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Multi-Region Detection of eye Conjunctiva Images Using DNCNN and YOLOv8 Algorithms

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Abstract
Artificial intelligence is encountered in many areas today. It makes our lives easier with its use in our daily lives. With the advancement of medical big data and artificial intelligence, eye images have begun to be used in the detection of endocrine, cardiovascular, neurological, renal, hematological and many other diseases. It is possible to find more connections between systemic disorders and eye disorders and apply them to increase the effectiveness of artificial intelligence. The eye is an anatomically complex organ. Detection of the conjunctiva regions of the eye generally plays an important role in the diagnosis of eye diseases and applications related to eye health. The conjunctiva is a thin membrane tissue that covers the inner surface of the eyelids and the white part of the eye. Detection and analysis of this region is used in the examination of inflammation, redness, dryness and other disorders in the eye. The relevant regions were found using conjunctiva images in the study. Conjunctiva region detection Images were taken from a public database and enhanced with the image enhancement method DNCNN. The YOLO algorithm is applied to raw images and DNCNN enhanced images separately using the same parameters. As a result, the effect of the deep learning based method on finding the truth in images is presented with F1-confidence curve, precision-confidence curve, recall-confidence curve, precision-recall curve and confusion matrix metrics. In the proposed method, the mAP value is given as 0.984 in all classes.

1. Introduction

The eyes are among the majority of vital systems in the body. Eyes are windows that connect us to the world. All our lives; genetics, age, existing diseases and environmental factors can threaten our eye health. There are multiple types of vision issues. Since the visual system is an important organ for humans, external eye abnormalities need to be detected early. The transparent membrane that encompasses the interior area of the eyelids and the white part of the eye is called the conjunctiva [1]. Human optics are safe from dust particles thanks to the conjunctiva. It acts as a lubricant and prevents friction when opening and closing the eye.

Three anatomical sections of the mucosa that make up the conjunctiva are (1) palpebral, (2) fornix, and (3) bulbar. Although it is more tightly fastened to the higher tarsus, the palpebral conjunctiva is bonded to both the lower and upper tarsi. Each eyelid's posterior third of the meibomian gland apertures is where the palpebral conjunctiva starts. Cells change at this mucocutaneous junction from the skin's keratinized stratified squamous epithelium to the marginal conjunctiva's nonkeratinized stratified squamous epithelium. The conjunctiva and lacrimal puncta join at this mucocutaneous junction as it comes to the nose [2]. The conjunctiva is highly vascularized and many microvessels are easily accessible for imaging studies. Figure 1 shows the anatomical structure of the eye conjunctiva.

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Colored slit-lamp photograph of right lower eyelid. (1) Mucocutaneous junction, (2) lacrimal punctum, (3) subtarsal groove, (4) tarsal conjunctiva, (5) forniceal conjunctiva, (6) bulbar conjunctiva, and (7) contact lens on limbus

Figure 1. Eye conjunctiva anatomy [2]

Ideal blood hemoglobin levels are associated with health issues and can be used as indicators of several disorders. A blood sample is typically used in an invasive manner utilizing various equipment to assess hemoglobin levels. Certain indications have historically been interpreted physically. Pallor of the face, nail beds, conjunctiva, and palm wrinkles are among these signs. Conjunctival pallor may be a more sensitive indicator of anemia than palm or nail bed pallor, according to studies [3]. In addition, diabetes can be detected using conjunctival images.

Numerous research is available in the literature using artificial intelligence techniques in the fields of classification, segmentation and detection of eye disorders. There are also studies conducted to detect diabetes and anemia using eye conjunctiva images.

In their study focusing on the problem of automatic classification of eye disorders, A. K. Bitto and I. Mahmud [4] distinguished between normal eyes, eyes with conjunctivitis, and eyes with cataracts using the convolutional neural network architectures of VGG-16, ResNet-50, and Inception-v3. In the dataset they used, Inception-v3 had the highest accuracy rate in detecting eye diseases with 97.08% verification accuracy, while ResNet-50 achieved the second highest accuracy with 95.68% and finally VGG-16 achieved 95.48%.

S. Dhalla et al. [5] used eye conjunctivitis images to detect anemia through computerized analysis. The paper examined the simultaneous picture segmentation five deep learning-based models' performance: UNet, UNet++, FCN, PSPNet, and LinkNet. A specially created dataset of 2592 palpebral pictures of pediatric nuclei is used for the experiments. LinkNet delivered the best results. For intersection-union (IoU) and dice score performance measurements, accuracy was 94.17%, 90.14%, and 93.78% in the pertinent dataset, respectively.

The goal of E. Purwanti et al. [6] is to use a deep learning method to classify images of the palpebral conjunctiva in order to diagnose anemia. There are three CNN designs in use: ResNet-50, MobileNetV2, and AlexNet. The accuracy of the AlexNet, ResNet-50, and MobileNetV2 designs was 97.19%, 97.94%, and 89.93%, respectively, according to the results.

X. Li et al. [7] aimed to automatically detect diabetes using conjunctival images. For this purpose, researchers designed a learning model. Both healthy people and individuals with type 2 diabetes provided images for the collection. Using conjunctival pictures, a hierarchical multitask network model (HMT-Net) was created. The model underwent thorough evaluation and comparison with alternative approaches. The proposed model achieved 75.17% accuracy.

A non-invasive optical system is suggested as the mechanism for automatic diabetes detection by E. R. Ghugare et al. [8]. The anterior conjunctiva and eye pallor are examined as part of the research in order to identify diabetes. The eyes of both non-diabetic and diabetic participants were analyzed using medical imaging. For the pertinent job, a CNN-based prediction model was developed. Ultimately, the method provided 96% accuracy.

Pallavi et al. [9] created a bot that is powered by artificial intelligence. Two models serve as the foundation for the bot service: one for segmenting the Region of Interest and the other for classifying anemic cases from normal ones. For the purpose of training the model, data were gathered from 160 anemics and 140 non-anemics people. For the segmentation method, we were able to obtain an Intercection Over Union (IOU) score of 0.922; for the classification model, we were able to obtain a validation accuracy of 0.9699 and a validation recall of 0.95.

The process and technology for obtaining significant information from a digital conjunctival image were detailed by G. Dimauro et al. [10]. Here, efficient characteristics are employed to guarantee that every picture is part of a diagnostic probability class for anemia. Conjunctiva photos were taken with a novel, user-friendly, low-cost apparatus intended to maximize ambient light independence. The palpebral conjunctiva was manually extracted from photos to assess the system's performance, or it could be done semi-automatically using the SLIC Superpixel technique. Tests were run on pictures that came from 102 individuals. A few classification methods for determining anemic status were tried, and SMOTE and ROSE procedures were assessed to balance the data set.

