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DEEP LEARNING-BASED RETINAL VESSEL SEGMENTATION: ATTENTION U-NET

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Abstract. Retinal vessel segmentation is critically important for the early diagnosis of ocular diseases such as diabetic retinopathy, macular degeneration, and retinopathy of prematurity (ROP). In this study, the performance of an Attention U-Net-based deep learning architecture was evaluated for vessel segmentation on fundus images. The model was trained and tested on the DRIVE (Digital Retinal Images for Vessel Extraction) dataset using appropriate preprocessing steps. The experiments yielded a test F1-score of 0.81 and a final test accuracy of approximately 0.97. Evaluation metrics included accuracy, sensitivity, specificity, precision, F1-score, Jaccard index (IoU), and Dice coefficient. Structural challenges such as class imbalance and the accurate detection of fine vessel structures were also addressed. Furthermore, the model was tested on retinal images from external datasets not seen during training, where it successfully produced accurate segmentation results. These outcomes demonstrate the model's strong generalization capability, confirming that it can effectively segment retinal vessels not only within the training domain but also across images from different sources. Overall, the results indicate that the Attention U-Net architecture offers a reliable and practical solution for retinal vessel segmentation in clinical applications.

Key words: retinal vessel segmentation, deep learning, UNet, Attention UNet, DRIVE Dataset

Introduction

Retinal blood vessels are the only terminal vascular structures that can be directly observed in the living human body. This unique characteristic allows retinal images to serve as critical biomarkers for the diagnosis of systemic diseases [1]. Accurate segmentation of retinal blood vessels plays an important role in the diagnosis and monitoring of conditions such as diabetic retinopathy, glaucoma, hypertension, and cardiovascular diseases [2]. Changes in vessel thickness, branching patterns, and vessel density may provide structural clues that can be detected even in the early stages of these diseases.

Traditional image processing techniques may fall short when dealing with challenges such as low-contrast vessel structures and background noise. In recent years, deep learning-based methods have played a significant role in overcoming these limitations. In particular, architectures based on convolutional neural networks (CNNs) have come to the forefront in the field of biomedical image segmentation. Convolutional neural networks (CNNs), especially with the U-Net architecture [3], have marked a turning point in biomedical image segmentation. The encoder–decoder structure of U-Net, along with its skip connections, enables it to model both low-level details and high-level contextual information simultaneously. In the context of retinal vessel segmentation, advanced architectures such as U-Net [3] and its attention-based variants have demonstrated remarkable success.

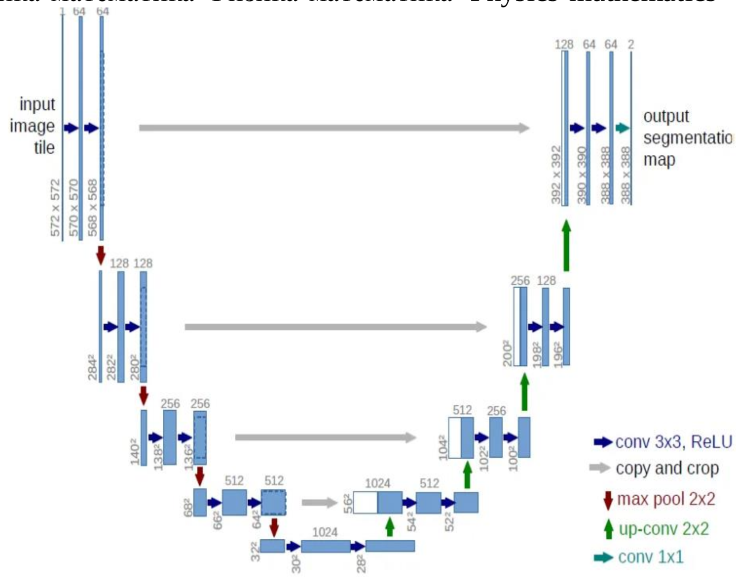


Figure 1. U-Net Architecture

This study evaluates the performance of an Attention U-Net-based architecture, implemented using the PyTorch deep learning framework, on the task of retinal vessel segmentation using the DRIVE dataset. To address various challenges such as class imbalance and fine vessels, a HybridLoss function was designed, combining Binary Cross Entropy (BCE), Dice Loss, and Focal Loss with weights (α, β, 1−α−β), emphasizing the positive class. The weights were automatically optimized using Softmax normalization. To ensure training stability, gradient clipping was also applied. The segmentation outputs were analyzed using accuracy, sensitivity, specificity, precision, F1 score, Dice coefficient, and Jaccard index (IoU) metrics, aiming to identify the most suitable architecture for clinical applications.

Accurate segmentation of retinal vessels is critically important for the early diagnosis and treatment planning of ophthalmic diseases such as diabetic retinopathy, glaucoma, hypertensive retinopathy, and retinopathy of prematurity (ROP) [4]. Traditional segmentation methods typically rely on matched filters [5] and morphological operations [6]. However, these techniques often struggle when faced with challenges such as low-contrast vessel structures and background noise [7].

In recent years, deep learning-based approaches have gained significant momentum in overcoming these limitations. Among them, the U-Net architecture—owing to its encoder-decoder structure and skip connections—has become one of the most widely used deep learning models for medical image segmentation tasks [3], [8]. Wang et al. [9] directly applied U-Net to retinal vessel segmentation and demonstrated its effectiveness in successfully transferring contextual information during the upsampling process [9].

