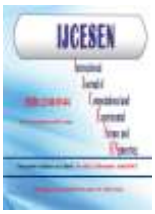
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Research Article

A Hybrid Attention-Based ML–DL Framework with Uncertainty Quantification for Automated Segmentation of Cotton Wool Spots and Major Conjunctivitis

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Abstract:

Human day to day activities and air pollution are the major cause for eye diseases which troubles from infant to old age persons. The ratio between the Ophthalmologists [3] and the number of patients suffering from eye diseases are increasing day by day, this leads technology to develop automatic technique for detection of eye diseases. In this paper a novel eye image segmentation technique has been discussed using AIML and deep learning algorithms, the proposed method is customized by deep learning U-Net++, CNN and Monte-Carlo Dropouts [1,2], and is built to segment CWS [4], lesions and enhances feature extraction in color fundus image. The architecture comprises of encoder and decoder with depth layer and various resolutions which are able to extract low and high level grained characteristics. A deep learning model is constructed for segmentation of conjunctiva nevus and major conjunctivitis by transformer Encoder (Swin/ViT) [6], Attention-U-Net++ Decoder using conjunctiva images or digital eye images. The segmentation includes diseases like cotton wool spots, conjunctiva nevus and major conjunctivitis using conjunctiva images and fundus images. Data augmentation is considered to ensure reliable results and to avoid over fitting of the model by increasing generalization capability. The segmentation model achieved a accuracy of about 96.32% and a dice coefficient of 88.60% in lesions segmentation for fundus images. The segmentation model for conjunctiva images provide test accuracy of 82.40% with a specificity of 94.55%.

1. Introduction

Eye diseases are becoming very common and some time becomes very dangerous and can lead to loss of vision, there are many reasons for eye diseases, due to air pollution, human day to day activities and many more. Eye diseases are classified in many ways, among them cotton wool spots or penjuncula [13] is a whitish or yellow pigemntated fluffy lesions rise on retinal nerve fiber called ischemia. Sometimes it may or may not visible to naked eye. In automatic detection it may appear with low contrast with the background of fundus image [1,5,6,7], sometimes similar to exudates appearance due to irregular shapes. So a thorough analysis is needed. A benign pigmented lesion present in the conjunctiva is a conjunctiva nevus. It appears with variability in color like brown and black, difficult to differentiate with melanoma [8] and hemorrhages also sometime with pinguecula. The structure is very irregular in shape, boundaries and has illumination artifacts [8].

Adenoviral conjunctivitis [3] is a highly contagious and acute condition in eye diseases causes due to viral infections which are characterized by diffuse conjunctiva hyperemia, conjunctiva edema, conjunctiva follicular reaction, also in some severe cases it may be Pseudo-membranes, in progressive cases it will be Sub-epithelial infiltrates [3]. The automatic detection of adenoviral conjunctivitis is a challenging since it appears same between allergic and bacterial conjunctivitis, inflammation is Diffuse, non-localized and reflection, illumination artifacts in conjunctiva images.

2. Related work

In this work for automatic detection of cotton wool spots a hybrid CNN model is combined with swin-Unet transformer architecture, which includes locality and inductive bias of CNN [6,8,9] with the long range dependency modeling of vision transformers. The conventional CNN extracts edges and textures effectively, context modeling but has limited receptive field view and inductive bias. The proposed approach has higher segmentation accuracy and robustness, identifies very small details and models long range dependencies.The input is a fundus image of various size and parameters. The preprocessing stage performs the resizing of image and normalization using green or red channel enhancement by CLAHE algorithm [9], further the illumination correction has been performed. The hybrid encoder uses CNN encoder with Unet++ [10] which performs convolution using convolution blocks and multi-scaled convolution encoder. This data will be transferred to Transformer Encoder which uses Swin / ViT which provides Self-Attention, Global Context and Vessel Density, basically used to capture Local redness & texture and Global inflammation spread, it learns the long range density patterns of vessel density, remodels redness gradients of the eye, and Essential for global inflammatory spread . The Multi-scale dilated convolution detects inflammation caused due to diffuse and non localization, it preserves image resolution and increase context.

