

Machine vs Deep Learning Algorithm Development for Cataract Detection Image Recognition

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Cite this paper as: Hera Dwi Novita, Samsul Arifin, Yuita Arum Sari, Sri Andarini, Seskoati Prayitnaningsih, Wayan Firdaus Mahmudy (2024) Machine vs Deep Learning Algorithm Development for Cataract Detection Image Recognition. *Frontiers in Health Informatics*, 13 (3), 2072-2084

ABSTRACT

Cataracts involving the eye's lens becoming cloudy are among the primary reasons for blindness in Indonesia and globally. The estimated annual cataract incidence is 0.1%, meaning one new cataract patient emerges every year among 1000 individuals. Indonesians tend to develop cataracts 15 years earlier than individuals in subtropical regions. In line with WHO recommendations in the IPCEC guidelines, empowering communities through promotive, preventive, curative, and rehabilitative efforts is crucial. This research aims to develop integrated AI-based cataract detection using GLCM (Gray Level Co-Occurrence Matrix) extraction methods with two machine learning algorithms, KNN (K-Nearest Neighbour) and SVM (Support Vector Machine), compared to the deep learning algorithm, CNN (Convolutional Neural Network), for image recognition. A non-implemented study design was employed to develop an AI system for cataract detection, utilizing 1,159 eye photos captured with smartphones and slit lamps. CNN achieved higher accuracy (95.31%) than SVM (81.39%) or KNN (85.34%), as well as higher sensitivity (96.15%) than SVM (84%) or KNN (94%). Among the machine learning models (SVM and KNN) and deep learning (CNN) in this study, the CNN algorithm produced the best results, with a performance score of specificity (95%), PPV (83%), and NPV (99%). We can utilize this cataract screening detection method to identify more cataract cases, thereby boosting the number of cataract surgical procedures.

Keywords: artificial intelligence, cataract, deep learning, image recognition, machine learning.

INTRODUCTION

In line with the Alma-Ata Declaration's vision of Health for All, by 2000, the World Health Organization (WHO) implemented the Risk Approach Strategy, highlighting that every community, family, and individual carries unique vulnerabilities to illness, accidents, or sudden death. Preventive healthcare can quantify and utilise some risks.[1] In 2019, an estimated 2.2 billion individuals worldwide experienced visual impairment and blindness, with over 65.2 million people globally afflicted with cataracts.[2] The prevalence of blindness

in the Indonesian population reached 0.4%. Regarding age-specific blindness rates in Indonesia, the highest incidence occurs in the 75-year-old and older age groups (8.4%), followed by 3.5% in the 65-74 age group and 1.1% in the 55-64 age group.[3]

In line with WHO recommendations in the IPCEC guidelines, empowering communities through promotional, preventive, curative, and rehabilitative efforts is crucial.[4] As technology has improved, especially artificial intelligence (AI), many studies have investigated how it can be used, especially in deep learning (DL), to help find eye diseases like diabetic retinopathy, glaucoma, AMD, and cataracts through digital fundus photography.[5,6] These studies have shown that DL is an effective and accurate way to do this. Some research efforts have successfully utilised smartphones combined with AI to aid clinicians in cataract detection and classification, with accuracies surpassing 90%.[7] Given the ongoing digital transformation and the high smartphone usage rate in Indonesia, with approximately 353.8 million smartphone users, there is a significant opportunity to develop integrated cataract screening tools. These tools could leverage smartphones and incorporate machine learning models for accurate cataract detection through image recognition.[8]

Despite numerous studies on cataract detection, no research has developed or compared three machine-learning algorithms for cataract detection. We anticipate that comprehending this cataract detection tool will forecast the likelihood of cataract occurrence in individuals in the future. This will facilitate preventive interventions, encourage individuals to adopt primary and secondary preventive measures, modify health behaviours to impede the formation or progression of cataracts, and ultimately, prevent and hinder the progression of cataracts, potentially improving the quality of life. Furthermore, we can use it to map high-risk cataract cases and hotspots, improve the identification of cataract cases in various regions, and advocate for stakeholders to develop cataract prevention programs.

