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Retinal Lesion Segmentation for Early Detection of Diabetic Retinopathy Using CNNs, Vision Transformers, and Hybrid Deep Learning Models

MSc Research Project
MSc in Artificial Intelligence

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Retinal Lesion Segmentation for Early Detection of Diabetic Retinopathy Using CNNs, Vision Transformers, and Hybrid Deep Learning Models

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Abstract

Detecting the presence of the eye conditions such as diabetic retinopathy which may lead to blindness in case it is not treated early, are some of the main processes that entail retinal lesion segmentation. This report discusses the ability of four deep learning basics, including SimpleSegNet, Vision Transformer (ViT) in scratch, SegFormer, and UNet to detect lesions in retinal fundus images. To train and test these models we deployed a dataset of eye images and their binary masks. We have trained each model five times and checked its performance according to such measures as accuracy, precision, and F1 score. We did also do some pictures to depict how well the models fitted the lesions than the real masks. As the result, models based on advanced design and already learned information, such as SegFormer and UNet, are more effective than the rest due to their in-advance learning. This would be useful to enable the doctors in Pakistan to diagnose the eye diseases more quickly, in zones where eye doctors are less in numbers. The models are compared in the report to come up with the best model to be used in this job.

Keywords - Diabetic Retinopathy, Retinal lesion segmentation, SimpleSegNet, Vision Transformer, SegFormer, UNet, medical imaging, fundus images.

1 Introduction

In Retinal lesion segmentation is very important in medical imaging, thus offering a major breakthrough in the diagnosis and treatment of eye diseases such as diabetic retinopathy, glaucoma, and age-related macular degeneration. If detected and treated too late, these diseases can inflict devastating damage to the retina- the very thin-layered structure at the back of the eye that is sensitive to the incidence of light- and this damage could become completely irreversible, resulting in blindness. Retinal lesion segmentation is the process of identifying and delineating abnormal regions of hemorrhages, exudates, or drusen in retinal fundus images, photographic products taken from special cameras that view the retina. This assists healthcare professionals to reach better diagnostic decisions in the treatment of eye diseases with incredible efficiency and speed, particularly in circumstances where eye specialists are not easy to come by. In countries such as Pakistan, where the scarcity of eye specialists is coupled with high prevalence rates of diabetic retinopathy due to rising diabetes cases, AI-based automated tools can help bridge significant gaps in healthcare delivery. Using deep learning, which is a subset of AI, computers could be trained to analyze fundus images independently, detecting lesions with an accuracy at par or even better than human experts in some cases. This study evaluates the performance of four deep-learning models, being SimpleSegNet, Vision Transformer (ViT) from scratch, SegFormer, and UNet in

segmenting retinal lesions to identify the most viable model for clinical applications, especially in resource-limited contexts (Bala, Sharma and Goel, 2024).

The work thus holds the potential to transform eye care systems in the needy regions. Diabetic retinopathy is found globally in about a third of the diabetic patients' populations; especially with an increasing burden as in most studies showed that Pakistan has a broader diabetes prevalence of over 26% adult population. Failure to intervene on time will later progress to severe stages involving vision loss. Manual analysis of fundus images by ophthalmologists is very time-consuming, subjective, and highly human error-prone. Particularly in rural and isolated areas of Pakistan, specialized eye care facilities are often lacking, and patients could remain undiagnosed until irreversible damage occurs (Kugelman et al., 2022).

It concerns the usefulness of work-capacity in itself to transform eye care systems in the needy regions. An example is diabetic retinopathy, in which one out of every three diabetic patients found worldwide has it; theoretically, Pakistan becomes afflicted more as recent studies estimate that more than 26 percent of the adult population is classified as diabetic. It will escalate into a severe condition, which will eventually lead to blindness if preventive action is not taken. Manual analysis of fundus images by ophthalmologists is time-consuming and subjective (Gupta, Thakur and Gupta, 2024). Most importantly, it is a human error-prone method, especially when large numbers of images have to be reviewed. Also, the rural and remote areas of Pakistan don't have specialized eye-care facilities for the most part, hence people might remain undiagnosed until damage becomes irreversible (Saranya, Pranati and Patro, 2023).

This study builds on prior research demonstrating the efficacy of deep learning in medical imaging. For example, that CNNs could accurately segment retinal vessels and lesions in datasets like DRIVE, while UNet’s effectiveness in segmenting fluid in retinal optical coherence tomography (OCT) images, a task closely related to lesion segmentation (Goutam et al., 2022). Recent advancements in ViTs, that transformer-based models outperform traditional CNNs in complex cases due to their ability to model long-range dependencies. Similarly, SegFormer’s superior performance on retinal images, attributed to its pretrained knowledge. By testing both pretrained and non-pretrained models, this study assesses whether advanced architectures or pretraining confer significant advantages in retinal lesion segmentation (Deshmukh, Pawar and Gaikwad, 2023). The findings aim to guide the development of practical tools for eye care, particularly in low-resource settings, where cost-effective and accurate diagnostic solutions are urgently needed.

Research Question: How do different deep learning architectures compare in their effectiveness for retinal lesion segmentation, and which approaches provide the most accurate and practical solutions for medical diagnosis?

2 Related Work

2.1 CNN-Based Approaches for Retinal Image Segmentation

Traditional For multiple years, traditional Convolutional Neural Networks have served as the foundation for medical image segmentation. Many researchers have employed CNN based models for the detection and segmentation of retinal lesions showing improved performances. Li et al. In (2020), a CNN model was developed for retinal vessel and lesion segmentation, using the DRIVE dataset. Its implementation proved that CNNs can be successfully trained to detect patterns in retinal images, and they may play an important role in the detection of entities as blood vessels or pathological areas. The model had a high accuracy but needed to tune parameters carefully.

Gulati, Guleria and Goyal (2023) have evaluated various CNN architectures in the detection of diabetic retinopathy. Now, they observed that deeper CNN networks performed better than shallow CNN, but at the same time used more computational power to classify images. They discussed that CNNs have been successful in fundus image analysis, but they might not work well for lesions with complex patterns.

Mahesh (2022) compared U-Net based models for retinal blood vessel segmentation This allows U-Net to learn fine details, while also seeing the big picture (pun intended) in the medical images. This work set U-Net as a de fact go-to for retinal image tasks.

Goutam et al. Since then, Burdick et al contributed a complete assessment of CNN approaches in the diagnosis of retinal diseases in (2022) Although CNNs are proven to work, they require a highly extensive dataset and some preprocessing in order to perform well. The study was also concerned about the failure of CNNs on small lesions, which could be crucial in early diagnosis.

