Infact: International Journal of Computers
Vol.9, No.01, Maret 2025
p-ISSN : 2527-8363, e-ISSN: 2829-0259
DOI:

The Implementation of a Convolutional Neural Network for The Detection of Cataract Disease Severity in Eyes

Fanny Fadlilatunnisa[1], Agung Mulyo Widodo [2]
[1,2] Department of Computer Science, Universitas Esa Unggul
[1,2]Jl. Arjuna Utara No.9, Duri Kepa, Kec. Kb. Jeruk, Kota Jakarta Barat, Daerah Khusus Ibukota Jakarta 11510

E-mail: fannyfadlila025@student.esaunggul.ac.id[1], agung.mulyo@esaunggul.ac.id[2]

Submitted: 09/03/2025 , Revision:20/03/2025, Accepted : 21/03/2025

Abstract

Cataract is a condition that causes clouding of the lens of the eye, leading to blindness and poor vision. According to the WHO, around 18 million people suffer from cataract-related blindness, making it one of the leading causes of blindness globally. Prompt and accurate diagnosis is essential to prevent more serious outcomes. This research aims to develop a deep learning model that utilises Convolutional Neural Networks (CNN) in categorising cataract severity into four groups: hypermature, normal, immature and mature. This model is expected to provide a more efficient and accurate alternative to traditional methods in diagnosing cataracts. To achieve this, we implemented transfer learning using three popular CNN architectures: VGG16, VGG19, and ResNet50. Experiments were conducted using a dataset of pre-labelled eye images for training. Model performance was evaluated by calculating F1-score, recall, accuracy, and precision using a confusion matrix. The results showed that VGG19 produced 88% accuracy and F1-score of 0.87, while VGG16 had the best accuracy. On the other hand, ResNet50 showed the lowest accuracy with 63% and F1-score of 0.59. These findings highlight the importance of selecting the right CNN architecture for cataract diagnosis, while underlining the potential application of deep learning in ophthalmology.

Keywords:
Cataract
Convolutional Neural Network (CNN)
Deep Learning

***Corresponding Author: Author's Name**
E-mail: corresponding_email@email.com

1. Introduction

The eyes are one of the main sensory organs in the human body and have been compared to a camera that records everything it sees, including different moments in life. If the eyes are damaged, a person's vision can be seriously impaired and may even lead to permanent blindness [1]. According to the World Health Organisation (WHO), around 18 million people are blind in both eyes as a result of cataracts [2]. Cataracts are cloudiness in the lens of the eye causing light to hang in the eyeball, resulting in blurred vision and eventually blindness [3]. According to data from the Rapid Assessment of Avoidable Blindness (RAAB) survey conducted in 15 Indonesian provinces between 2014 and 2016, the prevalence of visual impairment in the country's senior population over 50 is approximately 3%, with cataracts accounting for 81% of blindness cases [4]. Cataracts develop slowly and gradually affect vision. As a result, many people do not realize the signs of the condition and do not seek appropriate treatment, leading to vision loss. Traditional treatment requires an examination by an ophthalmologist, which often involves a manual process of analyzing eye images to determine the severity of the cataract. Limited resources and longer waiting times pose major barriers to cataract treatment [5]. Therefore, it is necessary to detect the severity of cataract disease in the eye before it causes blindness, through technological innovations that bring great opportunities in the health sector. One of the innovations that can be utilised is the use of deep learning, providing the basis for its application in ophthalmology, especially in the field of systemic prediction and diagnosis, prediction models utilising images have shown potential in ongoing disease risk assessment and early detection [6]. In order to extract patterns from data that are modeled after the human brain, deep learning makes use of deep neural networks. Specifically, techniques based on Convolutional Neural Networks (CNN) have shown great progress in picture recognition. These techniques are frequently applied to the classification and identification of images. CNN can determine which objects are in an image, allowing machines to recognise and distinguish one image from another [7].