OBJECTIVES

This study aims to develop and compare two machine learning algorithms (SVM and KNN) and one deep learning algorithm (CNN) for cataract detection to create a diagnostic tool that forecasts the likelihood of cataract occurrence.

METHODS

1. Datasets

From January to April 2023, we conducted data research in Mendalanwangi Village, Sidorahayu, Cepokomulyo, Malang, and De Heus in Pasuruan. The population consisted of smart health biomarkers research participants who had undergone an initial examination. Participants are men and women over 40 years old. Inclusion criteria for cases were males or females aged >40 years, residing in Sidorahayu, Mendalanwangi, and Cepokomulyo villages for a minimum of 6 months, diagnosed with cataracts based on LOCS III, willing to participate in the study, and providing informed consent. Exclusion criteria were cases that did not complete all required examinations. Subjects must have a sample size of at least 225 individuals. The researcher adds 10% to anticipate a dropout, so the total sample targeted is 248 individuals. The final sample includes a total of 244 completed responses.

2. Machine Learning Algorithm and Deep Learning Algorithm

Several different AI-based methods have been used in the past to find cataracts. These include k-means nearest neighbour (kNN) classification[7], support vector machine (SVM)[9], single layer perceptron (SLP)[10], and convolutional neural network (CNN).[11] Each method presents its advantages and limitations; for instance, SLP's inflexibility in decision boundary creation, CNN's computational time, memory issues, the requirement of extensive training data, and SVM's high-dimensional data handling. The GLCM method, a texture descriptor approach, offers excellent texture description with improved accuracy and computational time. The KNN classification method exhibits the advantages of quick and straightforward algorithms, accurate classification, and effectiveness for small-scale datasets. In this study, we compared classification algorithms to develop the finest model for the early detection of cataracts using three algorithms: KNN, SVM, and CNN.

3. Model Learning

We trained the three algorithms to create the best model for cataract detection. Each classification algorithm has hyperparameters, which, when adjusted, show very different performances. Therefore, finding the optimal hyperparameter combination is necessary. To confirm the model's ability to generalize, we split the data into training data (80%), test data (10%), and validation data (10%).[11] The model was trained using training data, test data were utilized to assess the actual classification effectiveness of the model once trained, and validation data were used to determine whether the data could be well generalised. Figure 1 illustrates the model learning process.

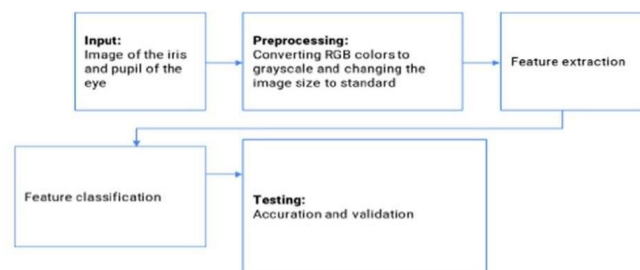


Figure 1. Model Learning for Cataract Detection

A digital matrix represents the image of the iris and pupil of the eye as the input data.[12] The dataset consists of 106 images of normal eyes and 138 images of cataract eyes with different shapes and positions captured by a smartphone camera. We label the images of normal eyes as a non-cataract class and those of cataract eyes as a cataract class. The images must be reprocessed to improve the accuracy of image classification.[13] Each image of the research subjects underwent a resizing process to ensure the size was uniform. The resized images feature a square format, with a width-to-height ratio of 1:1, and have dimensions of 64 x 64 pixels. We also convert the colour from RGB into greyscale to simplify the images and reduce memory space.

Next, we extract features using GLCM, a widely used texture analysis. The results obtained from the co-occurrence matrix are better than those of other texture discrimination methods. GLCM calculates statistical features based on the grey level of the image.[14] GLCM considers an image's intensity, greyscale values, or colour dimensions to evaluate its texture. Since these matrices are typically expansive and not densely filled, it is common to extract different measures from the matrix to derive a set of features that are more practical for use.

