Classification of Pupil Turbidity Based On Convolutional Neural Network (CNN) As An Early Detection of Cataract Step Using A Smartphone

Dewi Mutiara Sari, Riyanto Sigit, Dias Agata, And Muhammad Firdaus Maulana

Department of Informatics and Computer Engineering Politeknik Elektronika Negeri Surabaya Indonesia
dewi.mutiara@pens.ac.id, riyanto@pens.ac.id
diasagata@pens.ac.id, firdaus452maulana@gmail.com

Abstract: Cataracts are the number one cause of blindness in the world as well as in Indonesia according to the World Health Organization (WHO). The high cases of cataracts in Indonesia are not matched by adequate health facilities. The cataract surgery rate in Indonesia is still below the ideal cataract surgery rate. Examination using a slit lamp is carried out by professionals and special equipment, so it is relatively expensive. Prevention of cataracts can be conducted by an early detection of cataracts. This study aims to detect cataracts at an early stage by using data on the classification of pupil turbidity (turbid and normal). There are two main steps in this study, the first is iris detection using a Single Shot Multibox Detector (SSD) and then followed by pupil turbidity classification using a Convolutional Neural Network (CNN) with the MobileNet architectural model. The accuracy achieved by the system in classifying pupil turbidity is 83.3% using a dataset of 160 images of normal and cataract eyes.

Keywords : Pupil Turbidity; Iris Detection; Object Detection; Early Detction of Catarct.

I. INTRODUCTION

Cataracts are the most common cause of blindness in the world [1,2,3]. In fact, there are more cataract cases worldwide than all other serious eye diseases such as glaucoma, macular degeneration, and diabetic retinopathy combined. Around 2,000 cases of blindness or 2 percent in Indonesia, around 50 percent are caused by cataracts. Recently, the blindness rate has increased to 3 percent and cataracts have increased to 81 percent [4]. In 2018, 1.5 percent per two million population are cataract sufferers and every year 240 thousand people are at risk of becoming blind [1]. M. Siddik, Chair of the Indonesian Ophthalmologist Association (PERDAMI), said that ideally the cataract surgery rate would be 80 percent. Meanwhile in Indonesia it has only reached 45 percent (liputan6.com, 2019). The number of health facilities in Indonesia did not meet the enormous cases of the national blindness. Early detection of cataracts is conventionally carried out using a Slit-Lamp by an ophthalmologist. Slit-Lamp is a medical device that is able to see the state of the eye with beam lighting. The examination continued with the doctor's analysis based on the image results from the Slit-Lamp examination. Insufficient numbers of doctors in an area compared to other regions also makes health service facilities inaccessible to everyone equally.

Cataracts can be detected in the pupil area when the eye is examined externally. If the cloudy area in the pupil of the eye is relatively small then the cataract is considered at an

M. U. H. Al Rasyid and M. R. Mufid (eds.), *Proceedings of the International Conference on Applied Science and Technology on Engineering Science 2023 (iCAST-ES 2023)*, Advances in Engineering Research 230,
https://doi.org/10.2991/978-94-6463-364-1_28

early stage, but if the cloudy area in the pupil nearly or fully covers the lens, then the cataract is considered at an advanced stage [2]. Blindness that occurs in people with cataracts occurs gradually without pain over a long period of time. The symptom which occurs without pain is that causes many sufferers to not realize that they already have cataracts, and some even think that they are just nearsighted or farsighted [5]. Cataracts have symptoms that vary according to the type of cataract experienced, including glare when looking at a light source, mild to severe pain, retinal bleeding [6]. There has been research conducted regarding cataract detection. Sigit R., et al, carried out a machine learning-based cataract classification but the input images were images from Slit-lamp and desktop-based examinations [1]. Then research for early detection of cataracts has also been carried out by Triyana, E., et al, using the Smartphone-based Single Layer Perceptron method but the input image was still using Slit-lamp images [7].

Based on this background, this research created a system for pupil turbidity based on Convolutional Neural Network (CNN) as an early detection of cataract using a Smartphone. The system diagram of this study is illustrated in Fig 1.