A. The Dilated convolution is given by $y(p) = \sum_{k=1}^{K} x(p + r.k).w(k)$ Where r = dilation rate (e.g., 1, 2, 4, 8), x = input feature map, and w = convolution kernel
B. The Multi-scale aggregation is given by $F_{ms} = Conv_r(x)$, xε(1,2,4,8)
C. The Patch embedding is given by $Z_0 = [x_p^1 E; x_p^1 E; \ldots\ldots x_p^N E] + E_{pos}$
D. With Self-Attention given by Attention (Q, K,V) = softmax $(\frac{QK^T}{\sqrt{dk}})V$
E. The Transformer blocks anr expressed as $z_l' = z_{l-1}$ + MSA (LN(z_{l-1})) and $z_l = z_l'$ + MLP (LN(z_l'))

The AUNet++ [11] Decoder used to enhance the ROC of the region specific inflammation while suppressing background and the noise and increases boundary accuracy, which are performed by attention gate given by .α= σ(W^T . ReLU(W_xx + W_g g +b)) where $x' = \alpha.x$, x = encoder features, g = decoder gating signal. Nested U-Net++ skip fusion is given by $x^{i,j}$ = H([$X^{i,j-1}, X^{i+1,j+1}$,….]).For clinical implementation the Monte-Carlo Dropout [12] which uses Uncertainty Estimation are used which generates uncertainty maps of pixel level and detects regions of low model confidence which are must for safe clinical deployment.

F. The Predictive mean is given by $\mu(x)=\frac{1}{T}\sum_{t=1}^{T} pt(x)$
G. Predictive variance $\sigma^2(x) = \frac{1}{T}\sum_{t=1}^{T} pt(x)^2 - \mu(x)^2$
H. Entropy-based uncertainty $U(x) = -\sum_c \mu c(x) \log \mu c(x)$

The conjunctiva images are acquired by slit lamp test or from the digital photographs captured in a clinic, the conjunctiva images are also available in a open source public data base. The conjunctiva image are affected by in-appropriate illumination, anatomical clutter and reflections, which are need to be removed in preprocessing stage which performs following operations. Removes highlighted specular by corneal glare in painting or by suppression of reflection by threshold, color normalization by selecting RGB channels [14], adjusting improper illumination by homomorphic filtering and preserving red channel data, ROI extraction like bulbar conjunctiva, eyelids and iris using ML [15] and CNN algorithms. Vessel enhanced contrast normalization for vascular dilation and for enhances hyperemia. Resizing the input image to standard size of 512x512 which is a standardized size input for deep models

The novel segmentation technique uses attention U-Net++ as a backbone for dense skip connection by detecting conjunctiva inflammation due to fine grain and provides channel and spatial attention. For capturing diffuse redness, patchy inflammation [16], dilation rates and vascular spread the multi-scale dilation convolutions are applied.

The swin transform encoder provides global inflammation patterns for adenoviral conjunctivitis with window based full self attention and long range dependency models. The uncertainty aware predictions are detected by monte-carlo dropouts.

The output will be a binary segmented mask, probability map with pixel level infection likelihood and highlights low confidence regions by uncertainty map. The image level outputs provides whether adenoviral conjunctiva present or absent with severity grading like mild-moderate- severe, the confidence score in percentage, uncertainty aware diagnostic flag and overlay of attention maps and inflammation heat maps.