Attention U-Net has achieved improved segmentation performance, particularly in capturing fine vessel structures, by incorporating attention mechanisms into its skip connections [10]. UNet++ [11] enhanced segmentation performance through deep supervision and nested skip connections. R2U-Net [12] combined residual and recurrent blocks to achieve stronger representational capacity, especially when working with limited datasets. Meanwhile, M2U-Net [13], which integrates MobileNetV2 into the U-Net framework, improved computational efficiency, making it more suitable for real-world applications.

LadderNet [14] extended the U-Net architecture through multiple pathways, enabling richer contextual information flow, which facilitated more precise detection of vascular structures. Guo et al. [15] proposed the SA-UNet model by incorporating a spatial attention module into the U-Net framework. This model demonstrated enhanced segmentation performance, particularly in regions containing low-contrast and thin vessels. T-Net, introduced by Khan et al. [16], is a lightweight variant of U-Net designed to operate efficiently on resource-constrained devices.

Generative adversarial networks (GANs) have also been utilized to enhance segmentation accuracy. In particular, RV-GAN [17] achieved high accuracy by balancing the continuity of fine vessels with the reduction of false positive rates. Attention mechanisms and multi-scale feature refinement blocks, combined with transformer-based models and GANs, have further improved segmentation quality [18], [19]. VGA-Net [20] integrated graph convolutional networks with attention mechanisms, achieving superior performance in the segmentation of fine vessels. GCC-UNet [21] employed capsule convolutions to effectively learn both local and global vascular structures. SFNet [22] combined spatial and frequency-domain networks, demonstrating effective performance particularly in wide-field OCTA images. The RLAD framework [23] enhanced the generalization capacity of segmentation models by 8.1% through diffusion-based synthetic data generation. U-Net and its variants—whether in their conventional forms or advanced versions supported by GANs and transformers—remain among the most effective solutions in the field of retinal vessel segmentation.

Materials and methods of research

In this study, the Attention U-Net deep learning architecture was thoroughly examined for the task of retinal vessel segmentation. The model was developed within the PyTorch framework, and experimental data were recorded throughout the training processes. The DRIVE dataset was utilized for both training and evaluation phases. Retinal images were resized to 512×512 pixels, converted to grayscale, and processed using Contrast Limited Adaptive Histogram Equalization (CLAHE) and gamma correction ($\gamma = 1.2$), through the custom-developed RetinaDataset class. Finally, the preprocessed images were normalized to the range of [-1, 1].

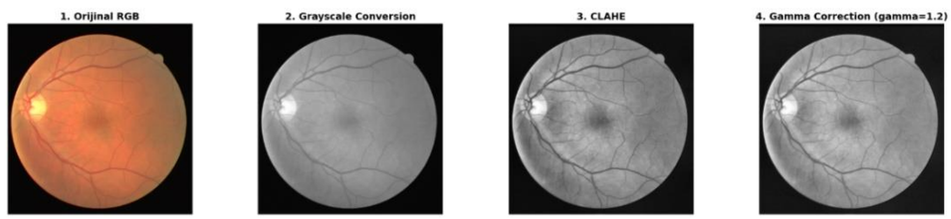


Figure 2. Retinal Image Preprocessing Steps:
Original RGB Image, Grayscale Conversion, CLAHE and Gamma Correction

The training was conducted over 100 epochs. The AdamW optimization algorithm was employed, with the learning rate dynamically adjusted using the OneCycleLR scheduler under a cosine annealing strategy. To mitigate the risk of overfitting, a weight decay parameter of 1e-4 was applied.

As the loss function, a three-component HybridLoss was designed to account for class imbalance and varying sample difficulties. This structure combines weighted Binary Cross Entropy (BCE), Dice Loss, and Focal Loss, with a weight of 15.0 assigned to the positive class to ensure balanced learning. The weights (α, β, $1 - \alpha - \beta$) were automatically optimized during training via Softmax normalization. To enhance training stability, gradient clipping was applied.

In the proposed architecture, multiple attention mechanisms were integrated to enhance feature representation and focus on vessel-like structures more effectively. Specifically, Channel Attention (CA) and Spatial Attention (SA) modules were applied at each encoding and decoding stage. The Channel Attention mechanism recalibrates the channel-wise feature responses by employing both average and max pooling, followed by a shared fully connected network and sigmoid activation. This process allows the model to emphasize informative feature maps while suppressing irrelevant ones.

In parallel, the Spatial Attention module captures spatial dependencies by applying convolutional operations over combined average-pooled and max-pooled spatial features, guiding the network to focus on vessel-relevant regions within each feature map. Additionally, Attention Gates (AGs) were incorporated into skip connections between the encoder and decoder, enabling the model to selectively highlight relevant spatial features during the upsampling process, thereby reducing the propagation of irrelevant background information. By combining channel-wise, spatial, and attention gating mechanisms, the model was able to dynamically prioritize informative features and improve vessel segmentation accuracy, particularly for thin and low-contrast vessels.