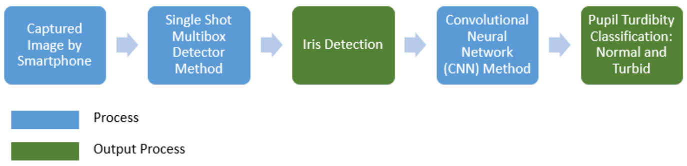

Captured Image by Smartphone
Single Shot Multibox Detector Method
Iris Detection
Convolutional Neural Network (CNN) Method
Pupil Turdibity Classification: Normal and Turbid
Process
Output Process

Fig 1. The Pipeline System of Pupil Turbidity Classification

II. METHOD

This section discussed into 2 parts: Iris detection by using Single Shot Multibox Detector (SSD) Method and pupil turbidity classification by using Convolutional Neural Network (CNN) Method.

A. *Iris Detection*

For iris detection, the method used in this research is Single Shot Multibox Detector (SSD). The architecture model of SSD is described in Fig 2.

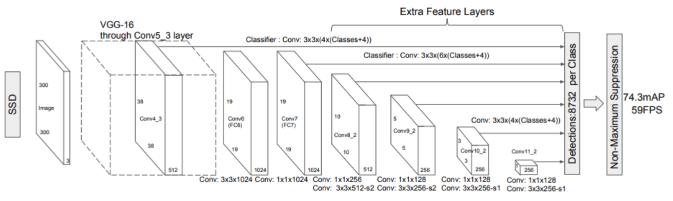

SSD
VGG-16 through Conv5_3 layer
Extra Feature Layers
Classifier : Conv: 3x3x(4x(Classes+4))
Classifier : Conv: 3x3x(6x(Classes+4))
Conv: 3x3x(4x(Classes+4))
Image
Conv4_3
Conv6 (FC6)
Conv7 (FC7)
Conv8_2
Conv9_2
Conv10_2
Conv11_2
Conv: 3x3x1024
Conv: 1x1x1024
Conv: 1x1x256 Conv: 3x3x512-s2
Conv: 1x1x128 Conv: 3x3x256-s2
Conv: 1x1x128 Conv: 3x3x256-s1
Conv: 1x1x128 Conv: 3x3x256-s1
Detections:8732 per Class
Non-Maximum Suppression
74.3mAP 59FPS

Fig 2. Architecture Model of Single Shot Multibox Detector (SSD) [9]

Based on Fig 2, the basic network used is VGG-16 with the input image size is 3000 x 300. There are some additional features that are embedded to the network, they are: aspect ratios and default boxes, convolutional predictors, and multi-scale feature maps. Both convolutional predictors and multi-scale feature maps are used for the detection. Then at the end of the architecture, there is a non-maximum suppression part as the last step of the final detection [8] [9]. In general, the process of iris detection is summarized in Fig 3.

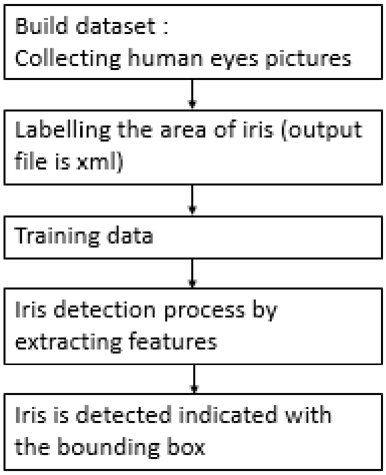

Build dataset :
Collecting human eyes pictures
Labelling the area of iris (output file is xml)
Training data
Iris detection process by extracting features
Iris is detected indicated with the bounding box

Fig 3. The Process of Iris Detection

The input for this process is streaming images from a smartphone camera to detect the iris area. This stage is carried out to ensure that the image taken is the iris of human's eye. The iris area detection process uses a Single Shot Multibox Detector (SSD) and MobileNet SSD as cross-trained model. Before doing the eye detection on a smartphone, the first step is to do data training to make a model of the SSD. This process begins with collecting images of the human eye to be used as a dataset. Fig 4 shows image samples suitable for dataset.