Convolutional Neural Networks (CNN) can extract features and gather additional information from images [8]. This allows the model to identify and distinguish different types of eye diseases based on the patterns in the image. Research Elkholy & Marzouk, 2024 showed the ability of CNN to detect eye diseases using Optical Coherence Tomography (OCT) images using the VGG16 architecture through the transfer learning method. Transfer learning is applied to speed up training and improve model performance. Utilizing parameters and weights that have been trained can improve the accuracy of the model [9]. The research conducted by Cahya et al., 2021 shows the CNN method for eye disease classification with the AlexNet architecture. In this study, the data processing stage is carried out by resizing the image [10]. Convolutional Neural Networks (CNN) were utilized in the study by KC et al. 2023 to classify eye fundus images using three different architectures: VGG16, VGG19, and ResNet50. Each architecture features a distinct number of layers, enabling varying capabilities in feature extraction from image data. To assess the accuracy and efficiency of the tested architectures, the study explored various deep convolutional artificial neural network models to enhance overall model performance [11]. In research Firdaus et al. 2022 using CNN for cataract disease classification, testing on several epochs resulted in varying model accuracy, in this study this CNN method can be rated as working very well in identifying cataract eyes and normal eyes [12]. Another Research Qulub et al. 2024 used the VGG16 architecture. The research was conducted by training and testing the classification model using a dataset of fundus photo images covering various eye diseases that cause blindness. Model evaluation by measuring accuracy, precision, and recall is measured using a confusion matrix. However, in this study, the prediction results are more inclined to one of the classes because the number of datasets is not balanced, so it is necessary to balance the dataset [13].

However, the detection of cataract disease in eye images using Convolutional Neural Networks (CNN) still faces challenges in achieving optimal classification performance. This motivates the development of a CNN-based model to detect cataracts using image objects. Data processing techniques such as data augmentation are used to enhance model generalization. In addition, several CNN architectures are tested to compare their performance in detecting cataract severity. Furthermore, hyperparameter optimization, including learning rate, number of epochs, and optimizer selection, along with experiments on different numbers of layers and batch sizes, are applied to find the combination that yields the highest model accuracy
This research is expected to contribute as follows:

- Providing benefits in quick and appropriate treatment to reduce the impact of vision impairment in the community.
- Not only raising awareness of the importance of early detection but also helping to make it easier to get access to eye health services, especially in remote areas with limited medical resources.
- This research is expected to contribute greatly to the advancement of science in the field of medical image processing, especially in detecting eye diseases quickly

2. Methods

In developing a cataract severity classification model. The research flow proposed in this study is depicted in **Figure 1**

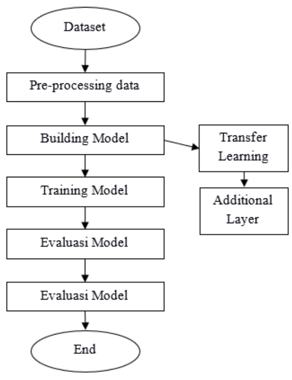

Figure 1 Research flow

2.1 Dataset

In the design of this deep learning model, public datasets available on the internet from 'Kaggle' and 'Opthalmology Site' are used. The number of images collected in the dataset consists of 840 images containing image data for classification or detection of cataracts in the eye. The dataset is labelled according to the severity of the cataract, which is divided into four classes or stages of cataract disease, namely Hypermature, Mature, Immature, and Normal. **Figure 2** shows the severity of cataracts that can impair vision.

Figure 2 Severity of cataract

- Normal: Healthy eyes with no signs of cataracts.
- Immature : A stage characterised by the onset of thicker opacities in certain areas, but not yet dominating the entire lens.
- Mature: This stage is characterised by opacities that have dominated the entire lens mass.
- Hypermature: At this stage, the opacity of the eye is very thick and has undergone a more advanced degeneration process.

2.2 Processing Data

These images of the dataset have been collected from various sources to ensure diversity in lighting conditions, angles, and image quality, which helps improve the model's robustness. To enhance the dataset, preprocessing techniques such as image resizing, normalization, and augmentation, which includes flipping, shifting horizontally and vertically, and using certain approaches to fill in blank spaces. Following that, the dataset was split into three categories: 15% validation, 15% testing, and 70% training.

After going through data processing, the number of images generated increased to 3991 images, as shown in **Table 1**

Table 1 Number of datasets after processing data

No.	Kelas	Train	Valid	Test
1	Normal	698	150	150
2	Immature	696	149	150
3	Mature	702	150	151
4	Hypermature	696	149	150

2.3 Convolutional Neural Network

One of the deep learning techniques for handling two-dimensional input, like pictures, is the convolutional neural network. Each CNN layer learns to identify various image classes by analyzing images at various resolutions using data preprocessing. The image processing results are processed and used as input to the next layer. As shown in **Figure 3**

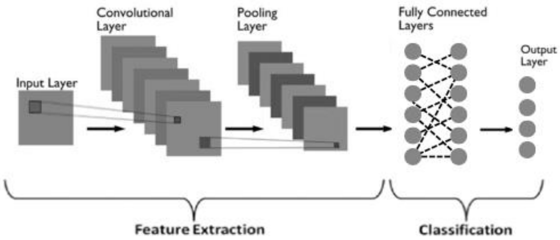

Figure 3 CNN architecture

The CNN architecture's primary components are separated into two sections: the fully connected layer and the feature extraction layer.