This study proposes three feature classification methods for cataract detection, particularly in image recognition:

k-means clustering, k-nearest neighbors (KNN), support vector machine (SVM), and deep learning using convolutional neural networks (CNN).[15] The purpose is to assess how well each approach identifies whether an image belongs to the cataract or non-cataract classes. The final process is testing the classification model's performance based on the accuracy level results.[16] The model recognizes the classification labels of images it has never encountered.

4. Model Validation

We evaluated and compared the classification models using the following metrics: accuracy, specificity, sensitivity, negative predictive value (NPV), and positive predictive value (PPV). We obtain the confusion matrix using true positive (TP), true negative (TN), false positive (FP), and false negative (FN). Görtler et al. (2022) utilise the confusion matrix, a compact chart, to evaluate a model's performance by analysing information on true and predicted values.[17]

Subsequently, the test data will be predicted to assess how well the methods employed classify cataracts. Additional parameters to be analyzed include the maximum false positive rate (f) and the minimum detection rate (d). Once optimal values for these parameters are obtained, testing will be conducted using K-Fold Cross Validation with the best values of f and d . A common approach for calculating accuracy is to create a confusion matrix, which illustrates the comparison between predicted results and actual classifications. In literature, the most used values of k are five (5) or ten (10), as these two values are believed to give test error rate estimates that suffer neither from extremely high bias nor very high variance. We used k -5 folds in this study.[18]

5. Model Implementation

We then implement the best machine learning model into web-based applications accessible from any device and operating system, thereby simplifying accessibility for everyone. In the earlier stages of model development, ensuring that the model performs well in cataract identification, remains efficient, and requires minimal computational resources to run on the web is crucial.

RESULTS

1. Image Datasets

Figure 2 displays the results of uniformizing image sizes. The number of images used for training data labelled as cataracts was 111, while non-cataract-labelled images were 85. We use the remaining images for the validation and testing data. The images' features are then extracted by forming a co-occurrence matrix from each image. Then, this matrix will calculate the GLCM extraction features, namely contrast, correlation, energy, and homogeneity, with each angle used at 0° , 45° , 90° , and 135° .



Figure 2. Sample of Eyes Dataset (64x64 pixel)

2. KNN

This study's experiment used a mixed dataset of 1159 photos from slit-lamp photos and smartphone cameras of cataracts and normal eyes. Here are the results of a cataract classification experiment using the KNN algorithm. In the pre-processing stage, photo cropping is carried out to center on the pupil, scaling the previous stage's results to a 1:1 scale, loading the image with RGB color, and resizing the image to 150x150 pixels.

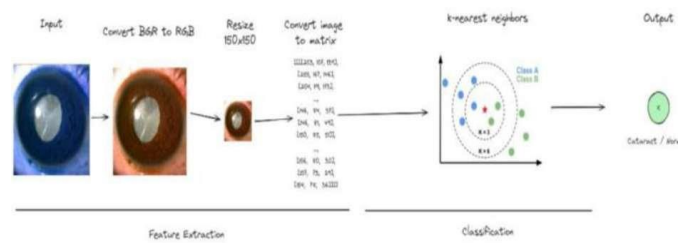


Figure 3. Flowchart of the k-Nearest Neighbors (kNN) algorithm based on image data for cataract detection.

3. SVM

This study conducted an experiment using 975 photos from slit-lamp cameras and 253 photos from smartphone cameras. Two ophthalmologists examined the photo data using the double blindness method and then processed the eye photos for assessment using GLCM data extraction and SVM classification. The training data included up to 80% of the samples, while 20% served as test data (Figure 4).

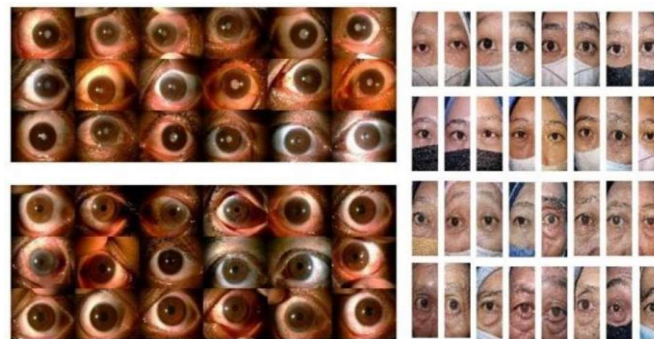


Figure 4. Results of the group's eye photos with a slit-lamp camera (left) and a smartphone (right).