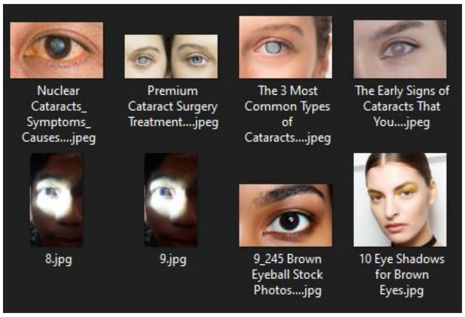

Nuclear Cataracts_ Symptoms_ Causes....jpeg
Premium Cataract Surgery Treatment....jpeg
The 3 Most Common Types of Cataracts....jpeg
The Early Signs of Cataracts That You....jpeg
8.jpg
9.jpg
9_245 Brown Eyeball Stock Photos....jpg
10 Eye Shadows for Brown Eyes.jpg

Fig 4. Sample of Eyes Dataset

The next step is to mark the iris area which will be used as training data and will generate an xml file. Fig. 5 shows the process of marking the iris area using labeling.

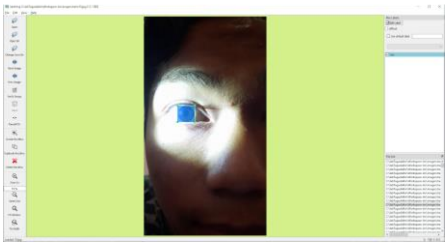
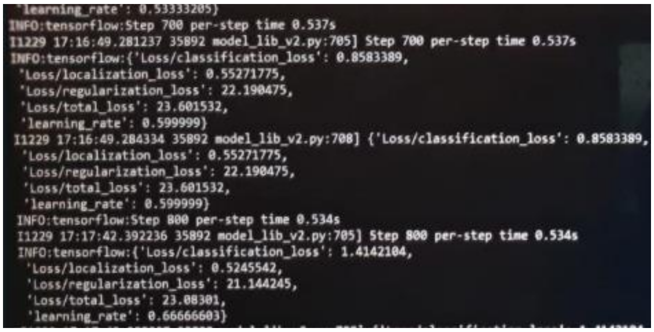


Fig 5. Labelling Process of Eye Area

The next step is data training using the pre-trained MobileNet SSD model as the basic model during data training. The training process is run through the command prompt (CMD) with commands according to the procedures in the training data program. The SSD model contains layers that apply the CNN method in recognizing images that enter the created model. Fig 6 shows an example of the data training process.



```
 'learning_rate': 0.53333205}
INFO:tensorflow:Step 700 per-step time 0.537s
I1229 17:16:49.281237 35892 model_lib_v2.py:705] Step 700 per-step time 0.537s
INFO:tensorflow:{'Loss/classification_loss': 0.8583389,
 'Loss/localization_loss': 0.55271775,
 'Loss/regularization_loss': 22.190475,
 'Loss/total_loss': 23.601532,
 'learning_rate': 0.599999}
I1229 17:16:49.284334 35892 model_lib_v2.py:708] {'Loss/classification_loss': 0.8583389,
 'Loss/localization_loss': 0.55271775,
 'Loss/regularization_loss': 22.190475,
 'Loss/total_loss': 23.601532,
 'learning_rate': 0.599999}
INFO:tensorflow:Step 800 per-step time 0.534s
I1229 17:17:42.392236 35892 model_lib_v2.py:705] Step 800 per-step time 0.534s
INFO:tensorflow:{'Loss/classification_loss': 1.4142104,
 'Loss/localization_loss': 0.5245542,
 'Loss/regularization_loss': 21.144245,
 'Loss/total_loss': 23.08301,
 'learning_rate': 0.66666603}
```

Fig 6. Data Training Process

The result of the xml file contains values in matrix form that can be used for direct eye area detection. Detection is carried out using a Single Shot Multibox Detector (SSD). The model that will be formed will have layers in which it is used to break down the features of the image. Fig. 7 is an experiment with the detection of the iris area on an Android smartphone.

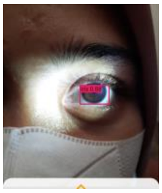


Fig 7. Eye Area Detection Using Android Smartphone

Fig 7 shows that after the system detects the eye area using the SSD model, the system will create a bounding box in the area around the eye. The bounding box will be used as cropping. Algorithm 3.3 is used to process images from the camera to get the eye area. The architecture of the detection model is presented in TABLE I. The figure displays several layers consisting of layers from the MobileNet model and in the last part there is an additional feature layer which is a part of the SSD layer.