Feature Extraction

- **Input layer**
  The initial layer where the input data is in the form of images. Each image is processed into a numerical representation in the form of a pixel matrix.
- **Convolutional layer**
  This layer performs convolution operations, where a filter (kernel) is applied to the input to extract features such as edges, textures, and patterns from the image. The resulting set of features from this layer are feature maps. **Figure 4** below shows the process of the convolution layer:

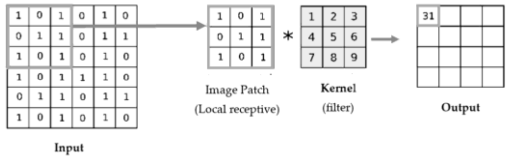

Figure 4 Overview of the convolutional layer process

- **Pooling Layer**
  Used to reduce the output dimension (down-sampling) while retaining important features, pooling is used. Max pooling and average pooling are the two primary categories of pooling techniques.

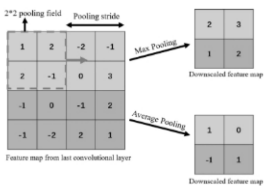

Figure 5 Overview of the pooling layer process

Classification

- **Fully Connected Layer**
  Following feature extraction, vectors from the previous layer are fed into the fully connected layer, which uses them to carry out the classification process. The model can comprehend the relationship between features thanks to this layer, which links all of the neurons from the previous layer to neurons in the current layer.
- **Output Layer**
  This last layer generates the predicted probabilities for each class. The softmax classifier activation function is used in the output layer for multi-class classification output using softmax activation

2.4 Transfer Learning

Transfer learning method allows the learning process of an already trained model to start from zero value (some weights are already embedded in the architecture) and model archetype, and at the same time solve various problems [14]. In the transfer learning process, features that have been learned by the model are reused as feature extractors. Often, the initial layer of the model is frozen, and only the final layer is changed or added to adapt to the new task. However, if the new dataset is large enough, the model can be fully customized through retraining (fine-tuning). As shown in **Figure 6**

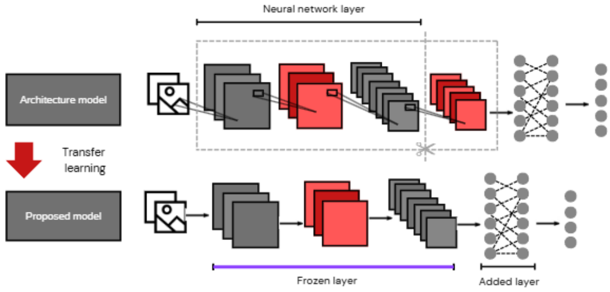

Figure 6 Transfer learning

In this research there are 3 architectures used:

1) VGG16

Oxford University's Visual Geometry Group (VGG) created the convolutional artificial neural network model known as VGG16. Under specific circumstances, VGG16 demonstrates that increasing the network's depth can enhance performance. Three fully connected layers, five union layers, and thirteen convolution layers make up the VGG16 network model [15].

2) VGG19

The University of Oxford's Visual Geometry Group (VGG) used Convolutional Neural Networks (CNNs) to develop a deep learning model known as VGG19. It has 19 layers, including 3 fully connected layers, 5 max pooling layers, and 16 convolutional layers. VGG19 is often used in transfer learning with weights trained on ImageNet datasets, which allows it to effectively extract image characteristics thanks to its deep architecture.

3) ResNet50

ResNet50 stands for the inventive use of residual connections, this architecture addresses the missing gradient problem faced during the training of Deep Neural Networks. The architecture consists of fifty layers, in addition to the convolution, union, and fully connected layers. Its residual block is an important element of this architecture as the shortcut connection allows the gradient to follow the current more directly during training [16].

2.5 System Design

Figure 7 shows the framework used to implement this research.

