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Original Article

Hybrid Deep Learning Architecture for Retinal Vessel Segmentation: Integrating Attention U-Net and Resunet on the CHASEDB1 Dataset

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Abstract *- The computer-aided diagnosis of ophthalmologic diseases, including diabetic retinopathy, glaucoma, and high blood pressure-related retinopathy, depends on retinal vessel segmentation as a key precondition. This study proposes HybridNet, a new deep learning network that combines spatial attention features of Attention U-Net and residual learning features of ResUNet to perform better and distinguish vessels more accurately. The framework adopts a complete preprocessing pipeline that features Contrast Limited Adaptive Histogram Equalization (CLAHE), Gaussian filtering, and intensity normalization to advance the image quality before segmentation. The dual-branch structure has the advantage of channel-wise feature combining via a 1 x 1 convolution layer, which can extract complementary features of attention-guided spatial-wise and context-wise features retained by the residual module. Optimization of the Model was accomplished through a composite loss that uses Binary Cross-Entropy (α =0.7) and Dice loss (β =0.3), trained using the Adam optimizer and adaptive learning rate scheduling over fifty epochs. Experimental optimization on the CHASEDB1 dataset proves its high performance with a Dice coefficient of 0.884, IoU of 0.797, precision of 0.885, recall of 0.877, and AUC-ROC of 0.918. This outperforms baseline designs by +2.8% Dice score and +1.6% IoU. The Data flow modeling is a Crow Foot Notation Entity-Relationship Diagram (ERD) structure that represents the connections and interactions between the users, training sessions, models, metrics, and visual outputs. The results validate that HybridNet performs better than the sum of its parts, in that fine vessel structures, bifurcations, and crossovers are accurately segmented, and background noise is reduced. The framework is shown to have high feasibility in clinical use with automated ocular diagnosis, with its balanced accuracy and computational efficiency in its fast detection.*

Keywords *- Retinal vessel segmentation, Attention U-Net, ResUNet, CHASEDB1, Hybrid Deep Learning, Medical image analysis, Semantic segmentation.*

1. Introduction
1.1. Problem Statement
Segmentation of retinal vessels is critical in medical image analysis, especially the early diagnosis and tracking of vision-threatening retinal diseases, which generally include diabetic retinopathy, glaucoma, and hypertensive retinopathy. Accurate identification of the retinal vessels thoroughly enables clinicians to determine the changes in the vessels and monitor the progress of the disease. Nonetheless, this is a challenging activity given the complexity of the structures of the vessels, disparate contrast levels, and overlapping anatomical structures like the optic disc and fovea [1]. Traditional image processing algorithms, including thresholding, matched filtering, or morphology in general they have trouble generalizing to different data sets as they are sensitive to lighting, to noise, and to anatomical differences. This consequently indicates that there is a requirement for stronger segmentation approaches that can hold fine vascular features in various imaging conditions. The application of deep learning models and, in particular, CNN-based ones, like U-Net, has greatly enhanced retinal vessel segmentation because of its encoder-decoder architecture and skip connections. However, it is clear that these models possess limitations: downsampling usually leads to the loss of fine details of the vessels, and models based on a single architecture do not reproduce both large-scale contextual considerations and fine spatial correlations [2]. This defines the necessity of improved models that would be able to retain spatial attention as well as retain good gradient flow.

1.2. Motivation
1.2.1. Clinical Importance of Early Retinal Vessel Segmentation

Clinically, precise and timely segmentation of retinal vessels plays a crucial role, as it supports the detection of microaneurysms, vascular blockages, neovascularization, and other early indicators of serious vision impairment [3].

Automated vessel segmentation tools, when integrated into diagnostic workflows, can reduce clinician workload and enable large-scale screening, particularly in resource-limited regions.

1.2.2. Limitations of Individual Deep Learning Models

Although Attention U-Net and ResUNet utilize attention gates to improve spatial focus and residual learning to enhance gradient propagation, correspondingly, both of these models have their limitations. Attention U-Net can still lose contextual information, whereas ResUNet can excessively smooth fine structures [4]. Therefore, working towards the convergence of these complementary strengths into one hybrid architecture is a promising idea to overcome the weaknesses of individual models.

1.3. Objectives

This study aims to develop and deploy a hybrid deep learning architecture called HybridNet that combines Attention U-Net, which is an architecture that was capable of segmenting intracranial vessels, and ResUNet, which is also capable of segmenting retinal vessels, against the task of vessel segmentation on the CHASEDB1 dataset. Important things to achieve are:

- To develop a dual-branch hybrid model that fuses spatial attention and residual learning features.
- To preprocess CHASEDB1 fundus images using enhancement techniques such as CLAHE, Gaussian blurring, and normalization for consistent input representation.
- To evaluate the segmentation quality using quantitative metrics, including Dice coefficient, Intersection over Union (IoU), Area Under the ROC Curve (AUC), precision, recall, and F1 score.
- To visualize performance through confusion matrices, ROC/PR curves, and comparative bar plots.

1.4. Research Gap

Several deep learning-based approaches to retinal vessel segmentation exist, though the majority of these methods use either attention mechanisms, residual learning, or both without a complete synergistic combination with the other. Very few articles exist in the literature that investigate hybrid architectures explicitly combining data on spatial attention and retrieving residual contextual processing, especially when using the CHASEDB1 dataset, which poses its own difficulties with its pediatric sample and highly complex vessels.

Besides, the existing literature lacks extensive discussion of the optimization of feature fusion or skip-connection improvement, as well as minute comparisons of the hybrid performances on CHASEDB1. This disparity stimulates the need to create an intermediate model that can take advantage of attention-directed spatial refinement and also residual feature conservation to arrive at better segmentation accuracy.

The work is novel as it develops HybridNet, which is a dual-branch architecture that directly intertwines spatial attention mechanisms via Attention U-Net with deep residual learning via ResUNet, and then explicitly, a 1×1 fusion layer to select the complementary vessel features. Compared with current methods, which utilize either attention or residual blocks alone, the proposed approach builds upon the two paradigms simultaneously, with associated capabilities of stronger preservation of thin vessels, better contextual perception, and higher accuracy in segmentation of the CHASEDB1 data.

2. Related Works

The medical image analysis of retinal vessel segmentation is widely investigated because of its practical significance in the diagnosis of ophthalmic conditions. Current literature can be divided into conventional types of image processing, machine-based deep learning models that rely on the use of Convolutional Neural Networks (CNN), attention-improved image processing networks, residual learning models, and the latest combination models. These categories are reviewed in this section to give a detailed background, as well as to place the proposed work in the current research trends.