TABLE I. ARCHITECTURE MODEL OF IRIS DETECTION

Type	**Filter Shape**	**Input Size**
Conv2D	32×3×3×3	1×300×300×3
DepthwiseConv2D	1×3×3×32 dw	1×150×150×32
Conv2D	64×1×1×32	1×150×150×32
DepthwiseConv2D	1×3×3×64 dw	1×150×150×64
Conv2D	128×1×1×64	1×75×75×64
DepthwiseConv2D	1×3×3×128 dw	1×75×75×128
Conv2D	128×1×1×128	1×75×75×128
DepthwiseConv2D	1×3×3×128 dw	1×75×75×128
Conv2D	256×1×1×128	1×38×38×128
DepthwiseConv2D	1×3×3×256 dw	1×38×38×256
Conv2D	256×1×1×256	1×38×38×256
DepthwiseConv2D	1×3×3×256 dw	1×38×38×256
Conv2D	512×1×1×256	1×19×19×256
5x Conv2DDepthwiseConv2D	1×3×3×512 dw 512×1×1×512	1×19×19×512
DepthwiseConv2D	1×3×3×512	1×19×19×512
Conv2D	1024×1×1×512	1×10×10×512
DepthwiseConv2D	1×3×3×1024	1×10×10×1024
Conv2D	1024×1×1×1024	1×10×10×1024
Conv2D	256×1×1×1024	1×10×10×1024
Conv2D	512×3×3×256	1×10×10×256
Conv2D	128×1×1×512	1×5×5×512
Conv2D	256×3×3×128	1×5×5×128
Conv2D	128×1×1×256	1×3×3×256
Conv2D	256×3×3×128	1×3×3×128
Conv2D	64×1×1×256	1×2×2×256
Conv2D	128×3×3×64	1×2×2×64

TABLE I displays the type column which contains the type of CNN layer used in the model, and the filter shape column contains the filter used to break down feature extraction on the layer. And the input size column is the size of the image that entered the layer after processing from the previous layer. In the blue table, an additional feature layer is used to classify and provides an offset relative to the original default box shape, the score of the class.

B. *Pupil Turbidity Classification*

Classification was performed with a Convolutional Neural Network on the extracted iris images. In the medical field, cataracts can be distinguished physically by looking at the opacity in the pupils of the eyes. Fig 8 shows the difference between turbid and normal pupil.

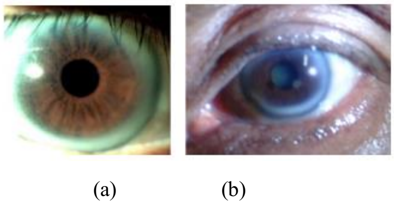


Fig 8. (a) Normal Pupil (b) Turbid Pupil

Convolutional Neural Network (CNN) is a type of neural network commonly used in image data. CNN can be used to detect and recognize objects in an image. CNN is a technique inspired by the way humans generate visual perception. Broadly speaking, a Convolutional Neural Network (CNN) is not much different from a normal neural network. CNN consists of neurons that have weights, biases and activation functions. The convolutional layer also consists of neurons arranged in such a way as to form a filter with length and height (pixels). CNN takes advantage of the convolution process by moving a convolution kernel (filter) of a certain size to an image, the computer gets new representative information from the multiplication of the part of the image with the filter used. The architecture of CNN is divided into 2 major parts, the Feature Extraction Layer and the Fully-Connected Layer (MLP). An architectural illustration from CNN is shown in Fig 9.