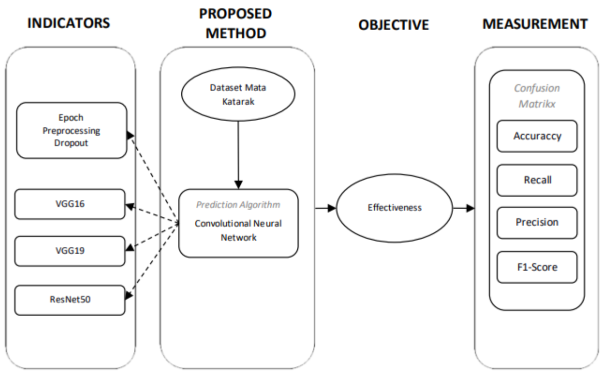

Figure 7 Framework

Based on **Figure 7**, in this study a Convolutional Neural Network (CNN) was used to classify cataracts based on a set of cataract eye images. With factors such as epochs, preprocessing, and dropouts affecting performance, the VGG16, VGG19, and ResNet50 models were tested. The main objective was to measure the effectiveness of the models. This was done using Confusion Matrix with metrics of accuracy, recall, precision, and F1-score.

1) Proposed Model Architecture

This study develops a model for detecting and classifying the severity of cataract disease by using images to distinguish between hypermature, mature, immature, and normal states. Convolutional Neural Networks (CNN) in this system enable the use of a pre-trained model to expedite training and enhance prediction accuracy through a transfer learning strategy. The authors of this study, however, changed the number of the last layer (the Fully Connected Layer). **Figure 8** shows an overview of the architecture employed in this investigation.

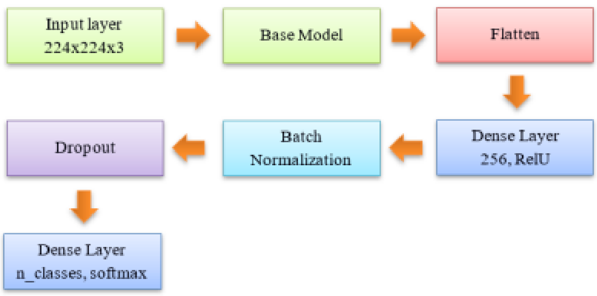

Figure 8 Modified model architecture

- **Input layer:** Accepts images with a resolution of 224 x 224 pixels and three color channels (RGB).
- **Base Model:** Base models such as VGG19, VGG16, and ResNet50 are used as feature extractors.
- **Flatten:** Transforms the extracted features from multidimensional to 1D vectors.
- **Dense layer (256, ReLU):** With 256 neurons, this layer is fully connected. To recover more intricate patterns, it features a ReLU activation function.
- **Batch Normalization:** Stabilizes the distribution of values in layers to speed up training and improve performance.

- **Dropout:** Applying a dropout rate of 0.5 indicates that 50% of the neuron units will be silenced at random.
- **Softmax Classifier:** An output layer with an output number of neurons equal to the number of classes (n_classes) and a softmax activation function for multi-class training.

2.6 Training Model

To avoid overfitting in improving models, techniques such as **early stopping** are used in training deep learning models. This technique prevents the model from being overtrained by stopping the training when the data performance no longer improves. In addition, **model checkpoints** automatically save the best model during training, so that the best performing model can be used without retraining. The implementation of **callback accuracy targets** is also used to manually stop training when the model has reached the set accuracy target.

2.7 Evaluasi Model

Used as a measure of how well the classification problem is solved. This matrix can be used for both binary and multiclass classification problems; they represent the actual and predicted total values. The number of negative examples that were really labeled as positive is indicated by the False Positive (FP) value, whereas the number of positive examples that were labeled as positive is indicated by the True Positive (TP) value. The number of negative cases that were truly correctly identified is shown by the True Negative (TN) output. The result for True Positives (FN) shows how many positive samples were truly correctly classified [17]. An overview of the confusion matrix is shown in **Figure 9**

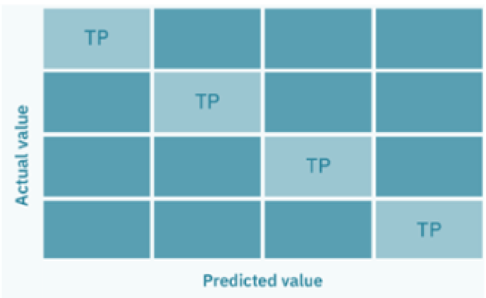

Figure 9 Confusion Matrix

This research assesses system performance based on F1 score, accuracy, recall, and precision. The calculation results of these performance measurements are shown in (1), (2), (3), and (4).

