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# Detection of Anemia Based on Conjunctival Images Using a Convolutional Neural Network (CNN) Method

**Rika Yulia Sari [1], Zahratul Fitri [2]*, Yessy Afrillia [3]**
Department of Informatics Engineering, Faculty of Engineering, Malikussaleh University
Jl.Kampus Bukit Indah, Blang Pulo, Kota Lhokseumawe, Aceh 24355, Indonesia[1,2,3]
E-Mail : rika.220170028@mhs.unimal.ac.id [1]; zahratulfitri@unimal.ac.id [2]; yesy.afrillia@unimal.ac.id [3];

**ABTRACT**

A hemoglobin level below 12 g/dL is the primary indicator of anemia, a condition commonly found in adolescent girls. Laboratory blood tests, as a conventional detection method, are invasive, time-consuming, and costly. This study developed a non-invasive classification system for anemia and non-anemia based on conjunctival images using a Convolutional Neural Network (CNN), implemented on a real-time website. A total of 433 conjunctival images were collected comprising 206 images of anemia and 227 of non-anemia sourced from smartphone cameras and the Kaggle dataset, divided in an 80:10:10 ratio for training, validation, and testing. Preprocessing included resizing to 150 150 pixels, augmentation (flip, rotation, zoom, translation, brightness), and pixel normalization. The CNN architecture consists of three convolutional layers (32, 64, and 128 filters), max pooling, dropout, and a fully connected layer with sigmoid activation, trained using the Adam optimizer and the binary cross-entropy loss function until the 43rd epoch. The model achieved an accuracy of 88.37%, precision of 0.89, recall of 0.88, and an F1-score of 0.88. The model was integrated with a Flask-based REST API and MediaPipe Face Landmarker to automatically detect the conjunctival Region of Interest (ROI) via camera or uploaded images, thereby potentially serving as a fast, practical, and easily accessible tool for the initial screening of anemia among adolescent girls in schools and primary health care facilities.

Keywords – Anemia, Conjungtiva, *Convolutional Neural Network*, *MediaPipe*

## 1. INTRODUCTION

Low hemoglobin levels are a hallmark of anemia, a global health condition that remains prevalent among adolescent girls to this day. As a result of these low hemoglobin levels, the blood s capacity to transport oxygen to all body tissues is reduced. Adolescent girls are known to have a higher risk of developing anemia compared to boys; this is influenced by the menstrual cycle, an unbalanced diet, and certain dietary habits that can lead to iron deficiency. The impact of anemia extends beyond reduced physical fitness and academic performance; it also affects reproductive health and has the potential to influence the quality of human resources in the future. (Lubis & Angraeni, 2022).

Efforts to address anemia among adolescents have, in fact, been a priority for the Indonesian government, one of which is implemented through the Iron-Fortified Tablet (TTD) distribution program. However, the effectiveness of this program is closely tied to the anemia screening process, which to this day still relies on laboratory blood tests as the primary method. Because this method is invasive and requires financial resources, time, and medical personnel, its implementation becomes less efficient when carried out on a large scale, particularly in school settings (Pradnyawati, 2024). This is what underscores the need to develop an early detection method that is more practical, rapid, and accessible.

Advances in digital image processing technology and deep learning have paved the way for the creation of non-invasive anemia detection systems, one of which involves analyzing images of the eye s conjunctiva. One of the most widely used methods in this approach is the Convolutional Neural Network (CNN), given its ability to automatically extract visual features, which yields relatively good image classification performance (Eriana & Zein, 2023).

Several previous studies have demonstrated the potential of this approach. Magdalena et al. (2022) reported that CNN-based anemia classification using conjunctival images of the eyelid achieved an accuracy rate of up to 94%. Amalia et al. (2023) applied a Transfer Learning approach using the AlexNet architecture to conjunctival images and achieved an accuracy of 85%. These findings indicate that CNN-based approaches hold promising prospects as a non-invasive method for detecting anemia.

Nevertheless, the implementation of a simple, practical, and real-time anemia detection system to support screening in school settings remains relatively limited. Some studies still focus on models that require significant computational resources, making them less than optimal for use in initial screening processes. Given these circumstances, this study aims to design an early anemia detection system based on conjunctival images using the Convolutional Neural Network (CNN) method as a fast, efficient, and easy-to-implement non-invasive screening alternative.

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## 2. LITERATURE REVIEW

### A. Anemia & the Eye's Conjungtiva

Anemia is a pathological condition characterized by a decrease in hemoglobin (Hb) levels below the normal threshold, thereby impairing the blood s ability to distribute oxygen to body tissues. According to World Health Organization (WHO) criteria, an adolescent girl is classified as anemic if her hemoglobin level is less than 12 g/dL (Helmyati et al., 2023). Iron deficiency, menstrual bleeding, and inadequate iron intake are among the primary causes of anemia, with iron-deficiency anemia being the most common type observed in adolescents. This condition causes various symptoms, such as a pale complexion, fatigue, dizziness, difficulty concentrating, and even a decline in cognitive ability which, if left untreated, can interfere with daily activities and reduce the patient s quality of life (Lodia Tuturop et al., 2023). The pallor of the conjunctiva, resulting from decreased hemoglobin levels, is a clinical sign that is relatively easy to observe with the naked eye. This visual characteristic forms the basis for the development of a non-invasive, digital-image-based technique for the early detection of anemia, utilizing a Convolutional Neural Network (CNN) algorithm (Widyaningrum & Setiyaningrum, 2024).