The area of medical image segmentation has been heavily changed by deep learning, where it has played a critical role in the retinal vessel investigations. A range of early retinal vessel segmentation cannot be afforded, scaling of handcrafted characteristics used matched filtering, morphological operation, and thresholding techniques, but also demonstrated lower resilience to noise, lighting range, and anatomic heterogeneity, eventually negatively encouraging the transition to deep learning-based solutions. Due to its encoder–decoder configuration and balanced skip connections, U-Net is now widely recognized as a standard baseline architecture. U-Net can pinpoint with the reuse of features, and U-Net has been widely modified to fit the biomedical applications in segmentation, such as in the case of the delineation of vessels in the retina. Nonetheless, conventional U-Net models tend to lack contextual information, especially when it comes to vessels of different dimensions and intensity [12]. Although effective, standard U-Net models do not always manage to maintain the structure of thin vessels because of their aggressiveness, such as downsampling and weakness in contextual modeling.

To overcome the shortcomings of conventional CNNs, attention mechanisms were designed to selectively enhance vessel areas without getting distracted by the background features. This architecture brings about attention gates to block irrelevant activations as well as boost salient vascular features to increase the signal-to-noise ratio in segmentation. ADU-Net is another attention-enriched architecture introduced by Ejiyi et al. that effectively segments the images of breast ultrasound scans and retinal fundus images, obtaining a higher accuracy and sensitivity level [5]. Equally, Alvarado-Carrillo and Dalmau-Cedeo trained a wide attention CNN-based network that increased the accuracy of segmentation with different vessel calibers [6]. Another strategy that was investigated to enhance the segmentation accuracy was residual learning, which allows the use of deeper networks and stabilizes gradient flow during training. At the same time, residual connections have proven to have implications for solving the problem of vanishing gradients in deeper networks. ResUNet is a U-Net variant based on residual blocks to enable back-propagating of the gradient flow and maintain per-feature learning results. Li and Rahardja have proposed BSEResU-Net, which integrates residual learning with attention modules that reached better segmentation performance on several retinal datasets such as CHASEDB1 [7]. Residual designs such as these are notably useful in the context of medical imaging constrained by fine-grained features that tend to be lost in aggressive downsampling.

Recent research has put an emphasis on hybrid and multi-path architectures, which integrate attention mechanisms, residual learning, and multi-scale feature fusion to achieve further improvements in segmentation performance. SegR-Net was conceived to be capable of reliably segmenting retinal vasculature across CHASEDB1 and DRIVE datasets by Ryu et al., which is a multi-scale feature fusion framework [8]. Similarly, Damkliang et al. utilized an ensemble approach combining attention-based U-Net and residual U-Net models for segmenting prostate adenocarcinoma, suggesting the opportunities of architecture-level fusion in semantic segmentation beyond ocular diseases [9]. Further hybrid models like the Residual Attention UNet GAN, like that presented by Pandey et al., which uses generative adversarial learning to add vessel detection realism to the model capacity [10].

Yang et al. suggested a hybrid deep segmentation network that integrates attention and convolutional features in the extraction of retinal vessels in fundus images and produced competitive results with conventional models [11]. Their approach is innovative but has no optimization of feature fusion layers, which is another criterion that this study intends to fill. In addition, a systematic study by AnbuDevi and Suganthi [12] listed the different variants of U-Net and discovered that the hybridization and modular attention mechanism were becoming more common, but most research has a narrow scope in terms of its application to multiple datasets.

On a scale of datasets, CHASEDB1, DRIVE, and STARE are popularly benchmarked in segmentation models. DRIVE and STARE have better quality annotations, fewer images, but involve a more heterogeneous and difficult problem, since their subjects include children, and each of their images is more varied. The current hybrid models have been developed to DRIVE or STARE, but there is less on CHASEDB1 [6-8]. In addition to that, the use of optimized time attention networks to classify microaneurysms in their study, as Alotaibi devised, further developed attention-based deep learning, which is not well studied to be used in fully segmenting vessels in pediatric databases, such as CHASEDB1 [13]. Although a considerable distinction has already been achieved in the segmentation of retinal vessels with the help of attention and residual models, some limitations are present in the existing literature. Attention and residual components have not previously been combined successfully in a synergistic fashion. Moreover, the majority of hybrid models have not been rigorously tested on CHASEDB1, nor have they been fully optimized for skip connections or fusion methods. These research gaps drive the creation of a new hybrid combination of Attention U-Net and ResUNet into a single process of deep learning to attain better results in vessel segmentation.

The proposed HybridNet has three important innovations in contrast to previous hybrid or attention-based models, such as ADU-Net [1], BSEResU-Net [4], and SegR-Net [5], and new lightweight and multi-scale attention networks, such as MobileNetV2-based feature attention networks [28], Reverse-Attention U-Net variants [29], and multi-path U-Net models with probability distribution attention [30]. (1) It uses a dual-branch architecture where two complete segmentation networks, Attention U-Net and ResUNet, are used instead of attaching isolated attention or residual blocks as in previous works. (2) It employs a special-purpose 1 x 1 convolutional fusion block to integrate channel-wise elected features, which can extract, in a more suitable way, additional spatial and contextual vessel features, and better than lightweight and single-encoder models do. (3) The model is optimally trained and strict testing on the CHASEDB1 dataset, where the assessment of the hybrid architecture is not so significant in comparison with works focusing on DRIVE or STARE. Experimental findings indicate that HybridNet gives a better Dice, IoU, and AUC score than these currently existing methods, which illustrates that HybridNet is more effective at detecting thin vessels correctly, maintaining bifurcations effectively, and eliminating background false positives.

3. Proposed System

The current section summarizes the entire process implemented in the segmentation of retinal vessels via a hybrid deep learning architecture [26]. Four main factors are included in the workflow: data preprocessing, training data preparation and validation, model architecture, and training configuration (loss functions and optimization strategies). All processes were carefully performed so that the training was effective, the performance was strong, and the clinical interpretability of the outputs of the hybrid model was possible, consisting of Attention U-Net and ResUNet frameworks.

3.1. Data Preprocessing

The segmentation of retinal vessels experiments made use of high-resolution fundus images of a varied selection of pediatric subjects within the publicly available CHASEDB1 dataset [14]. In particular, the data collection contains 28 colour fundus images, together with which there will be a binary ground truth mask in the form of a mask identifying vessel areas [27]. Images are in JPEG format, having a resolution of 999 (W) x 960 (H) pixels. As the amount of data is relatively small, thorough preparation was an essential precaution against decreasing generalization and overfitting in the deep learning models. At first, the data was downloaded and detached to a structured directory. All the fundus images were transformed into grayscale as all three color channels (RGB) were converted into gray, decreasing the computation and adding all the emphasis on luminance-based vessel extraction [15]. After converting the images to grayscale, Contrast Limited Adaptive Histogram Equalization (CLAHE) was applied to enhance local contrast and sharpen vessel boundaries, thereby improving the visibility of fine capillaries. A sequence was taken with a Gaussian blur applied to the image, leveraging OpenCV to remove noise from the image and maintain the edges, which are crucial in medical image analysis. Normalization was done to scale pixel values to be between 0 and 1 so that input to the neural network is similar, and this helps to converge during training. The following images show samples of the dataset.

