.join(bahan_dir, 'pco/')

    print("Jumlah Data Train Tiap Kelas")
    print('Jumlah gambar ovarium normal :', len(os.listdir(normal_dir)))
    print('Jumlah gambar ovarium PCO :', len(os.listdir(pco_dir)))

    Jumlah Data Train Tiap Kelas
    Jumlah gambar ovarium normal : 40
    Jumlah gambar ovarium PCO : 14
```

Figure 4. Calling X-ray class data

Pre-processing the image pre-processing process is carried out as follows:

1. Image Augmentation (Data Transformation)
   Image Augmentation is a technique commonly used in image processing and deep learning to increase the amount and variety of training data. Image Augmentation involves applying a series of transformations to the original image to produce realistic new variations. The process carried out is shown in Table 1.

Table 1. Image Augmentation

No	Process	Value
1	Rescale	1./255
2	Rotation_range	30
3	Width_shift_range	0.2
4	Height_shift_range	0.2
5	Zoom_range	0.1
6	Shear_range	0.3
7	Horizontal_flip	true
8	Vertical_flip	true
9	Fill_mode	'nearest'

```
[148] train_datagen = ImageDataGenerator(
                        rescale = 1./255,
                        rotation_range = 30,
                        horizontal_flip = True,
                        vertical_flip = True,
                        shear_range = 0.3,
                        fill_mode = 'nearest',
                        width_shift_range = 0.2,
                        height_shift_range = 0.2,
                        zoom_range = 0.1)

      val_datagen = ImageDataGenerator(
                        rescale = 1./255,
                        rotation_range = 30,
                        horizontal_flip = True,
                        vertical_flip = True,
                        shear_range = 0.3,
                        fill_mode = 'nearest',
                        width_shift_range = 0.2,
                        height_shift_range = 0.2,
                        zoom_range = 0.1)
```

Figure 5. Image Augmentation

2. Resize (Changing the size)
   The xray ovarian images used have different pixel resolution sizes. Before the feature extraction stage is carried out on the CNN architecture that will be used, a resizing of the

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pixel resolution size is carried out to 150 x 150. The purpose of resizing is to equalize the input size of the xray ovary image used.

```
#@title Target
train_generator = train_datagen.flow_from_directory(
      train_dir,
      target_size = (150,150),
      batch_size = 10,
      class_mode = 'categorical')

val_generator = val_datagen.flow_from_directory(
      validation_dir,
      target_size = (150,150),
      batch_size = 10,
      class_mode = 'categorical')

Found 48 images belonging to 2 classes.
Found 6 images belonging to 2 classes.
```

Figure 6. Resized

3. Split Data In the Convolutional Neural Network, learning (training) and testing (validation) will be carried out so that data is divided into two, namely training data of 90% and validation data of 10%. Distribution of data is done randomly (random) in each type of category (PCO and normal).

```
# Jumlah pembagian data training dan validasi
train_ratio = 0.9

# Pembagian training dan validasi
#   Training
source_00 = normal_dir
train_00 = train_normal
val_00 = validation_normal
train_val_split(source_00, train_00, val_00, train_ratio)
#   Validasi
source_01 = pco_dir
train_01 = train_pco
val_01 = validation_pco
train_val_split(source_01, train_01, val_01, train_ratio)

[31] print('Jumlah all normal :' , len(os.listdir(normal_dir)))
     print('Jumlah train normal :', len(os.listdir(train_normal)))
     print('Jumlah val normal :', len(os.listdir(validation_normal)))

     Jumlah all normal : 40
     Jumlah train normal : 36
     Jumlah val normal : 4

[150] print('Jumlah all PCO :' , len(os.listdir(pco_dir)))
      print('Jumlah train PCO :', len(os.listdir(train_pco)))
      print('Jumlah val PCO :', len(os.listdir(validation_pco)))