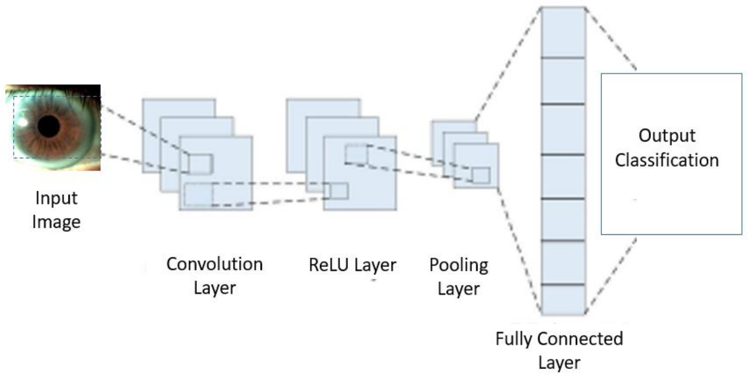
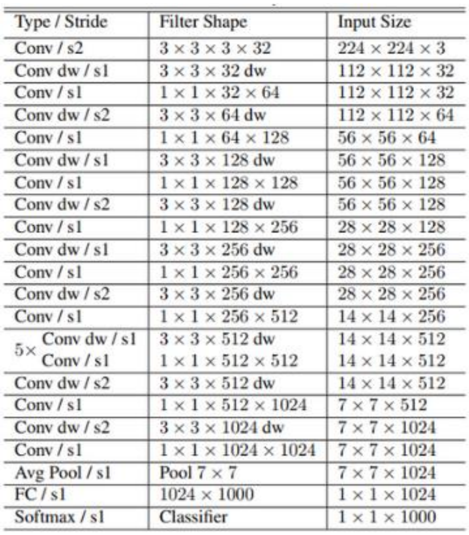


Fig 9. Architecture of CNN

Every layer has an input *i* which has width (*x*), height (*x*), and depth (*z*). Kernel Filers presents in each layer are notated as *Kr*, has dimensions width (*u*), height (*u*), and depth (*w*). Remember that the dimension input layer should be bigger than the dimension of Kernel Filters. The local connection is based on the kernels sharing the similar parameters (weight *WKr* and bias *BKr*) to generate the feature maps *hKr*. The size of the *hKr* is *x - u - 1*. The formulation of feature maps is described as Eq. 1,

$$hKr = f(WKr * i + BKr) \quad (1)$$

Then the next step is reducing network parameters. It happens in the Pooling Layer. Each feature map conducts a down-sampling or sub-sampling process. So, it turns to the smaller feature maps. Then the Fully Connected Layer represents the CNN classifier. Every neuron inside the layer is connected to all neurons in the prior layer. The method applied here is feed-forward ANN type. In the CNN, model architecture is the important thing to be considered as it impacts the performance in the various implementations. In this case, because the device that will be used is a smartphone, the chosen model is MobileNet. Mobileet uses depth wise separable convolutions, it turns the light neuron. The architecture model of MobileNet is illustrated in Fig 10.



Type / Stride	Filter Shape	Input Size
Conv / s2	3 × 3 × 3 × 32	224 × 224 × 3
Conv dw / s1	3 × 3 × 32 dw	112 × 112 × 32
Conv / s1	1 × 1 × 32 × 64	112 × 112 × 32
Conv dw / s2	3 × 3 × 64 dw	112 × 112 × 64
Conv / s1	1 × 1 × 64 × 128	56 × 56 × 64
Conv dw / s1	3 × 3 × 128 dw	56 × 56 × 128
Conv / s1	1 × 1 × 128 × 128	56 × 56 × 128
Conv dw / s2	3 × 3 × 128 dw	56 × 56 × 128
Conv / s1	1 × 1 × 128 × 256	28 × 28 × 128
Conv dw / s1	3 × 3 × 256 dw	28 × 28 × 256
Conv / s1	1 × 1 × 256 × 256	28 × 28 × 256
Conv dw / s2	3 × 3 × 256 dw	28 × 28 × 256
Conv / s1	1 × 1 × 256 × 512	14 × 14 × 256
5× Conv dw / s1	3 × 3 × 512 dw	14 × 14 × 512
5× Conv / s1	1 × 1 × 512 × 512	14 × 14 × 512
Conv dw / s2	3 × 3 × 512 dw	14 × 14 × 512
Conv / s1	1 × 1 × 512 × 1024	7 × 7 × 512
Conv dw / s2	3 × 3 × 1024 dw	7 × 7 × 1024
Conv / s1	1 × 1 × 1024 × 1024	7 × 7 × 1024
Avg Pool / s1	Pool 7 × 7	7 × 7 × 1024
FC / s1	1024 × 1000	1 × 1 × 1024
Softmax / s1	Classifier	1 × 1 × 1000

Fig 10. Architecture Model of MobileNet

The special feature of the MobileNet architectural model compared to other architectural models is dividing the convolution into 3x3 depth-wise conv and 1x1 pointwise conv, as shown in Fig. 11.