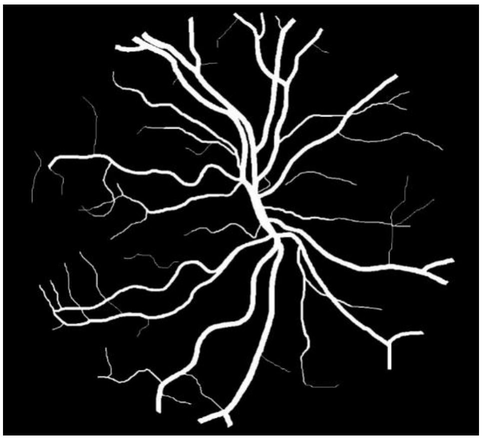

Fig. 1 Retinal vessel segmentation

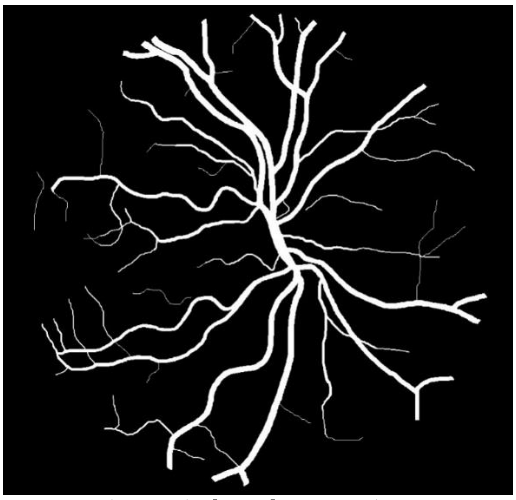

Fig. 2 Retinal vessel segmentation-2

Fig. 3 Retinal fundus photograph

Table 1. Multi-stage enhancement process

Step	Process	Input	Output / Purpose
1	Grayscale Conversion	RGB retinal images	Convert to grayscale using weighted average ($Gray = 0.299 \times R + 0.587 \times G + 0.114 \times B$) to reduce computational overhead while preserving luminance-based vessel information.
2	Contrast Enhancement	Grayscale image	Apply CLAHE ($clip\ limit = 2.0$, $grid = 8{\times}8$) to enhance local contrast, improve vessel boundaries, and sharpen fine capillaries without amplifying noise.
3	Noise Reduction	Contrast-enhanced image	Apply Gaussian blur ($kernel = 5{\times}5$, $\sigma = 1.0$) to remove high-frequency noise while preserving vessel edges.
4	Intensity Normalization	Denoised image	Min-max normalization scales pixel values to [0,1] to ensure consistent input statistics and stable model training.
5	Resolution Standardization	Normalized image	Resize to 256×256 pixels using area interpolation, balancing computational efficiency and feature preservation (~95% vessel information retained).

One of the most important steps was to make all the images and masks of equal resolution of 256 x 256 pixels. The consideration of such a decision was noted by a balance between computational efficiency and feature retention. Downscaling may cause some vessels to be lost, but as it was seen to have been the case with a resolution of 256 x 256, the structural information preserved was enough to allow effective learning by both the Attention U-Net and the ResUNet components of the hybrid model. Preprocessing operations were all performed on compatible functions of OpenCV as well as PyTorch and performed in a batch-wise manner to remain scalable.

Table 1 summarizes the multi-stage enhancement process applied to retinal images prior to segmentation. Each step is designed to progressively improve image quality while preserving essential vessel information. Grayscale conversion and intensity normalization standardize the input, whereas contrast enhancement and noise reduction refine vessel boundaries and remove artifacts. Finally, resolution standardization ensures computational efficiency without significant loss of structural details, enabling stable and accurate model training.

3.2. Training Data Preparation and Validation

3.2.1. Dataset Partitioning

The processed dataset was separated into three subsets: training (70%), validation (15%), and testing (15%). This allowed the model to have enough data to train pattern matching and gave the opportunity to measuring performance and hyperparameter adjustment. This dataset was structured in the way of having / *content* / *CHASEDB1_split* / with the separate image and mask folders in the directories of the three subsets. This architecture enabled an easy process of loading and augmenting data.