      Jumlah all PCO : 14
      Jumlah train PCO : 12
      Jumlah val PCO : 2
```

Figure 7. Split Data

Second Stage

The Convolutional Neural Network architecture is one of the methods in deep learning algorithms that implement artificial neural networks in living things. The method used in the Convolutional Neural Network with backpropagation (learning) and feedforward (classification). The stages in building a Convolutional Neural Network architecture include:

1. Convolution In the created Convolutional Neural Network architecture, do 3 times the convolution process. The first convolution process uses filter layer 16 and 3x3 kernel. The second convolution process uses filter layer 32 and 3x3 kernel. The first convolution process uses filter layer 64 and 3x3 kernel. The activation function performed on the convolution and hidden layers is Relu (Rectified Linear Unit).
2. Pooling In the CNN architecture that was created, do 2 times the pooling process using max-pooling with a 2x2 matrix form.
3. Flattening The pooling data which is in the form of a 2-dimensional array is then converted into a single vector one-dimensional data.
4. Full Connection Next, a dense process is carried out. The dense process was carried out 3 times. The first and second dense processes use 200 node units and use the Relu activation function. While the third dense process uses 2 units and uses the sigmoid activation function. A dropout process is also carried out, where this process is used to regulate parameters with the aim of avoiding overfitting. The dropout process is carried out 2 times.

Model CNN

```
#@title Model CNN
model = tf.keras.models.Sequential([
        tf.keras.layers.Conv2D(16, (3,3), activation = 'relu', input_shape = (150, 150, 3)),
        tf.keras.layers.MaxPooling2D(2,2),
        tf.keras.layers.Conv2D(32, (3,3), activation = 'relu'),
        tf.keras.layers.MaxPooling2D(2,2),
        tf.keras.layers.Conv2D(64, (3,3), activation = 'relu'),
        tf.keras.layers.MaxPooling2D(2,2),
        tf.keras.layers.Flatten(),
        tf.keras.layers.Dense(200, activation = 'relu'),
        tf.keras.layers.Dropout(0.3, seed=112),
        tf.keras.layers.Dense(500, activation = 'relu'),
        tf.keras.layers.Dropout(0.5, seed=112),
        tf.keras.layers.Dense(2, activation = 'sigmoid'),
])
```

Figure 8. Convolutional Neural Network Models

Third phase

The results of training and validation on the ovarian xray image dataset using the Convolutional Neural Network architecture that has been created, 40 iterations (epochs), and 4 step_per_epochs show an accuracy value of 0.8947 or 89.47% and a loss value of 0.2684 .

```
[157] history = model.fit(
                  train_generator,
                  steps_per_epoch = 4,
                  epochs = 40,
                  validation_data = val_generator,
                  validation_steps = 1,
                  verbose = 1,
                  callbacks = [callbacks])
```

Figure 9. Loss validation display

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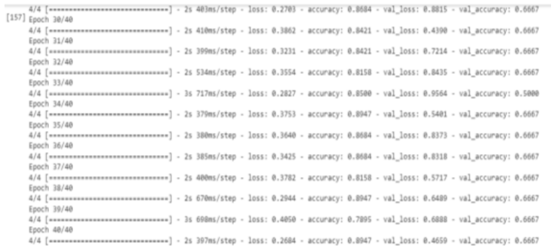