The model performance was evaluated using six core metrics: Dice Coefficient, Intersection over Union (IoU), Precision, Recall, F1-Score, and Accuracy. The Attention U-Net model was trained and tested under consistent conditions, including the same dataset, preprocessing steps, hyperparameters, and evaluation criteria throughout the experiments. This controlled setup ensured that the obtained performance results reflected the true capabilities of the Attention U-Net architecture, allowing for a fair and reliable assessment.

Results and its discussion

The hyperparameters used in this study are summarized in Table 1. All models were trained under identical configurations, and the comparative evaluation was conducted under similar conditions to ensure a fair and consistent performance analysis.

Table 1. Hyperparameter Values Used in Model Training

Hyperparameter	***Value***	***Hyperparameter***	***Value***	***Hyperparameter***	***Value***
adam_betas	[0.9,0.999]	**loss_function**	HybridLoss	**loss_alpha**	0,4
batch_size	4	**lr_scheduler**	OneCycleLR	**loss_beta**	0,4
Epochs	100	**optimizer**	AdamW	**loss_gamma**	2
validation_split	0,2	**weight_decay**	0,0001	**learning_rate (start)**	0,001

The model's performance metrics on the test dataset are presented in the graph below (Figure 3). The Attention U-Net model achieved a Dice coefficient of 80.09%, an F1-score of 80.06%, and an accuracy of 96.71% on the test set. These results clearly demonstrate the high performance of the Attention U-Net in the task of retinal vessel segmentation.

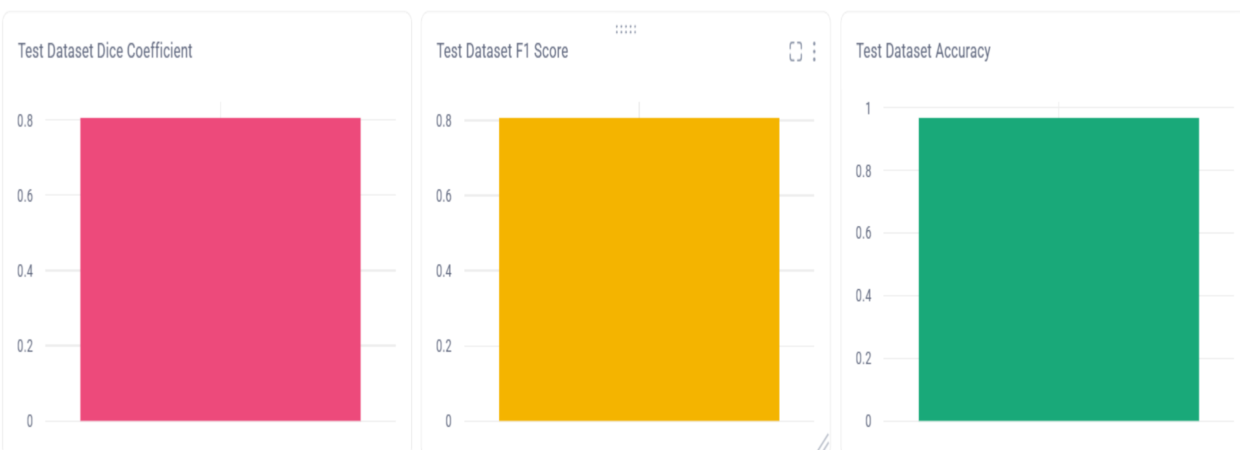


Figure 3. Model Performance Results on the Test Dataset Based on F1-Score, Dice Coefficient, and Accuracy Metrics.

The interpretation of these metrics alone is not sufficient. The general learning behavior of the models was also monitored through the training and validation process curves obtained throughout model training. These curves provided insights into the models' convergence patterns, stability, and potential overfitting tendencies.

1. Training and Validation Process Analysis

In this section, the training and validation performance of the Attention U-Net model is presented graphically. The evolution of core evaluation metrics—Dice Coefficient, Intersection over Union (IoU), Precision, Recall, F1-Score, and Accuracy—across epochs is visualized. Dice and IoU metrics reflect the overlap between predicted and true vessel regions, while Precision and Recall highlight the model's detection accuracy and completeness, respectively. F1-Score balances these two measures, and Accuracy indicates the model's overall pixel-level classification performance. The plotted curves help to assess not only how these metrics improved during training but also the model’s generalization capacity over unseen validation data.

To quantitatively evaluate segmentation performance, six core metrics were employed:

• Precision: Measures the proportion of correctly predicted vessel pixels to all pixels predicted as vessels.

▪ Precision = TP / (TP + FP)

• Recall: Measures the proportion of correctly predicted vessel pixels to all actual vessel pixels.

▪ Recall = TP / (TP + FN)

• Dice Coefficient: Calculates the overlap between predicted segmentation and ground truth, balancing both precision and recall.

▪ Dice = 2 × TP / (2 × TP + FP + FN)

• Intersection over Union (IoU): Also known as the Jaccard Index, measures the ratio of intersection to union between predicted and actual vessels.

▪ IoU = TP / (TP + FP + FN)

• F1-Score: The harmonic mean of precision and recall.

▪ F1-Score = 2 × (Precision × Recall) / (Precision + Recall)

• Accuracy: Represents the overall proportion of correctly classified vessel and background pixels.

