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# Personalized Medicine and Explainable AI for Diabetic Retinopathy and Tongue Segmentation: A Systematic Review of Current Approaches and Future Directions

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ABSTRACT

Retinopathy and tongue segmentation are important tasks in medical imaging and computer vision. This abstract focuses on the application of the U-Net architecture for accurate segmentation of retinopathy and tongue images.Retinopathy :Retinopathy refers to the damage to the retina caused by various eye disorders, with diabetic retinopathy being the most common type. Early detection and precise segmentation of retinopathy lesions are crucial for timely treatment and prevention of vision loss. The abstract highlights the use of U-Net, a convolutional neural network architecture specifically designed for image segmentation tasks, for retinopathy segmentation. It discusses the training process, data augmentation techniques, and evaluation metrics used to assess the performance of the U-Net model. The abstract also emphasizes the importance of large-scale retinal image datasets and the potential impact of U-Net-based retinopathy segmentation in clinical practice.Tongue Segmentation: Tongue segmentation plays a significant role in oral health analysis, speech recognition, and other medical applications. Accurate identification and delineation of the tongue's boundaries are crucial for analyzing tongue conditions and monitoring treatment progress. This abstract explores the utilization of the U-Net architecture for tongue segmentation. It discusses the preprocessing steps involved in preparing the tongue image dataset, the training procedure for the U-Net model, and the evaluation metrics used to assess the segmentation accuracy. The abstract highlights the advantages of U-Net, such as its ability to capture intricate tongue features and its robust performance in handling various tongue image variations.Overall, this abstract demonstrates the effectiveness of the U-Net architecture in retinopathy and tongue segmentation tasks. It underscores the potential impact of U-Net-based segmentation methods in improving diagnoses, treatments, and research in the fields of ophthalmology and oral healthcare.

## 1. Introduction

Diabetic retinopathy (DR) is a common complication of diabetes and a leading cause of blindness worldwide. Early detection and treatment of DR are crucial for preventing vision loss and improving patient outcomes. Medical imaging, such as fundus photography and optical coherence tomography, is widely used to diagnose and monitor DR. However, accurate and efficient image segmentation is necessary to identify the

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specific regions of the retina affected by DR and track disease progression.

Recent advances in artificial intelligence (AI) and machine learning have shown great promise for improving DR segmentation accuracy and efficiency. Moreover, the emerging field of personalized medicine holds the potential to tailor medical care to the individual patient and improve the effectiveness of DR diagnosis and treatment. In addition, explainable AI has become a topic of great interest, as it can provide clinicians and researchers with greater insight into how AI algorithms are making decisions about image segmentation, potentially leading to improved performance and reliability.

In this paper, we present a systematic review of current approaches and future directions for personalized medicine and explainable AI in DR segmentation. Specifically, we will examine the current state-of-the-art in DR segmentation using AI and machine learning techniques, as well as explore the potential of personalized medicine to improve DR diagnosis and treatment. Additionally, we will discuss the emerging field of explainable AI and its potential applications for DR segmentation, and identify key research gaps and opportunities for future investigation.

The ultimate goal of this research is to improve the accuracy, efficiency, and effectiveness of DR segmentation, leading to improved diagnosis and treatment outcomes for patients with this condition. By examining the current state of the art and future directions in personalized medicine and explainable AI for DR segmentation, this paper aims to provide a comprehensive understanding of the opportunities and challenges in this field, and guide future research in this important area of medical imaging and AI.

## Background and Significance

Diabetic retinopathy (DR) is a leading cause of vision loss and blindness worldwide, affecting approximately one-third of all diabetes patients [1]. Early detection and treatment of DR is critical for preventing irreversible vision loss and improving patient outcomes. Medical imaging, including fundus photography and optical coherence tomography, is widely used for DR screening, diagnosis, and monitoring. However, accurate and efficient image segmentation is necessary to identify the specific regions of the retina affected by DR, and track disease progression over time.

In recent years, there has been growing interest in the use of artificial intelligence (AI) and machine learning for medical image segmentation, including DR segmentation. AI algorithms have demonstrated impressive performance in accurately segmenting retinal images and detecting DR lesions, such as microaneurysms, hemorrhages, and exudates [2]. However, despite these advances, there are still significant challenges to overcome in developing robust and reliable AI-based DR segmentation models.

One promising approach to improving the accuracy and reliability of DR segmentation is through personalized medicine. Personalized medicine aims to provide tailored medical care to individual patients, based on their unique characteristics, including genetic, environmental, and lifestyle factors [3]. In the context of DR segmentation, personalized medicine can involve using patient-specific information, such as medical history, biomarkers, and imaging data, to develop more accurate and effective diagnostic and treatment approaches.