$$Accuracy = \frac{T_P+T_N}{T_P+T_N+F_P+F_N} \quad (1)$$

$$Precision = \frac{T_P}{T_P+F_P} \quad (2)$$

$$Recall = \frac{T_P}{T_P+T_N} \quad (3)$$

$$F1-Score = 2 \times \frac{recall \times precision}{recall \times precision} \quad (4)$$

3. Results and Discussion

3.1 Experiment Result A

In this study, hyperparameter adjustments were made to ensure that the model functions properly during training. These include batch size, learning rate, number of epochs, layers, and optimizer type shown in **Table 2**

Table 2 Hyperparameters experiment A

No.	Hyperparameters	
1	Batch Size	64
2	Layers	6
3	Epoch	10, 15, 25
4	Optimizer	Adam
5	Learning Rate	0.001

The model is trained using CNN architectures, namely VGG16, VGG19, and ResNet50 that have been modified at the last layer count (Fully Connected Layer) with Adam's optimizer using several different epoch counts, namely, 10, 15, and 25. A summary of the results of the performance parameters measured in this study including accuracy and loss of the proposed model at several epoch counts is shown in **Table 3**

Table 3 Training result of experiment A

Epoch	Arsitektur	Loss	Accuracy	Val_ loss	Val_ accuracy
10	VGG16	0.0247	0.9958	0.2614	0.9130
	VGG19	0.0176	0.9977	0.3274	0.8963
	ResNet50	0.6397	0.7374	1.8144	0.5033
15	VGG16	0.0056	1.0000	0.2354	0.9264
	VGG19	0.0143	0.9990	0.3218	0.8930
	ResNet50	0.4872	0.8169	0.9426	0.6505
25	VGG16	0.0361	0.9936	0.2287	0.9298
	VGG19	0.0377	0.9925	0.3211	0.8980
	ResNet50	0.3315	0.8721	1.8955	0.4950

The experimental results show that the VGG19 model with epoch 10 has the best performance, where the distance between the training loss value and the validation loss is small. This happens because the loss value of training and validation data has decreased significantly as shown in **Figure 10**

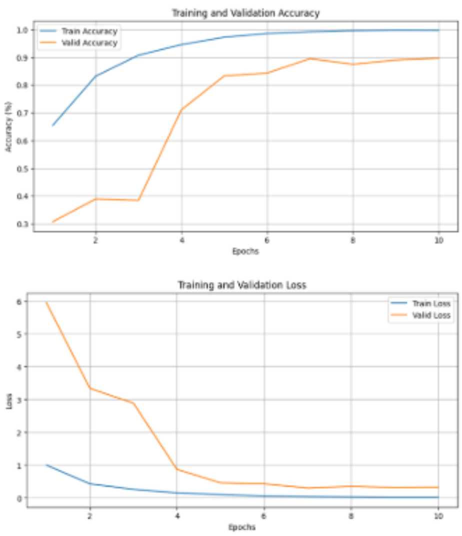

Figure 10 Graphics model VGG19 (epoch 10)

The VGG16 and ResNet50 models in each experiment showed symptoms of overfitting, with significant differences between the loss values of the training and validation data. This is due to the models overfitting the training data. Overall, only the VGG19 model with 10 epochs can achieve a balance of performance between training and validation data, other models show overfitting tendencies at various numbers of epochs including the VGG19 model at epochs 15 and 25.

Using confusion matrices like accuracy, precision, recall, or F1-score, the model's performance is assessed at the evaluation stage following training. The results of the model evaluation experiments are shown in **Figure 11**