### B. Digital Images Representation

Digital Image Representation A digital image is a discrete representation of a continuous function f(x,y), where x and y are spatial coordinates and f(x,y) is the light intensity (Tri Laksono et al., 2022). Research based on conjunctival color analysis generally utilizes three representations: RGB, an additive color model with a range of 0 255 per channel (Red, Green, Blue) stored in 24-bit format (Fatmawati et al., 2023). HSV separates the lighting component (Value) from the pure color information (Hue, Saturation), making it more sensitive to changes in pallor (Ariyanto & Prasetyo, 2022). An image histogram is a representation of the frequency distribution of pixel intensities that helps quantitatively distinguish color patterns between anemic and non-anemic images (Purwandari et al., 2021). In practice, RGB remains the primary input for CNN training, while HSV and histograms serve as tools for visual data exploration and validation (Wicaksono & Nugroho, 2024).

### C. *MediaPipe* & OpenCV

MediaPipe, an open-source framework from Google, provides a Face Landmarker that detects 468 facial landmarks in real time (Chandel et al., 2023) and is used to automatically and consistently define the Region of Interest (ROI) in the conjunctival area, with low computational overhead, making it suitable for web-based applications (Indiranjani, 2023). OpenCV, an open-source computer vision library released by Intel in 1999 (Rialdi, 2024), supports various programming languages and operating systems. Key functions relevant to this research workflow include cv2.VideoCapture() for video frame acquisition, cv2.cvtColor() for BGR RGB color space conversion, cv2.resize() for adjusting ROI dimensions, cv2.imwrite() for dataset storage, and cv2.normalize() for normalizing pixel intensity against real-time lighting variations.

### D. *Machine Learning & Deep Learning*

Machine Learning is a system that learns patterns from data without explicit instructions (Bintoro et al., 2024), with two main approaches: supervised learning, which trains models using feature-label pairs and is effective for classification though it requires labeled data; and unsupervised learning, which operates without labels and excels at clustering but is difficult to validate directly. Deep Learning builds upon this approach using multi-layered neural networks that learn hierarchical data representations from simple features in the outer layers to complex features in the inner layers through training with the backpropagation algorithm (Setiawan, 2021).

### E. *Convolutional Neural Network* (CNN)

A CNN is a form of the Multi-Layer Perceptron (MLP) specifically designed to handle data in a two-dimensional grid format, such as images (Adriyanto et al., 2022). In its architecture, a CNN consists of two groups of layers: a group of layers that extract features (convolutional layers and pooling layers) and a group of layers that perform classification (fully connected layers) (Ramadhani et al., 2022).

1 *A convolutional layer extracs features through kernel convolution operations on the input image, producing a feature map* (Muhammad & Wibowo, 2021), with the output size calculated using the equation $output = (W - N + 2p)/S + 1$ (Wardani & Leonardi, 2023).
2 ReLU introduces nonlinearity via the function max$(0, x)$ (Abadi & Wibowo, 2021).
3 *The pooling layer* (typically 2×2 max pooling with stride 2) reduces the dimension of the feature map by up to ±75% while mitigating the risk of overfitting (Ramadhani et al., 2022).
4 *The flatten layer* converts the *feature map into a vector before it is processed by the fully connected layer*.
5 *The fully connected layer* connects all neurons across layers to produce class probabilities (Muhammad & Wibowo, 2021).
6 *The sigmoid* activation function is used for binary classification, converting logits into probabilities between 0 and 1 via $\sigma(x) = 1/(1+e^{-x})$, with a threshold of 0,5 to determine the anemia/non-anemia class (Purba et al., 2025; König, 2022).

## 3. RESEARCH METHODOLOGY

This study was conducted at the Namo Rambe Community Health Center and Pancur Batu State

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Junior High School No. 2 from February to June 2026. Pancur Batu State Junior High School No. 2 was used for collecting the conjunctival image dataset, while the Namo Rambe Community Health Center served as the location for health workers to label the images as anemia or non-anemia. System development was supported by hardware consisting of computers, smartphones, and webcams, as well as software including Windows 10/11, Python 3.12, TensorFlow, OpenCV, MediaPipe Face Landmarker, Flask, Visual Studio Code, Google Colab, and Microsoft Edge.

## A. Research Design

This research scheme was designed as a systematic series of stages to ensure the research process proceeded in a focused manner, from problem formulation to system evaluation. The research began with the identification of the problem regarding the high prevalence of anemia among adolescent girls and the need for a non-invasive screening method using conjunctival images.

