Hybrid Guided Attention Residual U-Net

A

Course Project Report

Submitted in partial fulfilment of the
Requirements for the award of the Degree of

BACHELOR OF ENGINEERING

IN

INFORMATION TECHNOLOGY

By

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DECLARATION BY THE CANDIDATE

We, **Gajawada Rishi** and **K Srihas Reddy** bearing hall ticket numbers, **1602-21-737-042** and **1602-21-737-057** hereby declare that the course project report entitled **Hybrid Guided Attention Residual U Net** under the guidance of **DRL Prasanna, Assistant Professor,** Department of Information Technology, Vasavi College of Engineering, Hyderabad, is submitted in partial fulfilment of the requirement for the award of the degree of **Bachelor of Engineering** in **Information Technology**

This is a record of bonafide work carried out by us and the results embodied in this course project report have not been submitted to any other university or institute for the award of any other degree or diploma.

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BONAFIDE CERTIFICATE

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Abstract

Image segmentation is one of the most primitive tasks in terms of medical image processing, but is still an essential step in diagnosis and treatment planning. Despite being widely adopted after its introduction in thanks to its efficient use of skip connections in a symmetric encoder-decoder architecture to recover spatial information lost in down-sampling, U-net is still not able to take full advantage of blurry high-resolution images, as we showed when assessing its performance on retinal vessel segmentation in different datasets (reference). A major limitation of these end-to-end frameworks is the potential loss of structural information of thin, curve-like structures (such as retinal vessels) which can easily disappear by repeated convolution and down-sampling within high dimensional data. In this work, we introduce a new Deep Guidance Network (DGN) that is aimed at improving biomedical imaging segmentation. We achieve this by incorporating guided image filtering for detailed structure preservation, attention mechanisms to select pertinent regions, and residual modules to ensure only vital features are learned and reconstructed. These advancements allow the network to reconstruct detailed structural information within the network itself in a credible way, even for difficult instances involving narrow, intricate structures. In addition, our method is end-to-end trainable, which enhances the performance and reduces the computational demand. The experimental validation shows that the proposed network performs significantly better in terms of accuracy and robustness than the state-of-the-art methods, indicating a promising new solution to the advanced biomedical image segregation challenge.

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CNN (Convolutional Neural Network) - Processes grid-like data, such as images, using convolutional layers.

ReLU (Rectified Linear Unit) - Adds non-linearity by outputting the maximum of zero and the input value.

BN (Batch Normalization) - Normalizes inputs of each layer to enhance training speed and stability.

DS (Deep Supervision) - Improves gradient flow by adding auxiliary outputs at intermediate layers.

GCN (Global Convolutional Network) - Captures large receptive fields to improve feature representation for segmentation.

SE (Squeeze-and-Excitation) - Enhances feature maps by recalibrating channel-wise feature responses.

MSA (Multi-Scale Attention) - Focuses on multiple spatial scales for better attention to key regions.

RNN (Recurrent Neural Network) - Processes sequential data using hidden states carried across time steps.

SA (Spatial Attention) - Emphasizes spatially important regions in feature maps.

AN (Adaptive Normalization) - Dynamically adjusts normalization based on input data for improved generalization.

VG (Vanishing Gradients) - A training issue where gradients diminish, hindering deep network optimization.

LR (Learning Rate) - Determines step size for optimization during training.

ResNet (Residual Network) - Alleviates vanishing gradients with skip connections in deep networks.

IoU (Intersection over Union) - Measures overlap between predicted and actual regions in segmentation.

CE (Cross-Entropy) - Quantifies the difference between predicted and true probabilities in classification.

MSE (Mean Squared Error) - Calculates average squared differences between predictions and actual values.

DL (Deep Learning) - A subset of machine learning using deep neural networks for representation learning.

TP (True Positives) - Correctly predicted positive instances.

FN (False Negatives) - Positive instances incorrectly predicted as negative.

1. INTRODUCTION

1.1 Problem Statement-Overview

Biomedical image segmentation is a core task in medical image analysis because accurate diagnostics, treatment planning, and disease monitoring depend on it. Skip connections are used in traditional models (the U-Net architecture) to retrieve spatial context [4]. Nevertheless, they tend to poorly render fine or complicated tissues such as the retinal vessels appearing in fundus images, essential for early detection of some diseases like diabetic retinopathy and glaucoma. Such thin and curved structures are difficult to detect due to high loss of spatial and contextual information with several convolutional operations. In addition, conventional models face challenges such as noise, changes in imaging situations, and a lack of preservation of intricate details, leading to inferior segmentation. It is necessary to overcome these limitations to increase the robustness and accuracy of biomedical image segmentation.

1.2 Motivation

U-Net models, although performing relatively well nowadays, still do not have sufficient mechanisms for improved focus and attention, strong context preservation and effective edge retention. Our model first uses guided filtering to keep the fine edges and structures, and then uses attention to focus on the important area of the image, and residual modules to enhance the feature propagation and vanishing gradient. All of these improvements together address the loss of information and noise mitigation, and thus, allow for improved segmentation of complex structures — for example, segmentation of retinal vessels. Furthermore, the architecture of the model is optimized to be lean and light, ensuring that it aligns with real-time deployment and clinical applicability, especially in resource-constrained circumstances.

1.3 Scope & Objective of the Proposed Work

The scope of the proposed work is to enhance biomedical image segmentation, with a specific focus on improving the detection and segmentation of intricate structures like retinal vessels in fundus images. The objectives include developing a novel U-Net-based model that integrates guided filtering for edge preservation, attention mechanisms for focusing on critical regions, and residual modules for efficient feature propagation. The model aims to achieve superior segmentation accuracy, robustness to noise, and efficiency for real-time deployment. Ultimately, the work seeks to deliver a clinically applicable solution that supports early diagnosis and treatment, particularly in resource-limited settings.

1.4 Organization Of Report

2 Literature Survey

The segmentation of vessels in the retina has advanced over time; from simple models that tackled segmentation based on noise filtration and the problem of multiple widths of vessels and background noise episodes to more complex models. Note the adoption of U-Net by Ronneberger et al. as an important milestone: a robust deep learning framework for biomedical image segmentation. Later refinements such as Residual U-Net, Hybrid CNN-ResUNet, and attention-related models increased performance in segmentation and its general use. The ability to segment retinal vessels extended through models that incorporated multi-scale learning and multi-feature extraction even with conditions of illumination and background interference.