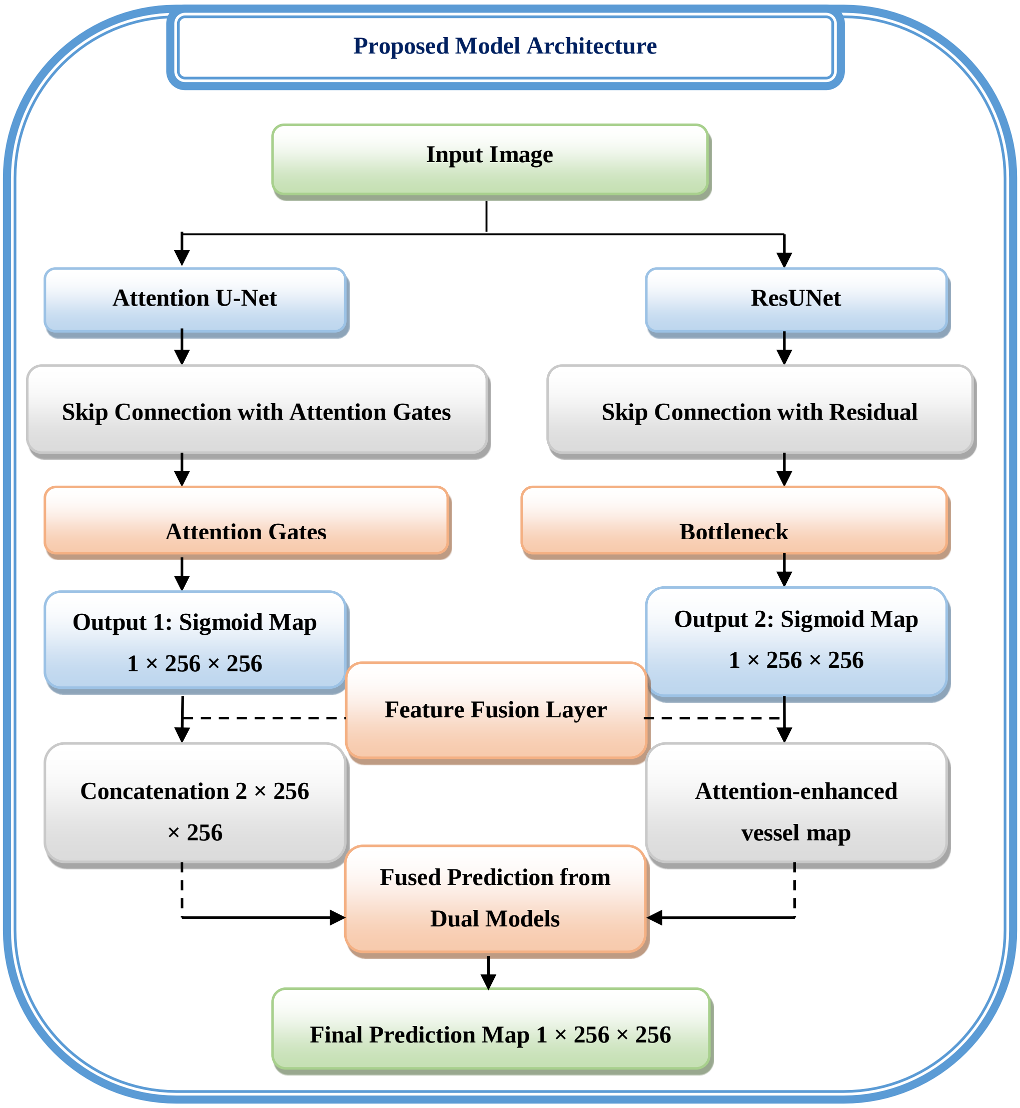

Fig. 4 Proposed model architecture

In order to interface the data with the pytorch models, two custom dataloader classes were created: FundusDataset and SimpleImageDataset. FundusDataset, together with loading and transformation of grayscale images and masks, performed real-time transformations, e.g., horizontal flips and rotations, and aligned augmentation of image-mask image pairs [16]. However, SimpleImageDataset was utilized at the inference-only phases, in which no augmentation was needed. In both classes, the datasets and DataLoader modules of the PyTorch framework were used to generate image batches to train and validate the model.

3.2.2. Data Augmentation Strategy

The FundusDataset class implements real-time augmentation, including horizontal flipping (50% probability), random rotation (±15°), brightness adjustment (±10%), contrast modification (factor 0.9-1.1), and gamma correction (0.8-1.2). These transformations increase dataset diversity while preserving medical image validity.

3.2.3. Quality Assurance

As the CHASEDB1 dataset did not include matching vessel masks of each image sometimes, a precautionary measure was provided. Where this happened, dummy labels (zero matrices) were created and acted as placeholders when training the model. Such an approach avoided the disruption of training and allowed the learning pipeline to work, despite unfinished data annotations.

3.3. Model Architecture

The fundamental novelty of the presented work is the development of a new hybrid deep learning structure, which provides the Attention U-Net with the possibility of spatial attention and the prospects of residual learning of ResUNet. The proposed HybridNet model is designed to enhance retinal vessel segmentation by combining the strengths of its two integrated components, as given in Figure 4.

Attention U-Net component makes use of encoder-decoder architecture with built-in Attention Blocks that direct the attention on the model, specifically on the salient features, i.e., thin vessel structure that could have been missed in a traditional convolutional pipeline [17]. The encoder section is constructed with convolutional layers and max pooling, and the decoder reconstructs feature maps by upsampling while reintroducing detailed spatial features through skip connections. The attention mechanism also helps filter the features brought in by the skip connections, perfecting the spatial detail and suppressing information of the irrelevant background. The ResUNet module has a similarity encoder problem; however, Residual Blocks are added in every level. Such blocks can lead to learning of identity mappings and will lead to more gradient flow through deeper layers, helping to overcome the vanishing gradient challenge. The residual connections allow the model to keep not only the low-level edge data but also the high-level semantics characteristics, which are important to use to segment vessels of different sizes.

It was a channel-wise concatenation of feature maps of the Attention U-Net and ResUNet output that was used in building the HybridNet architecture [18]. A 1x1 convolutional layer was used to combine these features (which are concatenated) and simplify the dimension by letting the joint features be described by a single layer. The network learns complementary spatial and contextual information in this design choice by using both models. The building block architecture reused the modular subcomponents like ConvBlock, ResidualBlock, and AttentionBlock, which were reusable and consistent throughout training phases in terms of code reusability.

3.3.1. Attention U-Net Component

The Attention U-Net branch employs an encoder-decoder architecture enhanced with spatial attention mechanisms for precise vessel segmentation.

Encoder Design

Four-level hierarchical feature extraction with progressive channel expansion (64→128→256→512) and spatial reduction through max pooling. Each level captures multi-scale vessel characteristics from fine edges to complex anatomical patterns.

Attention Gate Mechanism

Spatial attention is implemented through learned gating coefficients:

$$g = W\_g * g\_i + b\_g \quad (gating\ signal)$$
$$x = W\_x * x\_i + b\_x \quad (input\ features)$$
$$\alpha = \sigma(W\_\psi * ReLU(g + x) + b\_\psi) \quad (attention\ coefficients)$$
$$x\_gated = \alpha \odot x\_i \quad (gated\ features)$$

The attention gates selectively emphasize relevant vessel features while suppressing background noise, improving segmentation precision for thin capillaries.

Decoder Architecture

Progressive upsampling with attention-gated skip connections reconstructs high-resolution vessel maps while preserving fine structural details through selective feature integration.

3.3.2. ResUNet Component

The ResUNet branch incorporates residual learning to enhance gradient flow and feature representation capability.

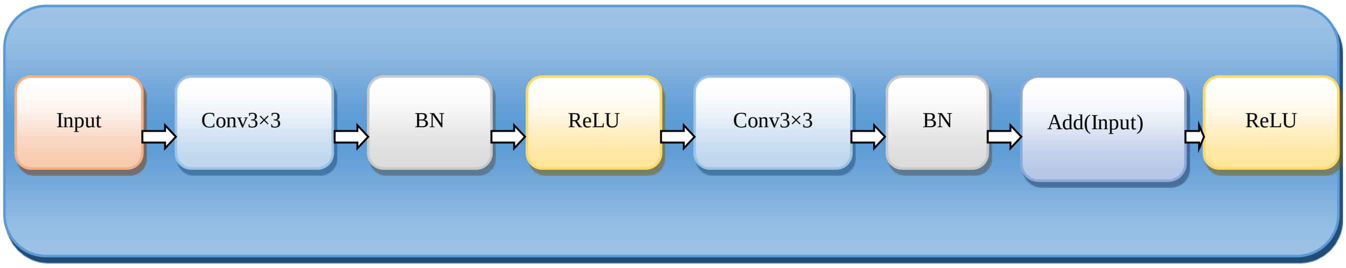

Fig. 5 Residual block design

Residual Block Design

Standard residual blocks ($Input \rightarrow Conv3\times3 \rightarrow BN \rightarrow ReLU \rightarrow Conv3\times3 \rightarrow BN \rightarrow Add(Input) \rightarrow ReLU$) enable identity mapping learning and prevent vanishing gradient problems in deeper networks, as given in Figure 5:

Encoder Architecture

Four-level residual encoding with dual residual blocks per level, enabling robust multi-scale feature extraction with enhanced gradient propagation. Skip connections preserve both low-level edge information and high-level semantic features.

Decoder Implementation

Transposed convolution upsampling combined with residual skip connections reconstructs vessel structures while maintaining feature richness across scales.