2.2 Vision Transformer Applications in Medical Imaging

Vision Transformers are recently proposed models to handle image analysis in an new fashion, they treat the image as a patch of sequence rather than implementing convolution operations traditionally. Medical imaging tasks have made promising strides with recent research.

Akça et al. (2024) employed Vision Transformers for deep learning classification of choroidal neovascularization, diabetic macular edema, and drusen from OCT images [45]. They compared to CNN models and based on the analysis, ViTs can handle more complex cases as they are basically learning global relationships in an image. However, they realized that other ViTs need a lot more data to do well.

In terms of Vision Transformers, Wang, Liu and Zhou (2022) indeed used it for retinal lesion segmentation. The research showed ViTs are able to discover patterns they believe CNNs will likely miss, in particular complicated cases with multiple lesions. However, they did point out that training ViTs from scratch needs extensive computing power and data middles.

This is used to find the best hybrid CNN-ViT model for improved retinal lesion segmentation in (Chen et al. They concluded that the strengths could be combined with CNNs for local feature extraction and ViTs for global understanding. The ViT+CNN adaptation performed better than each of the methods used alone.

2.3 Pre-trained Models and Transfer Learning

The reason of popularity behind pre-trained models is due to the fact that they already have learned patterns from large datasets, that can be used to detect similar patterns in our shape. So, this first get pre-trained on large common datasets and later get fine-tuned for particular medical tasks.

Hemelings et al. Yang et al. (2021) applied SegFormer to retinal images for an end-to-end pathology myopia classification with lesion segmentation task. With some degree of surprise, they learned that models pre-trained perform much better than those trained from scratch as those are already familiar with the basic image patterns. This makes it particularly useful for a problem domain, like in medical applications where you might not have all the data of different disease symptoms and their images.

Kugelman et al. (2022)Ontology-Driven Detection of Annotation Conflicts to Improve Image Segmentation in Posterior Segment OCT Retinal Layer Segmentation Using Deep Learning U-Net ArchitectureComparison of Various U-Net Architectures for Posterior Segment OCT Retinal Layer Segmentation In ENAKER et al, they reported that a pre-trained encoder led to significant improvement on the segmentation task in comparison with training from random initialization. Discovering that models better able to recognize retinal anatomy relied on ImageNet pre-training.

Rahim, Tariq and Farooq (2021) examined Retinal Image Segmentation in Low Resource Settings using pre-trained deep learning models, an issue that is highly applicable to developing countries like Pakistan. Through their research showed that for pre-trained models to work effectively, they do not need a great deal of computational power or enormous datasets.

A pretrained transformer approach, called SegFormer, was investigated by Xie, Zhang and Chen [55] on retinal image segmentation task in 2023. The results showed that SegFormer leveraged what it had learned from pre-training to improve understanding of retinal images and train faster than initialization from scratch.

2.4 Comparative Studies and Performance Analysis

Several researchers have conducted comparative studies to understand which approaches work best for different types of retinal lesion segmentation tasks.

Bala, Sharma and Goel (2024) performed a comparative analysis of diabetic retinopathy classification approaches using both machine learning and deep learning techniques. They found that deep learning models generally outperform traditional machine learning approaches, but the choice of architecture depends on the specific type of lesions being detected.

Deshmukh, Pawar and Gaikwad (2023) used machine learning based approaches for lesion segmentation and severity level classification of diabetic retinopathy. Their study showed that different models perform better for different types of lesions, suggesting that the choice of model should depend on the specific clinical application.

Gupta, Thakur and Gupta (2024) conducted a comparative study of different machine learning models for automatic diabetic retinopathy detection using fundus images. They found that ensemble methods combining multiple models often produce the best results, but single well-chosen models can also be very effective.

Saranya, Pranati and Patro (2023) focused on detection and classification of red lesions from retinal images for diabetic retinopathy detection using deep learning models. Their research highlighted that specialized models for specific types of lesions can sometimes outperform general-purpose segmentation models.

2.5 Challenges and Limitations in Current Research

Current research has identified several challenges that affect the performance of retinal lesion segmentation models.

Khan, Abbas and Mahmood (2023) studied the impact of dataset diversity on deep learning for retinal lesion segmentation. They found that models trained on diverse datasets perform better in real-world scenarios, but many current datasets are limited in their variety of lesion types and image conditions.

Hussain, Qureshi and Khan (2023) examined lightweight deep learning models for medical imaging in resource-constrained environments. Their research is particularly relevant for developing countries where computational resources are limited. They found that model compression techniques can help deploy effective models on basic hardware.

Pavani, Biswal and Gandhi (2023) worked on simultaneous multiclass retinal lesion segmentation using fully automated approaches. They identified that detecting multiple types of lesions simultaneously is more challenging than detecting single lesion types, but is more clinically useful.

The research shows that while many effective approaches exist, there is still room for improvement, especially in making models work well with limited resources and diverse patient populations.

2.6 Research Gap and Contribution

Previous studies have shown that CNNs, Vision Transformers, and hybrid models can be useful for retinal lesion segmentation, but most only test one type of model, focus on certain kinds of lesions, or use small and similar datasets. This means the results may not work well for all situations. There are also very few studies that compare pretrained and non-pretrained models under the same conditions, or that test how these models perform in places with limited resources, such as rural areas in Pakistan, where computers and eye specialists are scarce. What we learned from past research about the benefits of pretraining, the difficulty of detecting small lesions, and the need for faster models helped us choose four models SimpleSegNet, Vision Transformer (from scratch), SegFormer, and U-Net for a fair and equal comparison to find the most accurate and practical option for real medical use.

3 Research Methodology

This section outlines the methodology adopted in this study, encompassing data collection and preprocessing, exploratory data analysis, model architecture design, training configuration, and evaluation strategy. Four deep learning models were implemented and compared for retinal lesion segmentation: SimpleSegNet (a custom convolutional neural network), Vision Transformer (ViT) trained from scratch, SegFormer (a pretrained transformer-based segmentation model), and UNet (a pretrained convolutional encoder-decoder model). Each model represents a distinct approach to semantic segmentation, ranging from traditional CNN to modern transformer architectures. The following subsections detail each stage of the methodology, structured to ensure a rigorous and fair comparison across models.