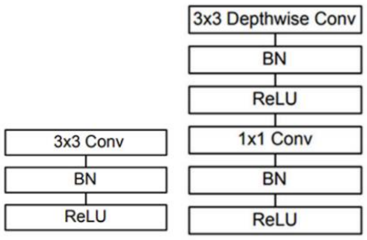


Fig 11. (a) *Standard Convolutional Layer* (b) *Depth-Wise Separable Convolution*

In training the MobileNet model for classification, this study used 160 images of normal and cloudy eyes (cataracts). The model gains about 95% accuracy and loses about 10%.

The system classifies the image obtained from the iris detection that has been cropped. Fig. 12 shows an experiment on classifying pupillary opacities with iris image input at the iris detection stage.

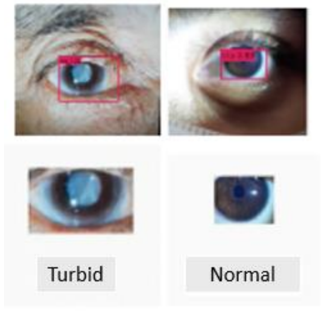


Fig 12. Classification of Pupil Turbidity a) Turbid Pupil b) Normal Pupil

The sample training data for cloudy pupils and normal pupils in this study are shown in TABLE II.

TABLE II. Sample of Data Training

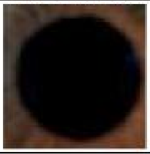
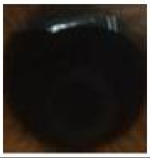
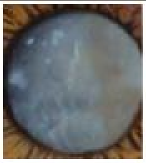
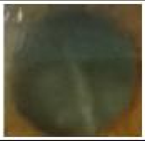
No.	Training Images	Condition
1		Normal
2		Normal
3		Turbid
4		Turbid

TABLE II shows the difference between normal eyes and cataract eyes in the pupil color of the eye. In normal eyes the pupil color tends to be black (darker), whereas in cataract eyes the pupil color tends to be white (lighter). Because in cataract eyes, there is cloudiness in the pupil of the eye that partially or completely covers the entire lens of the eye [3].

III. Result And Discussion

There are three main parts that will be discussed in this section: Accessing Smartphone Camera, Iris Detection, and Pupil Turbidity Classification. In addition, the experimental setup of this research is illustrated in Fig 13.

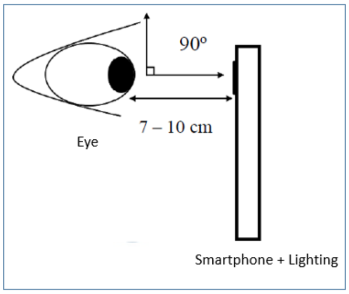


Fig 13. Experimental Setup Illustration

Based on Fig 13, the optimal distance between the camera and the eye is 7 - 10 cm with the perpendicular angle. Meanwhile for the lighting, it is conducted in the indoor room with the external lighting (not the flash of a smartphone) about 2 - 19 Lux with no shadow or reflection of the lighting. The resolution of the camera used in this research is 13 MP. Meanwhile, the detail specification of the PC device used is described in TABLE III.

TABLE III. Specification of PC

No.	Description	Specification
1	Processor	Intel(R) Core(TM) i7-7700HQ CPU @ 2.80GHz (8 CPUs), ~2.8GHz
2	Graphic	NVIDIA GeForce GTX 1050
3	RAM	16384 MB
4	Operating System	Windows 10 Home Single Language 64-bit (10.0, Build 19043)
5	Software Build	Android Studio
6	Library	OpenCV 3.4.13, TensorFlow 1.15, TFLite, Android SDK

The specification of smartphone used in this research is described in TABLE IV.