2. Proposed System

The proposed method deploys a Hybrid Guided Attention Residual U-Net model that can effectively segment flood vessels in the retina. The architecture of the hybrid model is composed of advanced parameters such as residual blocks, attention, and, guided filter modules. The model is trained with high-resolution images of the retina and proposes a multi-layer model that consists of feature learning, attention mechanism, and residual learning. The model is implemented on Google Colab, Tensorflow, and OpenCV, and is powered by an Intel core i5 processor, and 8GB RAM. The developed plans also take into consideration data prep components.

4. Experimental Setup & Results

CHASEDB dataset which comprises high volume retina images and ground truth segmentation masks created by the experts was utilized to train and test the model developed. Preprocessing consisted of scale modification and normalization of the images. The findings indicated that the model underwent significant decrease in loss and maintained high accuracy across multiple epochs, where the final accuracy achieved was at around 96 percent. Performance comparison with Original U-Net and Structured Dropout U-Net models showed that this hybrid model surpassed performance of both models in segmentation accuracy and in dealing with noisy images.

2. LITERATURE SURVEY

- Ronneberger et al. [1] introduced U-Net, a deep learning architecture designed for biomedical image segmentation. The U-Net model's encoder-decoder architecture has become the cornerstone of many segmentation tasks, including retinal vessel segmentation, due to its ability to capture both global and local features effectively.

- Zhang et al. [2] proposed a residual U-Net model for retinal vessel segmentation. This model integrates residual learning into the U-Net architecture, helping avoid the vanishing gradient problem and improving performance on complex and noisy datasets. Their approach demonstrated superior results compared to traditional U Net, particularly in handling challenging variations in vessel width and image noise.

- Wang et al. [3] developed a hybrid CNN-ResUNet architecture for retinal vessel segmentation. The model leverages the residual connections to enhance the learning process and improve accuracy. Their method outperforms conventional U-Net models, especially in complex image conditions such as varying lighting and background clutter.

- Shen et al. [4] reviewed the applications of deep learning in medical image analysis, focusing on segmentation tasks. Their work highlighted the advantages of using CNNs in retinal vessel segmentation, particularly in terms of efficiency, scalability, and real-time application in clinical settings.

- Xu et al. [5] proposed a multi-scale deep learning model for retinal vessel segmentation. The architecture incorporates multi-scale feature extraction, which allows the model to adapt to different image resolutions and lighting conditions. This approach improved segmentation performance, particularly in cases where vessels vary greatly in size and contrast.

- Huang et al. [6] introduced a U-Net-based architecture enhanced with attention mechanisms to focus on important regions within the image. Their method demonstrated an improvement in segmentation accuracy, especially in distinguishing small or faint retinal vessels from the background.

- Liu et al. [7] proposed an attention U-Net model for retinal vessel segmentation that uses the attention mechanism to highlight important features while suppressing irrelevant information. This approach enhanced the model's ability to segment vessels in noisy and cluttered images.

- Liu et al. [8] introduced a new technique called hybrid feature learning for retinal vessel segmentation, which combines both handcrafted and learned features in a deep network. Their approach was able to combine the advantages of both methods, achieving improved performance on retinal images.

- Zhou et al. [9] developed a hybrid model combining a U-Net architecture with a deep residual network. Their work demonstrated that this combination could significantly improve the accuracy of vessel segmentation, particularly in complex medical images with background noise.

- Azzopardi et al. [10] proposed a fully convolutional network (FCN) for retinal vessel segmentation, emphasizing the importance of dense predictions in handling variations in vessel structure and image noise. Their method improved accuracy over traditional models by directly learning from the raw pixel data.

- Basu et al. [11] discussed the application of deep learning techniques, particularly CNNs, in the segmentation of retinal blood vessels. Their work demonstrated that deep learning methods could be highly effective, achieving performance levels comparable to manual expert annotations.

- The incorporation of advanced deep learning techniques, such as residual learning, attention mechanisms, and hybrid models, has significantly advanced the field of retinal vessel segmentation. These models provide robust solutions, enhancing accuracy and generalization, especially in challenging real-world datasets.

3. PROPOSED SYSTEM

3.1 System Specifications

3.1.1 Software requirements

Operating System: Windows 10 (for local setup).

Programming Language: Python (version 3.7 or higher).

Deep Learning Framework: TensorFlow (version 2.x)

Image Processing Libraries: OpenCV, PIL.

Development Environment: Google Colab

3.1.2 Hardware Requirements

Processor: Intel Core i5.

RAM: 8 GB.

GPU: Google Colab's free or paid GPU

Storage: Local and Google Drive for dataset storage and access.