A. The conjunctiva image are represented by mathematical model given by $I_0 \varepsilon \mathbb{R}^{H \times W \times 3}$

Where H and W are the RGB channels in spatial domain

B. The Specular Highlight Removal is given by $I_s = I_0 \Theta (1- M_{spec})$ where Mspec is the detected specular mask

A. The color normalization is given by $I_N = \sum_{ref}^{1/2} a \sum_{src}^{1/2} (Is - \mu src) + \mu ref$

B. The Homomorphic Illumination Correction,where H(u,v)H(u,v)H(u,v) is a high-pass homomorphic filter. $I_L = \exp [F^{-1} (H(u,v).F(\log(I_N)))]$

C. Conjunctival ROI Extraction where eyelids and iris are not considered $I_{ROI} = I_l \Theta M_{ROI}$

D. Vessel-Enhanced Contrast Normalization is given by $Iv = \alpha . F_{franhi} (I_{ROI}) + (1-\alpha). I_{ROI}$

The segmentation is performed using novel segmentation algorithm called as Hybrid deep segmentation network which uses feature encoding with Attention-U-Net++ encoder, multi scale dilated convolution module [17], global context modeling, decoder with attention fusion. The expressions are given by

E. Feature encodeing is given by $F_e = \varepsilon_{AUN++} (I_{Prep})$

F. Multiscale dilated convolution module $F_d = conv D_k (F_e)$ where D_k is the dilation rate

G. The transformer encoder $Z = Transformer (F_d)$

H. For caputering long range inflammation patterns Attention (Q,K,V)= softmax $(\frac{QK^T}{\sqrt{dk}}).V$

İ. Decoder with attention fusion is given by $F_{dec} = D_{AUN++} (Z,F_e)$

J. Binary segmentation mask is given by M = {1, P>= T and 0, P< T

3. Object Detection Metrics

The lesion detection uses many parameter metrics, the commonly used are F- score [19], mean average precision, average precision, Recall, precision and intersection over union [18].

Intersection over union is required for object location. The combination of accuracy and recall is used to computes the area under the precision-recall curve [21] called average precision. Mean Average Precision gives the average AP values among various object classes.

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

$Recall = Correct\ Predictions$ x $total\ GroundTruth = (TP+FN)$

$F1Score = 2*(Precision*Recall)(Precision+Recall)$

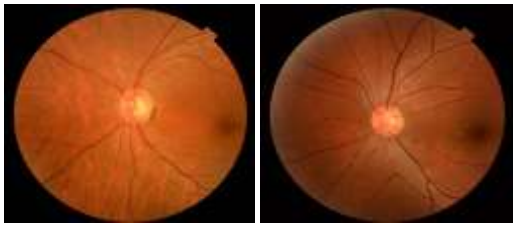


Figure 1: *Healthy fundus images [20]*

4. Conclusions

The proposed method automatically segments the input fundus image for detection of CWS. For conjunctiva images the proposed method segments major conjunctivitis with following parameters. The segmentation model achieved a accuracy of about 96.32% and a dice coefficient of 88.60% in lesions segmentation for fundus images. The segmentation model for conjunctiva images provides test accuracy of 82.40% with a specificity of 94.55%. Run on inter i5 Processor with 8 Gb RAM with 2.30 Ghz processor on Python platform.

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
- **Conflict of interest:** The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper
- **Acknowledgement:** The authors declare that they have nobody or no-company to acknowledge.
- **Author contributions:** The authors declare that they have equal right on this paper.
- **Funding information:** The authors declare that there is no funding to be acknowledged.
- **Data availability statement:** The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.
- **Use of AI Tools:** The author(s) declare that no generative AI or AI-assisted technologies were used in the writing process of this manuscript.

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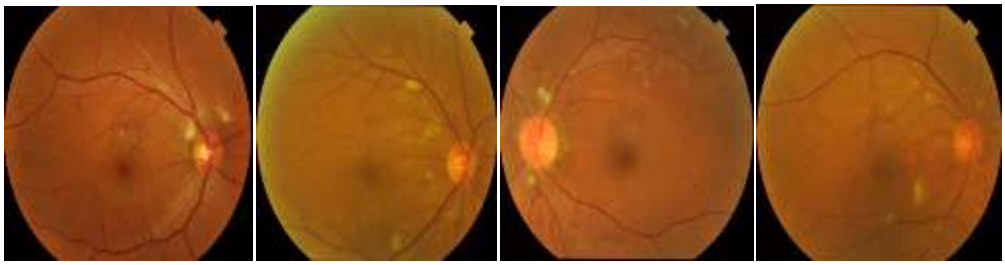