S. Wei et al. [11] aims to evaluate the applicability of the deep learning method in determining the rating of bulbar conjunctival injection. 1401 color anterior segment pictures that displayed the bulbar conjunctiva and cornea were gathered. The bulbar conjunctival injection scores, as recorded by human ophthalmologists, served as the ground truth. Two models based on convolutional neural networks were constructed and trained. Deep learning models have been assessed for efficiency using performance criteria. Accuracy of 87.12% were attained by the deep learning model.

Using smartphones and artificial intelligence approaches, S. H. Elgohary et al. [12] sought to create a remote, non-invasive, standardized solution that allows a fast scan to find hemoglobin levels. The conjunctiva is automatically generated as a Region of Interest from an image of the eye during the process. After that, characteristics are taken out of it in order to teach a machine learning system whether or not the patient is anemic. 200 participants participated in the study, which had 85% accuracy, 86% precision, and 81% recall rate.

P. Appiahene et al. [13] concentrated on pallor analysis and employed machine-learning algorithms to identify anemia using pictures of the eye's conjunctiva. The research employed a publicly accessible dataset of 710 pictures of the eye's conjunctiva. With the use of Gaussian Blur, Logistic Regression, and Convolutional Neural Networks, two methods for the detection of conjunctiva and anemia were created. These models were then deployed on a Fast API server that was coupled to a front-end React Native mobile application. The created model possessed 90% sensitivity and 95% specificity. It is integrated into a mobile application that can identify anemia with 92.50 accuracy by obtaining and analyzing the patient's conjunctiva.

Today, artificial intelligence technologies are developing rapidly in the field of health, as in every field. The eye is an organ where not only eye diseases but also diseases such as anemia and diabetes can be detected. Invasive methods such as blood sampling are used to diagnose such disorders. Instead of these, it is a more comfortable method to detect diseases using eye images. In the study, three different regions are detected using eye conjunctiva images. According to our research, no academic study has been found on the detection of regions in conjunctiva images. In cases where the number of experts is insufficient, automatic discrimination of the conjunctiva regions of the eye is beneficial.

The rest of the research is arranged as follows. In the second section, the technical background is given, including the data set used, the enhancement technique applied to the images, and the method applied to find the regions. In the third section, the suggested technique is presented. In the fourth section, the experimental results are given. Lastly, the fifth section gives the discussion and conclusions of the study.

2. Technical Background

Technical background information is important for understanding the proposed methodology. This section indicates the dataset used in the training and validation processes. The data is developed by pre-processing before being given as input to the method. YOLOv8 (You Only Look One-v8) is used to detect the regions

2.1. Dataset

The data set used was taken from the Roboflow site. The dataset named Eye conjunctiva contains 218 eye images. Of these, 152 are reserved for training, 32 for verification, and the remaining 34 for testing. The data is labeled in three categories. These; palpebral, forniceal and forniceal palpebral. Some example images of the dataset are displayed in the Figure 2 [14].

2.2. Improving the Image: DNCNN

In order to restore the original image by suppressing related noise, image denoising is an essential pre-processing step. Since noise depends on the high frequency composition of the image, denoising is a complicated process [15]. The primary goal is to strike a balance between minimizing information loss and lowering noise as much as feasible. Image noise can be eliminated by applying filter-based techniques like wavelet, mean, and median. The increased hardware capabilities of computers have led to a rise in the adoption of modern techniques

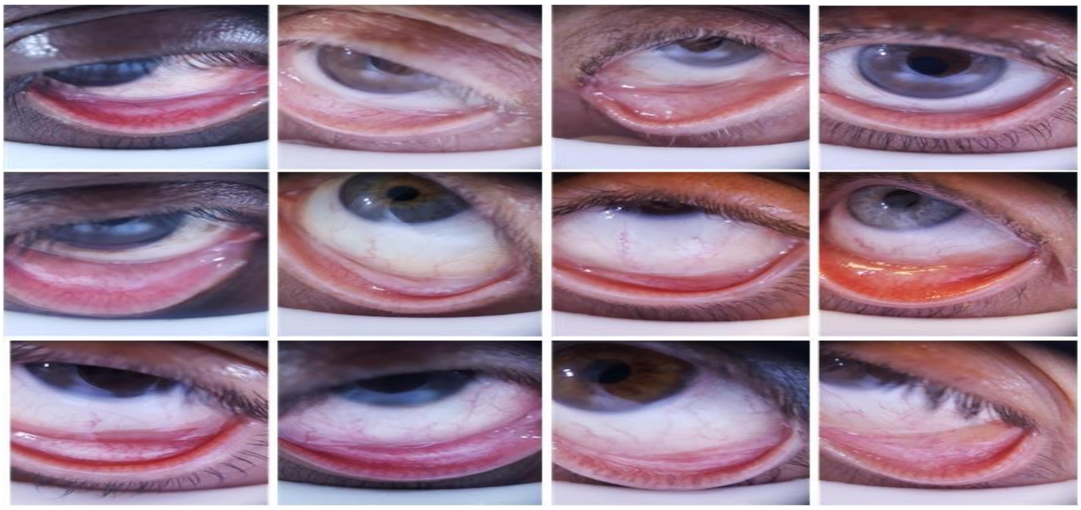

Figure 2. Some images from eye conjunctiva dataset [14]

The Deep CNN Residual Learning (DNCNN) [16] method is applied in this work to eliminate noise. Several attempts have been made by deep neural networks to address the noise removal issue. Thanks to advancements in deep learning techniques and the accessibility of access to large-scale datasets, CNN has recently shown exceptional efficacy in completing a range of vision tasks. In addition to solving challenges with image denoising, JPEG deblocking, and super-resolution, DNCNN, a model designed to handle a variety of low-level assignments, can also carry out blind reconstruction in the absence of any knowledge about the input image. Figure 3 displays the DNCNN network's design.

The DNCNN architecture consists of three different kinds of layers. (1) Convolution + ReLU: In the first layer, 64 filters with a size of 3 x 3 x x are utilized to create 64 feature maps. These maps are subsequently adjusted for nonlinearity using linear units (ReLU, max (0, ·)). In this case, x stands for the number of image channels; that is, x = 3 for a color image. (2) Conv+BN+ReLU: 64 filters with a size of $3 \times 3 \times 64$ are employed for $2 \sim (D-1)$ layers, and batch normalization is introduced in between the convolution and ReLU. (3) Conv: To rebuild the output for the final layer, c filters with a size of $3 \times 3 \times 64$ are employed. Through hidden layers, DNCNN can gradually extract the image framework from noise observation by combining convolution with ReLU. The DNCNN model employs the notion of residual learning. DNCNN predicts the residual image using just one residual unit, as opposed to the residual network's many residual units. Additionally, faster and more reliable training as well as better denoising performance can be achieved by combining batch normalization and residual learning with DNCNN [16].