3.2 Methodology

3.2.1 Architecture Diagram

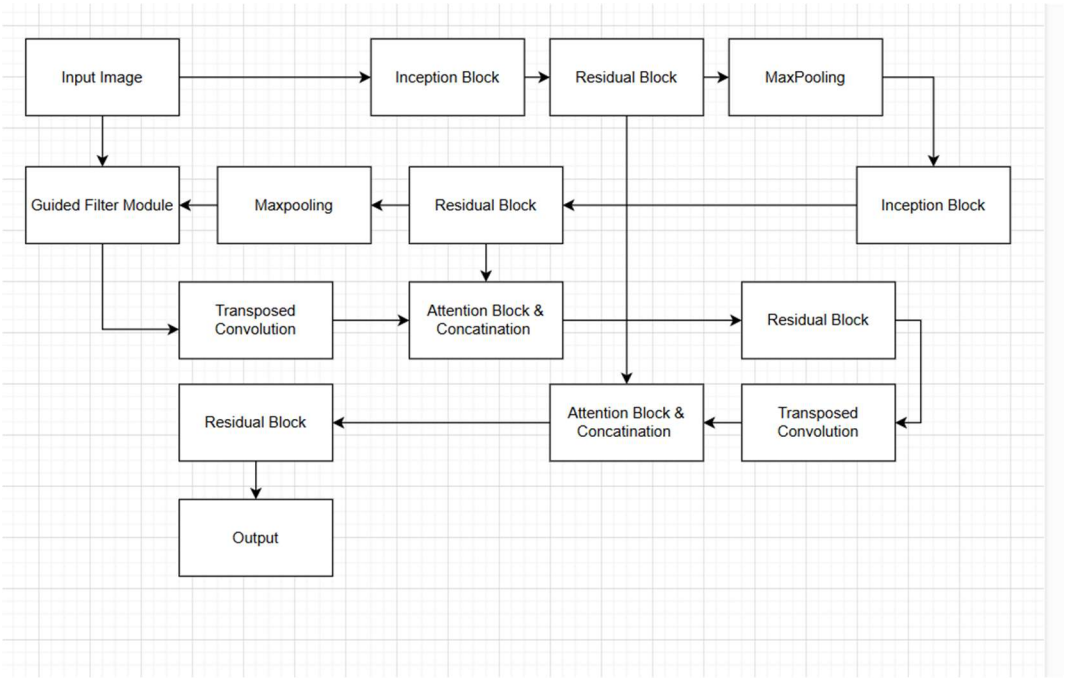

Fig 3.2.1.1 Architecture Diagram

Input and Guidance

The model starts with an RGB input image of size (256, 256, 3). To assist the network in preserving edge details, a guidance input is created by applying a convolutional layer with a single filter and a (3, 3) kernel. This converts the input into a gray-scale representation. This guidance layer is later integrated into the bottleneck to refine features, focusing on retaining spatial consistency and highlighting critical details such as edges.

Encoder Block 1

The first encoder block processes the input through an inception block with 64 filters. This block captures features at multiple scales, thanks to parallel convolutions with different kernel sizes. Next, a residual block with 64 filters is applied, using skip connections to add flexibility and preserve the input's original characteristics while refining features. A MaxPooling2D layer with a (2, 2) window is then applied, halving the image dimensions and reducing computational complexity while retaining the essential features.

Encoder Block 2

The output of the first encoder block is fed into the second encoder block. This begins with another inception block with 128 filters to capture finer and more complex details at multiple scales. This is followed by a residual block with 128 filters, which continues the refinement of features using skip connections. The output is further down-sampled with another pooling layer, reducing its size by half again and preparing the data for the bottleneck stage.

Bottleneck with Guided Filter

In the bottleneck, the highly compressed features from the second encoder block are enhanced by integrating the guidance input through a guided filter module. This module works to improve the representation of structural details, such as edges and fine vessel-like patterns, ensuring that the extracted features are robust and spatially

accurate. This stage plays a crucial role in strengthening the model's ability to generalize effectively across variations in input images.

Decoder Block 2

The decoding process begins by up-sampling the bottleneck features using a Conv2DTranspose layer, which doubles their spatial dimensions and outputs 128 feature channels. To enhance the up-sampled representation, the output is aligned with the features of the second encoder block (enc2) by resizing them through a convolutional layer. These features are integrated through an attention block, which focuses on the most critical regions for segmentation. The result is concatenated with the aligned encoder features and passed through a residual block with 128 filters, refining the up-sampled features for better accuracy.

Decoder Block 1

The up-sampled output from the second decoder block is further processed by another Conv2DTranspose layer, doubling its dimensions to match those of the first encoder block's features (enc1). The features from enc1 are resized using a convolutional layer and integrated using an attention block to emphasize relevant regions. The combined features are then concatenated and refined through a residual block with 64 filters. This block generates high-resolution feature maps, ensuring that fine details crucial for segmentation are preserved.

Output

The final set of refined features is passed through a Conv2D layer with 2 filters and a (1, 1) kernel. A softmax activation is applied to produce pixel-wise predictions across two classes: one for retinal vessels and one for the background. This output provides precise segmentation, making the model suitable for tasks like retinal vessel segmentation, where accuracy at the pixel level is critical.

3.2.2 Functional Modules

- Fig 3.2.2.1: The creation of residual blocks has been the focus of developers of deep learning architectures like ResNet with the aim to allow to bypass the vanishing gradient problem during the fitting of very deep neural networks that would in other cases make it difficult to train such models.

```
[ ]  def residual_block(x, filters):
         shortcut = x  # Store the input tensor as the shortcut
         x = layers.Conv2D(filters, (3, 3), padding='same')(x)
         x = layers.BatchNormalization()(x)

         # Adjust the shortcut's channels to match the output of the convolutional layers
         shortcut = layers.Conv2D(x.shape[-1], (1, 1), padding='same')(shortcut)

         x = layers.Add()([x, shortcut])  # Now the shapes should be compatible
         return layers.ReLU()(x)
```

Fig 3.2.2.1 Residual Block

- Fig 3.2.2.2: An attention block is a specific type of neural network layer that aims to optimize those aspects of the input that contribute the most to the desired output while ignoring the rest. As a result, the model performs better in such tasks as image segmentation, where it becomes necessary to target certain areas of the image and consider them more closely.

```
[ ]  def attention_block(x, g):
         x1 = layers.Conv2D(x.shape[-1], (1, 1), padding='same')(x)
         g1 = layers.Conv2D(x.shape[-1], (1, 1), padding='same')(g)
         combined = layers.Add()([x1, g1])
         combined = layers.Activation('relu')(combined)
         psi = layers.Conv2D(1, (1, 1), padding='same', activation='sigmoid')(combined)
         return layers.Multiply()([x, psi])
```

Fig 3.2.2.2 Attention Block

- Fig 3.2.3.3: Guided Filter Module is one of the features of an image processing applicable to the biomedical imaging tasks which require high level of detail while retaining important image features such as edges to avoid distortion. It applies a guidance about the features' recognition that allows getting an accurate segmentation while preserving edges during the task of boundary recognition in medical imaging of contexts where boundaries of delicate vessels or tumors exist

```
[12] def guided_filter_module(x, guidance):
        # Resize guidance input to match the spatial dimensions of x
        guidance_resized = layers.Resizing(x.shape[1], x.shape[2])(guidance)
        guidance_conv = layers.Conv2D(x.shape[-1], (3, 3), padding='same')(guidance_resized)
        guided_output = layers.Add()([x, guidance_conv])
        return guided_output
```