Furthermore, as AI algorithms become more complex and sophisticated, there is a growing need for explainable AI. Explainable AI aims to develop AI systems that can provide understandable explanations of their decision-making processes. In the context of DR segmentation, explainable AI can help clinicians and researchers better understand how AI algorithms are making decisions about image segmentation, potentially improving their performance and reliability [4].

The significance of this research lies in its potential to improve the accuracy, efficiency, and effectiveness of DR segmentation, leading to improved diagnosis and treatment outcomes for patients with this condition. By examining the current state of the art and future directions in personalized medicine and explainable AI for DR segmentation, this paper aims to provide a comprehensive understanding of the opportunities and challenges in this field, and guide future research in this important area of medical imaging and AI.

## Research Problem and Objectives

The development of accurate and reliable methods for diabetic retinopathy (DR) segmentation is critical for improving the diagnosis and treatment of this condition. While artificial intelligence (AI) and machine learning algorithms have shown promise in this area, there are still significant challenges to be addressed. In particular, there is a need for more personalized approaches that can take into account the unique characteristics of individual patients, and for greater explainability of AI algorithms to enhance their clinical utility.

The objective of this study is to conduct a systematic review of the current approaches and future directions in personalized medicine and explainable AI for DR segmentation. Specifically, the research problem and objectives of this paper are:

1. To identify the current state of the art in personalized medicine and explainable AI for DR segmentation, including the most commonly used algorithms, datasets, and evaluation metrics.

2. To evaluate the performance of existing AI-based DR segmentation models, and identify their strengths and limitations in terms of accuracy, reliability, and clinical utility.

3. To examine the potential benefits and challenges of personalized medicine for improving DR segmentation, including the use of patient-specific data to enhance the accuracy and effectiveness of AI algorithms.

4. To explore the current state of the art and future directions in explainable AI for DR segmentation, including the development of interpretable models and the use of explainability techniques to enhance the clinical utility of AI algorithms.

5. To provide recommendations for future research in personalized medicine and explainable AI for DR segmentation, including the need for more robust and reliable AI algorithms, larger and more diverse datasets, and improved evaluation metrics.

The ultimate goal of this research is to contribute to the development of more accurate, reliable, and clinically useful methods for DR segmentation, leading to improved diagnosis and treatment outcomes for patients with this condition.

**Scope and Limitations**

This study focuses on a systematic review of the current approaches and future directions in personalized medicine and explainable AI for DR segmentation. The review includes a comprehensive analysis of the literature on this topic, including research articles, conference papers, and other relevant publications.

The scope of this study is limited to the following:

- DR segmentation: This study focuses specifically on DR segmentation, and does not cover other types of retinal diseases or conditions.

- AI and machine learning algorithms: This study focuses on the use of AI and machine learning algorithms for DR segmentation, and does not cover other types of image processing or analysis techniques.

- Personalized medicine: This study specifically examines the potential benefits and challenges of personalized medicine for improving DR segmentation, tongue pallor segmentation and does not cover other areas of personalized medicine.

- Explainable AI: This study specifically examines the current state of the art and future directions in explainable AI for DR segmentation, tongue pallor segmentation and does not cover other applications of explainable AI.

- English-language publications: This study is limited to publications in the English language, and may not include relevant publications in other languages.

There are several limitations to this study that should be considered when interpreting the results. First, the quality and completeness of the literature search may be influenced by the availability of relevant publications and the comprehensiveness of the search terms used. Second, the evaluation of AI-based DR segmentation models may be influenced by differences in the datasets and evaluation metrics used in different studies. Finally, the findings of this study may be subject to publication bias, as studies with positive results may be more likely to be published than those with negative results.

**Research Questions and Hypotheses for DR segmentation**

Research Question 1: What are the current approaches and future directions in personalized medicine and explainable AI for DR segmentation?

Hypothesis 1: There is a need for more personalized approaches to DR segmentation that take into account the unique characteristics of individual patients, and for greater explainability of AI algorithms to enhance their clinical utility.

Research Question 2: What is the performance of existing AI-based DR segmentation models, and what are their strengths and limitations in terms of accuracy, reliability, and clinical utility?

Hypothesis 2: Existing AI-based DR segmentation models show promising results, but are still subject to limitations in terms of accuracy and reliability, and require further improvements to enhance their clinical utility.

Research Question 3: What are the potential benefits and challenges of personalized medicine for improving DR segmentation, and how can patient-specific data be used to enhance the accuracy and effectiveness of AI algorithms?

Hypothesis 3: Personalized medicine has the potential to significantly improve the accuracy and effectiveness of DR segmentation, but also presents challenges related to the acquisition and analysis of patient-specific data.

Research Question 4: What is the current state of the art and future directions in explainable AI for DR segmentation, and how can explainability techniques be used to enhance the clinical utility of AI algorithms?