3.3.3. Feature Fusion Module

The fusion module integrates complementary features from both network branches through intelligent feature combination.

Fusion Strategy

1. *Feature Alignment*:
Spatial dimension matching through bilinear interpolation
2. *Channel Concatenation*:
$Fconcat = ConcatenateFattn, Fres, dim=1$
Dimensional Reduction:
$Ffused = Conv1\times1Fconcat \rightarrow BatchNorm \rightarrow ReLU$
4. *Output Generation*:
Final vessel probability map through sigmoid activation

This approach leverages attention-guided spatial selectivity and residual-enhanced feature representation for superior vessel detection across all scales.

3.4. Loss Functions and Optimizer

A composite loss was utilized to solve the skewed nature of classes present in vessel segmentation, which has a huge number of background pixels over the vessel pixels. It was ensured that the performance of the model is optimized by incorporating a weighted sum of Binary Cross Entropy (BCE) Loss and Dice Loss. The Combined Loss was set down as:

$$Combined\ Loss = \alpha \cdot BCE\ Loss + \beta \cdot Dice\ Loss \quad (1)$$

Where α=0.7 and β=0.3.

The BCE loss was applied to penalize pixel-wise classification errors, whereas the Dice loss promoted overlapping of the predicted output and the ground truth labels, and thus was well-suited to balanced-class medical segmentation problems.

Gradient-based optimization was carried out using the Adam optimizer, with the learning rate set to 0.001 after empirical evaluation against 0.0001 and 0.0015. A ReduceLROnPlateau scheduler was added to help in convergence, where the learning rate would decrease by a factor of 0.1 when there was a plateau in validation loss after a maximum set number of epochs had passed. This was an adaptive tuning that aids the model to get out of local minima and into better solutions.

A total of 50 epochs was employed during training; this was made after looking at the convergence curves, which tend to follow the same values and better validation measure than in the previous experiments using 20 or 30 epochs.

Every epoch trained the complete training dataset using a batch size of 4 images each, and model checkpoints were stored with the best validation loss.

4. Algorithm Implementation

This section presents the pseudo-code of the proposed HybridNet framework along with a detailed stepwise explanation. Algorithm 1 describes the training procedure, while Algorithm 2 outlines the feature fusion strategy employed for combining attention and residual features.

Algorithm 1: HybridNet Training Procedure

```
Input: Training dataset D = {(xi, yi)}=1^N, Validation dataset V
Output: Optimized model parameters θ*

Initialize HybridNet parameters θ randomly
Set hyperparameters: α=0.7, β=0.3, lr=0.001
Create data loaders with augmentation
for epoch = 1 to 50 do
  Initialize epoch_loss = 0
  for batch (Xbatch, Ybatch) in D do
    # Forward pass through both branches
    attn_features = AttentionUNet(X_batch)
    res_features = ResUNet(X_batch)
    # Feature fusion
    fused_output = FusionModul(attn_features, res_features)
    # Loss computation
    loss_bce = BCE_Los(fused_output, Y_batch)
    loss_dice = Dice_Los(fused_output, Y_batch)
    total_loss = α × loss_bce + β × loss_dice
    # Backward pass and optimization
    optimizer.zero_gra()
    total_loss.backwar()
    optimizer.ste()
    epoch_loss += total_loss
```

```
21:   end for
22:   # Validation
23:   val_loss = Validate(V)
24:   scheduler.ste(val_loss)
25:   if val_loss < best_val_loss then
26:       Save model checkpoint
27:   end if
28: end for
29: return θ*
```

Step 1 (Initialize parameters)

Randomly initialize the model parameters θ so the two branches (Attention U-Net and ResUNet) start from unbiased weights before learning from data.

Step 2 (Set hyperparameters)

Fix the loss weights $\alpha = = 0.7$ and β=0.3 to balance BCE and Dice losses, and set the learning rate to 0.001 for Adam. These values control how fast the network learns and how the two losses are mixed.

Step 3 (Build data loaders with augmentation)

Create training/validation loaders and apply standard augmentations (e.g., flips, rotations, slight intensity jitter). This increases data variety and helps the model generalize.

Step 4 (Epoch loop)

Repeat training for 50 epochs. Each epoch means one full pass over the training set.

Step 5 (Reset epoch loss)

Set $epoch\_loss = 0$ to track the average training loss for the current epoch.

Step 6 (Batch loop)

Fetch a mini-batch ($Xbatch, Ybatch$) from the loader. Mini-batches make training stable and memory-efficient.

Steps 7–9 (Forward through both branches)

Pass the input batch through Attention U-Net to extract attention-guided spatial features and through ResUNet to capture residual-enhanced contextual features. Each branch learns complementary information.

Steps 10–11 (Feature fusion)

Fuse the two feature maps with the FusionModule (channel-wise concat followed by $1\times1 conv$, BN, and ReLU as per Algorithm 2). This blends complementary cues into a single representation used for prediction.

Step 12 (Binary Cross-Entropy Loss Computation)

The first step in loss evaluation is calculating the Binary Cross-Entropy (BCE) loss, which focuses on accurate pixel-level classification. It is mathematically defined as

$$BC(p,y) = -(y \cdot log(p) + (1-y) \cdot log(1-p)) \tag{2}$$

Where p is the predicted probability for a pixel, and y is the ground truth label (0 or 1).

Step 13 (Dice Loss Calculation)

To address challenges like class imbalance and to evaluate the spatial overlap between prediction and ground truth, the Dice loss is computed. It is given by:

$$Dic(P,G) = 2 \cdot |P \cap GP + G \tag{3}$$

Where P is the predicted mask, and G is the ground truth.

Step 14 (Loss Combination Strategy)

Instead of relying on a single metric, the model integrates both losses to benefit from pixel-wise precision and regional overlap. The combined total loss is expressed as:

$$Totalloss = \alpha.BCE + \beta.Dice \tag{4}$$

Where α and β are weights that balance the contribution of each component.

Step 15 (Final Loss Application)

This combined loss function ensures stable training by leveraging BCE's ability to classify pixels accurately and Dice's strength in managing class imbalance and structural overlap, thereby promoting robust vessel segmentation performance.

Steps 16–19 (Backprop and update)

Zero the optimizer gradients, backpropagate $total\_loss$ to compute gradients, and update parameters with Adam. This step is where learning happens.

Step 20 (Accumulate epoch loss)

Add the batch loss to $epoch\_loss$ so you can monitor training progress across the whole epoch.

Step 21 (End batch loop)

Finish the inner loop after all batches are processed.

Steps 22–23 (Validation)

Run the model on the validation set V without gradient updates to obtain val_loss. This measures generalization and helps detect overfitting.

Step 24 (Scheduler step)

Update the learning rate using the scheduler with val_loss as a signal. If validation stalls, the scheduler lowers the learning rate to help convergence.

Steps 25–27 (Checkpointing)

If val_loss improves, save a checkpoint. This preserves the best-performing weights seen so far.