```
    4/4 [==============================] - 2s 403ms/step - loss: 0.2703 - accuracy: 0.8684 - val_loss: 0.8815 - val_accuracy: 0.6667
[157] Epoch 30/40
    4/4 [==============================] - 2s 410ms/step - loss: 0.3862 - accuracy: 0.8421 - val_loss: 0.4390 - val_accuracy: 0.6667
    Epoch 31/40
    4/4 [==============================] - 2s 399ms/step - loss: 0.3231 - accuracy: 0.8421 - val_loss: 0.7214 - val_accuracy: 0.6667
    Epoch 32/40
    4/4 [==============================] - 2s 534ms/step - loss: 0.3554 - accuracy: 0.8158 - val_loss: 0.8435 - val_accuracy: 0.6667
    Epoch 33/40
    4/4 [==============================] - 3s 717ms/step - loss: 0.2827 - accuracy: 0.8500 - val_loss: 0.9564 - val_accuracy: 0.5000
    Epoch 34/40
    4/4 [==============================] - 2s 379ms/step - loss: 0.3753 - accuracy: 0.8947 - val_loss: 0.5401 - val_accuracy: 0.6667
    Epoch 35/40
    4/4 [==============================] - 2s 380ms/step - loss: 0.3640 - accuracy: 0.8684 - val_loss: 0.8373 - val_accuracy: 0.6667
    Epoch 36/40
    4/4 [==============================] - 2s 385ms/step - loss: 0.3425 - accuracy: 0.8684 - val_loss: 0.8318 - val_accuracy: 0.6667
    Epoch 37/40
    4/4 [==============================] - 2s 400ms/step - loss: 0.3782 - accuracy: 0.8158 - val_loss: 0.5717 - val_accuracy: 0.6667
    Epoch 38/40
    4/4 [==============================] - 2s 670ms/step - loss: 0.2944 - accuracy: 0.8947 - val_loss: 0.6489 - val_accuracy: 0.6667
    Epoch 39/40
    4/4 [==============================] - 3s 698ms/step - loss: 0.4050 - accuracy: 0.7895 - val_loss: 0.6888 - val_accuracy: 0.6667
    Epoch 40/40
    4/4 [==============================] - 2s 397ms/step - loss: 0.2684 - accuracy: 0.8947 - val_loss: 0.4659 - val_accuracy: 0.6667
```

Figure 10. Epoch displays

The Convolutional Neural Network (CNN) that has been created is a network architecture that is used for image processing tasks. CNN has convolution layers that are used to extract important features from the image, followed by pooling and fully connected layers to perform classification. This CNN has been trained with a dataset for 40 iterations (epochs) using a learning method that regulates learning steps based on data taken in step_per_epoch 4 times.

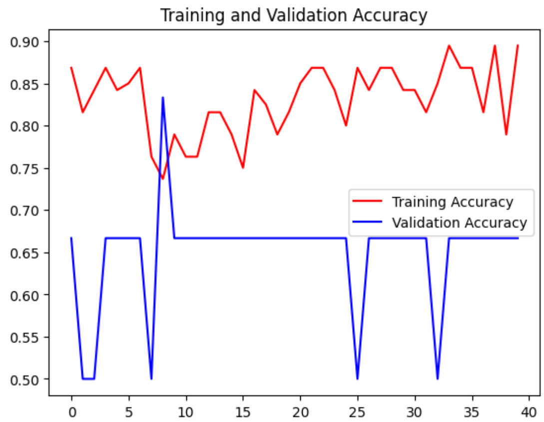

Figure 11. Accuracy Training and Validation

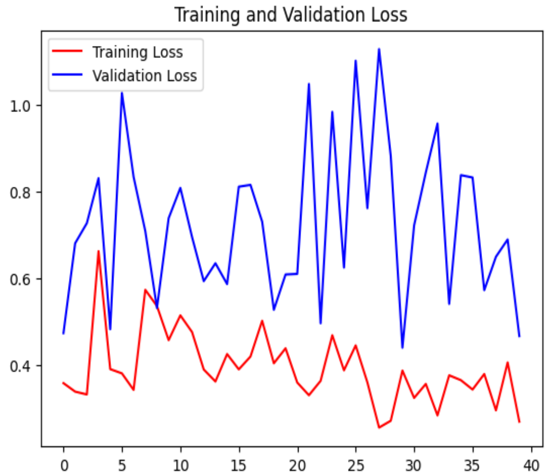

Figure 12. Training and Validation Loss

The training results from CNN show that when training reaches the 40th epoch, the accuracy achieved is 0.8947 or the equivalent of 89.47% as can be seen in Figure 11. This means that this model can recognize and classify images with that level of accuracy. In addition, the loss value at that time was 0.2684 as in Figure 12 which shows how well the model can minimize the difference between the predicted results and the actual value.

The results of high accuracy and low loss indicate that CNN has been successful in studying important patterns in the dataset used. However, it is also important to evaluate the model on never-before-seen test data to ensure that this level of accuracy also applies to never-before-seen data, and there is no overfitting.

CONCLUSION

Polycystic Ovarian Syndrome (PCOS) Symptoms that arise as a result of an increase in these hormones can be seen from the growth of hair on the legs, weight gain which results in not being ideal, irregular menstruation, unusual acne growth, and oily skin. Urgency this research requires a classification that has good accuracy in diagnosing early to minimize the rate of pregnancy failure. The aim of the research is to be able to model early detection of Polycystic Ovarian Syndrome with high accuracy so that it can help the health team in detecting Polycystic Ovarian Syndrome or not having Polycystic Ovarian Syndrome. The research