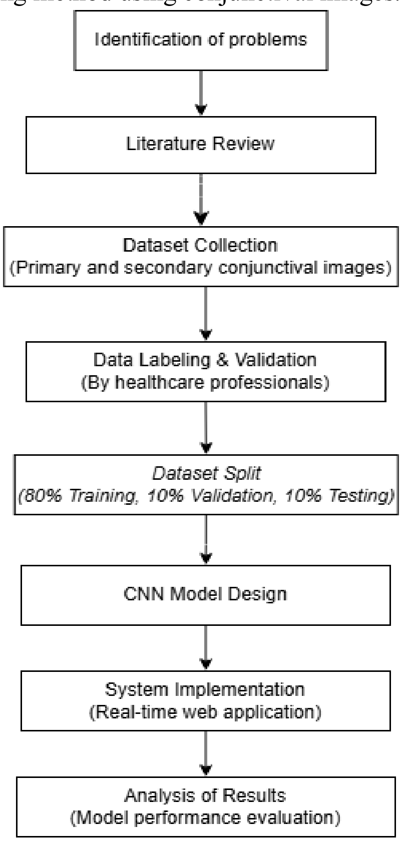


Figure 1. Research Framework

Next, a literature review was conducted by examining journals, books, and previous studies related to anemia, conjunctival imaging, and the application of Convolutional Neural Network (CNN) methods. The subsequent stage involved collecting a dataset consisting of primary data obtained from images captured using a smartphone camera and secondary data obtained from the Kaggle public dataset. All images were then labeled as either "anemia" or "non-anemia" and validated by healthcare professionals before being divided into training (80%), validation (10%), and test (10%) sets.

The next step was to design a CNN model from scratch, which included determining the network architecture, configuring the layers, setting hyperparameters, applying data preprocessing techniques, performing data augmentation, and analyzing color characteristics using the HSV and histogram approaches. After the training process was complete, the model was then implemented in a web application capable of detecting conditions in real-time using a connected laptop camera or webcam. In the final stage, the system is tested with new data collected directly to assess the model's performance. The results are then evaluated using accuracy, precision, recall, and F1-score to determine how accurately and reliably the system distinguishes between anemic and non-anemic conditions based on images of the user's eyes.

## B. *CNN Algorithm Schematic*

This study employs a CNN (Convolutional Neural Network) algorithm to classify conjunctival images into two categories: anemia and non-anemia. A CNN was chosen because it can automatically extract visual features without requiring manual feature extraction. The process begins by inputting RGB-formatted conjunctival images that have been standardized to a size of 150 × 150 pixels. This is followed by a preprocessing stage involving resizing and normalizing pixel values from the range of 0–255 to 0–1 to improve training stability and accelerate model convergence. Next, data augmentation including horizontal flipping, rotation, zooming, translation, and brightness adjustment is applied to the training data to enrich data variation and reduce the risk of overfitting.

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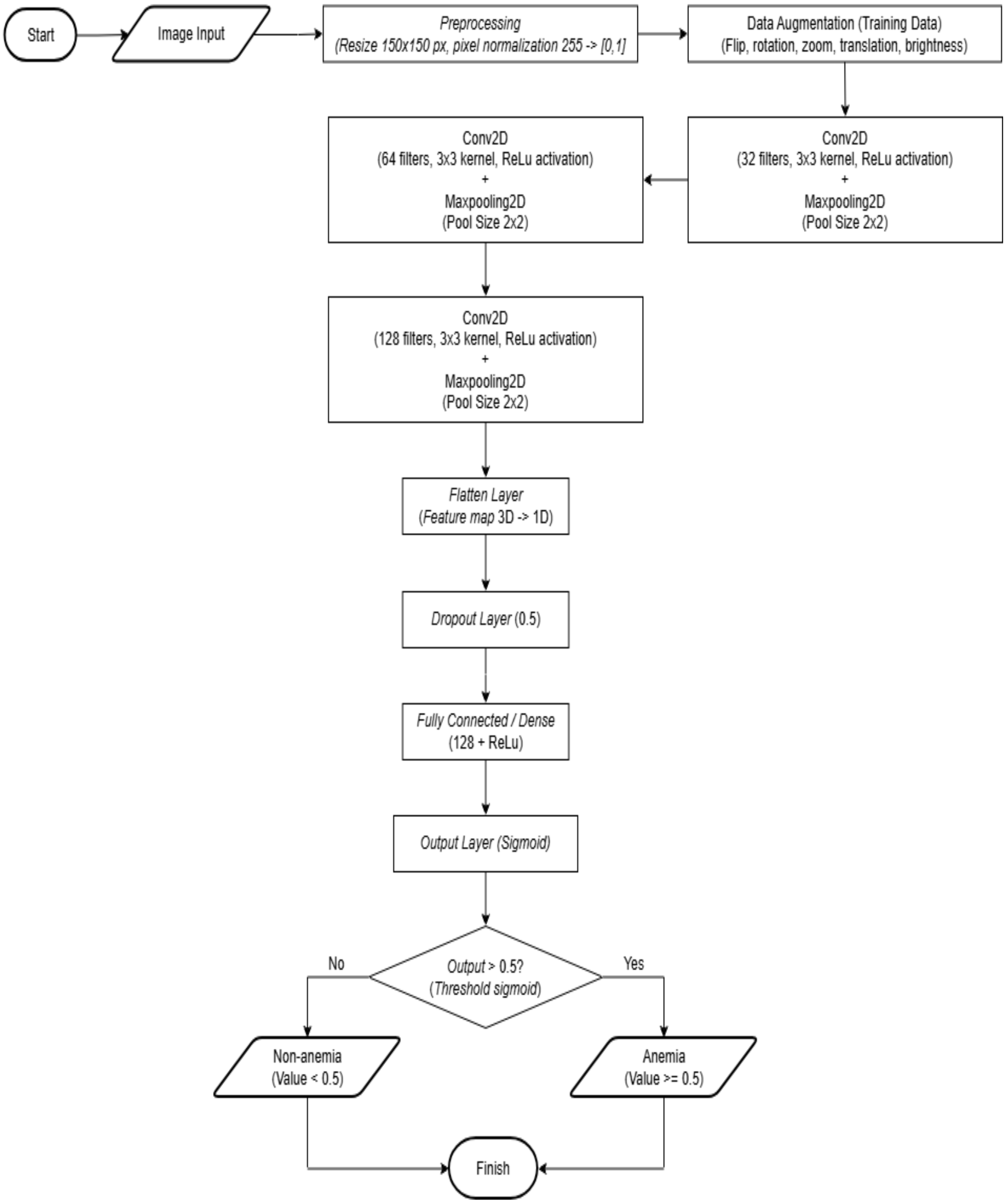