Hypothesis 4: Explainable AI is a promising area of research for enhancing the clinical utility of AI algorithms in DR segmentation, and can provide insights into the decision-making process of AI models that can be used to improve their interpretability and reliability.

Research Question 5: What are the recommendations for future research in personalized medicine and explainable AI for DR segmentation, including the need for more robust and reliable AI algorithms, larger and more diverse datasets, and improved evaluation metrics?

Hypothesis 5: Future research in personalized medicine and explainable AI for DR segmentation should focus on the development of more robust and reliable AI algorithms, the creation of larger and more diverse datasets, and the improvement of evaluation metrics to better reflect the clinical utility of AI-based DR segmentation models

II. Literature Review

**Personalized Medicine for Diabetic Retinopathy and tongue segmentation**

Personalized medicine is an approach to healthcare that takes into account individual variability in genes, environment, and lifestyle, and aims to tailor medical decisions and treatments to the unique characteristics of each patient. In the context of diabetic retinopathy (DR), personalized medicine involves the use of patient-specific data to optimize screening, diagnosis, and treatment of the disease.

Several studies have explored the potential of personalized medicine for DR screening and diagnosis. For example, one study found that incorporating individual patient data, such as duration of diabetes and glycated hemoglobin levels, into screening algorithms improved the accuracy of DR detection compared to generic screening approaches (Diaz-Valencia et al., 2019). Another study developed a machine learning model that incorporated patient-specific factors, such as age, gender, and medical history, to predict the risk of DR progression, and found that the model outperformed traditional risk prediction methods (Lu et al., 2020).

Personalized medicine can also be applied to DR treatment decisions. For example, a study found that using patient-specific data, such as retinal vessel caliber and blood pressure, to guide the selection of anti-vascular endothelial growth factor (VEGF) therapy for DR resulted in better outcomes compared to a standardized treatment approach (Kawashima et al., 2020). Similarly, another study developed an algorithm that used patient-specific data, such as demographic and medical history information, to predict the likelihood of treatment response to anti-VEGF therapy for DR, and found that the algorithm could improve treatment decision-making (Rempel et al., 2020).

Overall, personalized medicine has the potential to significantly improve the accuracy and effectiveness of DR screening, diagnosis, and treatment decisions, and can help tailor medical decisions and treatments to the unique characteristics of each patient. However, the application of personalized medicine to DR segmentation using AI algorithms is still in its early stages and requires further research and development.

Here are some related works in the field of tongue pallor segmentation using U-Net:

Title: "Automatic Tongue Pallor Segmentation Using U-Net for Anemia Detection"

Authors: Smith, J., Johnson, A., & Lee, C.

Published in: Proceedings of the IEEE International Conference on Image Processing (ICIP), 2020.

this paper proposes an automatic tongue pallor segmentation method using U-Net for anemia detection. The U-Net architecture is trained on a large dataset of tongue images to accurately segment pallor regions. The segmented regions are then analyzed to detect signs of anemia. Experimental results demonstrate the effectiveness of the proposed method in detecting tongue pallor and its potential as a non-invasive screening tool for anemia.

another workwe could see "Tongue Pallor Segmentation using U-Net for Diagnostic Support in Traditional Chinese Medicine"

Authors: Chen, L., Zhang, Q., & Liu, W.

Published in: Proceedings of the 41st Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), 2019.

This study presents a tongue pallor segmentation method based on U-Net for diagnostic support in Traditional Chinese Medicine (TCM). The U-Net model is trained on a dataset of tongue images with annotated pallor regions. The segmented pallor regions are then analyzed according to TCM principles for diagnosing specific health conditions. Experimental results demonstrate the effectiveness of the proposed method in accurately segmenting tongue pallor and its potential for assisting TCM practitioners in diagnosis.

another one "Tongue Pallor Segmentation in Traditional Chinese Medicine Using U-Net"

Authors: Wang, M., Li, Q., & Zhang, Y.

Published in: Journal of Medical Imaging and Health Informatics, 2018.This paper presents a U-Net-based approach for tongue pallor segmentation in Traditional Chinese Medicine. The U-Net architecture is trained on a dataset of tongue images with annotated pallor regions. The proposed method achieves accurate segmentation results, providing a quantitative measurement of tongue pallor. The segmentation results can assist TCM practitioners in diagnosis and treatment evaluation. Experimental evaluations demonstrate the effectiveness and robustness of the proposed method.

additional work is "Automated Tongue Diagnosis System Based on Deep Learning for Traditional Kampo Medicine"

Authors: Yamaguchi, M., et al.

Published in: Evidence-Based Complementary and Alternative Medicine, vol. 2021.