Figure 2: *Four Cotton wool spots fundus images[20]*



Figure 3: *Healthy image and Conjunctivitis of different grades [3,4]*

Table 1: *Literature review on AI, ML & DL models for conjunctiva images*

Model	Abstract	Method	Result
Conjunctive Net [9]	The diagnostic accuracy for conjunctivitis severity stages is increased by a deep learning-based model that uses sophisticated preprocessing techniques and a modified Otsu's method for better image segmentation.	(CNN) with transfer learning	High accuracy in classifying severity stages
IConDet [10]	An intelligent portable healthcare application designed for the detection of conjunctivitis, utilizing deep learning techniques to analyze eye images captured via mobile devices.	Deep Learning	Achieved 84% accuracy in initial detection
UNet++ Model [11]	A machine learning method that uses camera-based systems to take pictures of the eyes, preprocesses the images, and uses the UNett+ model for image segmentation to diagnose conjunctivitis.	UNet++	97.07% accuracy
AI-based Slit-Lamp Image Analysis [12]	Finds clinical signs of conjunctivitis, such as giant papillary conjunctivitis (GPC), atopic keratoconjunctivitis (AKC), vernal keratoconjunctivitis (VKC), and allergic conjunctivitis (AC), using explainable AI on slit-lamp images of the anterior surface of the eyes.	AI techniques	High accuracy
Eye Condition Detection with Deep Learning [13]	A convolutional neural network designed to detect various eye conditions, such as conjunctivitis, by analyzing images for visual symptoms.	(CNN)	High accuracy

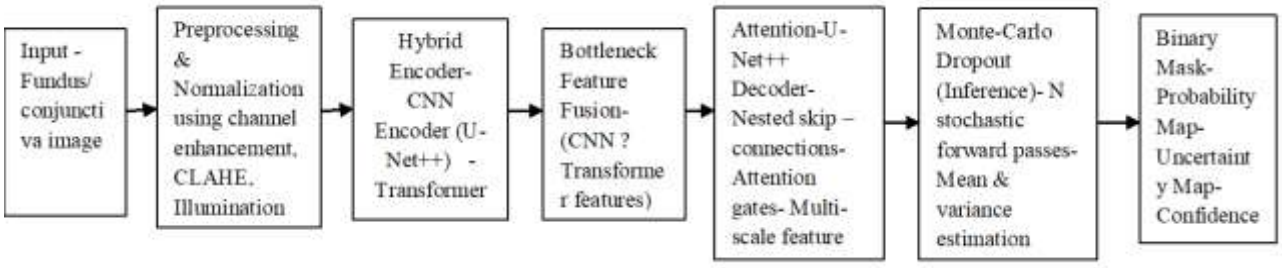


Figure 4: *Block diagram of CWS segmentation*

Table 2: *Studies related using eye conjunctiva images*

Authors	**Task**	**Dataset (Images)**	**Model**	**Results (Accuracy)**
Marouf, A et al.[5]	Conjunctiva Segmantation	2592	LinkNet	94.17 % 0.94 F1 Confidence
Nusair, O et al. [6]	Anemia Classification	654	ResNet-50	97.94 % 0.97 F1 Confidence
Aadil Qamar, M. [1]	Diabet Classification	611	HMT-Net	75.17 % 0.75 F1 Confidence
E Bawa, R. K et al. [2]	Diabet Classification	611	CNN	96 %