Figure 2. CNN Algorithm Diagram

The image is then processed through three convolutional layers (Conv2D) with a ReLU activation function, each using 32, 64, and 128 3 × 3 filters, where each layer is followed by a 2 × 2 MaxPooling2D layer to gradually extract features while reducing the dimension of the feature map. The extracted features are then converted into a one-dimensional vector using a Flatten layer, followed by a Dropout layer set to 0.5 to reduce overfitting, before being processed through a Fully Connected (Dense) layer consisting of 128 neurons with a ReLU activation function. In the final stage, the output layer uses a single neuron with a sigmoid activation function to generate a probability value between 0 and 1. This probability value is then compared to a threshold of 0.5, where values ≥ 0.5 are classified as non-anemia, while values < 0.5 are categorized as anemia. The CNN algorithm process ends after the system generates a final prediction for the analyzed conjunctival image.

## C. System Diagram

The system architecture for early anemia detection based on conjunctival images using the CNN algorithm is designed through a series of integrated stages, ranging from model development to real-time detection. In the initial stage, the conjunctival image dataset—labeled as "anemia" and "non-anemia"—is manually split into training, validation, and testing sets. All data then undergoes a preprocessing stage that includes cropping the Region of Interest (ROI), resizing the images, normalizing pixel values, and converting the color space from RGB to HSV to improve the stability of the conjunctival color representation against variations in lighting.

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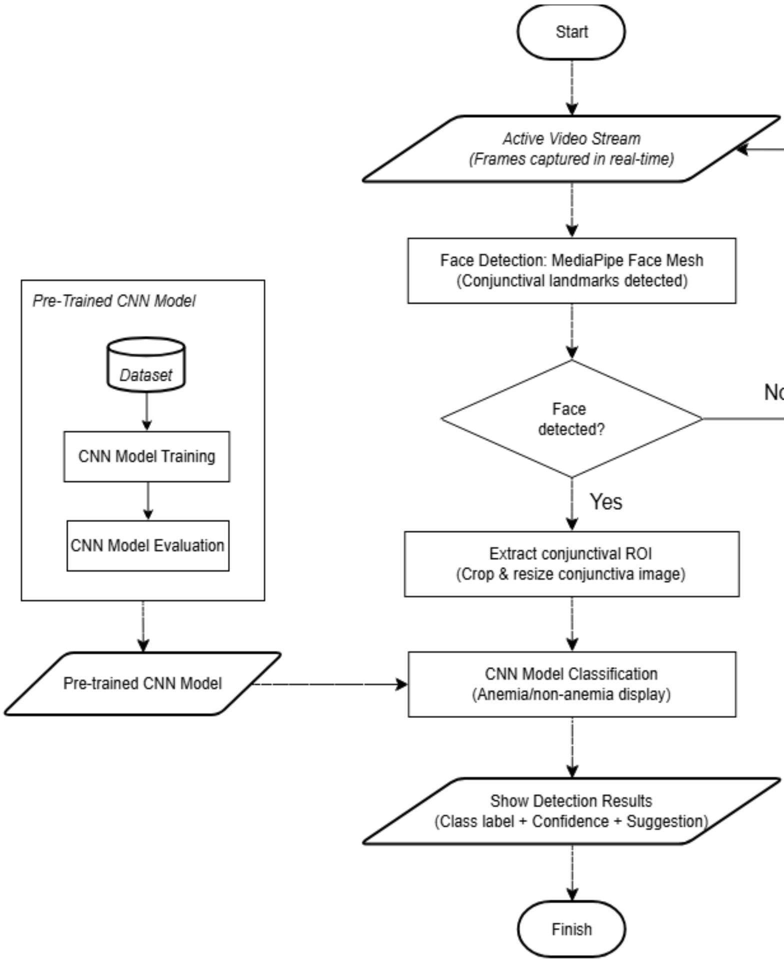