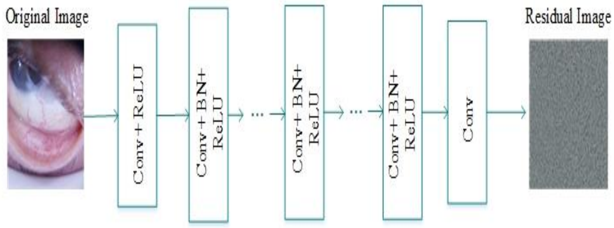

Figure 3. The structure of DNCNN

2.3. Multiple Object Detection: YOLOv8

The YOLOv8 algorithm's structure is first described in this section, which serves as a foundation for algorithm construction. The four components of the YOLOv8 algorithm are the entrance, spine, neck, and head. Figure 4 depicts the YOLOv8 algorithm's structure.

Backbone: In the YOLOv8 algorithm, the backbone network's job is to extract the target's general features. Three modules make up this backbone network: Conv, C2f, and SPPF. The Conv module uses autopad (k,p) to generate fill effects and is composed of three functional modules: Conv2d, BN, and SiLU activation function. The C2f module's design, which draws inspiration from ELAN and the C3 module, enables YOLOv8 to offer greater features while offering lightweight features that enable the acquisition of gradient flow information. SPPNet served as an inspiration for the redesign of the SPPF module. The SPP module gradually adopts several small-size pooling cores in place of a single large-size pooling core, maintaining its original functionality [17], 18].

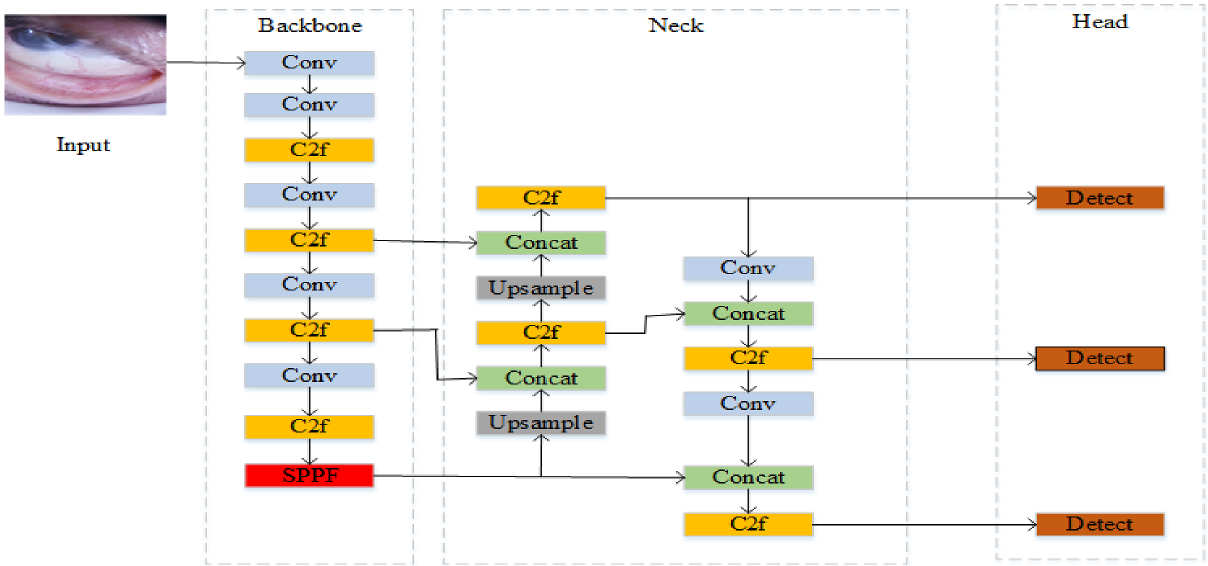

Figure 4. The architecture of YOLOv8

Neck: PAN-FPN module is used in the neck of YOLOv8 for efficient feature fusion at various scales. With the use of FPN and PAN architectures, this module employs a multi-scale fusion technique in which lower layers maintain precise position details while top layers acquire more information [19].

Header: The head of the YOLOv8 algorithm uses the Split Head structure, which is a common parser head structure. This structure uses the concept of DFL (Distributional Focal Loss) to distinguish between headings for classification and detection. Targets are predicted and regressed using the three detecting layers in the head of the YOLOv8, which correspond to three distinct kinds of anchors with various aspect proportions extracted from the Neck. The YOLOv8 algorithm's junction boxes are adaptable to the dataset and may automatically modify their corresponding junction boxes based on various datasets.

3. Proposed Method

The study aims to detect the palpebral, forniceal palpebral and forniceal regions in eye conjunctiva images. The proposed method is carried out in two stages. In the first stage, the DNCNN algorithm was applied to the images to be used to perform the method and the images were enhanced. The noisy signal is the DNCNN's input. DNCNN maps the remaining learning to train and utilize it to forecast the latent clean signal, in contrast to discriminative denoising, which aims to learn to map the noisy signal to the genuine signal [20].

In the second step of the study, the improved images were given to the YOLOv8 algorithm and the regions were detected. Simple block drawing of the proposed pipeline is as in Figure 5.

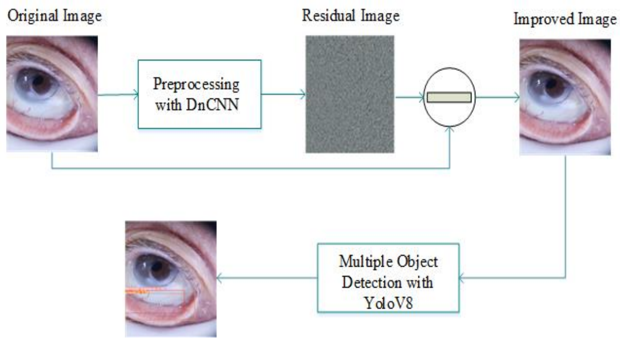

Figure 5. Simple block drawing of proposed pipeline

4. Experimental Results

In this article, it is aimed to detect the regions using eye conjunctiva images. First of all, the images to be used with deep learning technology are pre-processed and developed. Then, the network first produces images in the data set. The system is then tested with images to distinguish palpebral, forniceal palpebral, and forniceal regions. The application was run on a computer with an i7 processor, GPU card and 16GB RAM.

4. 1. Object Detection Metrics

Many metrics are utilized to test the effectiveness of algorithms for object detection. Frequently used metrics are Intersection over Union, Precision, Recall, Average Precision, Mean Average Precision (mAP) and F-score [21].