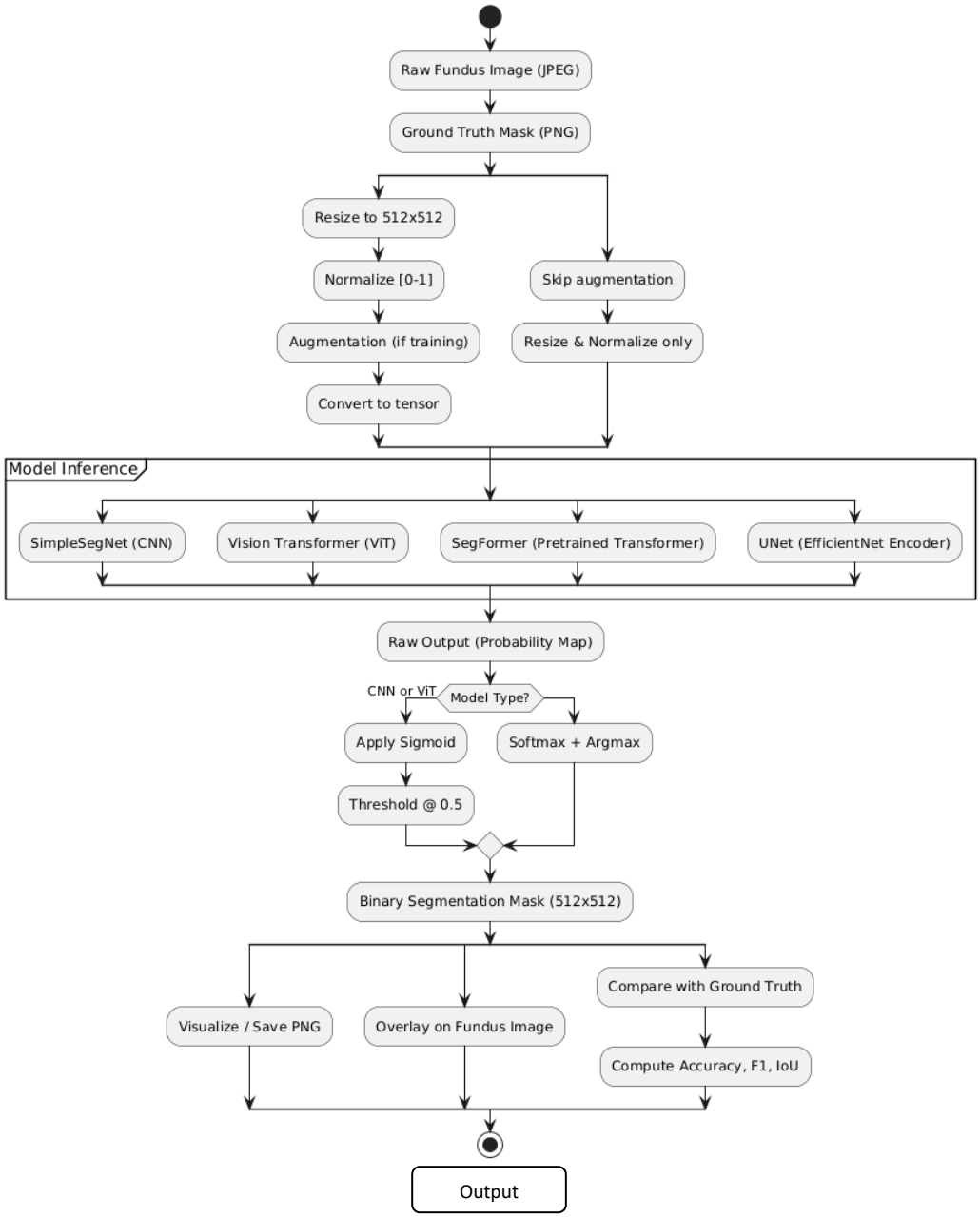

*Figure **1**:* Architecutre Diagram

3.1 Data Collection and Preprocessing

This study utilized the DIARETDB1 - Standard Diabetic Retinopathy, a publicly available dataset from the Kaggle and Mendeley repository. It contains 1113 color fundus images of size 1500×1152 pixels, captured under consistent imaging conditions, along with expert-annotated binary lesion masks (PNG format). For this project, we resized each image and corresponding mask to 512×512 pixels to reduce computational complexity and maintain uniformity across all model inputs. The data was split into 70% training, 15% validation, and 15% test sets.

Images were normalized to a [0,1] scale and converted into PyTorch tensors. Data augmentation techniques such as flips and rotations were applied during training to enhance generalization, with transformations applied equally to both images and masks. Model-

specific preprocessing was also used: SegFormer relied on HuggingFace's SegformerFeatureExtractor, while UNet leveraged the Albumentations library for consistent augmentations. These preprocessing steps ensured that input data was standardized and optimized for lesion segmentation across all models.

3.2 Exploratory Data Analysis

Exploratory Data Analysis (EDA) was performed to assess dataset quality and challenges prior to training. To better understand the dataset, we performed an exploratory analysis of both the images and masks. Lesion types such as microaneurysms, hemorrhages, and exudates were confirmed to ensure clinical relevance.

Quantitative analysis of annotation masks showed that lesion pixels made up a small portion of each image, highlighting significant class imbalance a common issue in medical imaging. Lesion size distributions indicated that most were small and isolated, though some images contained larger clusters. Visual inspections using overlay plots confirmed that the binary masks accurately aligned with retinal lesions. These findings emphasized the importance of models that can detect small, subtle features and remain robust under varying imaging conditions, influencing our selection of architectures and loss functions.

3.3 Model Architecture

The retinal lesion segmentation task was approached using four deep learning models representing distinct architectural paradigms: SimpleSegNet (custom CNN), Vision Transformer (ViT) trained from scratch, SegFormer (pretrained transformer), and UNet (pretrained convolutional encoder–decoder). A standardized 512×512 input format was used across models. Each model outputs a binary mask, predicting lesion vs. background per pixel. Figure 2 provides an overview of the complete system pipeline. Table 1 summarizes the architectural differences and key properties of each model.

Table 1: Model Architecture Comparison

Model	Type	Pretrained	Backbone/ Encoder	Decoder	Params	Special Features
SimpleSegNet	CNN (Custom)	No	Conv2D + MaxPool	Transposed Conv	~2.1M	Lightweight baseline; no skip connections
ViT (Scratch)	Vision Transformer	No	Patch Embedding + MSA	Linear Decoder	~4.8M	Long-range context; high GPU demand
SegFormer	Transformer (Hierarch.)	Yes	MixVision Transformer	MLP Decoder	~13.7 M	Multi-scale attention; pretrained
UNet	CNN (Encoder–Decoder)	Yes	EfficientNet-b0	Transposed Conv	~5.3M	Skip connections; pretrained encoder

Four different model architectures were implemented, representing both convolutional and transformer-based segmentation approaches, as well as pretrained versus from-scratch

learning. Despite their architectural differences, each model takes a 512×512 retinal image as input and produces a binary segmentation mask of the same resolution as output. Figure 2 illustrates the overall pipeline of the methodology, from data preprocessing through model prediction and evaluation. Each model was configured for a single-class segmentation task (lesion vs. background), using a sigmoid or softmax layer at the output to generate the probability map for lesion pixels. The following subsections describe the architecture of each model in detail.