				0.96 F1 Confidence
Bali, J et al. [10]	Anemia Classification	102	SMOTE+KNN	98% 0.98 F1 Confidence
Biswas, A et al. [11]	Bulbar Conjunctival Injection Rating	1401	CNN	87.12 % 0.87 F1 Confidence
Cengil, E. et al. [12]	Anemia Classification	318	KNN	84.6 % 0.84 F1 Confidence
Cervantes, Jair et al. [13]	Anemia Classification	710	CNN+ Logistic Regression+ Gaussian Blur	92.50 % 0.92 F1 Confidence
Bitlis Eren University, Department of Computer Engineering, Bitlis, Türkiye [21]	Multi-region Detection of Eye Conjunctiva	218	Yolov8	0.992 mAP 0.734 Precision Confidence 0.97 F1 Confidence
Bitlis Eren University, Department of Computer Engineering, Bitlis, Türkiye [21]	Multi-region Detection of Eye Conjunctiva	218	DNCNN+Yolov8	0.984 mAP 0.772 Precision Confidence 0.96 F1 Confidence
Proposed work	Cotton wool spots	530	U-Net++, Monte-Carlo Dropout	accuracy of 82.40% Specificity of 94.55%. dice coefficient of 88.60% accuracy of about 96.32%
Proposed work	Eye Conjunctiva nevus	640	U-Net++ , Swin	0.985 mAP 0.774 Precision Confidence 0.97 F1 Confidence