Intersection over Union (IoU): The relationship between a predicted and the ground truth bounding boxes is quantified using a metric called IoU. It is essential to assessing how accurate object localization is.

Average Precision (AP): The accuracy and recall value of the method are combined into a single value by AP, which computes the area under the precision-recall curve.

Mean Average Precision (mAP): The AP notion is expanded upon by mAP, which computes the average AP values among various object classes. This aids in providing a comprehensive evaluation of the model's effectiveness in situations involving multiple classes of item detection.

Precision: Tells how precise our model is. In other words, it tells you how many of the total palpebral regions detected are actually palpebral. It is the proportion of the overall number of palpable predictions the algorithm makes to the genuine positive, as shown in equation (1).

$$Precision = \frac{Correct\ Predictions}{Total\ Predictions} = \frac{TP}{(TP+FP)} \quad (1)$$

Recall: It tells us how good the model is at remembering classes from images, that is, how many of the total palpebral in the input image the model can detect. It is the proportion between the true positive generated by the model and the total of the true positive and false negative as shown in Equation (2).

$$Recall = \frac{Correct\ Predictions}{Total\ GroundTruth} = \frac{TP}{(TP+FN)} \quad (2)$$

F1 Score: The F1 Score is a comprehensive evaluation of a method's performance that considers both false positives and false negatives. It is calculated as the harmonic mean of precision and recall. The F1 Score equation is provided by equation (3).

$$F1\ Score = 2 * \frac{(Precision*Recall)}{(Precision+Recall)} \quad (3)$$

The F1 score provides a balance between precision and recall. This balance is very important, especially in data sets with class imbalance. For example, if a model provides very high precision but ignores sensitivity, this means that it misses true positives.

4.2. Results Obtained using Original Images

In the first part of the study, regions were detected with YOLOv8 using eye conjunctiva images. Yolov8m weight was used when training the model. Epoch is taken as 100 and batch 4. The confusion matrix of the model is as presented in Figure 6.a. The number of locations in the confusion matrix, sometimes referred to as the error matrix, where the true label and the predicted label coincide is represented by diagonal elements, while the points that the classifier incorrectly identified are represented by off-diagonal elements. Indicative of many accurate predictions, the confusion matrix's diagonal values increase with increasing complexity. Figure 6.b gives the normalized confusion matrix of the method.

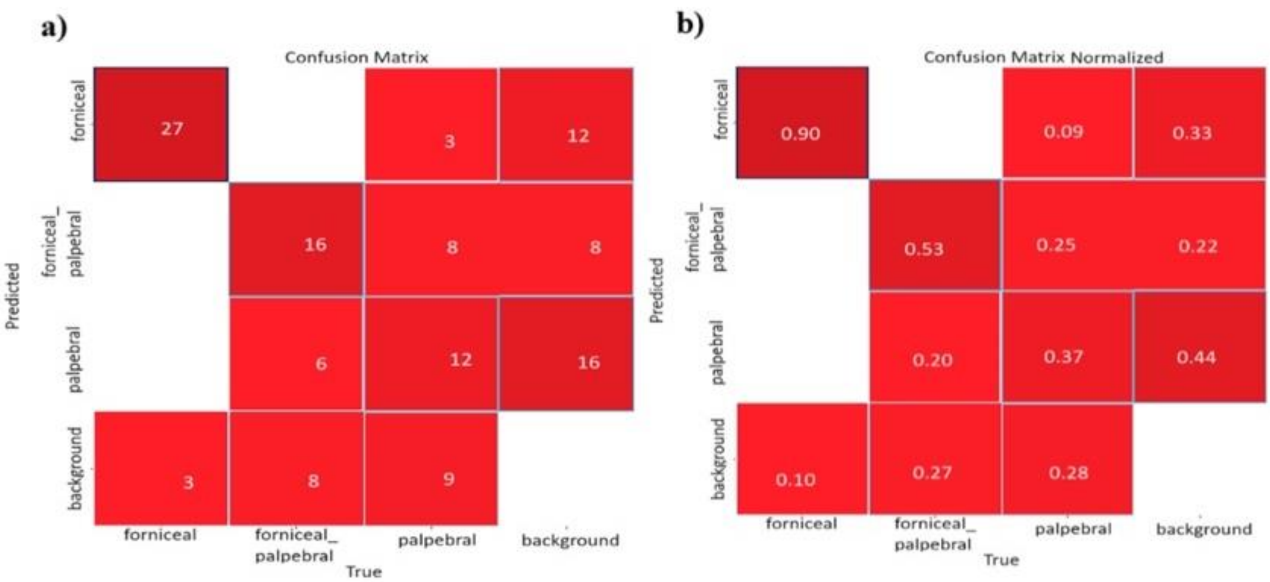

Figure 6. a) Confusion Matrix and, **b)** Normalized Confusion Matrix

The F1-Confidence curve and P curve of the method are given in Figure 6.a, and Figure 6.b, separately. When looking at the F1-Confidence curve, a value of 0.97 was reached for all classes. A 73.4% confidence interval is provided in the P-curve, which expresses the likelihood of acquiring test outcomes that are at least as extreme as the actually acquired results.