▪ Accuracy = (TP + TN) / (TP + TN + FP + FN)

Together, these metrics provide a comprehensive evaluation of both the pixel-level classification performance and the structural segmentation accuracy of the model.

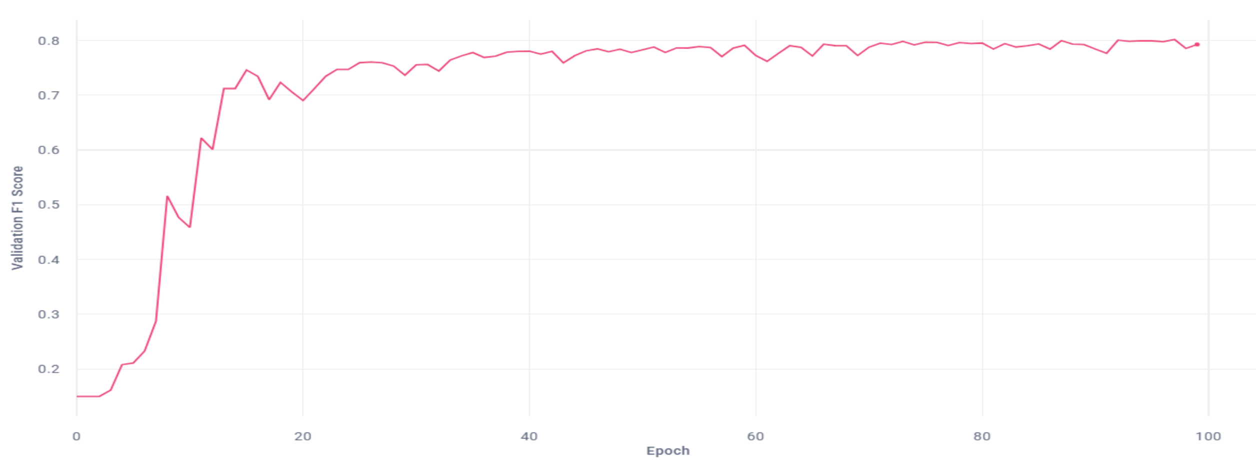


Figure 4. Variation of F1-Score on the Validation Set Throughout Epochs, Reflecting the Balance Between Precision and Recall.

Figure 5 presents the validation loss curve of the Attention U-Net model. A significant decrease in validation loss was observed during the first 40 epochs. In the subsequent epochs, the loss value stabilized within the range of approximately 0.12–0.15, maintaining a consistent trend. This indicates that the model did not exhibit overfitting during the training process and demonstrated strong generalization capability on the validation dataset.

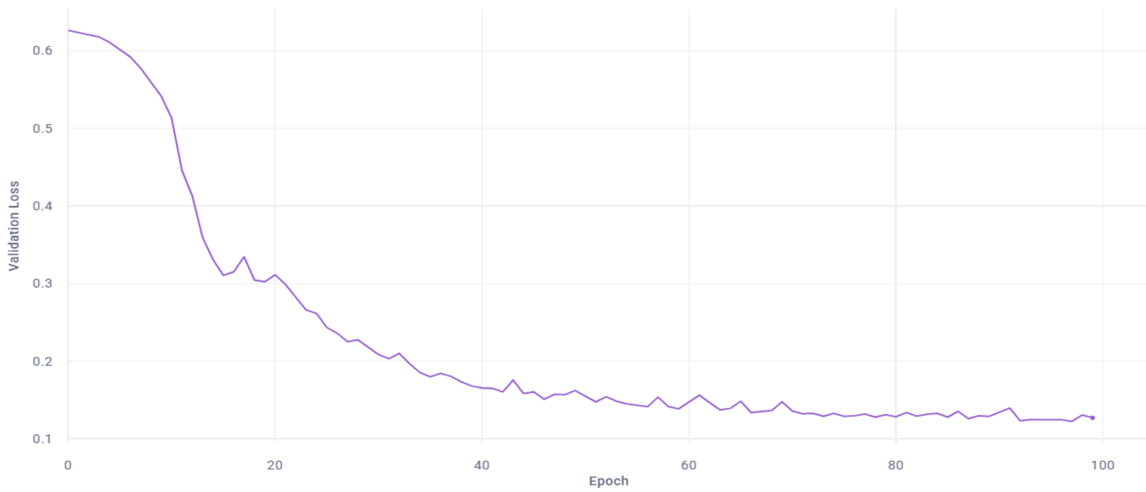


Figure 5. Variation of Validation Loss Values Across Epochs.

Figure 6 illustrates the variation of training loss across epochs for the Attention U-Net model. From the early epochs, the training loss consistently decreased, reaching approximately 0.12 by around the 80th epoch**,** and remained stable thereafter. This indicates that the model successfully adapted to the training data and performed stable optimization throughout the learning process. As no significant fluctuations or sudden increases were observed, it can be concluded that the training process progressed in a balanced manner, with model weights being updated appropriately.