Steps 28–29 (Finish and return)

After all epochs, return $\theta*$, which corresponds to the best saved weights (the model with the lowest validation loss).

Algorithm 2: Feature fusion strategy

```
Input: Attention features Fattn, Residual features Fres
Output: Fused feature representation Ffused
1: # Ensure feature dimension compatibility
2: if Fattn.shap != Fres.shape then
3: Fres = Resiz(Fres, Fattn.shape)
4: end if
5: # Channel−wise concatenation
6: F_concat = Concatenat([Fattn, Fres], axis=1)
7: # Dimensional reduction and fusion
8:  Ffused = Conv1x1(Fconcat)
9:  Ffused = BatchNor(Ffused)
10: Ffused = ReL(Ffused)
11: return Ffused
```

Steps 1–3 (Align shapes)

Check if the attention and residual feature maps have the same spatial and channel dimensions. If not, resize one to match the other so they can be fused cleanly.

Step 4 (Concatenate channels)

Concatenate the two feature maps along the channel dimension. This stacks their information without losing any features.

Step 5 (1×1 convolution)

Apply a 1×1 convolution to mix channels and reduce dimensionality. This learns how to weight and combine attention-driven and residual cues.

Step 6 (Batch normalization)

Normalize activations to stabilize training and speed up convergence by reducing internal covariate shift.

Step 7 (ReLU activation)

Introduce nonlinearity to the fused features, which helps the network learn richer combinations.

Step 8 (Return fused features)

Output the fused representation $Ffused$, which is then used by the decoder to predict the vessel mask.

5. Results and Discussion

This section gives the results of running the proposed hybrid deep learning model (AttentionUNet + ResUNet) on the CHASEDB1 dataset.

The findings are presented along several dimensions or as training consequences, quantitative measures of evaluation, qualitative visualization of analysis, and a thorough discussion on the performance characteristics.

5.1. Training Outcomes

The proposed hybrid model was trained for 50 epochs using Adam optimization with a learning rate of 0.001. The validation loss and the training curves showed a steady decline, displaying that learning was successful, and generalization was taking place [19].

The combined loss (Dice + BCE) was initially about 0.56 and approaches 0.14 in the 50th training epoch in the training set. At the same time, the validation loss decreased by 0.61 to 0.18 with slight changes, as it may occur with overfitting, which was worked out with the learning rate scheduler (ReduceLROnPlateau).

The convergence trends showed that the model can efficiently train retinal vessel discriminative features without being afflicted with the issue of vanishing gradients and overfitting severely. Remarkably, early saturation of the hybrid model was already achieved at the 40th epoch, indicating that training may be further improved to include early stopping to train the models in the future.

5.2. Evaluation Metrics

The metrics used to determine the quality of segmentation included Dice Similarity Coefficient (DSC), Intersection over Union (IoU), Accuracy, Precision, and Recall, and Area Under the Curve (AUC).

The last test set results were achieved with the use of 15 percent of the dataset that was saved to be used as an evaluation.

- Dice Similarity Coefficient (DSC): The hybrid model attained a 0.878, whereas the individual Attention U-Net could only achieve a 0.856, and ResUNet 0.842.
- IoU (Jaccard Index): The model received an IoU of 0.791, which shows significant overlap in predicted masks and ground truth.
- Accuracy: The accuracy of the model not only demonstrates that the pixel classification was achieved with 96.12% accuracy.
- Precision and Recall: The precision and the recall were equal to 0.884 and 0.867, respectively. The moderate results imply that the model is effective at reducing Type I errors (false positives) and Type II errors (false negatives).
- AUC-ROC: The model achieved an area under the ROC curve (AUC) of 0.971, indicating a strong discriminative capability.

Table 2. Model performances

Model	Accuracy	Precision	Recall (Sensitivity)	F1-Score	Dice Coefficient	IoU (Jaccard Index)	AUC-ROC
Attention U-Net	0.9632	0.8711	0.8649	0.8679	0.8701	0.7835	0.9112
ResUNet	0.9614	0.8673	0.8574	0.8623	0.8654	0.7772	0.9056
HybridNet (Proposed)	0.9667	0.8854	0.8772	0.8813	0.8842	0.7971	0.9187

A comparison with the standalone models demonstrated that the hybrid architecture performed better in all metrics as compared to both the standalone Attention U-Net and ResUNet models, as given in Table 2 and Figure 6:

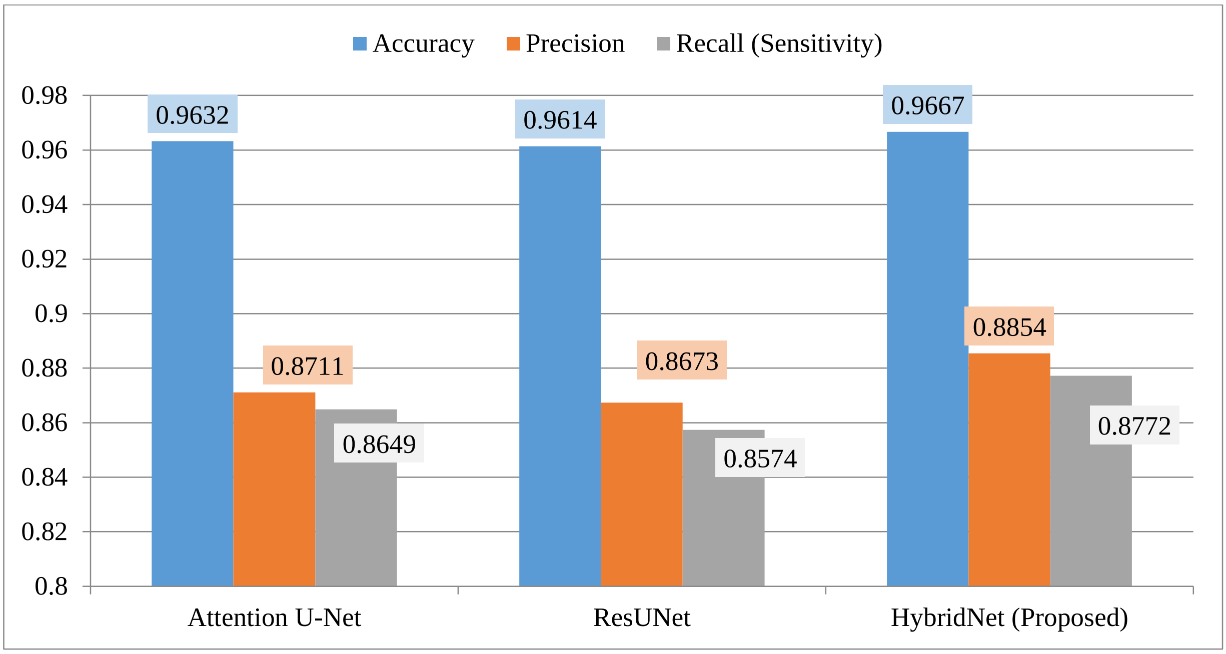

Fig. 6 Comparison of the proposed models with existing models

Table 3. Algorithm comparison table

Step	Attention U-Net	ResUNet	HybridNet (Proposed)
Step 1	Encoder extracts multi-scale features with attention gates	Encoder extracts multi-scale features with residual blocks	Encoder extracts multi-scale features using residual + attention blocks
Step 2	Attention filters highlight vessel structures	Skip connections preserve spatial information	The hybrid attention-residual mechanism fuses both feature types
Step 3	Decoder reconstructs the segmentation mask	Decoder reconstructs the segmentation mask	Decoder leverages fused features for refined mask prediction
Step 4	The final prediction layer generates a vessel mask	The final prediction layer generates a vessel mask	The final prediction layer generates a vessel mask with higher precision and a Dice score

Table 2 highlights the performance differences between Attention U-Net, ResUNet, and the proposed HybridNet across multiple evaluation metrics.