stage has 3 stages including the first stage of identifying problems and collecting datasets from Telkom University dataverse in the form of images and literature reviews of various sources. The second stage is Pre Processing of image data, Data Training, modeling design by managing image data and classifying using the Convolutional Neural Network Algorithm deep learning model and testing. The third stage is evaluating the test results and discussing the results of accuracy in determining the status of Normal Polycystic Ovarian Syndrome or PCOS. The results of training and validation on the ovarian xray image dataset using the CNN architecture that has been made, 40 iterations (epochs), and 4 step_per_epochs show an accuracy value of 0.8947 or 89.47% and a loss value of 0.2684. suggestions for further research: Ensure that the dataset used covers a wide range of Polycystic Ovarian Syndrome (PCOS) cases by including patient characteristics, including factors such as age, body mass index (BMI), and other clinical symptoms and use various evaluation metrics such as accuracy, sensitivity. , specificity, and area under the receiver operating characteristic curve (AUC-ROC) to power the model.
The constraints in selecting appropriate evaluation metrics to assess model performance in a medical context are significant. Determining whether the model is sensitive to actual PCOS cases is also a

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challenge. Future research F1-score measures the balance between precision (Precision) and sensitivity (Recall). This is useful when there is a need to measure overall model performance and want to measure overall model performance, not just focus on a single metric.

REFERENCE

[1] D. A. Devi and F. Kartini, "Women, Midwives and Midwifery : Volume 2, Issue 3, 2022 https://wmmjournal.org Corresponding The Mental Health in Women with Polycystic Ovary Syndrome (PCOS): A Scoping Review," 2022, doi: 10.36749/wmm.2.3.1-19.2022.

[2] B. Rachana, T. Priyanka, K. N. Sahana, T. R. Supritha, B. D. Parameshachari, and R. Sunitha, "Detection of polycystic ovarian syndrome using follicle recognition technique," *Global Transitions Proceedings*, vol. 2, no. 2, pp. 304–308, Nov. 2021, doi: 10.1016/j.gltp.2021.08.010.

[3] T. N. Ravishankar, H. Makarand Jadhav, N. Satheesh Kumar, S. Ambala, and M. Pillai N, "A deep learning approach for ovarian cysts detection and classification (OCD-FCNN) using fuzzy convolutional neural network," *Measurement: Sensors*, vol. 27, Jun. 2023, doi: 10.1016/j.measen.2023.100797.

[4] A.-L. Barbotin *et al.*, "Hypothalamic neuroglial plasticity is regulated by anti-Müllerian hormone and disrupted in polycystic ovary syndrome," 2023. [Online]. Available: www.thelancet.com

[5] G. Ravichandran *et al.*, "Food advanced glycation end products as potential endocrine disruptors: An emerging threat to contemporary and future generation," *Environment International*, vol. 123. Elsevier Ltd, pp. 486–500, Feb. 01, 2019. doi: 10.1016/j.envint.2018.12.032.

[6] S. Alam Suha and M. N. Islam, "Exploring the dominant features and data-driven detection of polycystic ovary syndrome through modified stacking ensemble machine learning technique," *Heliyon*, vol. 9, no. 3, Mar. 2023, doi: 10.1016/j.heliyon.2023.e14518.

[7] F. Handayani, A. Fauzi, and A. Sihombing, "Penerapan Metode Certainty Factor Dalam Mendiagnosa Penyakit Polycystic Ovary Syndrome," *Jurnal Teknik Informatika Kaputama (JTIK)*, vol. 6, no. 1, 2022, doi: https://doi.org/10.59697/jtik.v6i1.390.

[8] X. Zhang *et al.*, "Raman spectroscopy of follicular fluid and plasma with machine-learning algorithms for polycystic ovary syndrome screening," *Mol Cell Endocrinol*, vol. 523, Mar. 2021, doi: 10.1016/j.mce.2020.111139.