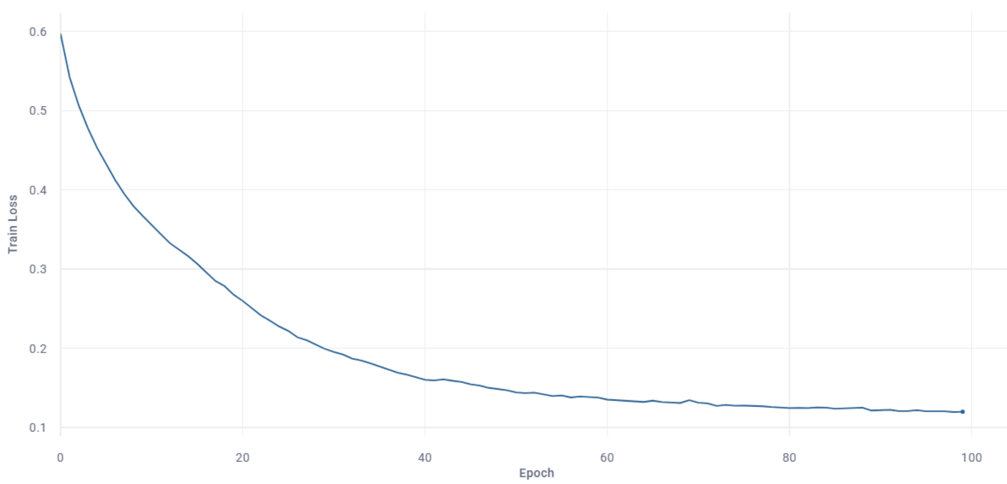


Figure 6. Epoch-wise Variation of the Model’s Training Loss Throughout the Training Process.

2. Comparison of Validation Metrics

(Dice Coefficient, Accuracy, Precision, Recall, and IoU):

The following graphs **(**Figures 7 –11**)** present the performance of the model across various metrics during the validation process. The Attention U-Net model demonstrated stable and high performance across key evaluation metrics, including accuracy**,** Dice coefficient**,** recall **(**sensitivity**)**, and specificity, indicating a balanced and robust segmentation performance.

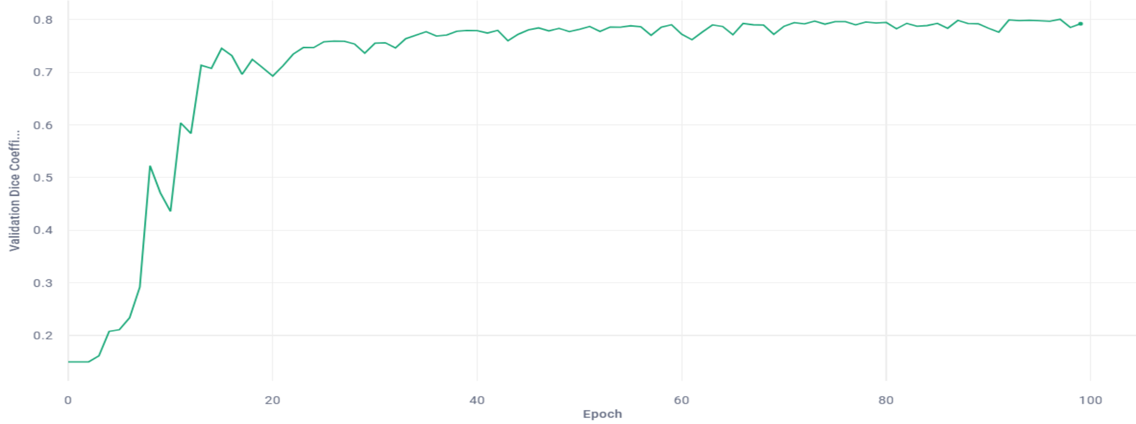


Figure 7. Epoch-wise Variation of Dice Scores on the Validation Dataset.

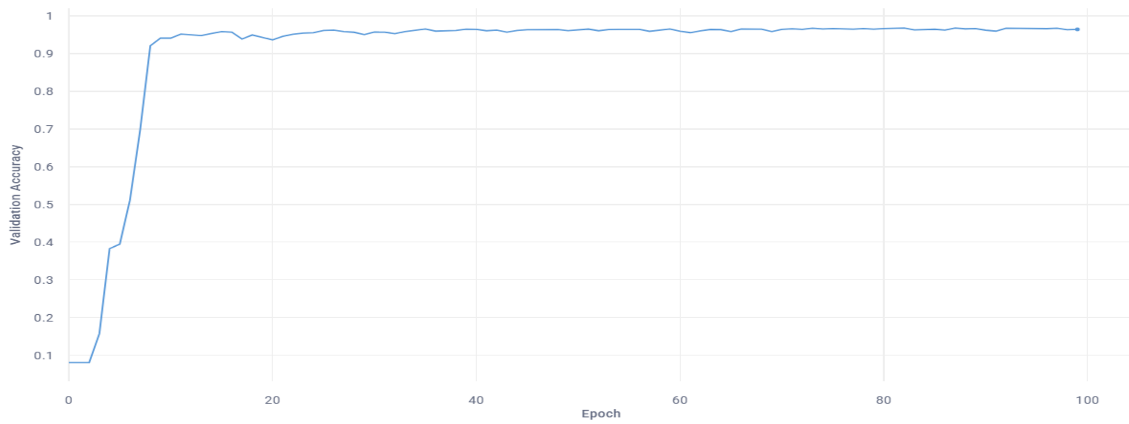


Figure 8. Epoch-wise Variation of Accuracy Values on the Validation Dataset.