We manually crop the photo sample to extract only the iris and pupil, then input the cropped photo into the system to extract 1/3 of the original photo. Next, we resize the photo to maintain its 512-pixel size, then apply a median blur to eliminate noise, resulting in a smoother and cleaner image. Next, we convert the photo into a greyscale format, proceed with a segmentation process to create a monochromatic image that identifies the cloudiness of the lens, and then modify the image format to a black ratio, ensuring the model interprets only black and white with a ratio of one. The final step in the photo processing process involves augmenting the data train with flips, random rotations, and transposes to balance the distribution of normal photo samples and cataract photos (Figure 5).

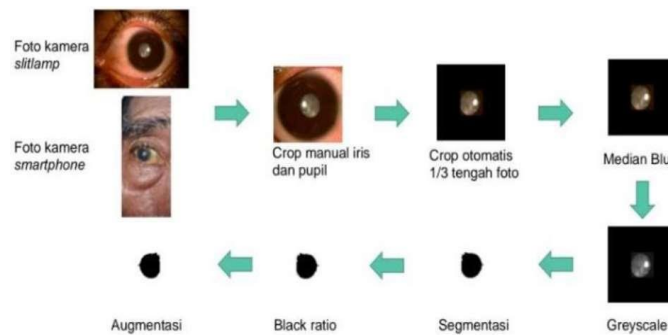


Figure 5. Pre-processing of sample eye photos

4. CNN

This study experimented with a mixed dataset of slit lamp photos and mobile phones in cataracts and normal eyes, totaling 1159 photos. Here are the results of a cataract classification experiment using the CNN algorithm:

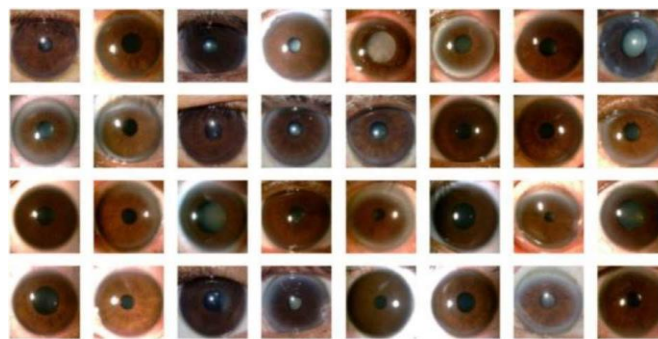


Figure 6. Pre-processing results with scaling, resizing, and cropping 1:1 (manual)

The procedure separates the input of image data, extracts features by pooling data using convolution and ReLu, and creates a flattened layer for layer-by-layer classification. It eliminates unrelated data until it yields either cataract or non-cataract outcomes.

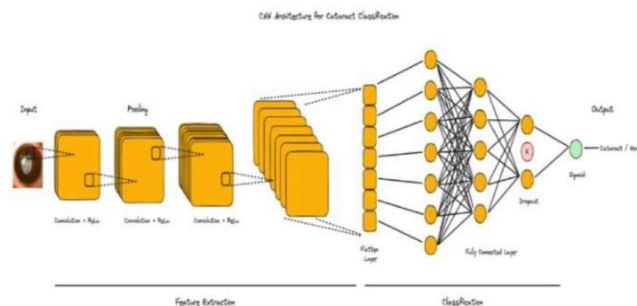


Figure 7. Cataract Classification Architectural Process with CNN.