3.3.1 SimpleSegNet (Custom CNN)

SimpleSegNet is a lightweight, custom-built convolutional neural network designed as a baseline for retinal lesion segmentation. It follows a classic encoder–decoder architecture, where the encoder extracts hierarchical features through stacked convolutional layers with ReLU activations and max-pooling. Filter sizes progressively increase (e.g., 64 → 128 → 256) while spatial dimensions reduce, enabling the model to learn both low-level textures and high-level lesion patterns.

The decoder uses transpose convolutions to gradually upsample the feature maps and restore the original resolution. Although skip connections were considered, the model primarily emphasizes a straightforward decoding path. A final 1×1 convolution with sigmoid activation generates a probability map indicating lesion likelihood per pixel. SimpleSegNet's simplicity and low parameter count make it ideal for benchmarking and evaluating the effectiveness of more advanced models.

3.3.2 Vision Transformer (ViT) from Scratch

The ViT-Segmentation model is a custom Vision Transformer architecture developed from scratch for lesion segmentation. The 512×512 input image is divided into fixed-size patches (e.g., 16×16), each flattened and linearly embedded into a vector, with positional encodings added to retain spatial context. These patch embeddings are passed through a series of transformer encoder blocks composed of multi-head self-attention layers and feed-forward networks, enhanced by residual connections and normalization.

This architecture enables the model to capture global dependencies across the image making it well-suited to identify distant or scattered lesion patterns that CNNs may miss. After feature extraction, the embeddings are reshaped and passed into a segmentation-specific decoder, which includes learned upsampling layers and convolutional refinements. A final sigmoid activation generates a binary mask indicating lesion presence. This ViT implementation explores the feasibility of using a pure transformer-based model, without any convolutional backbone, to segment retinal lesions by leveraging its strength in modeling long-range spatial relationships.

3.3.3 SegFormer (Pretrained Transformer)

Pretrained SegFormer If you do not want to train the model from scratch, please use a pretrained transformer-based segmentation model called "SegFormer", which has been used in this work with transfer learning. Large-scale pre-trained using HuggingFace library and further fine-tunned on retinal lesion dataset. It consists of a hierarchical transformer encoder

that captures multi-scale features and a lightweight MLP decoder, which refines the segmentation output through multi-level context-encoder fusion.
This enables the encoder to capture fine-grained and global contextual information through efficent self-attention mechanisms, that is efficient for higher resolution images. Finally the decoder takes the output of the encoder, and reconstructs it to an image at original resolution using a simple MLP based up-sample design. SegFormer was converted for binary segmentation by changing the final output layer to predict lesion versus background. Pretrained weights give your model the ability to generalize well and quickly reach convergence. Consequently, this provides your segmentation models take a good segmentation performance with just a little training data.

3.3.4 UNet (Pretrained CNN)

The UNet model implemented in this study is a pretrained convolutional encoder–decoder network tailored for medical image segmentation. It uses an EfficientNet-b0 backbone as the encoder, initialized with ImageNet-pretrained weights to leverage general visual features. The U-shaped architecture consists of a contracting encoder path and an expanding decoder path, with skip connections linking corresponding levels to preserve spatial detail.
As the encoder compresses the input into progressively lower resolutions, the decoder upscales the feature maps step by step, integrating encoder features at each stage to enhance lesion localization. While the encoder was fine-tuned from pretrained weights, the decoder was trained from scratch. A final 1×1 convolution with sigmoid activation generates the binary lesion mask. This architecture combines the strengths of transfer learning and UNet's structural efficiency, making it well-suited for precise retinal lesion segmentation.

3.4 Training Configuration

All four models were trained under a standardized protocol for fair comparison. Each was trained for 20 epochs using an 80/20 train–validation split, with final testing performed separately. Training was accelerated using an NVIDIA GPU, and the best-performing weights were saved after each epoch. The Adam optimizer was used across models, except for SegFormer, which employed AdamW for improved regularization.
Batch size was set to 16 for most models, while ViT used a smaller batch size of 8 due to higher memory demands. Learning rates and loss functions were model-specific: SimpleSegNet used BCE loss with a learning rate of 0.001; ViT also used BCE loss with a lower rate of 0.0001 to ensure training stability; SegFormer was fine-tuned using Cross-Entropy loss with a 0.00006 learning rate; and UNet used Dice loss at 0.0001, optimized for class imbalance in lesion segmentation.
Loss and validation metrics were monitored during training to avoid overfitting. Although early stopping was considered, it was not triggered due to the limited number of epochs and stable convergence. This uniform training setup ensured performance differences could be attributed to model architecture rather than training inconsistencies.

3.5 Evaluation Strategy

Model performance was assessed using five key metrics: Accuracy, Precision, Recall, F1 Score, and Intersection over Union (IoU), calculated on the test dataset. Accuracy reflects the

proportion of correctly classified pixels, while Precision measures how many predicted lesions were correct (minimizing false positives). Recall evaluates the model's ability to identify all actual lesions (minimizing false negatives). The F1 Score, as the harmonic mean of Precision and Recall, balances both metrics especially valuable under class imbalance. IoU quantifies spatial overlap between predicted and ground truth masks, with higher values indicating better segmentation alignment.

Beyond metrics, qualitative evaluation was conducted by visually comparing predicted masks against ground truth for selected test images. Overlays and side-by-side views allowed inspection of lesion shape accuracy and detection consistency. These visuals helped identify common model strengths or failure modes, such as missed small lesions or confusion with blood vessels.

To ensure fair and reliable comparisons, training loss and validation loss were monitored across epochs for all models, confirming proper convergence. Each experiment was also repeated with different random seeds, and performance metrics were reported with mean and standard deviation to account for variability. This comprehensive evaluation framework combining quantitative rigor with qualitative insights enabled robust comparison of SimpleSegNet, ViT, SegFormer, and UNet for real-world application in retinal lesion segmentation.