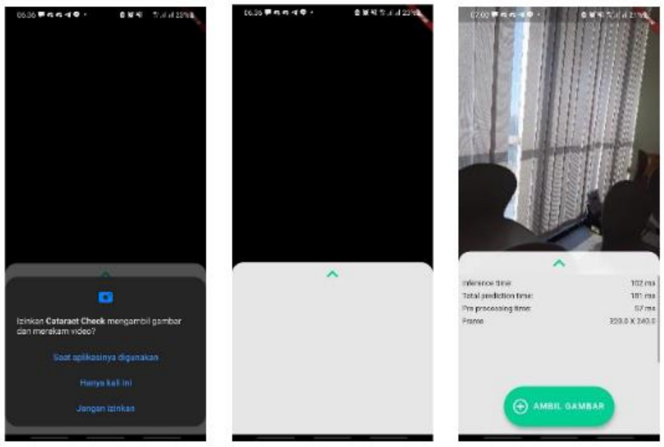
TABLE IV. Specification of Smartphone

No.	Description	Specification
1	Processor	Octa-core (4x2.3 GHz Cortex-A73 & 4x1.7 GHz Cortex-A53)

2	RAM	6.00 GB
3	Sistem Operasi	Android 11, One UI 3.1
4	Resolusi Kamera	48 MP, f/2.0, 26mm (wide), 1/2.0", 0.8µm, PDAF

A. Accessing Smartphone Camera

The System testing is carried out by running the program on an Android smartphone to check whether the application is granting permission to access the Android smartphone camera and getting real-time images from the smartphone camera. An illustration of camera access on a smartphone is shown in Fig 14.


Izinkan **Cataract Check** mengambil gambar dan merekam video?

Inference time: 102 ms
Total prediction time: 181 ms
Pre processing time: 57 ms
Frame 320.0 X 240.0

(a) (b) (c)

Fig 14. (a) Application Asking for Accessing Smartphone Camera (b) Accessing Smartphone Camera is Rejected (c) Accessing Smartphone Camera is Accepted

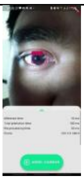
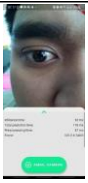
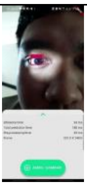
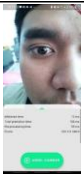
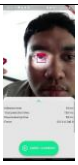
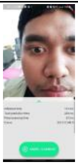
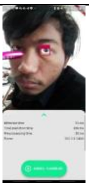
Fig 14 (a) shows an application requesting for camera access from a smartphone. If the user rejects the application's request to access the android smartphone camera, the application will not be able to get images from the camera, shown in Fig 14 (b). Fig 14 (c) shows an application given access to use the smartphone camera and obtain images via the smartphone camera.

B. Iris Detection

This test was carried out by trying the results of training data in the form of the MobileNet SSD model which has been converted to a lite model to be able to run on Android smartphones. The iris detection stage is used to detect the eye area in images taken from Android smartphone cameras. Iris detection testing was carried out using a distance of 5, 7, 10, and 15 cm with additional light and without additional light. The test was also carried out on Android directly. The results of iris testing are summarized in TABLE V.

TABLE V. IRIS DETECTION RESULT

Identify applicable sponsor/s here. If no sponsors, delete this text box (*sponsors).*

No.	Distance	External Lighting	Iris Detection Result
1	5 cm	Yes	 Detected
		No	 Not Detected
2	7 cm	Yes	 Detected
		No	 Not Detected
3	10 cm	Yes	 Detected
		No	 Not Detected
4	15 cm	Yes	 Detected

		No	Not Detected

Based on the iris detection experiment in TABLE V, it is concluded that the system can detect the iris if there is external lighting.

C. Pupil Turbidity Classification

This test was carried out by trying the results of training data in the form of a classification model using Mobilenet which has been converted to a lite model to run on an Android smartphone. The classification stage is used to classify images of the iris area that have been cropped at the iris detection stage. TABLE VI shows the Confussion Matrix which was made by testing 12 normal and cloudy eye images from the testing data. After going through a training process with a total data of around 160 images of normal eyes and cataract eyes, it produces a CNN model with a base model using MobileNet to lighten the model when running on an Android smartphone. Fig 15 shows a graph of loss and accuracy during training.