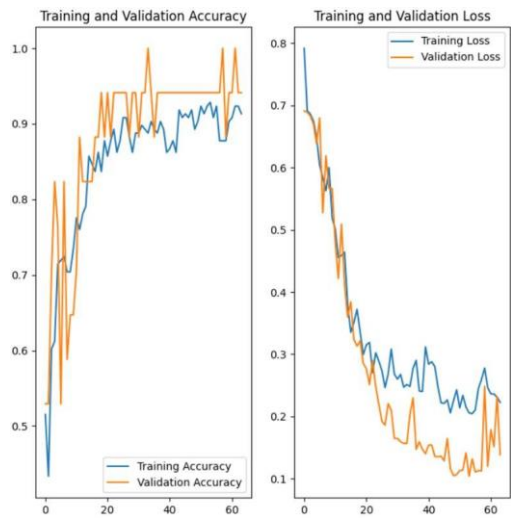


Figure 8. Comparison of CNN Model Performance.

5. Performance Metrics

The model must classify unseen images and evaluate their performance. This study compares the model's assigned labels to the actual labels. Results indicate that the CNN model outperforms the KNN and SVM models across various metrics, including accuracy, sensitivity, and likelihood ratios, as illustrated in Figure 9 and Table 1.

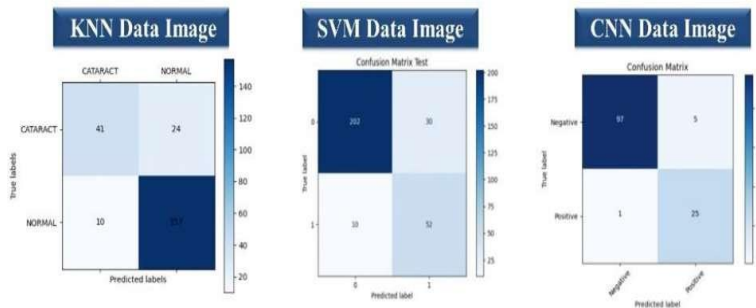


Figure 9. Analysis results of the training and testing data with an 80:20 ratio (80% training; 20% testing) between the KNN, SVM, and CNN groups.

Table 1. Comparison of Image Data Accuracy Values Using 5-Fold Cross Validation

Algoritma (80:20)	Sensi- tivity	Specificity	PPV	NPV	Accuracy
Machine Learning SVM	84%	87%	63%	95%	86.39%

Machine Learning KNN	94%	63%	87%	80%	85.34%
Deep Learning CNN	96%	95%	83%	99%	95.31%*

*Accurate Significant

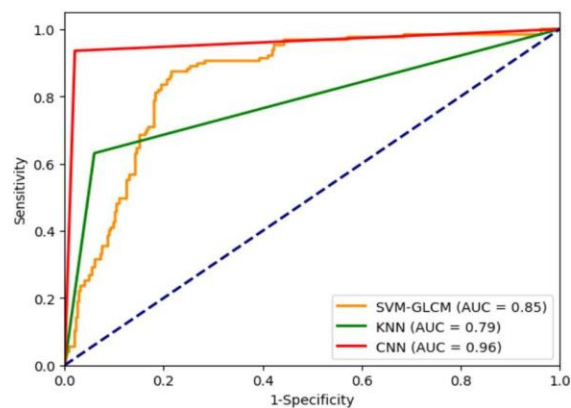


Figure 10. Results of accuracy comparison on image data. The best accuracy value is achieved using the CNN Deep Learning algorithm.

DISCUSSION

1. KNN

K-nearest neighbor (k-NN) is a method of classifying objects based on the nearest training data points (neighbors). The proximity of neighbors is typically calculated using Euclidean distance. The k-NN method consists of two phases: training and classification. In the training phase, the algorithm stores feature vectors and classifications from the training data. During the classification phase, the same features are calculated for the test data, for which the classifications are unknown.[19] The results of this study indicate that an 80-20 classification split yields an accuracy of 85.34%, with a sensitivity of 94% and a specificity of 63%. The 80-20 classification means that 80% of the data is used for training, while 20% is reserved for testing. An accuracy of 80% from the k-NN model implies that it successfully classified 83% of the test data correctly.[20,21] To improve accuracy, strategies may include selecting an optimal value for k, utilizing different distance metrics, increasing the training data size, enhancing data quality, employing cross-validation, implementing bagging, using weighted k-NN values, and applying resampling techniques. Syaliman et al. (2017) investigated methods to enhance k-NN accuracy by combining local mean-based k-nearest neighbor (LMkNN) and distance-weighted k-nearest neighbor (DWkNN).[22] Additionally, Yujie et al. (2023) noted that employing various distance metrics during the distance calculation for training and testing samples significantly improved classification accuracy in the k-NN model.[23]