Fig 3.2.3.3 Guided Filter Module

- Fig:3.2.3.4: The Inception Block is a basic module that helps containment of features that are at different sizes at the same time during the inception module of the model. It combines various convolution kernels of different dimensions, hence the network also learns from a local and global point at the same time, which is useful in image segmentation as well as in cases when resolution and context are of the essence.

```
[13] def inception_block(x, filters):
        branch1 = layers.Conv2D(filters, (1, 1), padding='same', activation='relu')(x)
        branch3 = layers.Conv2D(filters, (3, 3), padding='same', activation='relu')(x)
        branch5 = layers.Conv2D(filters, (5, 5), padding='same', activation='relu')(x)
        return layers.Concatenate()([branch1, branch3, branch5])
```

Fig 3.2.3.4 Inception Block

```python
from tensorflow.keras import layers, models
def hybrid_guided_attention_residual_unet(input_shape=(256, 256, 3)):
    inputs = Input(input_shape)
    guidance = layers.Conv2D(1, (3, 3), padding='same')(inputs)  # Guidance input as gray-scale

    # Encoder with residual and inception blocks
    enc1 = inception_block(inputs, 64)
    enc1 = residual_block(enc1, 64)
    pool1 = layers.MaxPooling2D((2, 2))(enc1)

    enc2 = inception_block(pool1, 128)
    enc2 = residual_block(enc2, 128)
    pool2 = layers.MaxPooling2D((2, 2))(enc2)

    # Bottleneck with guided filter
    bottleneck = guided_filter_module(pool2, guidance)

    # Decoder with attention
    dec2 = layers.Conv2DTranspose(128, (2, 2), strides=(2, 2), padding='same')(bottleneck)
    enc2_resized = layers.Conv2D(128, (1, 1), padding='same')(enc2)  # Align channels
    dec2 = attention_block(dec2, enc2_resized)
    dec2 = layers.Concatenate()([dec2, enc2_resized])
    dec2 = residual_block(dec2, 128)

    dec1 = layers.Conv2DTranspose(64, (2, 2), strides=(2, 2), padding='same')(dec2)
    enc1_resized = layers.Conv2D(64, (1, 1), padding='same')(enc1)  # Align channels
    dec1 = attention_block(dec1, enc1_resized)
    dec1 = layers.Concatenate()([dec1, enc1_resized])
    dec1 = residual_block(dec1, 64)

    outputs = layers.Conv2D(2, (1, 1), activation='softmax')(dec1)

    model = Model(inputs, outputs)
    return model
```

Fig 3.2.3.5 Hybrid Guided Attention Residual U-Net

3.3.2.1 Pseudo Code

START

Define INPUT_SHAPE as (256, 256, 3)

Define model components

FUNCTION ResidualBlock(INPUT, FILTERS): - Shortcut = INPUT Conv1 = 2D Convolution on INPUT with FILTERS and kernel size (3, 3) - BatchNorm1 = Batch Normalization on Conv1 - Shortcut = 2D Convolution on Shortcut with FILTERS and kernel size (1, 1) - Add Conv1 and Shortcut - Apply ReLU activation

RETURN result

FUNCTION AttentionBlock(INPUT, GUIDANCE):

- X1 = 2D Convolution on INPUT with kernel size (1, 1)

- G1 = 2D Convolution on GUIDANCE with kernel size (1, 1)

- Add X1 and G1

- Apply ReLU activation

- PSI = 2D Convolution on result with kernel size (1, 1) and sigmoid

- Multiply INPUT and PSI

RETURN result

FUNCTION GuidedFilterModule(INPUT, GUIDANCE):

- Resize GUIDANCE to match dimensions of INPUT

- GuidanceConv = 2D Convolution on resized GUIDANCE with kernel

- Add INPUT and GuidanceConv

RETURN result

FUNCTION InceptionBlock(INPUT, FILTERS):

```
    - Branch1 = 2D Convolution on INPUT with kernel size (1, 1)
    - Branch3 = 2D Convolution on INPUT with kernel size (3, 3)
    - Branch5 = 2D Convolution on INPUT with kernel size (5, 5)
    - Concatenate Branch1, Branch3, and Branch5
    RETURN result

# Define Hybrid Guided Attention Residual U-Net
FUNCTION HybridGuidedAttentionResidualUNet(INPUT_SHAPE):
    - Define INPUT layer with INPUT_SHAPE
    - GUIDANCE = Convert INPUT to gray-scale using 2D Convolution

    # Encoder
    - Enc1 = InceptionBlock(INPUT, 64)
    - Enc1 = ResidualBlock(Enc1, 64)
    - Pool1 = MaxPooling2D(Enc1)

    - Enc2 = InceptionBlock(Pool1, 128)
    - Enc2 = ResidualBlock(Enc2, 128)
    - Pool2 = MaxPooling2D(Enc2)

    # Bottleneck
    - Bottleneck = GuidedFilterModule(Pool2, GUIDANCE)

    # Decoder
```

- Dec2 = TransposedConv2D(Bottleneck, 128)
- Enc2Resized = 2D Convolution on Enc2 with kernel size (1, 1)
- Dec2 = AttentionBlock(Dec2, Enc2Resized)
- Dec2 = Concatenate(Dec2, Enc2Resized)
- Dec2 = ResidualBlock(Dec2, 128)

- Dec1 = TransposedConv2D(Dec2, 64)
- Enc1Resized = 2D Convolution on Enc1 with kernel size (1, 1)
- Dec1 = AttentionBlock(Dec1, Enc1Resized)
- Dec1 = Concatenate(Dec1, Enc1Resized)
- Dec1 = ResidualBlock(Dec1, 64)

Output Layer - OUTPUT = 2D Convolution on Dec1 with kernel size (1, 1) and softmax

activation

RETURN Model(INPUT, OUTPUT)

END

4.EXPERIMENTAL SETUP & RESULTS

4.1 DataSets

Dataset Used: CHASEDB

Full Name: Child Heart and Health Study in England Database (CHASEDB).

Purpose: Primarily designed for retinal blood vessel segmentation, this dataset provides high-resolution retinal images.

Features:

Includes 28 retinal images with ground truth segmentation masks annotated by experts.