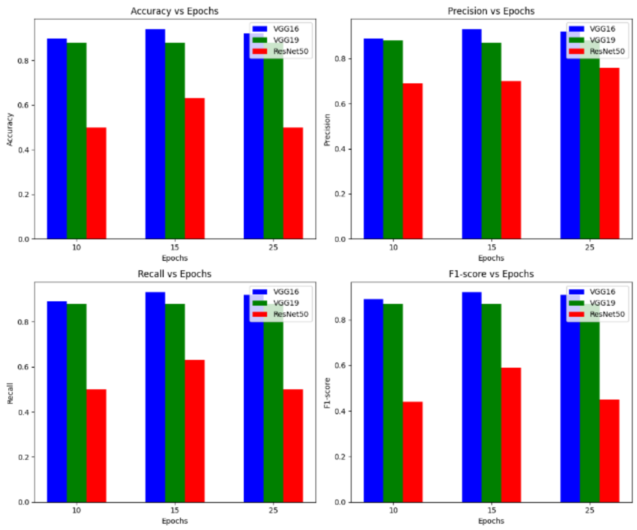

Figure 11 Evaluation result of experiment A

3.2 Experiment Result B

Table 5 shows another experiment with adjusted hyperparameters with reduced of some additional layers and epochs.

Table 4 Hyperparameters experiment B

No.	Hyperparameters	
1	Batch Size	64
2	Layers	3
3	Epoch	15
4	Optimizer	Adam
5	Learning Rate	0.001

In this research, model training experiments were also conducted using datasets without applying data preprocessing such as augmentation. In addition, this research only adds some layers to the fully connected layer, such as flatten and activation softmax classifier based on four classes. Additional layers such as dropout, batch normalisation, and dense layer with 256 neurons with ReLU activation were not used in this experiment. The following summarises the results of the training experiments for each model shown in **Figure 12**

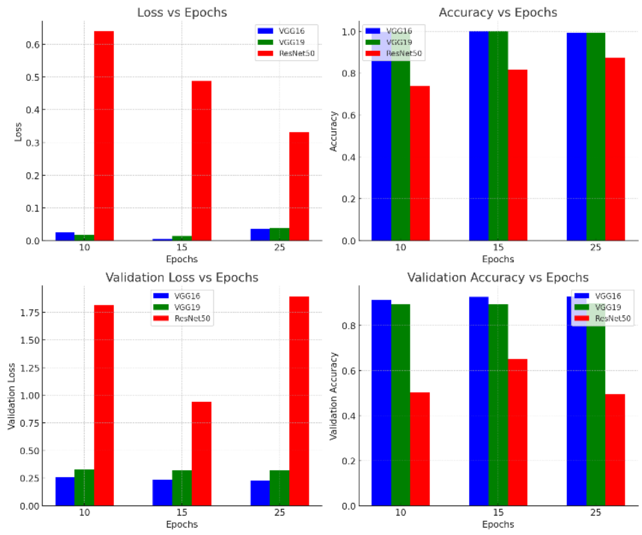

Figure 12 Training result of experiment B

Figure 12 shows that all three models experienced overfitting. VGG16 and VGG19 show better overfitting control than ResNet50. After the training is completed, the models are evaluated at the evaluation stage to measure their performance using confusion matrices such as accuracy, precision, recall, or F1 score.

The following summarizes the results of each model's evaluation experiment shown in **Figure 13**

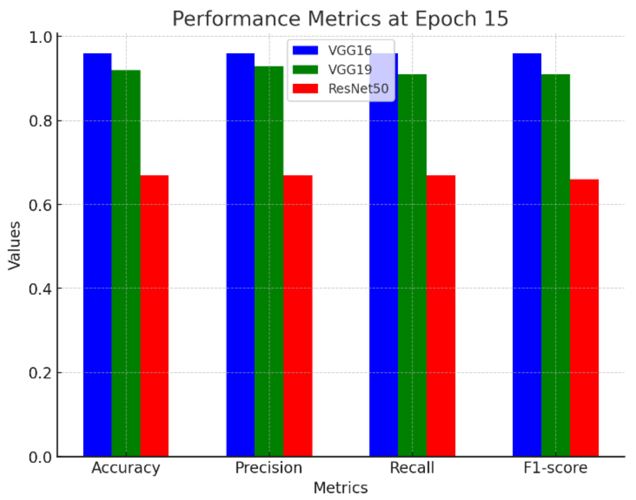

Figure 13 Evaluation result of experiment B

Figure 13 shows that in experiment B of the model evaluation task, the VGG16 and VGG19 models performed better than ResNet50. The maximum accuracy, 96%, was achieved by VGG16, with precision, recall, and F1-score values reaching 0.96 on the weighted average and macro. In addition, VGG19 with an accuracy rate of 92% and other metrics above 0.91. ResNet50 performed much worse, with only 67% accuracy and other metrics in the range of 0.66-0.67. Accordingly, ResNet50 is still far behind VGG16 and VGG19 for the datasets and tasks evaluated in experiment B.