2. SVM

The SVM algorithm aims to identify the best possible hyperplane for classification in a high-dimensional space, maximizing the margin of partition between classes while minimizing the rate of classification errors. It alters the original space to create an optimal hyperplane in the feature space, effectively splitting the data into distinct classes with the widest margin.[24] SVM showed an accuracy of 86.39%, as indicated in Table 1.

The sample in this study consisted of patient eye photographs captured using two distinct methods and devices: images taken with a slit-lamp camera and those obtained with a smartphone camera. The slit lamp images were captured using a DC-3 8 MP camera integrated into the Topcon SL-D2 bio microscopy slit lamp, with a 10x magnification in photo mode. The images were acquired using an Android smartphone's 12 MP rear camera, positioned perpendicularly to the patient's eye at 15-20 cm, with the flashlight activated. No prior research has employed both methods within a single study. Previous studies utilized smartphone camera images for cataract diagnosis[10,25], while others utilized eye photographs taken with a Nikon D90 camera. [26] Additionally, Wu et al. (2019) employed slit-lamp photographs as part of their research sample.[27]

In the training data for this study, the slit-lamp images demonstrated a higher accuracy of 83.19% across 975 samples compared to the smartphone camera. Subsequently, testing with additional data yielded an accuracy of 86.39%, with a sensitivity of 83.87%, specificity of 87.06%, positive predictive value (PPV) of 63.41%, and negative predictive value (NPV) of 95.28%. These results align with previous research by Wu et al., which reported an impressive accuracy of 99.93% using slit-lamp photographs with a substantial sample size of 37,638 images.[27] The significant differences in sample size and classification methods may account for the variations in accuracy between these studies; nonetheless, the reported results are deemed satisfactory.

3. CNN

The cataract detection model using a Convolutional Neural Network (CNN) leverages the strengths of CNNs in image processing and pattern recognition to identify cataracts from eye images. Widely applied in various image processing tasks, CNNs are particularly effective at recognizing visual features such as edges and textures characteristic of cataracts. This detection model consists of several convolutional layers that gradually extract local features from the input images. This process involves applying filters (kernels) to the images to detect essential visual elements. During training, the CNN iteratively updates parameters such as weights and biases using backpropagation techniques to enhance prediction accuracy by minimizing model errors.

Images captured with a smartphone camera undergo processing through convolutional layers. Each layer extracts specific features, from basic elements like edges and textures to more complex features in deeper layers. Following the convolutional layers, activation functions such as Rectified Linear Unit (ReLU) are employed to introduce non-linearity into the model, enabling the CNN to learn more intricate relationships among the extracted features. Subsequent pooling layers, such as max pooling, are utilized to reduce the dimensionality of the feature maps generated by the convolutional layers. This process retains critical information while decreasing data size, thus improving computational efficiency. Max pooling selects the maximum value within each filter window, preserving the most prominent features.

After passing through multiple convolutional and pooling layers, the extracted features are processed by fully connected layers. These layers integrate all the extracted features to make final predictions about the presence of cataracts in the images. By connecting all neurons from the previous layers, fully connected layers function similarly to traditional neural networks, albeit with features optimized by earlier layers.

The cataract detection model was evaluated using data divided into 80% for training and 20% for testing. The testing results indicated that the model achieved an accuracy of 95%, with a sensitivity of 96%, demonstrating its capability to detect cataract cases accurately and a specificity of 95%, indicating its proficiency in correctly identifying healthy eyes. The CNN's ability to automatically learn complex features without manual intervention makes it particularly suitable for such tasks. Moreover, dropout and regularization are employed to mitigate overfitting, ensuring that the model generalizes well to previously unseen data. Thus, CNNs are highly effective and reliable tools for cataract detection, providing accurate and efficient solutions even amidst high data variability.