Figure 3. System Diagram

Next, the CNN model is trained using the training data to learn the visual patterns of the conjunctiva, then evaluated using the validation data based on accuracy, precision, recall, and F1-score metrics until a ready-to-use CNN model is produced. During the implementation phase, the system activates the camera to capture images in real-time; each frame is processed using MediaPipe Face Landmarker to detect faces and determine conjunctival landmark points. If a face is successfully detected, the conjunctival area is extracted as a region of interest (ROI) and resized to match the CNN model's input dimensions. The extracted image is then classified by the CNN model to determine whether the subject has anemia or not. The detection results are subsequently displayed to the user in the form of a classification label, a confidence score indicating the model's level of certainty, and initial recommendations based on the prediction results. This process occurs repeatedly while the camera is active, enabling the system to perform real-time early detection of anemia.

## 4. RESULT AND DISCUSSION

This study developed an early-detection system for anemia based on conjunctival images using the Convolutional Neural Network (CNN) method. The system classifies conjunctival images into two categories anemia and non-anemia enabling its use as a non-invasive initial screening tool. The study used a dataset of 433 conjunctival images, consisting of 206 images of anemia and 227 images of non-anemia. All images underwent preprocessing before being used in the model training process. The research stages included dataset collection, data preprocessing (resizing images to 150×150 pixels, augmentation, and rescaling), designing and training the CNN model using Python on the Google Colab platform, and implementing a web-based detection system using Flask integrated with OpenCV and MediaPipe Face Landmarker to detect the conjunctival area in real time. The results show that the CNN is capable of classifying conjunctival images with a test accuracy of 88.37%, and the system successfully implements real-time detection by displaying classification results along with confidence scores.

### A. Research Dataset

The research dataset consists of conjunctival eye images grouped into anemia and non-anemia categories, collected from two sources. Primary data was obtained by directly capturing images using a smartphone camera from female adolescent respondents at SMP Negeri 2 Pancur Batu, with labels validated by healthcare professionals at the

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Namo Rambe Community Health Center, resulting in 214 images. Secondary data was obtained from the public Kaggle dataset (Fartale et al., 2024), comprising 219 images to increase the variety of data characteristics. The total dataset used consisted of 433 images, divided into 80% training data, 10% validation data, and 10% test data, as presented in Table 1.

Table 1. Distribution of the Eye Conjunctiva Image Dataset

| Class | Training | Valid | Test | Total |
|---|---|---|---|---|
| Anemia | 170 | 18 | 18 | 206 |
| Non-Anemia | 177 | 25 | 25 | 227 |
| Total | 347 | 43 | 43 | 433 |

Based on the distribution in Table 1, the research dataset has been divided into training data, validation data, and test data to support the CNN model training and evaluation process. Examples of conjunctival images used in this study, both from the primary and secondary datasets, are shown in Figure 4.

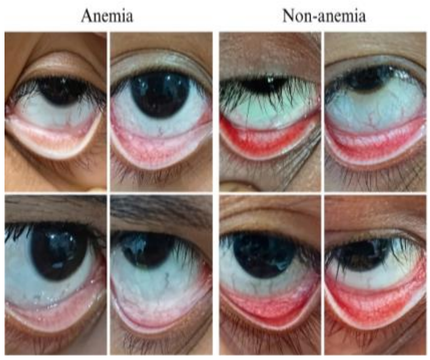


Figure 4. Sample Images from the Primary and Secondary Datasets

## B. *Data Preprocessing*

Data preprocessing consists of three stages: resizing, data augmentation, and normalization (rescaling), all of which are applied automatically using the TensorFlow library. In the resizing stage, images are loaded using the image_dataset_from_directory() function with the parameter image_size=(150,150), so that each image has dimensions of 150×150 pixels to meet the CNN model's input requirements.

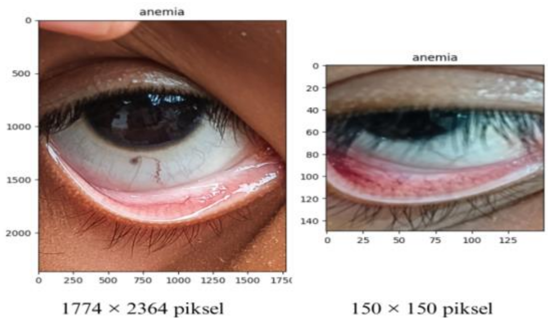


Figure 5. Images Resizing Results (150x150 Pixels)

Data augmentation is applied via tf.keras.Sequential, which combines five transformation layers: Random Flip (horizontal), Random Rotation (±10%), Random Zoom (±10%), Random Translation (±10%), and Random Brightness (±5%). The augmentation layers are integrated directly into the model architecture so that they are active only during training (training=True) and are not applied to validation or test data, allowing the model to learn variations in the shape, angle, scale, position, and lighting of conjunctival images without increasing the amount of original data. The final step is to normalize the pixel values using a Rescaling layer (1./255) integrated into the model architecture, so that the pixel value range changes from 0–255 to 0–1:

$$x' = x / 255 = 128 / 255 = 0{,}502$$

By incorporating rescaling into the model architecture, pixel value standardization is consistently applied during both training and inference in real-time web-based systems, eliminating the need for separate manual preprocessing on the application side.