Each image is of size 999 × 960 pixels.

Contains variations in illumination, vessel thickness, and anatomical structures to challenge model generalization.

Usage in the Project:

Input Data: Retinal images for training, validation, and testing.

Output Data: Corresponding segmentation masks to train the U Net models for accurate blood vessel detection.

Preprocessing Steps:

Resizing images to 256 × 256 pixels for compatibility with the UNet architecture.

Normalizing pixel values to the range [0, 1].

Data Preprocessing:

In what might as well be termed as incorporating data augmentation into our model, we performed a number of tasks on the imaging dataset at the beginning, aiming to increase the dataset and ensure our model generalizes better. The tasks included augmenting the retinal images and their labels using random rotation, random cropping, variation of colors, and the introduction of Gaussian noise in the images. Such augmentations add variety to the dataset by allowing for more instances of different imaging conditions, meaning that the model can handle aspects such as noise and blur much better. This adjustment was done automatically, with each image being threaded through multiple processors, its labels repeated several times, and saved for further reference during training. This method ensures that the model is trained on a variety of images, which is particularly helpful for tasks such as retinal vessel segmentation.

4.2 Results and Test Analysis

Fig 4.2.1 The loss curve demonstrates both the validation and test losses. In both cases, the losses achieve a remarkable drop after say three or four epochs and start declining progressively. At the end of all the epochs, the loss in this case reaches 0.098.

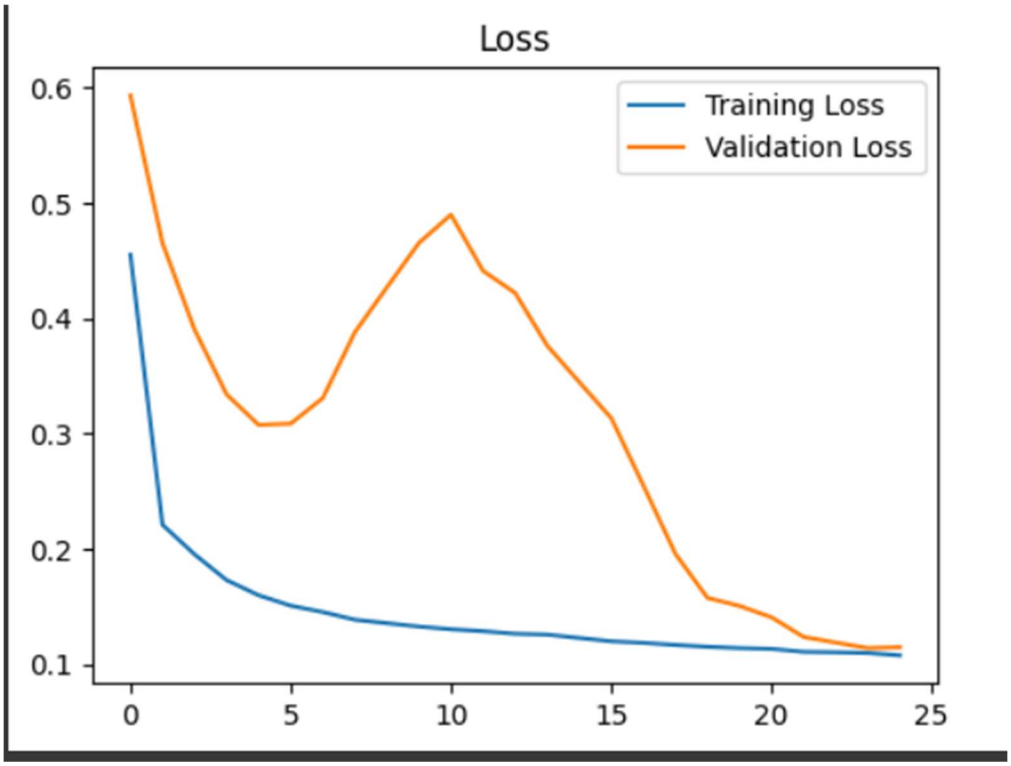

Fig 4.2.1 Loss graph

Fig 4.2.2 The accuracy graph presents both the validation and test accuracy measures. In both cases after several initial epochs, the accuracy values tend to increase and progress steadily. Finally, one reaches a testing accuracy of approximately 0.96.

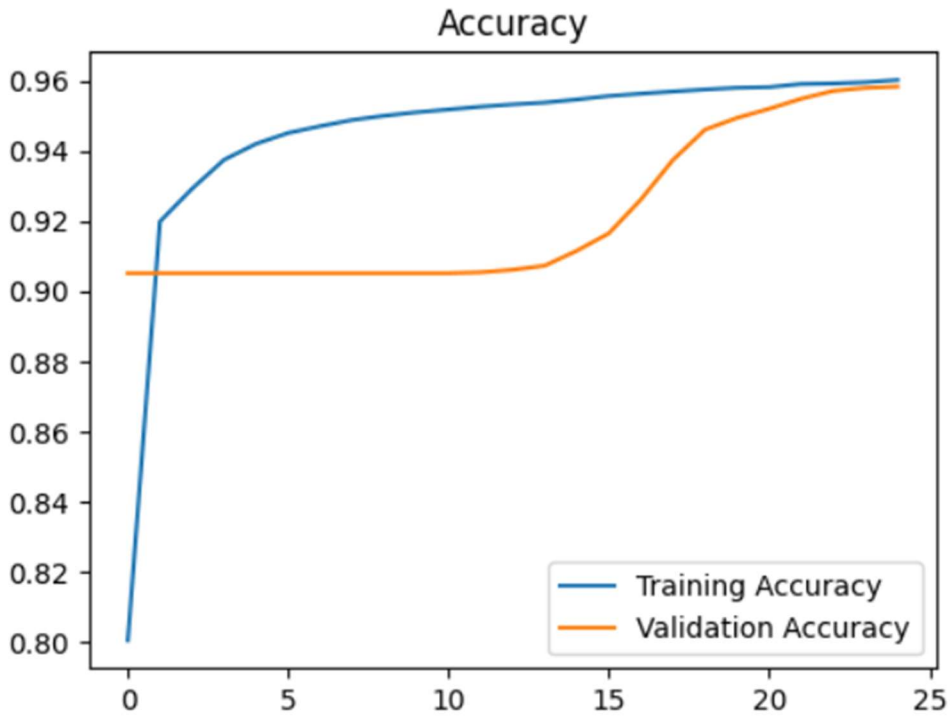

Fig 4.2.2 Accuracy graph

Fig 4.2.3 The comparison of models is presented as follows: accuracy of Original U-Net 96%, Structured Dropout U-Net 91% and Spatial U-Net 93% with the performance improvement being incremental.