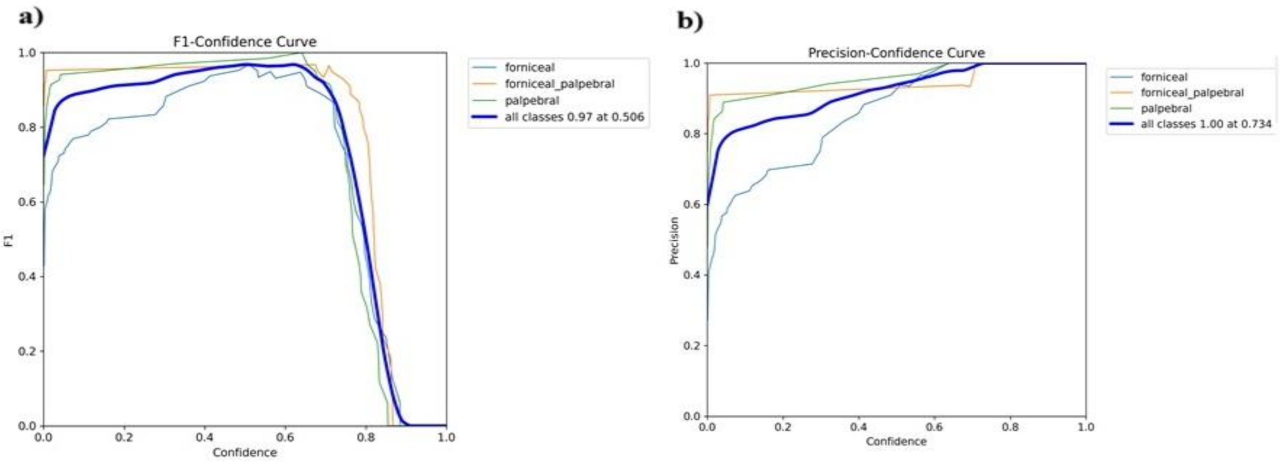

Figure 7. a) F1-Confidence Curve and, **b)** Precision-Confidence Curve

Figure 8.a, and Figure 8.b display the model's Precision-Recall and Recall-Confidence curves, respectively. The trade-off between recall and precision for different threshold levels is displayed on the precision-recall curve. High precision and recall are shown by a high area under the curve. Here, forniceal, forniceal palpebral, and palpebral values were found to be 0.990, 0.991, and 0.995, respectively. Finding the area under the precision-recall curve is the general definition of average precision, or AP. The mean of AP is called mAP. In certain situations, AP is determined for every class and averaged to provide mAP. They mean the same thing in other contexts, though. mAP establishes a balance between the precision (sensitivity) and recall of the results that the model correctly detects in different equivalent values. It is expressed that the model is not only examined by making correct detections, but also by keeping false positives low. mAP also evaluates the accuracy of the confidence values that the model assigns to its predictions. Incorrectly high confidence scores can lead to false positives and cause serious problems in practice. Recall is the quantity of accurate positive predictions generated relative to all possible positive predictions. Recall gives an indicator of missed positive predictions, in contrast to precision, which only comments on correct positive predictions out of all positive predictions. The mAP value for all classes is 0.992. When we look at the Recall-Confidence curve, it is seen as 1 for all classes.

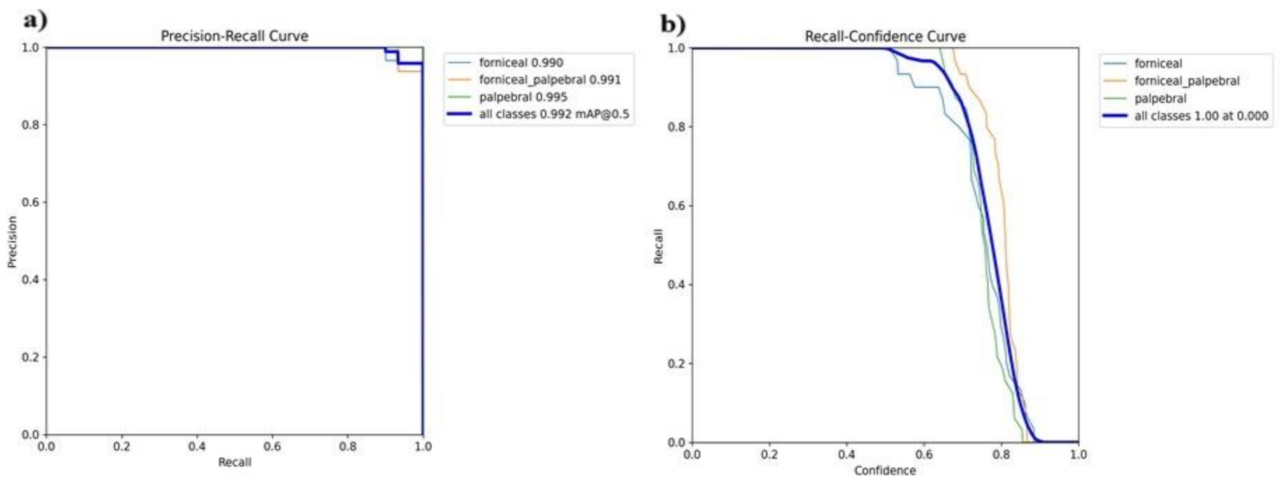

Figure 8. a) Precision-Recall Curve and **b)** Recall-Confidence Curve

Training results of the method are presented in Figure 9. 34 images were used for testing. Some of the results obtained from these are as given in Figure 10.