## C. Visual Analysis of RGB & HSV Color Spaces

Before training the model, a visual analysis of the color characteristics of conjunctival images in the RGB and HSV color spaces was performed using the cv2.cvtColor() function with the cv2.COLOR_RGB2HSV parameter to understand color distribution patterns and evaluate image quality. In the RGB representation, the conjunctiva appears relatively pale, whereas in the HSV color space, color information is separated into Hue, Saturation, and Value components, allowing color and brightness to be observed separately particularly in the Saturation component, which shows differences in color saturation levels between anemic conjunctiva (tending to be pale) and non-anemic conjunctiva (normal pink).

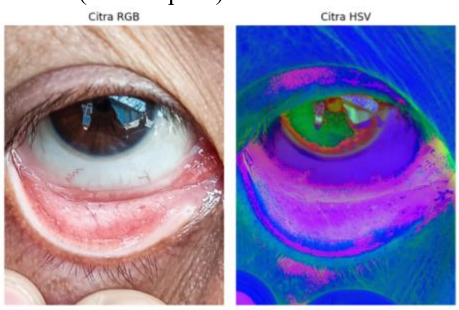


Figure 6. Comparison of RGB and HSV Channels in Conjunctival images

Pixel intensity histogram analysis was also performed on the RGB channels and HSV components to quantitatively observe color distribution using the cv2.calcHist() function. This analysis was used solely for the purpose of exploring and interpreting the dataset's characteristics; the model training process continued to use 150×150-pixel RGB images, while feature learning was performed automatically by the convolutional layer.

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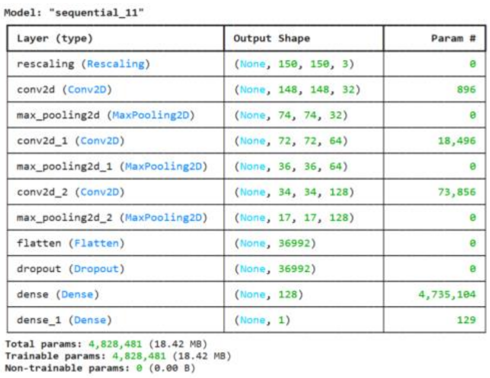
### D. CNN Model Architecture

The designed CNN architecture consists of an input layer, several convolutional layers, a pooling layer, a flattening layer, a fully connected layer, and an output layer with a sigmoid activation function for binary classification. The hyperparameter configuration was determined through several experiments, with the optimal configuration presented in Table 2.

Table 2. *CNN Model Hyperparameters*

| Hyperparameter | Value |
|---|---|
| Data Split | 80:10:10 |
| Batch Size | 16 |
| Epoch (maximum) | 50 |
| Optimizer | Adam |
| Loss Function | Binary Crossentropy |

The Adam optimizer was chosen for its ability to adaptively adjust the learning rate for each parameter, resulting in more efficient and stable convergence. The model accepts 150×150-pixel inputs with 3 RGB color channels. The model architecture summary is shown in Figure 7.


Model: "sequential_11"

| Layer (type) | Output Shape | Param # |
|---|---|---|
| rescaling (Rescaling) | (None, 150, 150, 3) | 0 |
| conv2d (Conv2D) | (None, 148, 148, 32) | 896 |
| max_pooling2d (MaxPooling2D) | (None, 74, 74, 32) | 0 |
| conv2d_1 (Conv2D) | (None, 72, 72, 64) | 18,496 |
| max_pooling2d_1 (MaxPooling2D) | (None, 36, 36, 64) | 0 |
| conv2d_2 (Conv2D) | (None, 34, 34, 128) | 73,856 |
| max_pooling2d_2 (MaxPooling2D) | (None, 17, 17, 128) | 0 |
| flatten (Flatten) | (None, 36992) | 0 |
| dropout (Dropout) | (None, 36992) | 0 |
| dense (Dense) | (None, 128) | 4,735,104 |
| dense_1 (Dense) | (None, 1) | 129 |

Total params: 4,828,481 (18.42 MB)
Trainable params: 4,828,481 (18.42 MB)
Non-trainable params: 0 (0.00 B)

Figure 7. Model *Summary* of the CNN Architecture

The output size of each convolutional layer is calculated using the equation:

$$output = (W - N + 2p) / s + 1$$

where W is the input image size, N is the kernel/filter size, p is the padding size, and s is the stride size. Each convolutional layer performs a convolution operation between the filter and the input image to extract features such as edges, colors, and textures, followed by a ReLU activation function that preserves positive values and sets negative values to zero so that the model can learn nonlinear patterns. A pooling layer (max pooling) is then used to reduce the dimension of the feature map while retaining the most dominant information, thereby reducing computational load and the risk of overfitting. A flatten layer converts the two-dimensional feature map into a one-dimensional vector before passing it to the fully connected layer, which connects all neurons to learn high-level feature combinations. In the output layer, the sigmoid activation function is used to generate probability values between 0 and 1 that represent the anemia or non-anemia class.