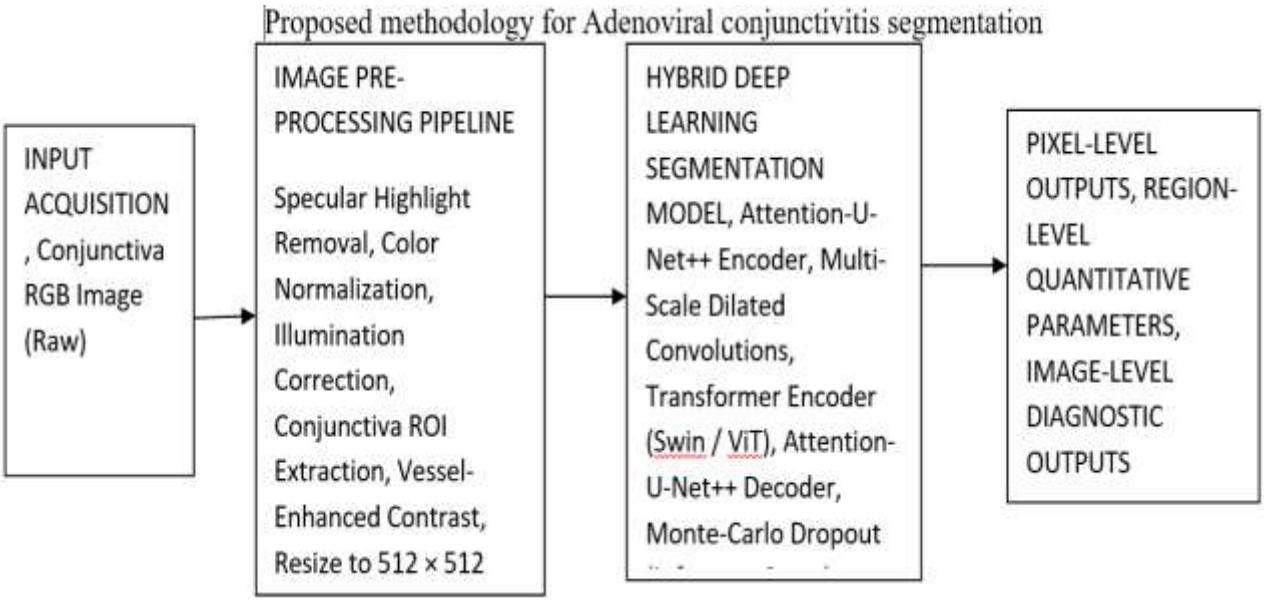


***Figure 5** : Adenoviral conjunctiva segmentation model*

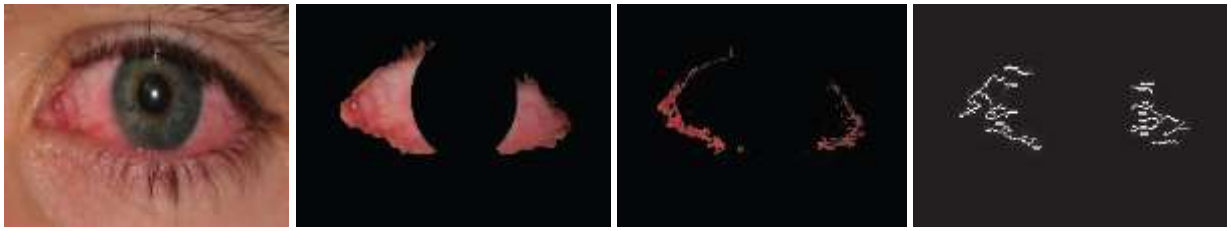


***Figure: 6** Sample image, **Figure 7 :** Sclera segmented image, **Figure 8**: Redness segmented area, **Figure 9:** Vascularization on segmented Sclera*

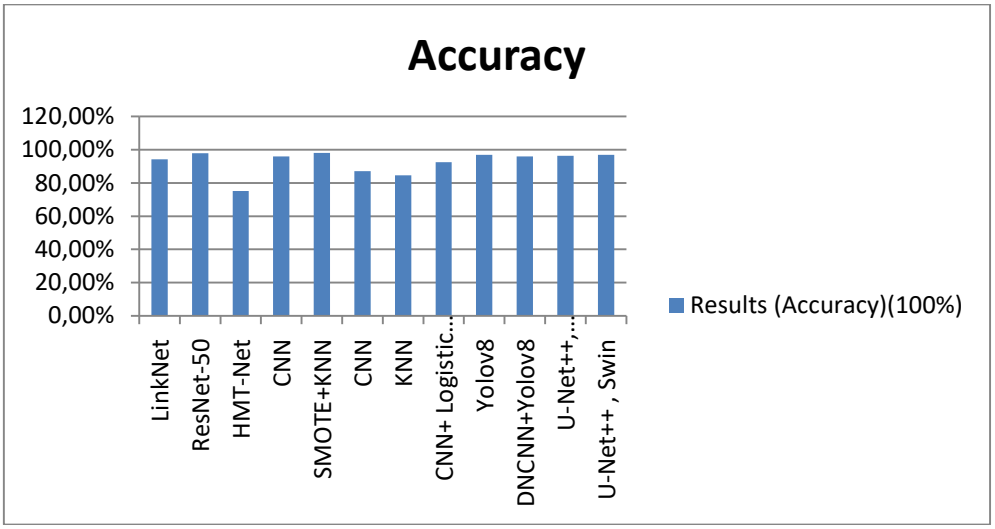


Figure 10: *Comparison of accuracy between existing models and proposed model*

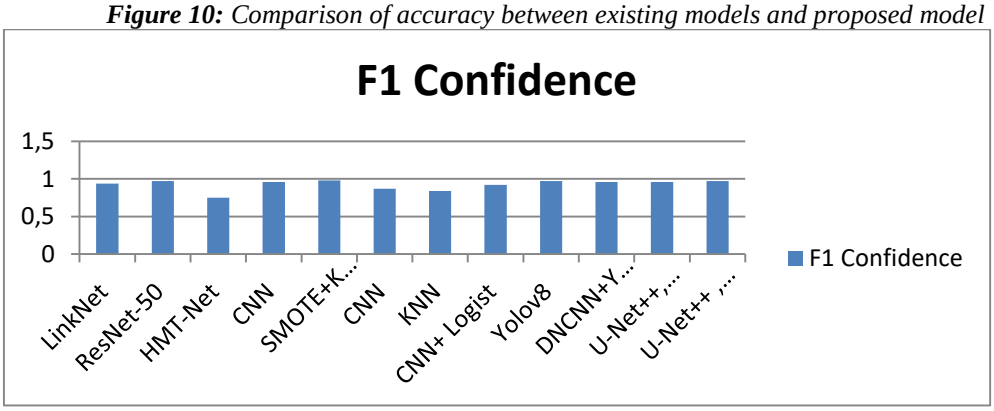


Figure 11: *Comparison of F1 score between existing models and proposed model*

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