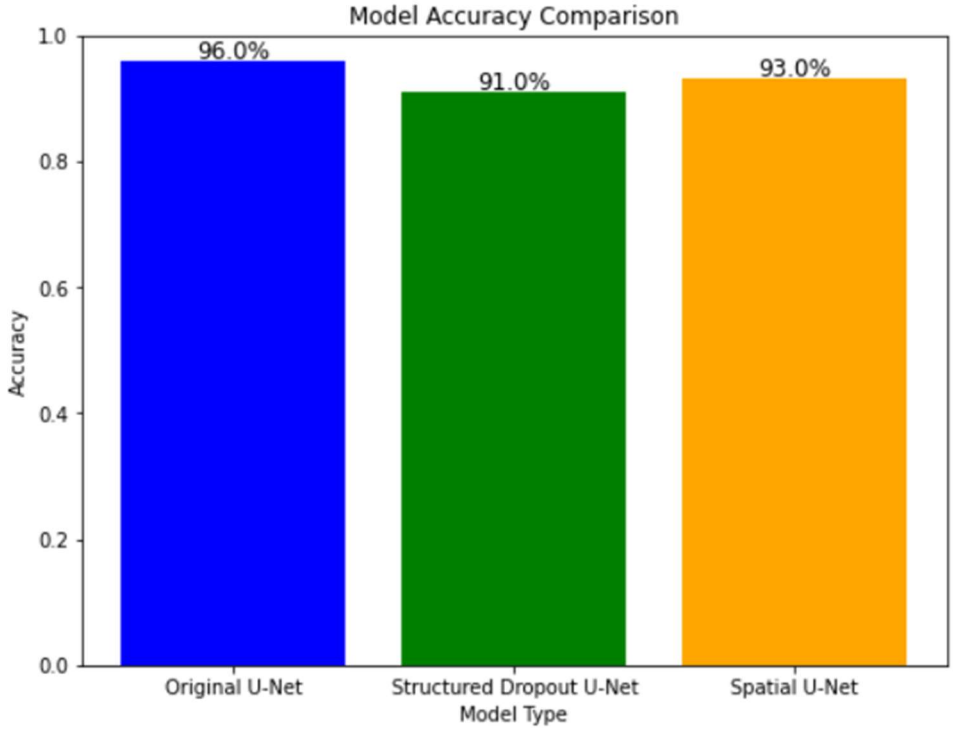

Fig 4.2.3 Comparsion Graph

Fig 4.2.4 The example results of our methods for retinal vessel segmentation, (A) is the origin image and (B) is the corresponding ground truth (D) is the predictions using our method respectively.