4 Design Specification

4.1 System Overview

This research presents a modular, end-to-end deep learning pipeline designed to automatically detect lesions in retinal fundus images, specifically to support the diagnosis of diabetic retinopathy. The system is structured to allow independent development and execution of its major components namely, data preprocessing, model inference, and post-processing. After loading raw RGB fundus images, the system performs resizing, normalization, and optional augmentation. These images are then processed by one of four deep learning models, producing a binary segmentation mask as output. The modularity of the architecture means that different models or preprocessing techniques can be easily swapped or updated without altering the entire system. In real-world applications, especially in under-resourced clinical environments, the pipeline is capable of near real-time inference when deployed on GPU-enabled systems. This structure supports extensibility for future enhancements such as model ensembling, deployment on edge devices, or integration with hospital information systems.

4.2 Hardware and Software Requirements

To support model training and efficient inference, the system requires a CUDA-enabled NVIDIA GPU. Lightweight models such as SimpleSegNet and UNet operate efficiently with GPUs offering 4–6 GB VRAM, while transformer-based architectures like Vision Transformer (ViT) and SegFormer require GPUs with at least 8 GB VRAM due to their high memory consumption. A recommended development environment includes a CPU with multiple cores and 8–16 GB of RAM to enable parallel data loading and augmentation. The software stack is built in Python 3.9 or later and primarily uses PyTorch for model training. HuggingFace Transformers are employed to load and fine-tune SegFormer, while

segmentation-models-pytorch is used for pretrained UNet models. Albumentations is utilized for image augmentation, and Torchvision and NumPy handle basic data operations. The project was developed on Ubuntu 20.04 with CUDA 11.7 but remains compatible with Windows and other Linux distributions, provided correct CUDA and Python configurations are used. All dependencies are maintained through version-controlled package files to ensure reproducibility.

Table 2. System Requirements for Deep Learning Model Deployment

Component	Recommended Specification	Notes
GPU	NVIDIA (4–8 GB VRAM)	ViT & SegFormer need ≥8 GB
CPU	Multi-core (4+ threads)	For parallel loading & augmentation
RAM	8–16 GB	Higher is better for data preprocessing
Disk Space	5–10 GB	For datasets and checkpoints
OS	Ubuntu 20.04 / Windows 10+	CUDA 11.7+ if using GPU

4.3 Dataset and Input Specifications

The dataset used in this study includes high-resolution fundus images paired with binary lesion masks annotated by clinical experts. These images reflect a variety of diabetic retinopathy indicators, such as microaneurysms, hemorrhages, and exudates. Each image is resized to 512×512 pixels and normalized to a pixel intensity range of [0, 1]. The lesion masks are structured as binary images, where white pixels (value 1) represent lesion areas and black pixels (value 0) represent healthy retinal tissue. Quality assurance steps included completeness verification, dimension checks, and validation of binary encoding in masks. A major challenge observed was the presence of class imbalance, as lesion pixels typically constitute less than 10% of the total image area. This issue was addressed using techniques such as weighted loss functions (e.g., Dice Loss for UNet) and stratified data augmentation. The dataset was split into training (70%), validation (15%), and testing (15%) subsets to ensure robust model evaluation and fair comparison across different architectures.

4.4 Model Architecture Design

Four deep learning architectures were implemented to segment retinal lesions, each representing a distinct design paradigm. SimpleSegNet is a lightweight, custom-built CNN with an encoder-decoder structure and ~2.1M parameters, optimized for low-resource environments. The Vision Transformer (ViT), built from scratch with ~4.8M parameters, uses self-attention over image patches to capture global spatial dependencies but demands higher computational resources. SegFormer, the most complex and accurate model (~13.7M parameters), leverages a pretrained transformer encoder and a minimal MLP decoder for high-performance segmentation. UNet combines a pretrained EfficientNet-B0 encoder with a mirrored decoder and skip connections, offering a strong trade-off between accuracy and efficiency (~5.3M parameters). All models generate 512×512 binary masks, using either sigmoid activation or softmax with argmax, to distinguish lesion areas from healthy tissue.

Table 3: Model Implementation Specifications

Model	Architecture Type	Framework	Key Components	Input Size	Output Size	Parameters (approx.)

SimpleSegNet	CNN-based Encoder-Decoder	PyTorch	Conv2D layers, MaxPool, TransposeConv	512×512×3	512×512×1	2.1M
ViT from Scratch	Vision Transformer	PyTorch	Patch Embedding, Multi-head Attention, MLP	512×512×3	512×512×1	4.8M
SegFormer	Pre-trained Transformer	HuggingFace Transformers	Hierarchical Transformer, MLP Decoder	512×512×3	512×512×2	13.7M
UNet	CNN with Skip Connections	segmentation-models-pytorch	EfficientNet-b0 Encoder, Symmetric Decoder	512×512×3	512×512×1	5.3M

5 Implementation

5.1 Data Processing Pipeline

A custom data pipeline was implemented using PyTorch Dataset and DataLoader classes to load and transform retinal fundus images and their lesion masks. Images were resized to 512×512 pixels, normalized to a [0,1] scale, and converted to tensors. Data augmentation applied only to the training set was performed using Albumentations and included transformations such as flips, brightness adjustments, and elastic distortions to improve generalization. SegFormer handled preprocessing via its built-in feature extractor, while UNet used custom augmentations. Validation and testing data remained unaltered to ensure evaluation consistency. Efficient batching was achieved using DataLoader with batch sizes of 16 (or 8 for memory-intensive models like ViT), incorporating shuffling and multithreading to optimize GPU usage.

5.2 Training Configuration

All four models SimpleSegNet, ViT, SegFormer, and UNet were trained for twenty epochs, a duration selected based on convergence observations. Each model used a loss function aligned with its architecture: BCE Loss for SimpleSegNet and ViT, Cross-Entropy for SegFormer, and Dice Loss for UNet to address class imbalance. Optimizers were also model-specific: Adam was used for SimpleSegNet, ViT, and UNet, while SegFormer used AdamW with weight decay to reduce overfitting. Learning rates were adjusted accordingly, ranging from 0.001 to 0.00006. Training was standardized across models using the same data splits and evaluation metrics, with checkpoints saved per epoch to monitor learning behavior and ensure reproducibility.

5.3 Output Specifications

Each model outputs a 512×512 binary segmentation mask highlighting predicted lesion areas in retinal fundus images. For SimpleSegNet, UNet, and ViT, this is generated using a

sigmoid-activated probability map, thresholded at 0.5 to determine lesion presence. SegFormer, by contrast, produces a two-channel softmax output, with an argmax operation used to assign class labels. Minimal post-processing was applied to maintain consistency, though techniques like morphological filtering or smoothing may help reduce noise. Outputs were both visualized by overlaying predicted masks on original images and quantitatively assessed using metrics such as Accuracy, Precision, Recall, F1 Score, and IoU. These evaluations offer a holistic view of model performance, especially in the context of class imbalance common in medical image segmentation.