[9] A. Y. Pratama and Y. Pristyanto, "Classification Of Corn Plant Diseases Using Various Convolutional Neural Network," *JITK (Jurnal Ilmu Pengetahuan dan Teknologi Komputer)*, vol. 9, no. 1, pp. 49–56, Aug. 2023, doi: 10.33480/jitk.v9i1.4258.

[10] Y. A. Suwitono and F. J. Kaunang, "Implementasi Algoritma Convolutional Neural Network (CNN) Untuk Klasifikasi Daun Dengan Metode Data Mining SEMMA Menggunakan Keras," *Jurnal Komtika (Komputasi dan Informatika)*, vol. 6, no. 2, pp. 109–121, Nov. 2022, doi: 10.31603/komtika.v6i2.8054.

[11] P. Azzahra and E. Haerani, "Penerapan dan Implementasi Metode Certainty Factor Dalam Sistem Pakar Diagnosa Awal Gangguan Menstruasi PALM-COEIN," *Building of Informatics, Technology and Science (BITS)*, vol. 4, no. 2, Sep. 2022, doi: 10.47065/bits.v4i2.1805.

[12] Nurdin *et al.*, "Sms Encryption Application Using 3Des (Triple Data Encryption Standard) Algorithm Based on Android," in *Journal of Physics: Conference Series*, Institute of Physics Publishing, Nov. 2019. doi: 10.1088/1742-6596/1363/1/012077.

[13] D. A. Kurnia, D. Sudrajat, N. Rahaningsih, A. R. Rinaldi, and F. A. Pratama, "The selection of candidate of call center operator 112 using analytical hierarchy process method," in *Journal of Physics: Conference Series*, Institute of Physics Publishing, Oct. 2019. doi: 10.1088/1742-6596/1360/1/012015.

[14] N. Triadha Pitaloka, "Pcos Disease Classification Using Feature Selection Rfecv And Eda With KNN Algorithm Method," *Jurnal Teknik Informatika (JUTIF)*, vol. 4, no. 4, pp. 693–701, 2023, doi: 10.52436/1.jutif.2023.4.4.693.

[15] A. Yuliadha and R. H. Setyaningrum, "Psikoneuroimunologi Depresi pada Polycystic Ovary Syndrome (PCOS)," *Smart Medical Journal*, vol. 5, no. 1, p. 38, Apr. 2022, doi: 10.13057/smj.v5i1.43238.

[16] K. Nisa, B. Putra Dewa, and S. K. Wibisono, "Model Comparison of Random Forest and Logistic Regression Algorithms in PCOS Disease Detection," *KSATRIA : Jurnal Penerapan Sistem Informasi (Komputer&Manajemen)*, vol. 4, no. 1, pp. 73–79, 2023, doi: https://doi.org/10.30645/kesatria.v4i1.11 9.

[17] D. A. Kurnia, O. Mohd, F. Abdollah, D. Sudrajat, and Y. A. Wijaya, "Face Recognition Techniques : A Systematic Literature Review (Research Trends, Datasets, And Methods) 1," *J Theor Appl Inf Technol*, vol. 15, no. 21, 2021, [Online]. Available: https://www.qsrinternational.com

[18] D. A. Kurnia, A. Setiawan, D. R. Amalia, R. W. Arifin, and D. Setiyadi, "Image Processing Identifacation for Indonesian Cake Cuisine using CNN Classification Technique," in *Journal of Physics: Conference Series*, IOP Publishing Ltd, Feb. 2021. doi: 10.1088/1742-6596/1783/1/012047.

[19] D. Sudrajat, R. D. Dana, N. Rahaningsih, A. R. Dikananda, and D. A. Kurnia, "Clustering student's satisfaction in complex adaptive blended learning with the six value system using the K-means algorithm," *Universal Journal of Educational Research*, vol. 7, no. 9, pp. 1990–1995, 2019, doi: 10.13189/ujer.2019.070920.

[20] R. D. Dana, D. Soilihudin, R. H. Silalahi, D. A. Kurnia, and U. Hayati, "Competency test clustering through the application of Principal Component Analysis (PCA) and the K-Means algorithm," *IOP Conf Ser Mater Sci Eng*, vol. 1088, no. 1, p. 012038, Feb. 2021, doi: 10.1088/1757-899x/1088/1/012038.

[21] E. Sutisna and L. H. Vonti, "Innovation Development Strategy for Hybrid Learning," vol. 9, no. 1, pp. 103–114, 2020, doi: https://doi.org/10.25134/erjee.v9i1.3783.

[22] Nurdin *et al.*, "The Implementation of Backtracking Algorithm on Crossword Puzzle Games Based on Android," *J Phys Conf Ser*, vol. 1363, no. 1, 2019, doi: 10.1088/1742-6596/1363/1/012075.

[23] R. Novianti, S.Psi, M.Pd, E. Puspitasari, and I. Maria, "Parental Involvement in Children'S Learning Activities During the Covid-19 Pandemic," *JURNAL PAJAR (Pendidikan dan Pengajaran)*, vol. 5, no. 2, pp. 384–390, 2021, doi: 10.33578/pjr.v5i2.8220.