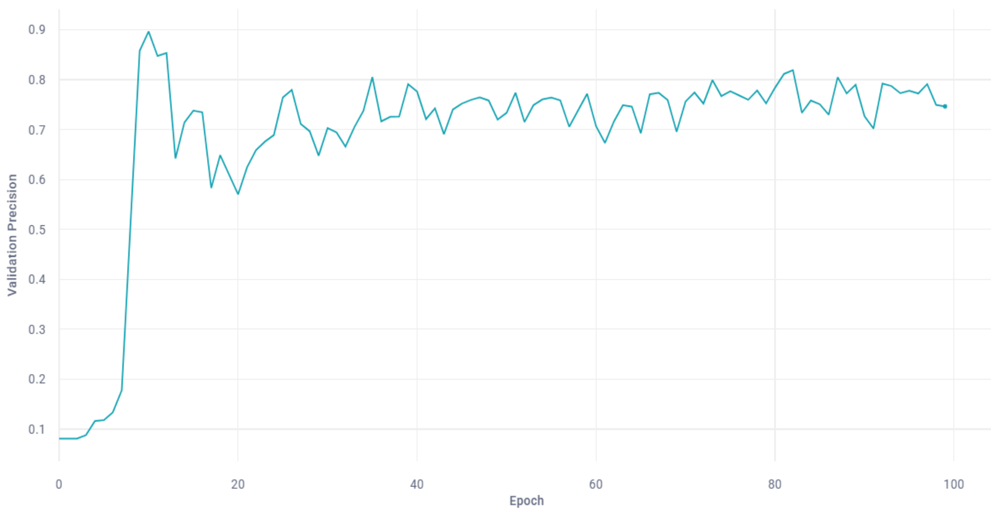


Figure 9. Epoch-wise Variation of Precision Values on the Validation Dataset.

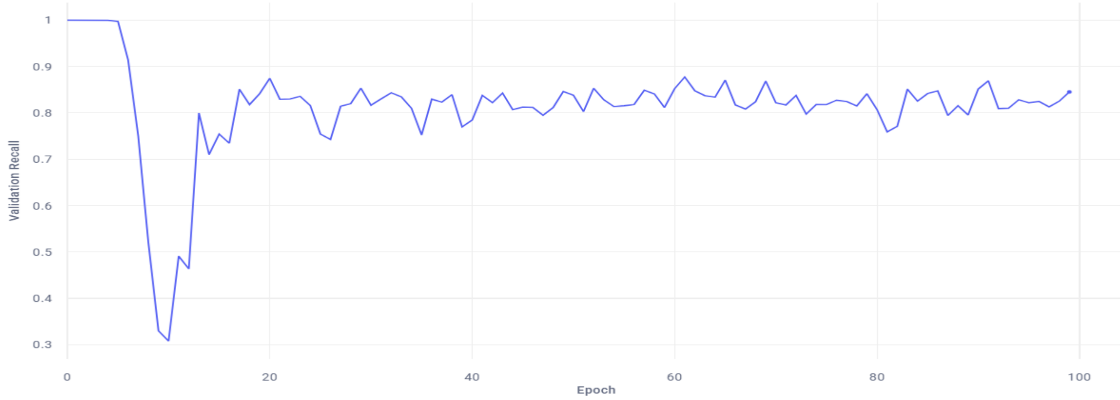


Figure 10. Epoch-wise Variation of Recall Values on the Validation Dataset.

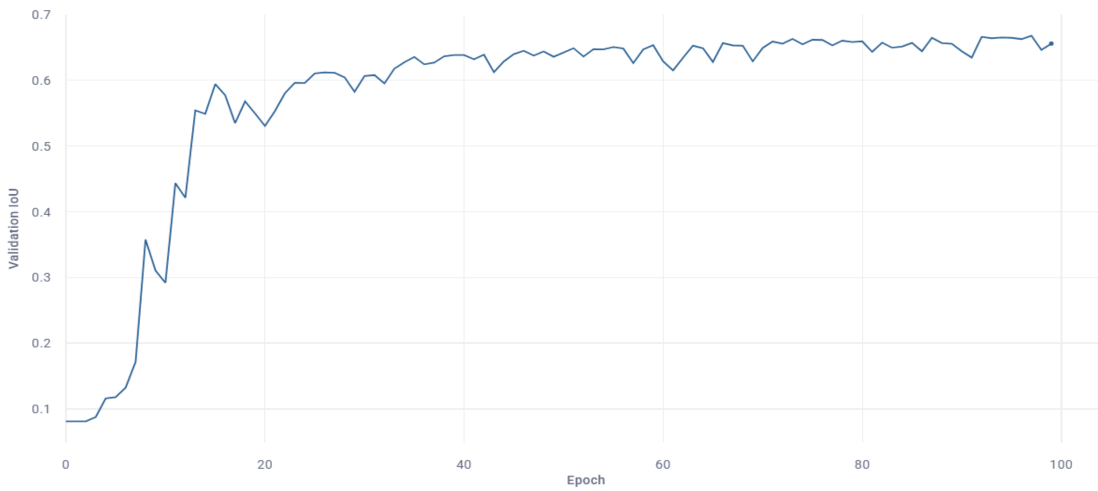


Figure 11. Epoch-wise Variation of Intersection over Union (IoU) Values on the Validation Dataset.