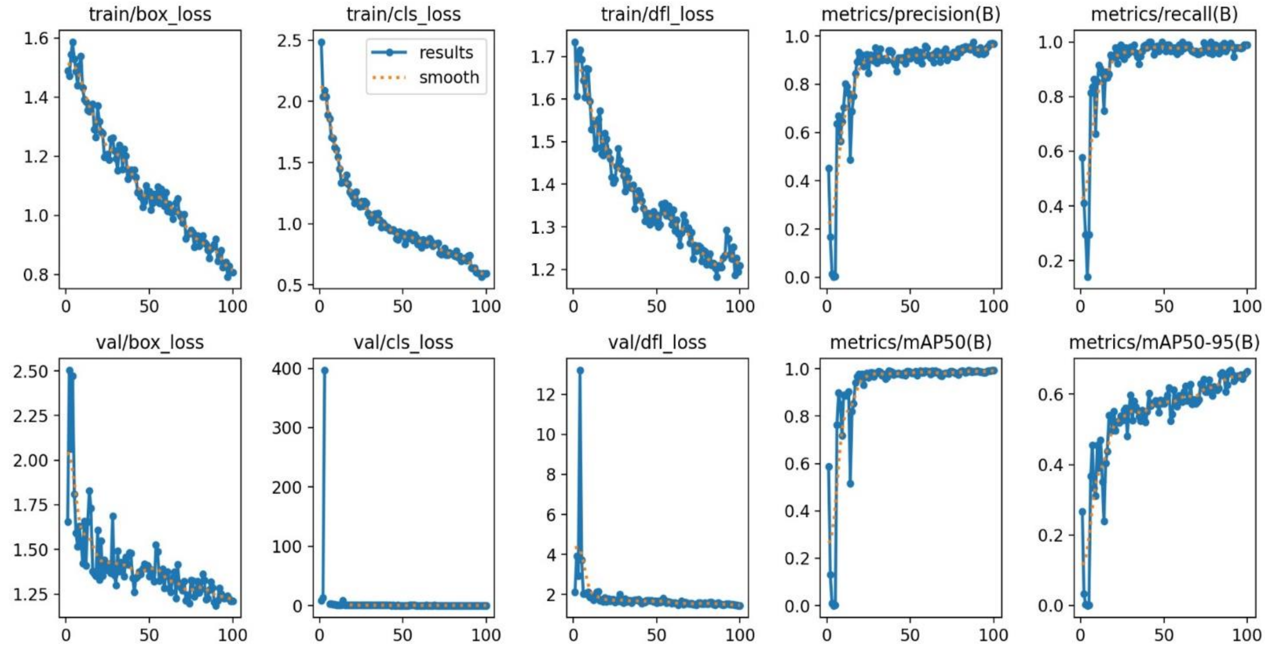

Figure 9. Training Results of the YoloV8m Model on the Eye Conjunctiva Dataset

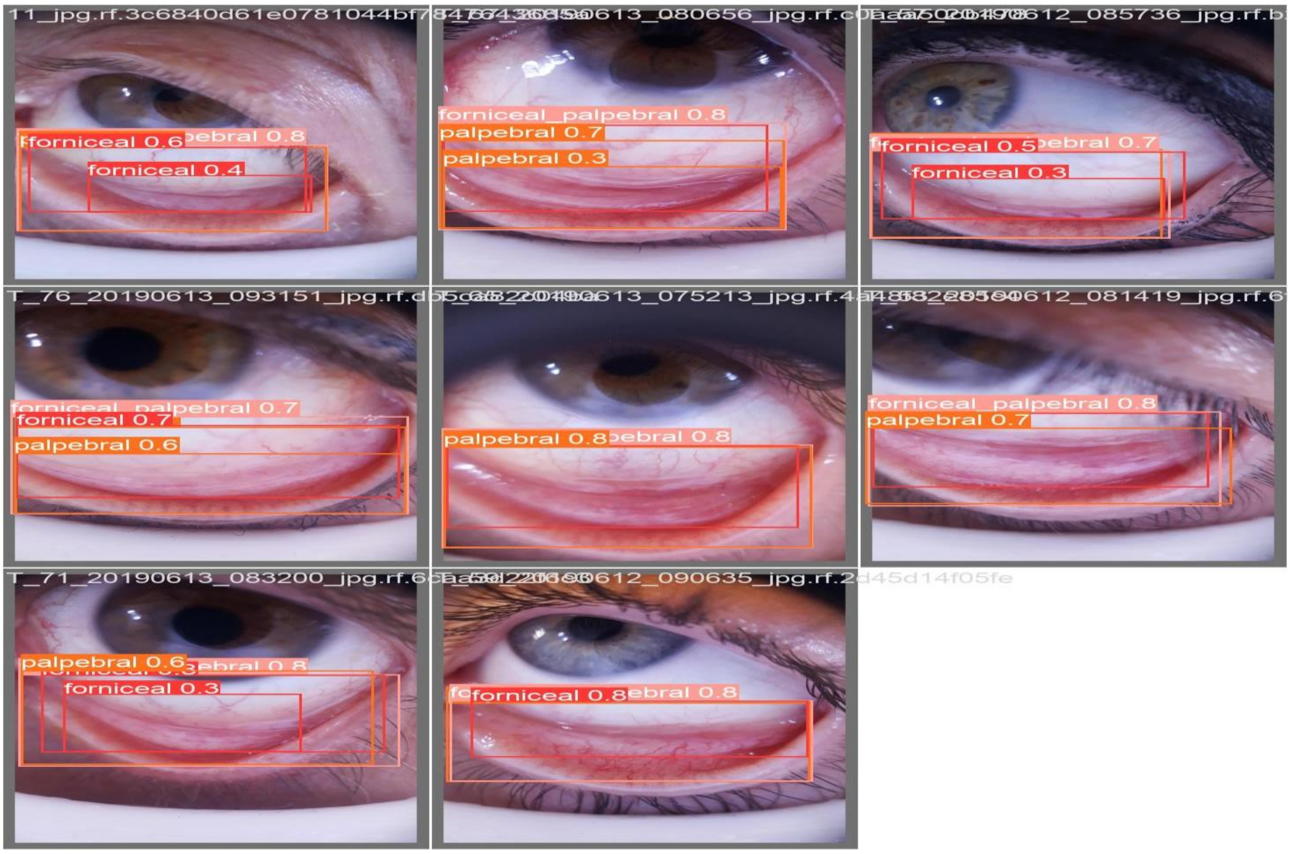

Figure 10. Test results of the YoloV8m Model on the Eye Conjunctiva Dataset

4.3. Results Obtained using Images Enhanced using DNCNN

In the study, it was observed that the proposed image enhancement method positively affected the performance results. Figure 11.a gives the relevant confusion matrix. Figure 11.b presents the normalized confusion matrix.

F1-Confidence and Precision-Confidence curves are given in Figure 12.a, and 12.b, respectively. When we look at the curves, the precision-confidence value was 0.734 in all classes in the method performed with raw data, and 0.772 in all classes when the data obtained with DNCNN was used.