3.3 Discussion

1) Experiment A

Experiment A aims to evaluate the performance of three deep learning architectures, namely VGG16, VGG19, and ResNet50, in classifying the dataset used. Based on the results obtained :

- VGG16 showed the highest accuracy in all experiments, with the highest accuracy of 94% at epoch 15. However, despite having the best performance, the model training results showed an overfitting pattern in each experiment. This is shown by the significant difference between the accuracy values in the training and validation data.
- The VGG19 architecture has a more stable performance than VGG16, with a constant accuracy of 88% across all trials. Interestingly, at epoch 10, the model shows a goodfit pattern compared to other epochs, which suggests that the model can achieve a balance between training and validation accuracy at a certain number of epochs.
- On the other hand, ResNet50 showed much worse performance than the other two models. The highest accuracy achieved was only 63% at epoch 15, and the model experienced fluctuations in performance at each epoch. This suggests that ResNet50 may not be suitable for this dataset or requires further hyperparameter tuning for better performance.

2) Experiment B

In experiment B all three models showed indications of overfitting, where training accuracy was very high, but validation accuracy tended to be lower. Based on the results obtained:

- VGG16 again showed the best performance with the highest accuracy of 96% in all trials. However, the overfitting pattern is still evident from the validation loss value which is still quite high compared to the training loss.
- The VGG19 architecture has an accuracy of 92%, showing stable performance, but still experiencing overfitting, although to a lesser extent than VGG16.
- ResNet50 was again the worst performing model in this experiment, with the highest accuracy of only 67%. The high validation loss value indicates that this model has difficulty in generalising to new data, which could be due to the higher complexity of the model compared to VGG16 and VGG19.

4. Conclusions

Detection and classification of cataract severity based on images using deep learning, one of which is the CNN method with experiments on VGG16, VGG19, and ResNet architectures that have been modified in the final layer. The results of experiment A show that the proposed VGG19 model with epoch 10 gives the best results in classifying the image dataset into each class with an accuracy of 88%, a loss value of 0.0176, and a precision value of 0.88, recall 0.88, f1-score 0.87. Meanwhile, experiment B showed that all three model experiments experienced overfitting, with the lowest accuracy on the ResNet50 architecture of 0.67.

In future research, it is important to explore the use of other CNN architectures such as DenseNet, MobileNet, EfficientNet, or other architectures. Furthermore, in addition to model development, it is also important to develop a tool to detect cataract severity. Such tools can be integrated with hardware such as cameras or smartphones to provide fast and effective diagnosis using the proposed model. In addition, research can concentrate on more advanced data processing. This could include improving data quality through more sophisticated augmentation methods or the use of larger and more varied datasets to increase the generalization capacity of the model.

Acknowledgments

I want to thank my supervisors for their crucial advice, tolerance, and support during the study process. Their knowledge and perceptive advice have been crucial in determining the course of this study and guaranteeing its effective conclusion.

I also want to thank my family and friends for their constant support, as well as my classmates and coworkers for their collaboration and support. Their encouragement and faith in my work have been a huge source of support. Lastly, I want to express my gratitude to everyone who helped me finish this research, whether directly or indirectly. I appreciate your encouragement and support.

References:

[1] Moh. Ichsan, “Edukasi Kesehatan Mata dan Deteksi Dini Gangguan Mata pada Santri di Pondok Pesantren,” Madago Community Empowerment for Health Journal, vol. 1, no. 2, pp. 32–39, Jul. 2022, doi: 10.33860/mce.v1i2.658.

[2] S. R. Flaxman et al., “Global causes of blindness and distance vision impairment 1990–2020: a systematic review and meta-analysis,” The Lancet Global Health, vol. 5, no. 12, pp. e1221–e1234, Dec. 2017, doi: 10.1016/S2214-109X(17)30393-5.

[3] D. A. Sari, Masriadi, and Arman, “Faktor Risiko Kejadian Katarak Pada Pasien Pria Usia 40-55 Tahun Dirumah Sakit Pertamina Balikpapan,” Jurnal Kesehatan, vol. 1, no. 2, 2018, doi: https://doi.org/10.33096/woh.v1i2.645.