3. Confusion Matrix Analysis

The confusion matrix of the model on the test dataset is presented below (Figure 12). The Attention U-Net demonstrated an overall balanced segmentation performance, characterized by a high true positive (TP) rate and a low false positive (FP) rate.

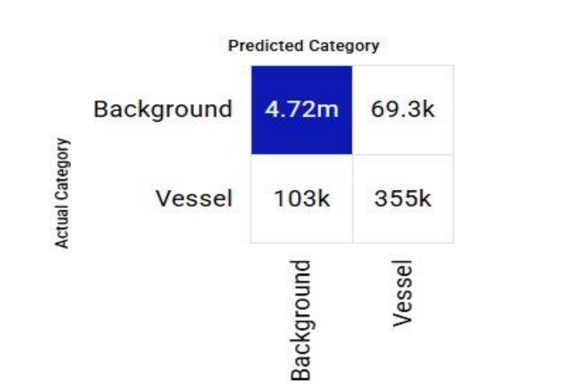


Figure 12. Confusion Matrix Output of the Model.

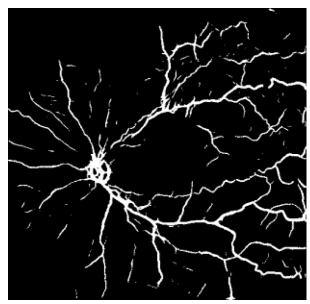
4. General Evaluation

Considering all these results, Attention U-Net has been evaluated as a reliable and recommendable model, distinguished by its balanced performance across all metrics, low validation loss, and overall stability. However, it was also observed that employing a hybrid loss function, combining binary cross-entropy and Dice loss, is necessary to better capture thin vessel-like structures and to minimize class imbalance effects.

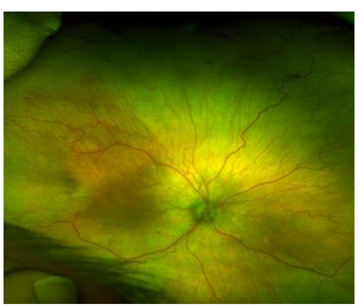
The performance of the Attention U-Net model was evaluated not only on the test images of the DRIVE dataset but also in terms of its generalization capability. For this purpose, the model was tested on two retinal images from a different dataset that it had never encountered during training. In **Figure 13**, the original fundus images and the corresponding segmentation outputs generated by the model are presented side by side. Importantly, no special preprocessing or additional enhancement was applied to these new images. The model was tested directly on these raw images and was able to produce high-quality vessel segmentation results. This demonstrates that the Attention U-Net model does not rely solely on the training data and can effectively handle data from different sources with varying image characteristics.

In conclusion, even on these new images from a different dataset, without any preprocessing, the model successfully segmented fine vessels, accurately delineated vascular structures, and exhibited strong generalization capability. This is a significant advantage for the model's practical applicability in clinical environments.

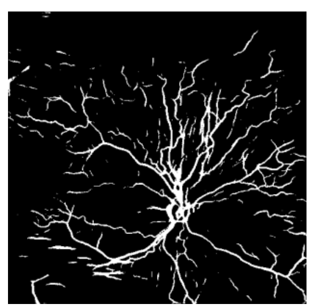
(a) Original Image 1



(b) Segmentation Output 1



(c) Original Image 2



(d) Segmentation Output 2

Figure 13. Generalization performance of the model on unseen images without additional preprocessing.

In this study, the performance of the Attention U-Net architecture was thoroughly analyzed for the retinal vessel segmentation problem. Evaluation metrics such as F1-score, accuracy, recall (sensitivity), and specificity, obtained throughout the validation process, demonstrated that the model achieved an overall balanced and successful segmentation performance (Figures 5–11).

In particular, the rapid increase in the F1-score from the early epochs and its stabilization within the 0.75–0.80 range after the 20th epoch indicate the model's strong learning capability and robust generalization performance.

Analysis of the validation loss curve (Figure 5) revealed that from approximately the 40th epoch, the model maintained a stable and low loss within the 0.12–0.15 range. Similarly, the training loss curve exhibited a continuously decreasing and stable pattern (Figure 6). This indicates that the model did not show a tendency toward overfitting and was able to establish a strong balance between the training and validation datasets.In the segmentation outputs, the model not only accurately detected vessel structures but also maintained a controlled false positive rate, supported by a balanced trade-off between precision and recall.

One of the key factors contributing to the model's success was the use of the HybridLoss function. This function combines Binary Cross-Entropy (BCE), Dice loss, and Focal loss with dynamically adjusted weights. It enhanced the model's adaptability in addressing critical challenges such as class imbalance, detection of fine vessel structures, and edge accuracy.Analysis of the weight evolution of the loss components throughout the training process showed that different types of loss functions were prioritized at different stages. This highlights the adaptive nature of the loss function, which offers a significant advantage in sensitive domains like medical imaging.

Despite the limited sample size of the DRIVE dataset, the stable validation curves and metric values obtained from the Attention U-Net model indicate that the architecture can deliver effective results even with small datasets. However, evaluating the model on larger and more diverse datasets represents an important direction for future work, as it would provide deeper insights into the generalizability of the segmentation performance.