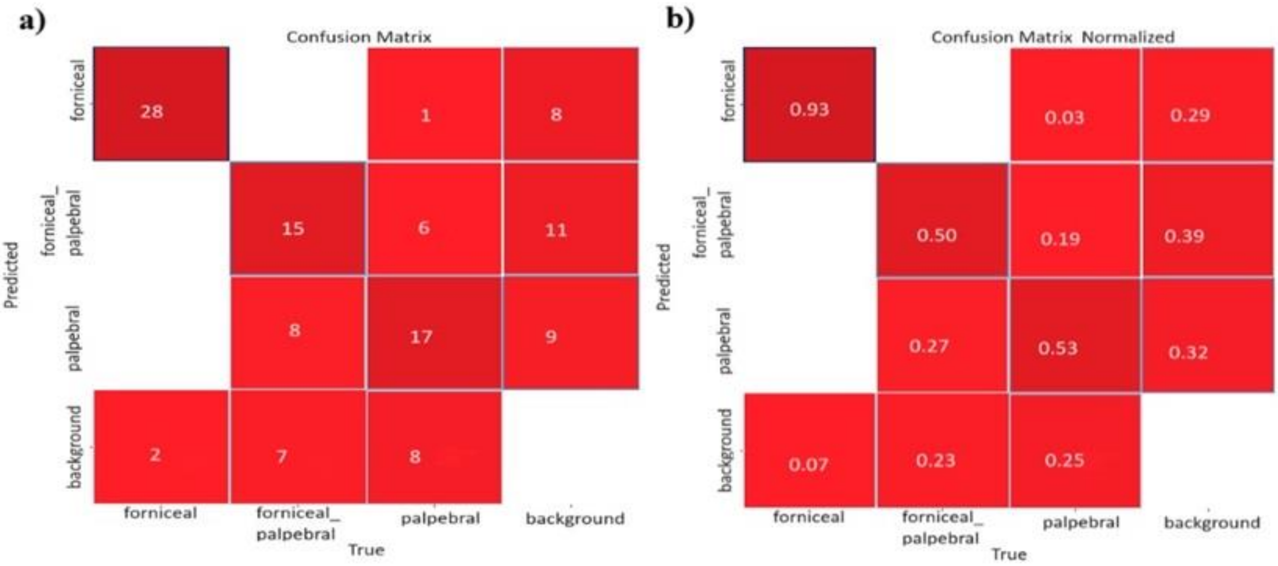

Figure 11. a) Confusion Matrix and, b) Normalized Confusion Matrix

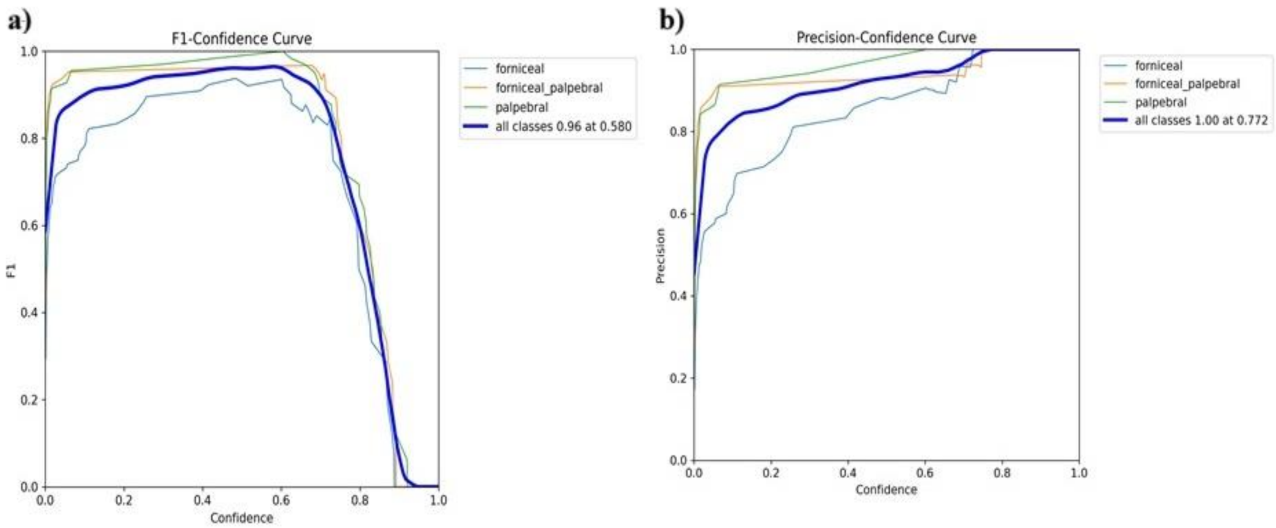

Figure 12. a) F1-Confidence Curve and, **b)** Precision-Confidence Curve

Figure 13.a gives the Precision-Recall curve. Forniceal 0.973, forniceal_palpebral 0.983, palpebral 0.995 and mAP value in all classes were obtained as 0.984. The Recall-Confidence curve is given in Figure 13.b. The training results of the model trained with DNCNN-improved images are presented in Figure 14. The results of some of the test images are presented in Figure 15.

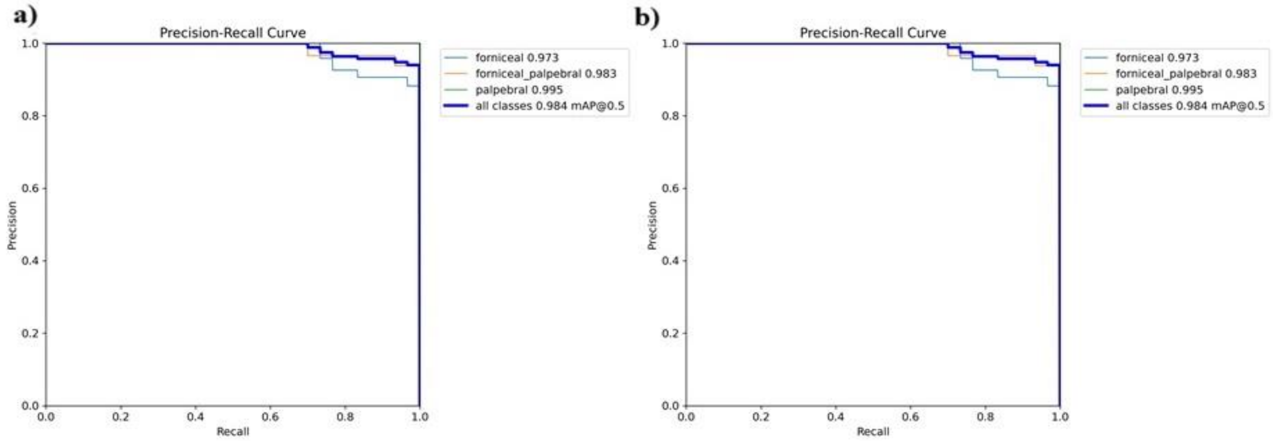

Figure 13. a) Precision-Recall Curve and **b)** Recall-Confidence Curve

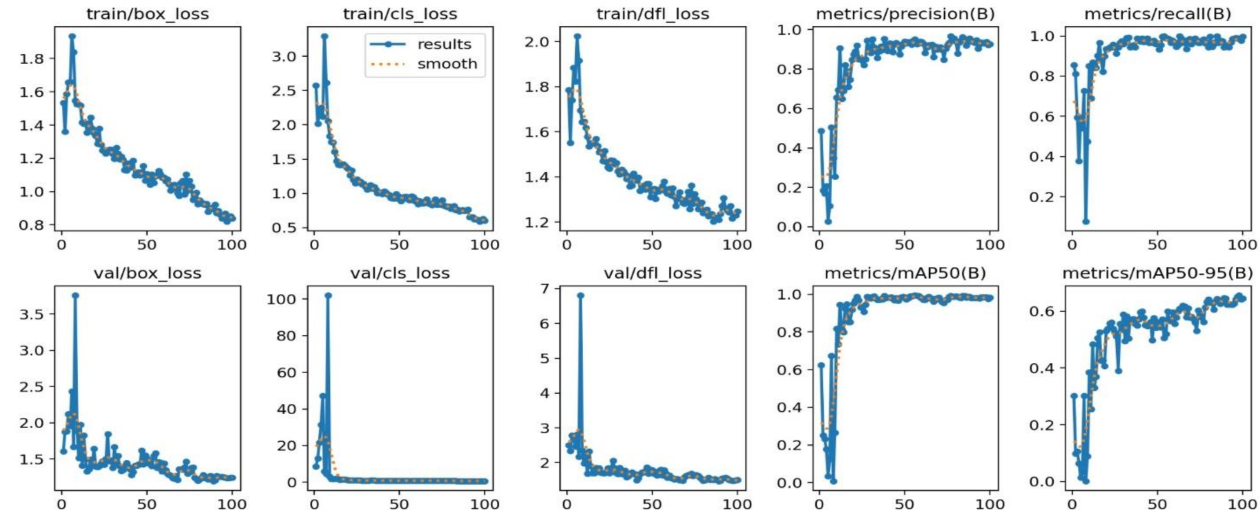

Figure 14. Training Results of YoloV8m Model on DNCNN-improved Eye Conjunctiva Dataset