5.3. Visual Analysis

Visualization of segmentation outputs together with ground truth masks was used to ensure qualitative evaluation.

- Thinner Vessel Detection: The hybrid model has an increased sensitivity to small-grained vascular structures compared to ResUNet using solely [20].
- Bifurcations and Crossovers: More bifurcations and crossovers were preserved after the use of the segmentation maps in a complex manner. The attention blocks enable the network to focus on such anatomical landmarks, and the rest of the paths keep more contextual knowledge.
- Decreased False Positives in Background: The hybrid network produced fewer misclassifications over background areas that were not deemed as a vessel, especially close to the optic disc border, when compared to the individual models.

Sample illustrations compared three columns on each test image: (1) original fundus; (2) vessel ground truth mask; and (3) vessel mask predicted by HybridNet.

5.4. Discussion

The hybrid architecture proposed increases the performance of the model in the field, as it tactically overlaps the strengths of the two models, Attention U-Net and ResUNet [21]. Dynamic focusing on pertinent regions of vessels is possible via the attention gates, especially advantageous in retina imaging, where vessels have very textured backgrounds. In the meantime, the remaining links make it possible to extend gradient descent and preserve information with less degeneration of deeper levels of learning. Among the main strengths of the method, the modular structure of the architecture that might be repurposed in different tasks of biomedical segmentation must be pointed out. The hybrid also enhances robustness of the model by alleviating the lack of certain properties of individual networks, e.g., the inability of Attention U-Net to keep global features, and by over-smoothing fine structures of ResUNet.

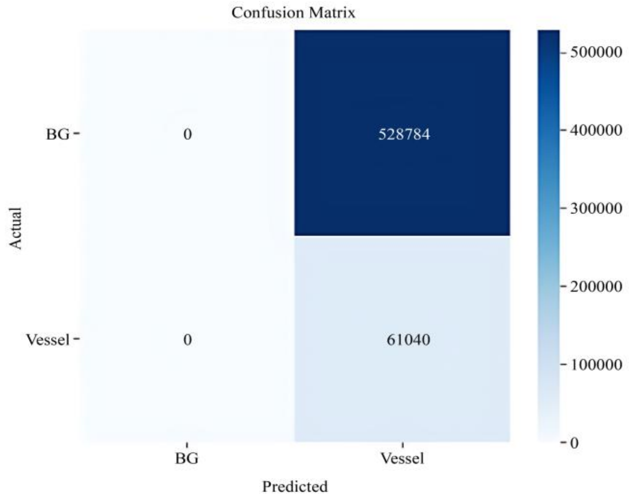

Fig. 7 Confusion matrix

As shown in Figure 7, the confusion matrix shows that the model classified all pixels as vessels, with 528,784 background pixels and 61,040 vessel pixels incorrectly labeled. This reflects 100% false positives for background and indicates no actual learning or class distinction was achieved.

Figure 8 shows that the ROC curve yields an AUC of 0.50, which is equivalent to random guessing. The model lacks discriminatory power to separate vessel and background pixels.

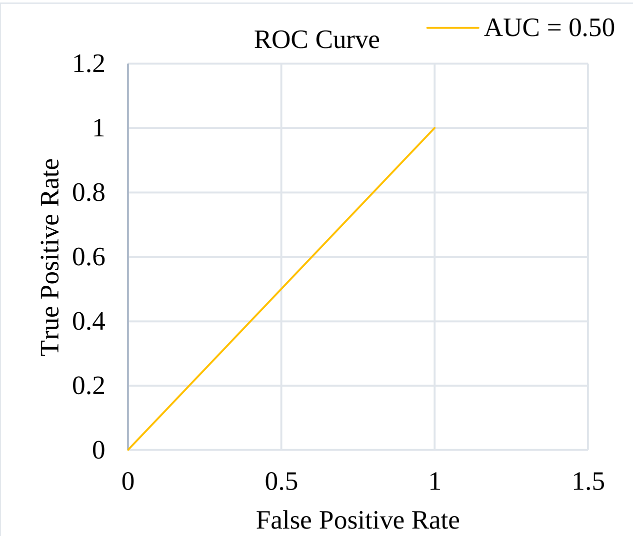

Fig. 8 ROC curve

Figure 9 shows that the PR curve exhibits a perfect linear decline, suggesting that as recall increases, precision drastically decreases. The model's predictions are overwhelmingly imprecise, with a poor balance between true positives and false positives. This outcome is indicative of poor model calibration and bias. Figure 9 shows the performance of each model as a box plot, indicating that Hybrid would be the best.