A comprehensive evaluation was conducted not only based on metric scores but also by focusing on training and validation curves, overfitting behavior, loss function stability, and the model's overall learning dynamics. Considering both the theoretical structure and practical application results of the Attention U-Net, it was concluded that this architecture offers a reliable and applicable solution for medical image segmentation problems.

Conclusıon

In this study, a deep learning-based Attention U-Net architecture was implemented for retinal vessel segmentation, and its performance was evaluated in detail. The findings demonstrated that the model provided a reliable and balanced segmentation performance, as evidenced by its stable trends in validation loss, F1-score, and the precision–recall balance.

The applied HybridLoss function, which combined different loss components in a learnable and adaptive manner, contributed significantly to the training process. This approach proved particularly effective in addressing class imbalance and in accurately segmenting fine vessel structures. Such a strategy offers a valuable contribution in sensitive domains like medical imaging, as it ensures flexible and stable learning.

For future studies, it is recommended to evaluate the model on larger, more diverse, and multi-modal datasets to assess its generalizability. Additionally, conducting comparative analyses with Transformer-based architectures could contribute to advancements in the field. Moreover, the design of lightweight models suitable for integration into real-time systems is considered an important research direction, especially for clinical applications.

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ТЕРЕҢ ҮЙРЕНУГЕ НЕГІЗДЕЛГЕН ТОР ТАМЫРЛАРЫН СЕГМЕНТАЦИЯЛАУ: ATTENTION U-NET

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Аңдатпа. Тор қабықша (ретина) тамырларын сегменттеу – қант диабетіне байланысты ретинопатия, макулалық дегенерация және шала туған нәрестелердің ретинопатиясы (ROP) сияқты көз ауруларын ерте анықтау үшін аса маңызды. Бұл зерттеуде көз түбінің кескіндеріндегі тамырларды сегменттеу үшін Attention U-Net негізіндегі терең оқыту архитектурасының өнімділігі бағаланды. Модель DRIVE (Digital Retinal Images for Vessel Extraction) деректер жиынтығында тиісті алдын ала өңдеу сатыларын қолданып үйретілді және тексерілді. Эксперименттер нәтижесінде тест жиынында F1 көрсеткіші 0.81 және соңғы дәлдік шамамен 0.97 болды. Бағалау көрсеткіштеріне дәлдік (accuracy), сезімталдық (sensitivity), ерекшелік (specificity), нақтылық (precision), F1 көрсеткіші, Жаккар индексі (IoU) және Дайс коэффициенті кірді. Класс теңгерімсіздігі және ұсақ тамыр құрылымдарын дәл анықтау сияқты құрылымдық қиындықтар да ескерілді. Сонымен қатар, модель оқыту кезінде қолданылмаған сыртқы деректер жиынтығындағы тор қабықша кескіндерінде де сыналып, жоғары дәлдікпен сегменттеу нәтижелерін көрсетті. Бұл нәтижелер модельдің жалпы қолданылу қабілетінің жоғары екенін көрсетеді, және ол тек үйретілген деректерге ғана емес, басқа көздерден алынған кескіндерге де тиімді қолдануға болатынын дәлелдейді. Жалпы, нәтижелер Attention U-Net архитектурасы клиникалық қолдану үшін сенімді әрі тиімді шешім екенін көрсетеді.
Түйін сөздер: тор тамырларын сегментациялау, терең үйрену, U-Net, Attention U-Net, DRIVE деректер жинағы

СЕГМЕНТАЦИЯ СЕТЧАТКИ НА ОСНОВЕ ГЛУБОКОГО ОБУЧЕНИЯ: ATTENTION U-NET

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Аннотация. Сегментация сосудов сетчатки имеет решающее значение для ранней диагностики офтальмологических заболеваний, таких как диабетическая ретинопатия, макулярная дегенерация и ретинопатия недоношенных (ROP). В данном исследовании была оценена эффективность архитектуры глубокого обучения на основе Attention U-Net для сегментации сосудов на изображениях глазного дна. Модель обучалась и тестировалась на наборе данных DRIVE (Digital Retinal Images for Vessel Extraction) с использованием соответствующих этапов предобработки. Эксперименты показали F1-оценку 0.81 и итоговую точность около 0.97 на тестовом наборе. Метрики оценки включали точность, чувствительность, специфичность, точность (precision), F1-оценку, индекс Жаккара (IoU) и коэффициент Дайса. Были также учтены структурные сложности, такие как дисбаланс классов и точное обнаружение тонких сосудистых структур. Кроме того, модель тестировалась на изображениях сетчатки из внешних наборов данных, не использовавшихся в обучении, где также достигла высоких результатов сегментации. Эти результаты демонстрируют высокую способность модели к обобщению и подтверждают, что она может эффективно сегментировать сосуды сетчатки не только в пределах обучающего домена, но и на изображениях из различных источников. В целом, результаты показывают, что архитектура Attention U-Net предлагает надежное и практичное решение для сегментации сосудов сетчатки в клинических приложениях.

Ключевые слова: сегментация сосудов сетчатки, глубокое обучение, U-Net, Attention U-Net, набор данных DRIVE