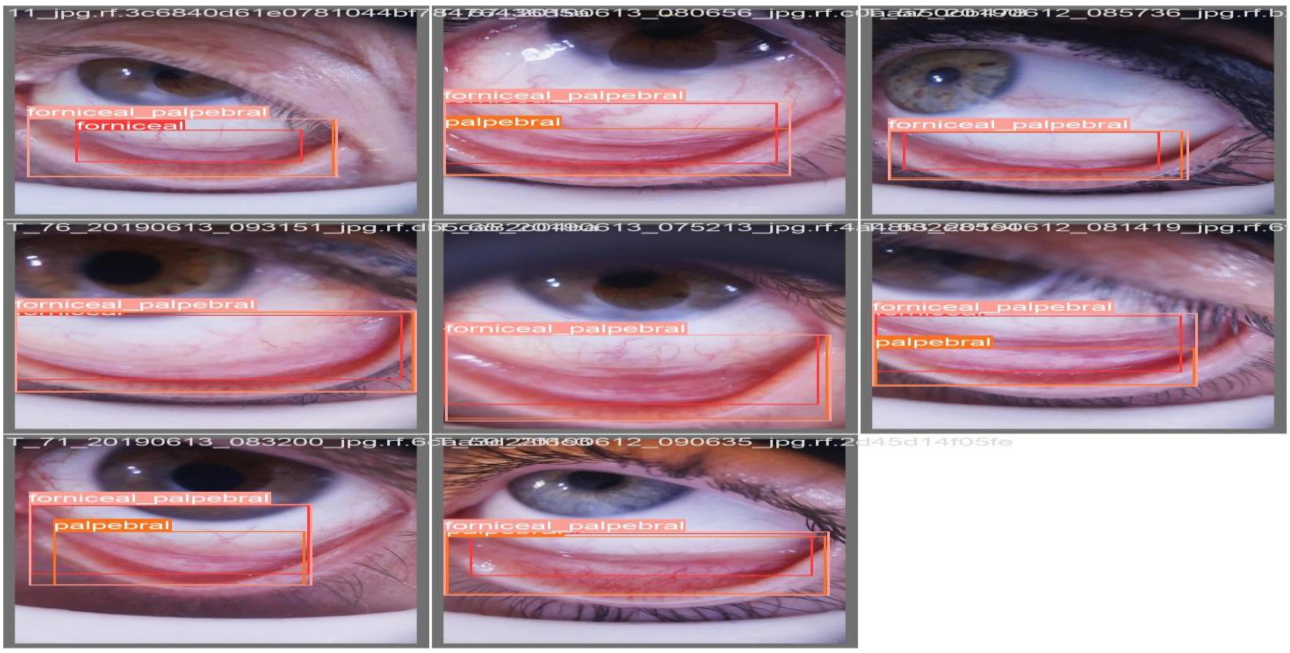

Figure 15. Test results of the YoloV8m Model on enhanced images

Table 1. Studies related using eye conjunctiva images

Authors/Year	Task	Dataset	Model	Results
S. Dhalla et al.[5]/2023	Conjunctiva Segmantation	2592 images	LinkNet	94.17 % Acc.
E. Purwanti et al. [6]/2023	Anemia Classification	654 images	ResNet-50	97.94 % Acc.
X. Li et al. [7]]/2022	Diabet Classification	611 images	HMT-Net	75.17 % Acc.
E. R. Ghugare et al. [8]/ 2023	Diabet Classification	611 images	CNN	96 % Acc.
B. B. Pallavi et al. [9]/2023	Anemia Classification	300 images	CNN	97 % Acc.
B. B. Pallavi et al. [9]/2023	Anemia Segmantation	300 images	CNN	92.2 % IOU
G. Dimauro et al. [10]/2017	Anemia Classification	102 images	SMOTE+KNN	98% Acc.
S. Wei et al. [11]/2023	Bulbar Conjunctival Injection Rating	1401 images	CNN	87.12 % Acc.
S. H. Elgohary et al. [12]/2022	Anemia Classification	318 images	KNN	84.6 % Acc.
P. Appiahene et al. [13]/2023	Anemia Classification	710 images	CNN+Logistic Regression+ Gaussian Blur	92.50 % Acc.
This paper	Multi-region Detection of Eye Conjunctiva	218 images	Yolov8	0.992 mAP 0.734 Precision Confidence 0.97 F1 Confidence
This paper	Multi-region Detection of Eye Conjunctiva	218 images	DNCNN+Yolov8	0.984 mAP 0.772 Precision Confidence 0.96 F1 Confidence

5. Discussion

In the study, the locations of the conjunctiva images, including palpebral, forniceal-palpebral and forniceal, were determined. Palpebral regions of the eye are used to detect disease. By taking a picture of the palpebral conjunctiva, doctors can determine if a blood sample is required or if the patient even needs to notify them. This helps to narrow down the pool of potential blood sample donors. Additionally, it can draw attention to possible anemia and make it possible for many people to be screened for anemia, especially in environments with low resources.

A thorough understanding of the architecture of the conjunctiva, particularly the eyelid, is necessary to build a treatment that bolsters the anemia diagnosis. The conjunctiva is a mucous membrane that surrounds the arches but does not touch the cornea. It stretches from the inner palpebral borders to the eyeball. The plentiful abundance of microvessels ensures a high degree of vascularization, which generates the palpebral conjunctiva a great nominee for physical examination observation. Compared to the bulbar conjunctiva, the palpebral conjunctiva more clearly displays the vascularization of the underlying region, highlighting even the smallest variations in blood color.

Many studies have been conducted using images of the eye conjunctiva. Table 1 lists some studies in the literature using eye conjunctiva images. Looking at the table, it can be seen that these images can be used to classify diseases such as anemia and diabetes. When the accuracy rates are examined, it is seen that the methods need to be improved. According to our research, no academic study has been found on the detection of regions in conjunctiva images. Therefore, it was not included in the comparison table. In addition, the results of the realization of raw images with the YOLOv8 algorithm are given. Looking at the table, we see the effect of pre-processing images with the deep learning method on performance.

6. Conclusion

Using eye conjunctiva images, diseases such as anemia and diabetes can be detected. Automatic disease detection with artificial intelligence is frequently preferred in the health field in terms of patient comfort and the convenience it provides to the specialist. The proposed method enables the detection of regions in eye conjunctiva images with acceptable high accuracy rates. The use of the method in detecting regions in eye conjunctiva images will provide convenience to specialists. Nonetheless, it's critical that the AI techniques applied in the medical industry deliver excellent results. One stage that will be used to identify the disorders is the identification of the conjunctiva regions. As a result, the approach needs to be improved going forward

Statement of Research and Publication Ethics

The study is complied with research and publication ethics.

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