### E. CNN Model Training Results

Model training was performed using TensorFlow Keras on Google Colab with 347 training images and 43 validation images, a maximum of 50 epochs, the Adam optimizer, and the Binary Cross-Entropy loss function. Training results at various epoch stages are presented in Table 3.

Table 3. CNN Model Training Results

| Epoch | Accuracy | Loss | Validation Accuracy | Validation Loss |
|---|---|---|---|---|
| 1 | 0.4323 | 0.7532 | 0.4186 | 0.6973 |
| 2 | 0.4899 | 0.6954 | 0.5814 | 0.6913 |
| 3 | 0.5130 | 0.6943 | 0.4651 | 0.6919 |
| 4 | 0.4784 | 0.6940 | 0.6512 | 0.6884 |
| 5 | 0.5014 | 0.6924 | 0.7674 | 0.6844 |
| ..... | ..... | ..... | ..... | ..... |
| 39 | 0.8069 | 0.4245 | 0.8605 | 0.3886 |
| 40 | 0.8012 | 0.4202 | 0.8837 | 0.3224 |
| 41 | 0.8156 | 0.3921 | 0.8372 | 0.3481 |
| 42 | 0.8213 | 0.3893 | 0.8837 | 0.3437 |
| 43 | 0.8357 | 0.3889 | 0.8605 | 0.3649 |

Training accuracy increased from 0.4323 in the first epoch to 0.8357 in the 43rd epoch, while training loss decreased from 0.7532 to 0.3889. A similar pattern was observed in the validation data, with the highest validation accuracy of 0.9070 at epochs 30 and 35, and the lowest validation loss of 0.1980 at epoch 35.

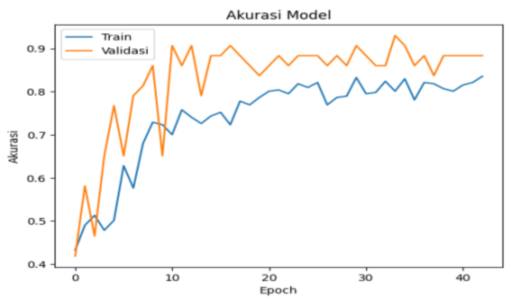



Figure 8. Training & Validation Accuracy Graphs

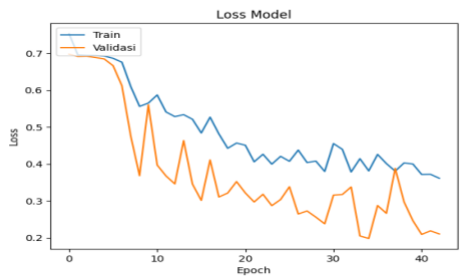



Figure 9. Training & Validation Loss Graphs

The training accuracy graph shows a steady upward trend, while the validation accuracy fluctuates but continues to increase; in fact, at some epochs it is higher than the training accuracy because the training data undergoes augmentation and dropout, resulting in greater variability compared to the validation data. The ReduceLROnPlateau mechanism gradually reduces the learning rate from

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0.001 to 0.000125, and EarlyStopping halts training at the 43rd epoch, with the best weights saved from the 35th epoch (lowest validation loss of 0.1980).

### F. Model Evaluation

Evaluation was performed using 43 test images (18 anemia images, 25 non-anemia images) that the model had not seen during training. Model performance was evaluated using a confusion matrix as well as accuracy, precision, recall, and F1-score.

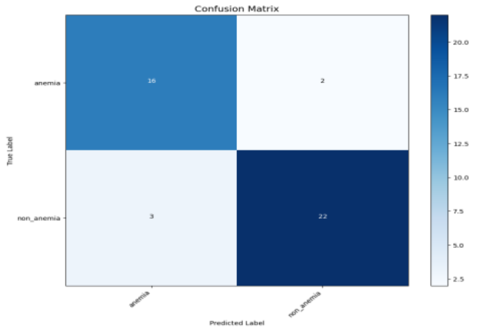


Figure 10. *Confusion Matrix* for the Test Data

In this study, the model's performance was analyzed using evaluation metrics including accuracy, precision, recall, and F1-score. All metrics were calculated based on the prediction results on the test dataset to measure the model's ability to accurately classify each class.

Table 4. *Classification Report Results*

| Class | Acc. | Prec. | Rec. | F1 | Sup. |
|---|---|---|---|---|---|
| Anemia | 88% | 0,84 | 0,89 | 0,86 | 18 |
| Non-anemia | 88% | 0,92 | 0,88 | 0,90 | 25 |
| Macro Avg | - | 0,88 | 0,88 | 0,88 | 43 |
| Weighted Avg | - | 0,89 | 0,88 | 0,88 | 43 |

The CNN model developed was able to classify images of the conjunctiva with an overall accuracy of 88.37%, an average precision-weighted of 0.89, a recall of 0.88, and an F1-score of 0.88. The non-anemia class showed a slightly higher precision (0.92) than the anemia class (0.84), indicating that the model rarely misclassified non-anemia images as anemia. Conversely, the recall for the anemia class (0.89) is slightly higher than that for the non-anemia class (0.88), demonstrating the model's ability to identify the majority of anemia cases. This evaluation approach is consistent with the studies by Wardani & Leonardi (2023) and Muqsith et al. (2025), which used similar metrics to assess model performance.