[4] Kemenkes RI, “Katarak Penyebab Terbanyak Gangguan Penglihatan di Indonesia,” https://sehatnegeriku.kemkes.go.id/baca/umum/20211012/5738714/katarak-penyebab-terbanyak-gangguan-penglihatan-di-indonesia/.

[5] D. Tognetto et al., “Artificial intelligence applications and cataract management: A systematic review,” Survey of Ophthalmology, vol. 67, no. 3. Elsevier Inc., pp. 817–829, May 01, 2022. doi: 10.1016/j.survophthal.2021.09.004.

[6] Y. Y. Tan et al., “Prognostic potentials of AI in ophthalmology: systemic disease forecasting via retinal imaging,” Eye and Vision, vol. 11, no. 1. BioMed Central Ltd, Dec. 01, 2024. doi: 10.1186/s40662-024-00384-3.

[7] D. Marcella, Yohannes, and S. Devella, “Klasifikasi Penyakit Mata Menggunakan Convolutional Neural

Network Dengan Arsitektur VGG-19," vol. 3, no. 1, pp. 60–70, 2022, doi: https://doi.org/10.35957/algoritme.v3i1.3331.

[8] D. Gunawan and H. Setiawan, "Convolutional Neural Network dalam Analisis Citra Medis," 2022. doi: https://doi.org/10.24002/konstelasi.v2i2.5367.

[9] M. Elkholy and M. A. Marzouk, "Deep learning-based classification of eye diseases using Convolutional Neural Network for OCT images," Frontiers in Computer Science, vol. 5, Jan. 2024, doi: 10.3389/fcomp.2023.1252295.

[10] N. F. Cahya, N. Hardi, D. Riana, and S. Hadianti, "Klasifikasi Penyakit Mata Menggunakan Convolutional Neural Network (CNN)," SISTEMASI: Jurnal Sistem Informasi, vol. 10, 2021, doi: DOI:https://doi.org/10.32520/stmsi.v10i3.1248.

[11] J. KC, A. Acharya, K. Devkota, and S. Shrestha, "Deep Convolutional Neural Network and Transfer Learning to Classify Cataract Based on Fundus Images," vol. 3, no. 2, Jan. 2023, doi: https://dx.doi.org/10.30630/joiv.6.1.856.

[12] H. D. Firdaus, B. Imran, L. Darmawan Bakti, and E. Suryadi, "KLASIFIKASI PENYAKIT KATARAK PADA MATA MENGGUNAKAN METODE CONVOLUTIONAL NEURAL NETWORK (CNN) BERBASIS WEB," Jurnal Kecerdasan Buatan dan Teknologi Informasi (JKBTI), vol. 1, no. 3, pp. 18–26, Dec. 2022, doi: https://doi.org/10.69916/jkbti.v1i3.6.

[13] M. S. Qulub and S. Agustin, "INDENTIFIKASI PENYAKIT MATA DENGAN KLASIFIKASI CITRA FOTO FUNDUS MENGUNAKAN CONVOLUTIONAL NEURAL NETWORK (CNN)," Jurnal Mahasiswa Teknik Informatika, vol. 8, no. 5, Oct. 2024, doi: ttps://doi.org/10.36040/jati.v8i5.10974.

[14] J. Pardede and A. S. Purohita, "The Advantage of Transfer Learning with Pre-Trained Model in CNN Towards Ct-Scan Classification," vol. 9, no. 2, 2023, doi: https://doi.org/10.23917/khif.v9i2.19872.

[15] H. Yang, J. Ni, J. Gao, Z. Han, and T. Luan, "A novel method for peanut variety identification and classification by Improved VGG16," Scientific Reports, vol. 11, no. 1, Dec. 2021, doi: 10.1038/s41598-021-95240-y.

[16] K. B. Vardhan, M. Nidhish, S. Kiran C., D. Nahid Shameem, V. Sai Charan, and B. R.M., "Eye Disease Detection Using Deep Learning Models with Transfer Learning Techniques," ICST Transactions on Scalable Information Systems, vol. 11, Jul. 2024, doi: 10.4108/eetsis.5971.

[17] A. Kulkarni, D. Chong, and F. A. Batarseh, "Foundations of data imbalance and solutions for a data democracy," in Data Democracy: At the Nexus of Artificial Intelligence, Software Development, and Knowledge Engineering, Elsevier, 2020, pp. 83–106. doi: 10.1016/B978-0-12-818366-3.00005-8.