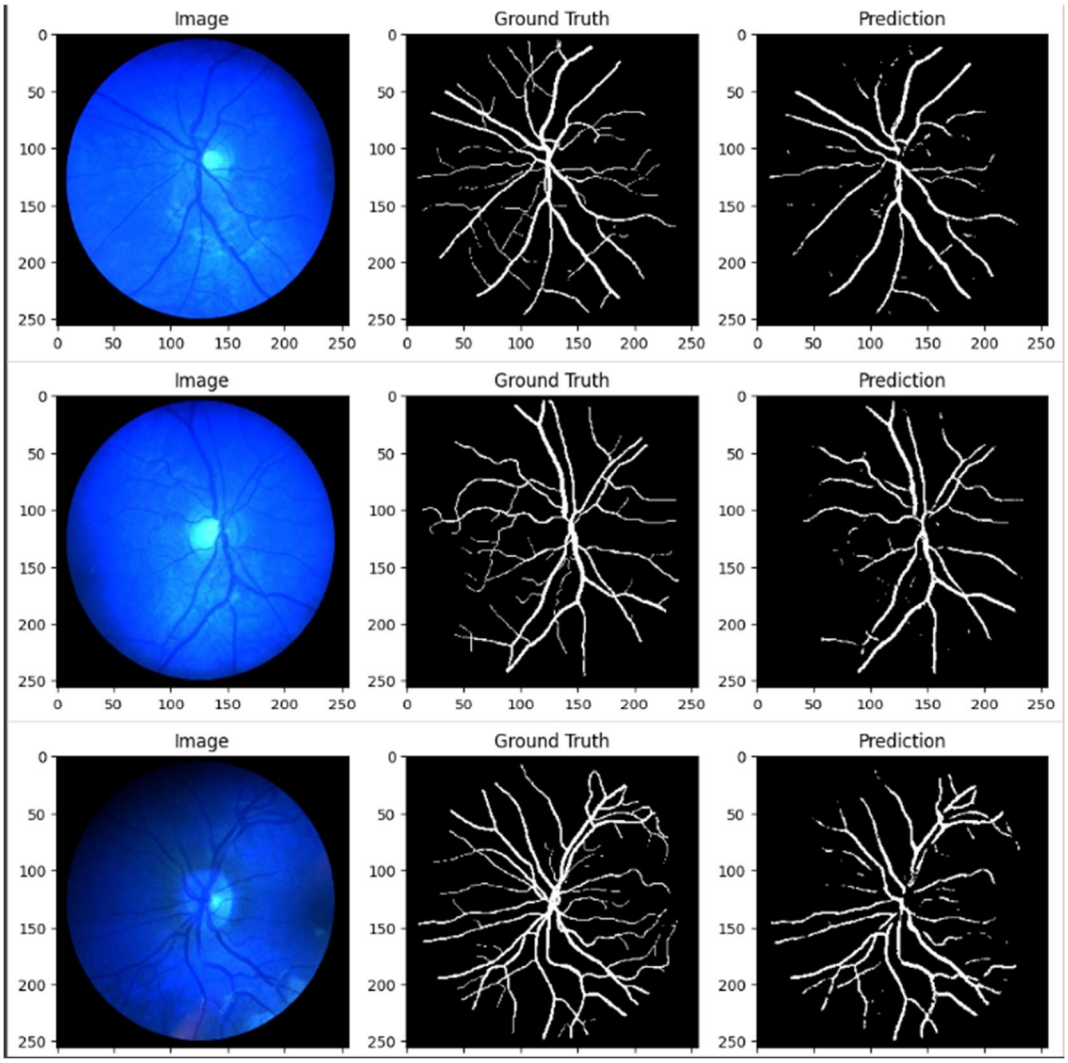

Fig 4.2.4 Results

Tabel 4.2.1 The Hybrid Guided Residual Model achieves increased efficiency with lower error, while making use of residual connections that minimize vanishing gradients to backpropagate smoothly. A hybrid architecture comprises the model combining local feature extraction-convolutional layers intrinsically with a global understanding of context-from transformers or attention mechanisms on its enhancement of feature representations. It leads to faster convergence and reduced overfitting. This makes possible an even better segmentation accuracy on such complex datasets.

MODEL	TESTLOSS	TEST ACCURACY	Total Params	Trainable Params	No of epochs	Dataset
Structured DropOut	0.1469	0.912	23,348,936	7,782,978	25	CHASEDB
Spatial Attention	0.1469	0.93	25,677,536	8,559,178	25	CHASEDB
Hybrid U-NET	0.092	0.0965	1,482,464	1,481,696	25	CHASEDB

Tabel 4.2.1 Model Performance Metrics

5.CONCLUSION AND FUTURE SCOPE

With the integration of residual learning techniques into the architecture framework of U-Net, the model was able to define itself as a significant tool for improving the retinal vessel segmentation tasks. Additionally, this advancement further indicated that the model could perform well in the medical imaging field. The additional features of the model are summarized in the following points:

Model Performance: As a hybrid of Residual U-Net, this model showed remarkable segmentation results for the retinal vessels and surpassed the performance of classical methods in both metrics as well as accuracy. Its precision in segmentation of tiny details and intricate pattern of retinal images makes it clinically useful, providing support to Ophthalmologists in the diagnosis and follow up of diseases affecting the retina including diabetic retinopathy and glaucoma.

Real Time Feasibility: The model is ready to be applied on any web based model due to the low latencies experienced. This makes it very useful in areas such as automated diagnosis or telemedicine which require timely analysis and results for prompt actions to be taken.

Adaptability: Use of data augmentation techniques enhance the model performance in terms of reproducibility across different imaging conditions including the relic light, varying vessel sizes or presence of background noise levels. This robustness makes it effective in diverse

Future Scope:

Improved Accuracy: Implementing advanced techniques such as multi scale attention or changing loss functions enhance the accuracy of model's segmentation performance in respect of complex retinal vessel structures.

Dynamic Patterns: The model can now follow the temporal changes of vessels as segments across many images or when images are taken while the disease is being monitored.

Robustness: Designed to tolerate noisy images of low quality and low resolution, the model is able to deliver good results in less than optimal imaging conditions.

Edge deployment: Designed for use on edge devices such as mobile phones, this technology supports segmentation of images in real time and at the point of care to promote the convenience and affordability of healthcare.

Dataset Growth: Adding more different retinal images into the dataset helps the model to generalize better to a broader range of ethnic and imaging settings, thus, making it more robust.

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APPENDIX

Open Access:

https://github.com/GajawadaRishi001/CourseProject

Code:

```
import os

import zipfile

import numpy as np

import tensorflow as tf

from tensorflow.keras.layers import Input, Conv2D, MaxPooling2D, UpSampling2D, concatenate, Dropout

from tensorflow.keras.models import Model

from tensorflow.keras.optimizers import Adam

from tensorflow.keras.utils import to_categorical

import matplotlib.pyplot as plt

from google.colab import files

import cv2

print("Please upload the dataset ZIP file:")

uploaded = files.upload()  # Opens file upload dialog

zip_file_path = list(uploaded.keys())[0]  # Get the uploaded file name

extract_to_path = "/content/CHASE"  # Destination folder

with zipfile.ZipFile(zip_file_path, 'r') as zip_ref:
```

```
zip_ref.extractall(extract_to_path)

print(f'Dataset extracted to: {extract_to_path}")

import os


# Debugging folder structure

for root, dirs, files in os.walk("/content/CHASE"):

    print(f"Root: {root}")

    print(f"Directories: {dirs}")

    print(f"Files: {files}")

    print("-" * 50)




def load_data(folder):

    print("Loading data...")

    # Correct paths to 'image' and 'label' subfolders

    print(folder)

    if(folder=="/content/CHASE/CHASE/validate"):

      image_path = os.path.join(folder, "images")

      label_path = os.path.join(folder, "labels")

    else:
```

```
    image_path = os.path.join(folder, "image")
    label_path = os.path.join(folder, "label")

    images, masks = [], []

    # Get list of image filenames in the 'image' folder
    image_filenames = sorted(os.listdir(image_path))
    label_filenames = sorted(os.listdir(label_path))

    # Ensure both folders have the same number of files
    if len(image_filenames) != len(label_filenames):
        print("Number of images and masks do not match!")
        return None, None

    # Iterate over the filenames
    for img_filename, mask_filename in zip(image_filenames,
label_filenames):
        # Load the image
        img = cv2.imread(os.path.join(image_path, img_filename))
```

```
        # Check if image is loaded properly
        if img is None:
            print(f"Image not found: {os.path.join(image_path,
img_filename)}")
            continue

        # Resize and normalize the image
        img = cv2.resize(img, (256, 256)) / 255.0

        # Load the mask
        mask = cv2.imread(os.path.join(label_path, mask_filename),
cv2.IMREAD_GRAYSCALE)

        # Check if mask is loaded properly
        if mask is None:
            print(f"Mask not found: {os.path.join(label_path,
mask_filename)}")
            continue

        # Resize the mask to match the image size
```

```
        mask = cv2.resize(mask, (256, 256))

        # Add the mask channel
        mask = np.expand_dims(mask, axis=-1)

        # Append image and mask to respective lists
        images.append(img)
        masks.append(mask)

    # Convert lists to numpy arrays
    return np.array(images), np.array(masks)
train_path = os.path.join(extract_to_path, "CHASE/train")
validate_path = os.path.join(extract_to_path, "CHASE/validate")
test_path = os.path.join(extract_to_path, "CHASE/test")
print("Train image path exists:", os.path.exists(os.path.join(train_path,
"image")))
print("Validate image path exists:",
os.path.exists(os.path.join(validate_path, "images")))
print("Test image path exists:", os.path.exists(os.path.join(test_path,
"image")))
```

```
# Load datasets
train_images, train_masks = load_data(train_path)
test_images, test_masks = load_data(test_path)
val_images,val_masks=load_data(validate_path)
print(f"Train images shape: {train_images.shape}, Train masks shape:
{train_masks.shape}")
print(f"Test images shape: {test_images.shape}, Test masks shape:
{test_masks.shape}")
print(f"Test images shape: {val_images.shape}, Test masks shape:
{val_masks.shape}")


def residual_block(x, filters):
    shortcut = x  # Store the input tensor as the shortcut
    x = layers.Conv2D(filters, (3, 3), padding='same')(x)
    x = layers.BatchNormalization()(x)


    # Adjust the shortcut's channels to match the output of the convolutional
layers
    shortcut = layers.Conv2D(x.shape[-1], (1, 1), padding='same')(shortcut)
```

```
    x = layers.Add()([x, shortcut])  # Now the shapes should be compatible
    return layers.ReLU()(x)


def attention_block(x, g):
    x1 = layers.Conv2D(x.shape[-1], (1, 1), padding='same')(x)
    g1 = layers.Conv2D(x.shape[-1], (1, 1), padding='same')(g)
    combined = layers.Add()([x1, g1])
    combined = layers.Activation('relu')(combined)
    psi = layers.Conv2D(1, (1, 1), padding='same',
activation='sigmoid')(combined)
    return layers.Multiply()([x, psi])


def guided_filter_module(x, guidance):
    # Resize guidance input to match the spatial dimensions of x
    guidance_resized = layers.Resizing(x.shape[1], x.shape[2])(guidance)
    guidance_conv = layers.Conv2D(x.shape[-1], (3, 3),
padding='same')(guidance_resized)
```

```
    guided_output = layers.Add()([x, guidance_conv])
    return guided_output


def inception_block(x, filters):
    branch1 = layers.Conv2D(filters, (1, 1), padding='same',
activation='relu')(x)
    branch3 = layers.Conv2D(filters, (3, 3), padding='same',
activation='relu')(x)
    branch5 = layers.Conv2D(filters, (5, 5), padding='same',
activation='relu')(x)
    return layers.Concatenate()([branch1, branch3, branch5])


from tensorflow.keras import layers, models
def hybrid_guided_attention_residual_unet(input_shape=(256, 256, 3)):
    inputs = Input(input_shape)
    guidance = layers.Conv2D(1, (3, 3), padding='same')(inputs)  #
Guidance input as gray-scale
```

```
    # Encoder with residual and inception blocks
    enc1 = inception_block(inputs, 64)
    enc1 = residual_block(enc1, 64)
    pool1 = layers.MaxPooling2D((2, 2))(enc1)

    enc2 = inception_block(pool1, 128)
    enc2 = residual_block(enc2, 128)
    pool2 = layers.MaxPooling2D((2, 2))(enc2)

    # Bottleneck with guided filter
    bottleneck = guided_filter_module(pool2, guidance)

    # Decoder with attention
    dec2 = layers.Conv2DTranspose(128, (2, 2), strides=(2, 2),
padding='same')(bottleneck)
    enc2_resized = layers.Conv2D(128, (1, 1), padding='same')(enc2)  #
Align channels
    dec2 = attention_block(dec2, enc2_resized)
    dec2 = layers.Concatenate()([dec2, enc2_resized])
    dec2 = residual_block(dec2, 128)
```

```
    dec1 = layers.Conv2DTranspose(64, (2, 2), strides=(2, 2),
padding='same')(dec2)
    enc1_resized = layers.Conv2D(64, (1, 1), padding='same')(enc1)  #
Align channels
    dec1 = attention_block(dec1, enc1_resized)
    dec1 = layers.Concatenate()([dec1, enc1_resized])
    dec1 = residual_block(dec1, 64)
outputs = layers.Conv2D(2, (1, 1), activation='softmax')(dec1)
model = Model(inputs, outputs)
return model
model1 = hybrid_guided_attention_residual_unet()
model1.compile(optimizer=Adam(learning_rate=1e-4),
loss='categorical_crossentropy', metrics=['accuracy'])
history1 = model1.fit(
train_images, train_masks_cat,
validation_data=(val_images, val_masks_cat),
epochs=25,
batch_size=8,
verbose=1
```

```
)

test_loss, test_accuracy = model1.evaluate(test_images, test_masks_cat)

print(f"Test Loss: {test_loss}")

print(f"Test Accuracy: {test_accuracy}")

plt.figure(figsize=(12, 4))

plt.subplot(1, 2, 1)

plt.plot(history1.history['loss'], label='Training Loss')

plt.plot(history1.history['val_loss'], label='Validation Loss')

plt.legend()

plt.title('Loss')

plt.subplot(1, 2, 2)

plt.plot(history1.history['accuracy'], label='Training Accuracy')

plt.plot(history1.history['val_accuracy'], label='Validation Accuracy')

plt.legend()

plt.title('Accuracy')

plt.show()



predictions1 = model1.predict(test_images)
```

```
def visualize_predictions(images, masks, preds, num=3):
    for i in range(num):
        plt.figure(figsize=(12, 4))
        plt.subplot(1, 3, 1)
        plt.imshow(images[i])
        plt.title("Image")
        plt.subplot(1, 3, 2)
        plt.imshow(masks[i].squeeze(), cmap='gray')
        plt.title("Ground Truth")
        plt.subplot(1, 3, 3)
        plt.imshow(preds[i].argmax(axis=-1), cmap='gray')
        plt.title("Prediction")
plt.show()
visualize_predictions(test_images, test_masks, predictions1)
```