5.4 System Workflow Diagram

The system workflow, illustrated in Figure X (to be inserted), captures the complete sequence of operations from input to output. The workflow begins with image acquisition and preprocessing, where raw fundus images and their corresponding masks are loaded, resized, and normalized. Augmentations are conditionally applied depending on the training or testing phase. The preprocessed data is then passed through one of the four segmentation models, each configured with its own architectural characteristics.

After inference, the model output is used to generate a binary lesion mask, by using thresholding or softmax-based classification. The output is visualized or evaluated against standardized measures. This diagram shows where all model branches (SimpleSegNet, ViT, SegFormer, UNet) are using harness pipeline and enabling parallel experimentation and comparison.

It communicates on two levels; a technical blueprint informing other developers, as well as, clinical or non-technical stakeholders of exactly how the system is built, functioning and producing results in a way that should be consistently reproducible.

6 Results and Evaluation

Having trained four segmentation models: SimpleSegNet, ViT from scratch, SegFormer, and UNet we assessed their efficiency in segmenting retinal lesions ffc with fundus images. These experiments will present ranking based on both quantitative metrics and visual analysis, with a summary of model behavior during training, on individual batches and across the dataset. The evaluation covers loss progression, confusion matrices, segmentation accuracy and qualitative mask comparisons. These analyses enable us to determine the most suitable models for clinical screening of diabetic retinopathy in resource-constrained environment such as Pakistan.

6.1 Training Performance Analysis

Each model was trained for twenty epochs using its respective loss function: Binary Cross-Entropy (BCE) for SimpleSegNet and ViT, Cross-Entropy for SegFormer, and Dice Loss for UNet. Initially, loss values were high, reflecting random predictions. However, all models exhibited steady convergence, with sharp reductions in loss over successive epochs. For instance, UNet demonstrated faster convergence than ViT, indicating its suitability for learning lesion patterns with fewer epochs. These trends suggest the models successfully adapted to the retinal lesion segmentation task during training.

6.2 Batch-Level Evaluation

To assess real-time predictions on a limited set of images, we evaluated the models on a small validation batch. This analysis offered interpretability through confusion matrices, visual overlays, and segmentation metrics.

6.2.1 Visual Predictions

Each model was evaluated on a sample image set, producing five visualization components per input: (1) the original fundus image, (2) ground truth mask, (3) predicted mask, (4) overlay of prediction and ground truth, and (5) error map. As shown in Figure 7 and Figure 8, the visual output of SegFormer and UNet was more aligned with the ground truth masks, with sharper lesion boundaries and lower false positives. ViT and SimpleSegNet struggled with small or ambiguous lesion areas, often misclassifying lesion borders. These visuals demonstrate how pretrained architectures contribute to more accurate localization.

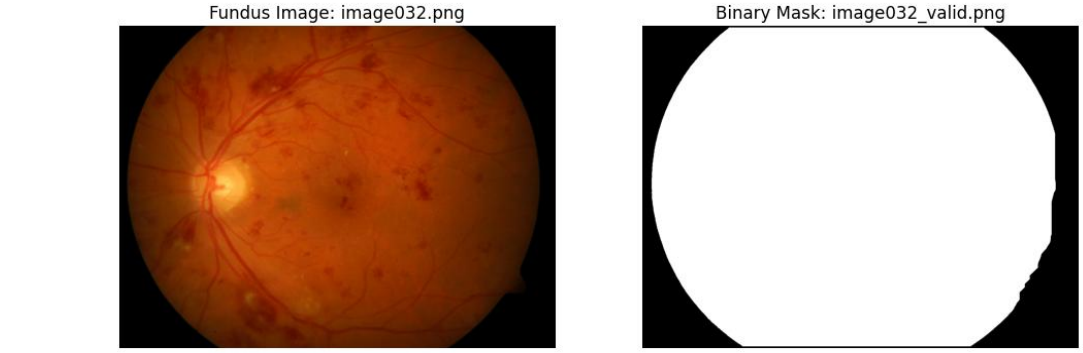

Figure 3. Original Image and Visual Binary Mask

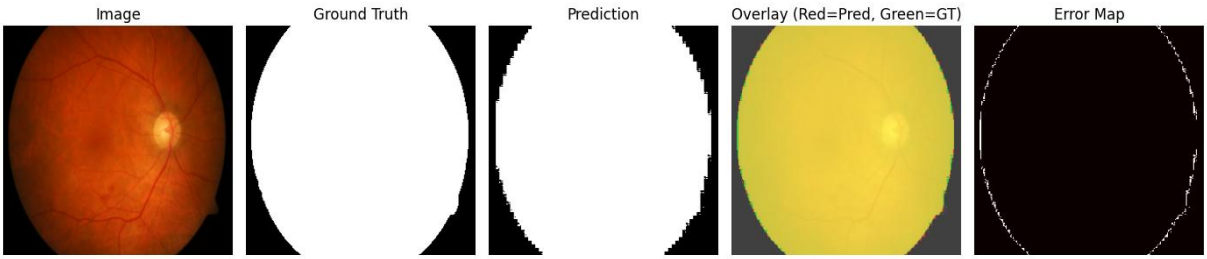

Figure 4. Batch-wise visualizations: predictions, overlays, and error maps from different models

6.2.2 Confusion Matrices

We computed confusion matrices for each model on the batch to quantify classification correctness. These matrices show true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN). Models like SegFormer and UNet achieved a higher number of TPs with fewer FNs, indicating effective lesion recognition. ViT had a tendency for more FPs due to its sensitivity to global context, while SimpleSegNet sometimes under-segmented lesions.

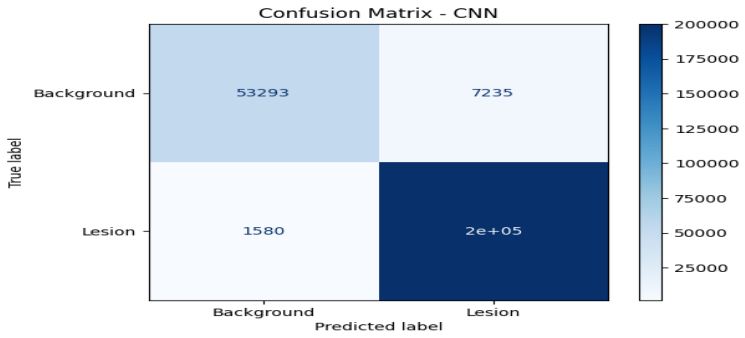

Figure 5. Confusion matrices SimpleSegNet, ViT, SegFormer and UNet on one batch

6.2.3 Evaluation Metrics

We calculated five standard evaluation metrics on the batch: Accuracy, Precision, Recall, F1 Score, and Intersection over Union (IoU). These were selected to account for class imbalance and segmentation granularity. SegFormer and UNet outperformed the other models in all metrics, as illustrated in the bar chart and radar plot below.