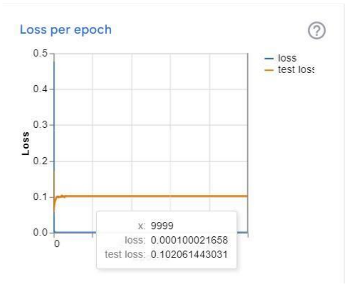


Fig 15. Loss Graph of Training Mode

Based on Fig 15, the graph shows a stable value in 0.1 with the beginning epoch is unstable. Table

TABLE VI. CONFUSION MATRIX

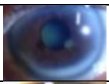
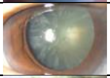
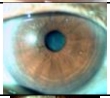
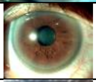
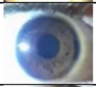
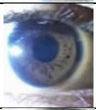
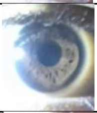
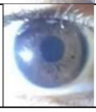
		Aktual	
		Normal	**Turbid**
Prediksi	**Normal**	9	3
	Turbid	1	11

Based on TABLE VI, the system can correctly classify 12 images of normal eyes and 11 images of cloudy or cataract eyes. Table 4.6 shows that the True Positive (TP) values are 9 which in the table above is a Normal eye prediction system and these predictions are correct. Furthermore, the True Negative (TN) value is 11 data, which is a system that predicts cloudy eyes and the prediction is correct. The False Positive (FP) value is 3, and the False Negative (FN) value is 1. These two values are the opposite of the TP and TN values. By identifying these four values, it is possible to calculate the accuracy value of the image classification model of normal eyes and cloudy eyes. Using a total of 24 tested data can be calculated with Eq. (2).

$$\begin{aligned} \text{Accuracy} &= (TP+TN) / (TP+FP+FN+TN) \quad (2) \\ &= (9+11) / (9+3+1+11) \\ &= 0833 \\ &= 0.833*100\%=83.3\% \end{aligned}$$

From the calculation of Eq.2, it is clear that the model has an accuracy of 83.3%. The results of the pupil turbidity classification test using data testing are summarized in TABLE VII.

TABLE VII. RESULT OF PUPIL TURBIDITY CLASSIFICATION

No.	Input Picture	*Confidence Value*	Classification Result	Actual Condition
1		63.15%	Turbid	Turbid
2		99.99%	Turbid	Turbid
3		99.95%	Turbid	Turbid
4		84.54%	Normal	Turbid
5		97.53%	Normal	Normal
6		80.98%	Turbid	Normal
7		72.00%	Normal	Normal
8		64.76%	Normal	Normal

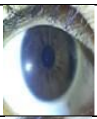
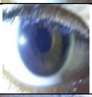
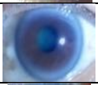
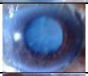
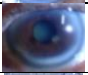
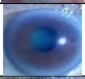
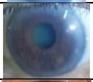
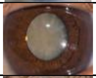
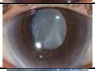
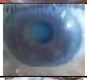
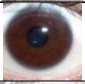
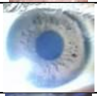
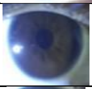
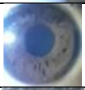
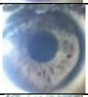
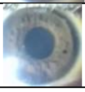
9		90.47%	Normal	Normal
10		72.27%	Turbid	Normal
11		76.21%	Turbid	Turbid
12		99.97%	Turbid	Turbid
13		90.39%	Turbid	Turbid
14		90.59%	Turbid	Turbid
15		89.72%	Turbid	Turbid
16		99.88%	Turbid	Turbid
17		99.92%	Turbid	Turbid
18		95.31%	Turbid	Turbid
19		97.23%	Normal	Normal
20		90.18%	Normal	Normal
21		86.36%	Normal	Normal
22		68.66%	Turbid	Normal
23		99.45%	Normal	Normal
24		95.20%	Normal	Normal

TABLE VII is the result of classification testing using data testing. TABLE VII displays that there is a Confidence Value column which is a value that is influenced by the many variations and similarities of the class types classified. The higher the confidence value, the closer the image similarity to a class.

IV. Conclussion

Based on the results of testing and analysis that has been done, it can be concluded that the process of detecting cataracts is done by detecting the iris area first. The iris area detection process was using Single Shot Multibox Detection (SSD) and MobileNet SSD as a cross-trained model. Early classification of cataracts through the classification of pupillary opacities is carried out by using the Convolutional Neural Network (CNN) method. The system can detect cataracts from a distance of 5 to 15 cm using external lighting with a classification accuracy of 83.3%. For future work, the system will be add the expert system algorithm such that it can classify the type of cataract.

V. Acknowledgment

Thanks to Penelitian Lokal PENS for giving the funding to this research.

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