While deep learning methods have been extensively utilized for cataract classification, they are often viewed as black boxes, lacking transparency regarding their predictive outcomes. Therefore, reliable explanations for predictions made by deep learning methods are necessary. Zhang et al. (2017) visualized the distribution of weights in the convolutional layers to elucidate the predictive results of deep learning methods, likely analysing similarities among the weights of convolutional layers to explain the predicted outcomes. [28]

Comparison Between Machine and Deep Learning Algorithms

Based on all image data experiments conducted in this study, the Deep Learning CNN algorithm achieved the best accuracy at 95.31%. This indicates that using deep learning algorithms can enhance the prediction of cataract risk factors based on image data compared to other machine learning experiments. This finding is consistent with research by Junayed et al. (2021), which reported an accuracy of 99.13% using the CataractNet CNN algorithm for cataract detection from fundus photographs. [11] This accuracy was obtained with an 80% training data to 20% testing data ratio and preprocessing techniques, including image normalization, augmentation, and implementation.

While machine learning algorithms also demonstrated good accuracy with image data, they did not surpass the accuracy achieved by the CNN algorithm in this study. For instance, research by Yang et al., Harini et al., Sigit et al., and Cao et al. reported accuracies of 93.2%, 93.33%, 85%, and 94.83%, respectively. [11] Additionally, Fuadah et al. utilized the k-NN machine learning algorithm to detect cataracts with 40 cataract images and 40 non-cataract images, achieving a commendable accuracy of 94.5% on 80 testing images. This high accuracy was attributed to statistical texture analysis in feature extraction, a method not employed in the current study. [25]

IMPLEMENTATION

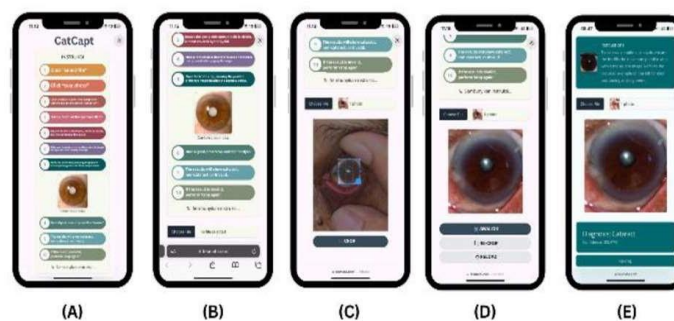


Figure 11. The Interface of CatCapt Application.

These results enable the development of a lightweight version of the model, making it suitable for integration into web-based applications. We have successfully implemented the model in a web application. The CNN model can capture smartphone images tailored to their device specifications. We created this web application using TypeScript and React, utilizing Visual Studio Code as our integrated development environment (IDE). Various third-party libraries, including TensorFlow, TensorFlow.js, Matplotlib, Scikit-learn, Scikit-image, NumPy, Pandas, and Pillow, support the application by facilitating CNN models for detecting cataracts and non-cataracts. Figure 11 illustrates the prototype interface of the application.

The CatCapt application features a main activity (Figure 11 A) and a start activity that allows users to capture a photo or select an image from the gallery (Figure 11 B). Users can then crop the image to isolate the pupil area as the region of interest (RoI) (Figure 11 C), view the extracted pupil area (Figure 11 D), and receive a diagnosis based on the eye image (Figure 11 E).

CONCLUSION

In conclusion, the deep learning model developed for cataract detection using a CNN achieved outstanding results, with accuracy at 95.13%, sensitivity at 96.15%, and specificity at 95.09%. Despite SVM's strong performance, KNN was less effective. For future research, we aim to develop a widely accessible smartphone application that can be used across various device brands, making it particularly applicable to developing countries like Indonesia, which has many rural areas. This approach will enable many users to benefit from cataract detection tools.

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