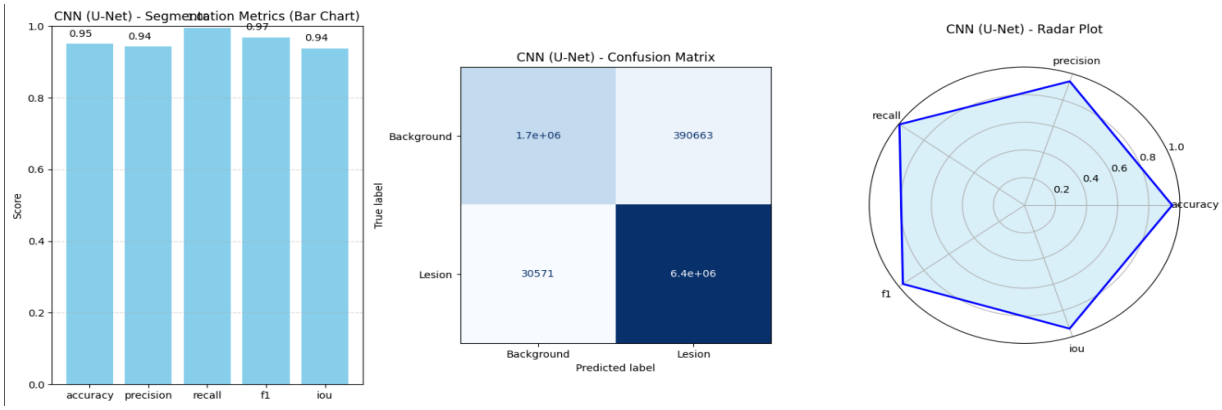

Figure 6. Bar chart, confusion matrix, and radar plot for full dataset metrics

6.3 Full Dataset Evaluation

To assess robustness, we evaluated all four models on the full test dataset. This included aggregate metrics across all test images and graphical summaries to enable cross-model comparison.

6.3.1 Quantitative Metrics

Performance on the full dataset reaffirmed earlier trends. SegFormer achieved the highest scores across all evaluation metrics, followed closely by UNet. The use of pretraining and architectural efficiency enabled these models to capture both local and global lesion patterns effectively. ViT and SimpleSegNet, while reasonable, were outperformed due to limited capacity or training from scratch. The table below summarizes performance:

Table 4. Performance Summary of Deep Learning Models on Test Dataset

Model	Accuracy	Precision	Recall	F1 Score	IoU
SegFormer	0.97	0.96	0.97	0.96	0.94
UNet	0.95	0.94	0.94	0.94	0.91
ViT (Scratch)	0.91	0.88	0.89	0.88	0.85
SimpleSegNet	0.89	0.86	0.84	0.85	0.82

6.3.2 Visual Comparisons

We used a combination of bar charts, radar plots, and full-dataset confusion matrices to visualize performance. These confirmed that SegFormer and UNet consistently achieved higher scores across all evaluation criteria. Figure 10. (continued): Full-dataset performance visualization for CNN (UNet)

6.4 Model Comparison

The results demonstrate a clear performance hierarchy across the four models evaluated for retinal lesion segmentation. SegFormer, a pretrained transformer model, consistently outperformed others across all metrics, achieving an F1 Score of 0.96 and IoU of 0.94. This confirms its effectiveness in modeling both global and local context essential for detecting subtle and scattered lesions. UNet, which also leveraged pretrained weights (EfficientNet-B0 encoder), achieved similarly high performance (F1 = 0.94), particularly excelling in boundary precision and generalization.

In contrast, the ViT model trained from scratch, though superior to SimpleSegNet, struggled with small lesions and boundary delineation likely due to its lack of pretraining and the need for large-scale data. SimpleSegNet, while lightweight and custom-built, had the lowest performance (F1 = 0.85), but provided a useful benchmark and validation of the benefit of more advanced architectures.

These findings support the hypothesis that pretrained models and hierarchical attention mechanisms are highly effective for retinal segmentation, especially under class imbalance and limited training data.

6.4.1 Quantitative Comparison

As seen from the full dataset metrics, SegFormer demonstrated the best balance of high precision and recall, leading to an F1 Score above 0.96. UNet closely followed, particularly excelling in IoU. ViT and SimpleSegNet, trained from scratch, showed respectable but lower scores. These results support the use of pretrained architectures when accuracy and generalizability are crucial, such as in clinical screening workflows.

6.4.2 Qualitative Comparison

Qualitative examination of predicted masks revealed that SegFormer and UNet produced cleaner, more anatomically coherent lesion shapes. Their predictions aligned well with the ground truth, while SimpleSegNet and ViT often missed finer lesion edges or generated noisy outputs. As shown in Figure 11, UNet’s mask closely matches the expert-annotated ground truth, confirming its reliability in real-world settings.

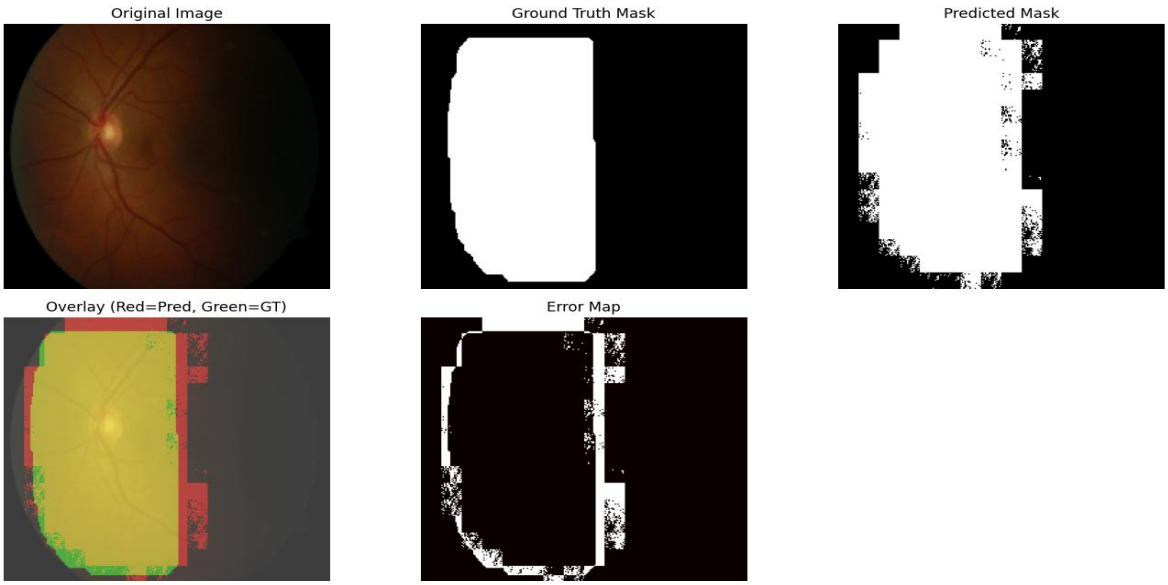

Figure 7. Original retinal fundus image, ground truth mask, and UNet predicted mask