### G. Implementation of a Web-Based Detection System

The trained CNN model was integrated into a web-based early anemia detection system using a REST API with the Flask framework as the bridge between the web interface (frontend) and the CNN model on the backend.


Figure 11. System Landing Page

The system provides two detection methods: via live camera and image upload. Images submitted are received by the REST API via the /predict endpoint, then processed through Region of Interest (ROI) extraction using MediaPipe Face Landmarker (with OpenCV Haar Cascade as an alternative method), preprocessing (resizing to 150×150 pixels and converting from BGR to RGB), and classification using the CNN model. The prediction results consisting of the Anemia/Non-anemia class and a confidence score are returned in JSON format and displayed on the website interface, while also being stored in the detection history database.

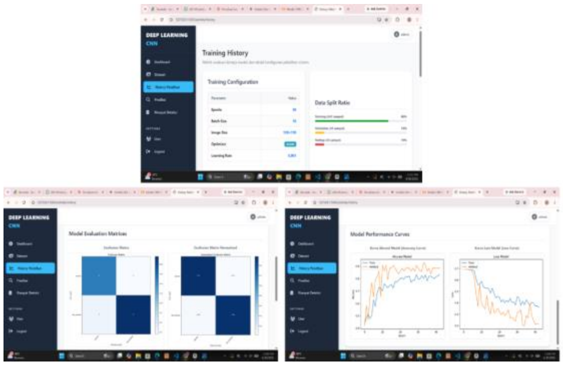

Figure 12. Training History Page

The website was developed using the Flask framework and includes the following pages: Landing Page, Login, Dashboard, Dataset, Training History, Prediction, Detection History, and User. The Landing Page provides general system information and a navigation menu leading to the detection pages, while the Prediction page is the main feature that allows users to perform detection via a live camera or by uploading images.

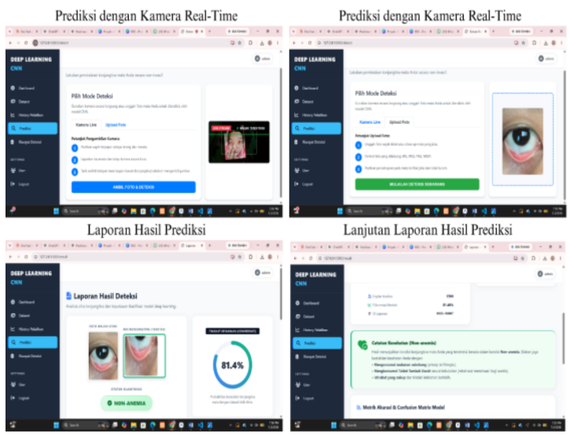


Figure 13. Prediction & Detection Results Page

System testing was conducted using 43 independent test images to evaluate the system's ability to detect ROIs, perform classification, and present results via the website interface. The confidence score is calculated from the sigmoid output probability p for the non-anemia class (positive class) with a threshold of 0.5:

$$\text{Confidence} = p\times100\% \text{ jika } p \geq 0{,}5 \text{ (non-anemia)};$$
$$\text{Confidence} = (1-p)\times100\% \text{ jika } p < 0{,}5 \text{ (anemia)}$$

Table 5. Summary of System Testing Results

| Keterangan | Jumlah | Persentase |
|---|---|---|
| Correct Classification | 26 | 60.5% |
| Incorrect Classification | 17 | 39.5% |
| Total Data | 43 | 100% |

Test results show that the system is capable of performing all detection stages in an integrated manner, ranging from ROI detection, preprocessing, and CNN classification to the presentation of results on the web interface, with confidence scores consistently falling within the 50–100% range. Although most images were processed successfully, classification errors and ROI detection failures were still observed. Classification errors are generally caused by similarities in conjunctival color characteristics across classes, while ROI detection failures are influenced by image quality factors such as uneven lighting, a tilted face, a partially covered conjunctiva, or an out-of-focus image.

## 5. Conclusion

Based on the results of the design, implementation, and testing, it can be concluded that an early-detection system for anemia based on conjunctival images has been successfully developed as a real-time web application using Flask, integrated with MediaPipe Face Landmarker to automatically detect the conjunctival ROI. The Convolutional Neural Network (CNN) algorithm was successfully applied to classify images of anemia and non-anemia through the stages of preprocessing, data augmentation, and model training, yielding an accuracy of 88.37%, precision of 0.89, recall of 0.88, and an F1-score of 0.88. Testing on the website showed that most images were classified correctly, although there were some errors due to lighting conditions, camera angles, and similarities in conjunctival color. Overall, this system has the potential to serve as a non-invasive, practical, and easily accessible tool for the initial screening of anemia.

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