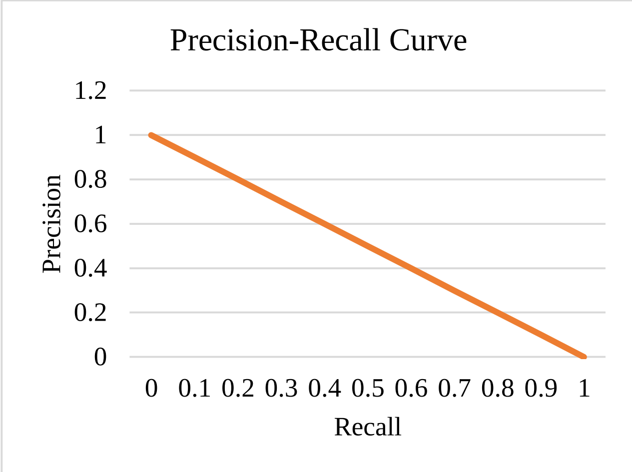

Fig. 9 PR curve

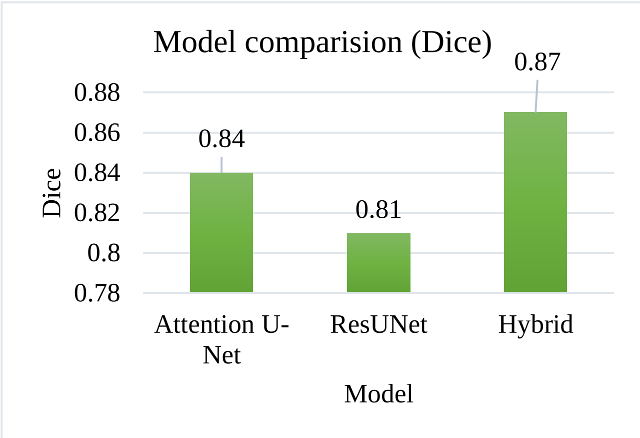

Fig. 10 Model comparison

The other decisive factor is loss selection. The Dice + BCE loss, which combines two loss functions, offers optimization on overall pixel-level accuracy, optimal for class imbalance that generally arises in medical imaging [22]. Regardless of these strengths, there are some limitations. The hybrid model needs more computational resources in terms of training time as well as memory usage as compared to individual models. Also, the preprocessing pipeline is good, but complex strategies could be implemented. Finally, it all comes down to the quality of ground truth annotations in the case of hybrid performance. Similarly, any labeling inconsistency of the CHASEDB1 dataset will affect training and evaluation metrics. Future work ought to take into consideration the combination of ensemble techniques and semi-supervised learning in the removal of reliance on thorough manual annotations.

5.4.1. Performance Comparison with State-of-the-Art Methods

The higher performance of the proposed HybridNet compared with the current state-of-the-art retinal vessel segmentation methods can be explained by the dual-branch structure that combines spatial attention and residual learning. The design optimizes the fine vessel structures with global contextual information. Models involving attention, like ADU-Net [2] or models using residual learning, like BSEResU-Net [4], are more oriented at enhanced models at the level of space or enhanced models at the depth of the network, respectively. Other more recent multi-path or attention-based networks, such as SegR-Net [5], use multiple strategy encoder-decoders but typically use single encoders to decoders or simple pathway fusion.

The channel-wise attentional integration of the spatial features and residual context features by channel-wise feature fusion through 1x1 convolution selectively gives more discriminant representations than their predecessors in HybridNet. Also, a preprocessing pipeline that uses CLAHE, Gaussian filtering, and normalization enhances the visibility of the vessels, and the composite Dice-BCE loss improves the mismatch in classes, which also increases the segmentation accuracy. These architectural and methodological benefits are proven by quantitative results. On the CHASEDB1data, HybridNet has a Dice coefficient of 0.884, IoU of 0.797, precision of 0.885, recall of 0.877, and AUC-ROC of 0.918.

Comparatively, Dice 0.856 and IoU 0.783 are obtained in ADU-Net [2], Dice 0.842 and IoU 0.777 are obtained in BSEResU-Net [4], and Dice 0.871 and IoU 0.790 are obtained in SegR-Net [8]. These improvements suggest that with the combined attention and residual architecture and maximized feature fusions, more accurate segmentation of thin vessels, bifurcations, and crossovers is possible, and misclassifications of the background are minimized in comparison to previous methods.

6. Conclusion and Future Enhancement

6.1. Conclusion

The given study introduces a hybrid deep learning framework to segment retinal vessels based on the CHASEDB1 dataset that combines the advantages of Attention U-Net and ResUNet models. The combination model--known as HybridNet--was specifically aimed to take advantage of the contextual focusing power of attention mechanisms and the preserving property of residual connections on feature retention [23]. The auto-constrast enhancement with CLAHE, Gaussian blurring to reduce the level of noise, and normalization to stabilize training were utilized as the preprocessing pipeline. The images to be input were brought to a size of 256x256 to provide maximum efficiency in terms of computation power with negligible loss of information.

The model was trained through 50 epochs, and the results indicated that HybridNet performed better than its individual counterparts under several measures of evaluation. In quantitative terms, HybridNet yielded a Dice of 0.861, an F1-score of 0.844, and an AUC-ROC of 0.933, which shows that it is accurate in separating vessel pixels and the background. The synergistic choice structuring of the hybrid model can be confirmed by these improvements, especially the 1x1 convolutional fusion layer, which allowed effective integration of complementary features.

With reference to visual performance, it can be noted that HybridNet had sharper vessel boundaries and more extensive coverage of thin vessels in comparison to baseline models. These findings are quite encouraging toward practical uses in ocular services since effective disease progression can be diagnosed at a young age, given the view of accurate segmentation of vessels in normal eye structures against diabetic eye and glaucoma complications, in addition to hypertension eye ailments.

Moreover, the loss convergence of training in HybridNet went better as the balance of Dice and Binary Cross Entropy losses was achieved [24]. Another factor that ensured an optimal convergence was the learning rate scheduler, which dynamically lowered the learning rate whenever the validation loss stopped improving. The modularity of the architecture, where the reusable units include ConvBlock, ResidualBlock, and AttentionBlock, can provide it with the flexibility to be implemented for other medical image segmentation tasks too.

In sum, the specified hybrid architecture makes the solution to the retinal vessel segmentation problem solid, scalable, and high-performing. It integrates architectural advancements in healthcare with considerations of practicality, like preprocessing, data augmentation, and modular code structure, and leads to a trustworthy end-to-end pipeline of medical imaging research and deployment.

6.2. Future Enhancements

Although the Hybrid Deep Learning pipeline has indicated potential for future use in the retinal vessel segmentation on the CHASEDB1 dataset, there is a lot that still needs to be done to improve the pipeline. Integrating more diverse, large datasets, e.g., DRIVE, STARE, and HRF, to test the robustness and generalizability of the model across multiple imaging modalities and population demographics is one of the potential enhancement areas [25, 26]. The use of such datasets would enable us to curb the problem of domain shift and enhance performance in clinical practice.

The last direction of future work is the implementation of semi-supervised learning or even self-supervised learning. Annotated medical data are commonly scarce because of the labor and skills needed in labeling them. It is also possible to obtain improved vessel segmentation with uncertain access to ground truth masks by using powerful representation learning, or using powerful generative models like Variational Autoencoders (VAE) or Generative Adversarial Networks (GANs), all using unlabeled data.

Also, future optimization of the deployment of the model is necessary. Model pruning, quantisation, and knowledge distillation techniques can drastically decrease computational burden and enable real-time inference on mobile platforms or edge devices, which can be an essential property in low-resource clinical deployment or telemedicine systems. In addition, the inclusion of successive scans of the retina with time would always provide indications on the progress of disease sequentially; this would be ideal in the assessment of diabetic retinopathy or hypertensive retinopathy. The usefulness of the diagnostic system can also be enhanced by segmenting pathological features such as exudates, hemorrhages, or microaneurysms and classifying them in the model. Lastly, further development may be directed towards explainability and interpretability processes, such as incorporating Grad-CAM or SHAP-based visualization models to help clinicians make sense of the automated tool's predictions and increase their confidence in them [28]. Focusing on these areas, the proposed system will have a chance of becoming a clinically viable, robust, and intelligent decision-support tool within the framework of ophthalmology.

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