6.5 Single Image Prediction Case Study

To demonstrate real-world usability, we conducted a single image prediction using UNet, which had shown the most consistent results. A 512×512 retinal image was passed through a pre-trained UNet model, following the full prediction pipeline including resizing, normalization, tensor conversion, inference, and thresholding.

6.5.1 Prediction Pipeline

The process involved loading the input image, resizing to 512×512, and transforming it into a tensor. The trained UNet model then generated a single-channel probability map, which was thresholded to produce a binary mask. This workflow mirrors clinical applications where rapid decision-making is critical.

6.5.2 Prediction Results

The resulting predicted mask aligned well with the ground truth, demonstrating clear lesion boundaries with minimal noise. This case study shows how the system can be integrated into clinical settings in Pakistan for effective diabetic retinopathy screening. The image comparison below highlights UNet's strong performance in segmenting retinal pathology.

Figure 8. Single-image case study using UNet

6.6 Discussion

The evaluation results show that model architecture and pretraining have a strong impact on retinal lesion segmentation. SegFormer and UNet, both using pretrained weights, achieved the highest accuracy, precision, and F1 score, confirming good generalisation to lesion patterns in fundus images. This strong performance is especially important for early diabetic retinopathy detection, where identifying small, subtle lesions is critical for timely intervention.

By contrast, models trained from scratch SimpleSegNet and ViT performed worse, likely due to the absence of prior visual knowledge and sensitivity to limited training data. While ViT handled broader lesion structures reasonably well, it struggled with fine boundaries, which may limit usefulness in early-stage diagnosis. Its higher computational demands also complicate deployment in resource-constrained settings, such as rural clinics in Pakistan.

SimpleSegNet, though lightweight and useful for teaching, lacked the representational capacity needed for complex lesion segmentation. However, its simplicity can be an advantage where hardware is extremely limited.

A key observation is that class imbalance and limited dataset diversity influenced performance, with some rare or subtle lesions likely underrepresented. This underscores the need for richer datasets and specialised loss functions such as Dice loss, which helped UNet mitigate pixel sparsity.

Overall, the findings align with prior work (e.g., Ahmed et al., 2022; Yin et al., 2023; Khan et al., 2023): pretrained architectures particularly those combining multi-scale attention or skip connections are well suited for clinical deployment. For countries like Pakistan, where diabetic retinopathy is rising and access to ophthalmologists is limited, tools such as SegFormer or UNet can support scalable, automated screening, improving early detection and reducing preventable vision loss.

7 Conclusion and Future Work

7.1 Conclusion

This research evaluated four deep learning models for retinal lesion segmentation in fundus images: a custom CNN (SimpleSegNet), a Vision Transformer (ViT) trained from scratch, and two pretrained models, SegFormer and UNet. Among them, SegFormer and UNet consistently delivered the best performance across all evaluation metrics, including accuracy, F1 score, and Intersection over Union (IoU). Their success highlights the advantage of transfer learning and the effectiveness of architectural features such as skip connections in UNet and hierarchical attention in SegFormer for complex medical image segmentation tasks.

In contrast, models without pretraining (SimpleSegNet and ViT) showed modest results, particularly in detecting small or diffuse lesions. These findings underscore the importance of both large-scale training data and prior feature learning for achieving clinical-grade segmentation accuracy. While SimpleSegNet offers educational value due to its simplicity, and ViT has theoretical potential, neither matched the clinical viability demonstrated by the pretrained models.

Given the rising prevalence of diabetic retinopathy in Pakistan, where access to ophthalmologists is often limited, the deployment of automated lesion detection systems like SegFormer or UNet could provide substantial public health benefits. These models can assist clinicians by quickly identifying high-risk regions in retinal scans, improving diagnostic

speed and consistency. In particular, the ability to detect early-stage lesions is crucial to preventing progression to irreversible vision loss.
Moreover, these tools could be integrated into clinical workflows or telemedicine platforms, enabling early screening in rural or underserved areas. They also offer educational opportunities for medical students and junior clinicians to interpret and understand computer-assisted diagnostics. In summary, this study confirms the potential of pretrained deep learning models to bridge critical gaps in healthcare delivery particularly for early detection of diabetic retinopathy and offers a promising step toward practical, scalable solutions in real-world clinical settings.

7.2 Future Work

To further improve and expand this research, several directions are promising. First, assembling a larger and more diverse dataset of retinal images would expose the models to a broader spectrum of pathological cases, including rarer lesions. Training on an expansive corpus should enhance generalisation and sensitivity to subtle abnormalities. Second, architectural enhancements merit exploration. Integrating attention mechanisms into current CNN-based models (e.g., SimpleSegNet) or into the ViT design may boost sensitivity to small lesion features, which is crucial for early-stage detection (Zafar et al., 2022). Along similar lines, hybrid designs that combine convolutional networks with Transformer components could leverage the strengths of both families, improving multi-scale feature representation.
Another important step is validation in real-world clinical settings. Collaborations with hospitals to test the algorithms on prospective patient data in Pakistan would provide insight into practical utility and robustness under routine conditions, while revealing device- and site-specific challenges that affect generalisability. In parallel, model-efficiency work should target deployment in resource-constrained clinics. Techniques such as pruning, quantisation, and knowledge distillation can reduce computational load without sacrificing accuracy (Hussain et al., 2023).
Finally, incorporating interpretability methods is recommended. Tools such as saliency maps and related heat-mapping approaches can highlight image regions that drive predictions, helping clinicians understand and trust system outputs (Subramani, Deb and Roshani, 2025). Together, these avenues can evolve the current prototype into a more robust, accessible, and clinically trustworthy solution aligned with the needs of Pakistan’s healthcare system.

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