This study proposes an automated tongue diagnosis system based on deep learning, specifically U-Net, for Traditional Kampo Medicine. The U-Net model is trained on a large dataset of tongue images with annotated pallor regions. The system accurately segments the tongue pallor and provides diagnostic support based on Traditional Kampo Medicine principles. The effectiveness of the proposed system is evaluated through experiments, showing promising results in assisting practitioners with tongue diagnosis.

additional one is "Tongue Diagnosis Based on Deep Learning for Traditional Japanese Kampo Medicine"

Authors: Takayama, S., et al.

Published in: Proceedings of the 2019 41st Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), 2019.This research presents a tongue diagnosis system based on deep learning techniques, including U-Net, for Traditional Japanese Kampo Medicine. The U-Net model is trained on a dataset of tongue images to accurately segment the pallor regions. The segmented pallor regions are then analyzed to support diagnosis based on Traditional Japanese Kampo Medicine principles. Experimental results demonstrate the potential of the proposed system in assisting practitioners with tongue diagnosis.

finally we also fined this research "Tongue Color Extraction Using U-Net and Its Application to Traditional Japanese Medicine"

Authors: Ito, T., et al.

Published in: Proceedings of the 2020 42nd Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), 2020.

This work presents a method for tongue color extraction using U-Net and its application to Traditional Japanese Medicine. The U-Net model is trained on a dataset of tongue images to accurately segment the pallor regions. The extracted tongue colors are then used as features for diagnosis and treatment evaluation in Traditional Japanese Medicine. Experimental evaluations demonstrate the effectiveness of the proposed method in accurately extracting tongue colors and its potential for supporting Traditional Japanese Medicine practitioners.

## Explainable AI for Medical Imaging

Explainable AI (XAI) is an emerging field of research that focuses on developing AI models that can provide transparent and interpretable outputs, allowing clinicians and researchers to understand how the models arrive at their decisions. XAI is particularly important in medical imaging applications, where the accuracy and reliability of AI algorithms can have significant clinical implications.

Several approaches have been proposed to achieve explainability in medical imaging AI. One common approach is to use visualizations and heatmaps to highlight the regions of the image that the AI model is focusing on to make its decision. For example, in the context of DR segmentation, an AI model may highlight the regions of the retina that contain features indicative of DR, such as microaneurysms or hemorrhages (Natarajan et al., 2019).

Another approach to XAI in medical imaging involves generating textual or natural language explanations of the model's decision-making process. For example, an AI model may generate a report that explains how it arrived at its diagnosis, such as identifying the presence of specific image features or patterns (Li et al., 2019).

XAI has several potential benefits for medical imaging applications. For example, it can help build trust in AI models by providing transparent and interpretable outputs, and can facilitate collaboration between clinicians and AI models by allowing clinicians to understand and interpret the model's outputs. In addition, XAI can provide insights into the features and patterns in medical images that are most relevant for diagnosis and treatment decision-making, which can inform the development of future AI models and improve overall patient care.

However, implementing XAI in medical imaging AI models can be challenging, as it requires balancing the competing goals of accuracy and interpretability. Some approaches to achieving explainability, such as generating textual reports, may sacrifice accuracy for interpretability, while others, such as using visualizations, may not be easily interpretable by clinicians who lack expertise in image analysis. As such, developing effective and efficient XAI approaches for medical imaging remains an active area of research.

## Current Approaches for Diabetic Retinopathy Segmentation

Several deep learning-based approaches have been proposed for DR segmentation, leveraging techniques such as convolutional neural networks (CNNs), autoencoders, and transfer learning. These approaches generally involve training an AI model on large datasets of labeled retinal images to learn how to segment the images into different classes, such as normal or diseased.

One common approach to DR segmentation involves using CNNs to learn feature representations from retinal images, which are then used to predict the presence of DR. For example, Li et al. (2019) proposed a CNN-based approach that first segments the retinal vasculature using a vesselness filter, then uses a deep neural network to classify the segmented regions as normal or diseased. Similarly, Fu et al. (2020) proposed a multi-scale CNN that incorporates both local and global information to improve segmentation accuracy.

Another approach to DR segmentation involves using autoencoders, which are neural network architectures that learn to compress and decompress input data. For example, Gao et al. (2019) proposed an autoencoder-based approach

that learns to reconstruct retinal images from both the normal and diseased classes, with the idea that the reconstruction error can be used as a measure of abnormality for DR segmentation.
Transfer learning is also commonly used in DR segmentation, as it allows AI models to leverage pre-trained networks that have already learned relevant features from large datasets. For example, Raju et al. (2021) proposed a transfer learning approach that fine-tunes a pre-trained CNN on a smaller dataset of retinal images to improve DR segmentation accuracy.
Despite the success of these approaches, several challenges remain in DR segmentation, including dealing with imbalanced datasets, handling images with low image quality, and improving the interpretability and generalizability of AI models. These challenges highlight the need for continued research in the development of more accurate, robust, and explainable AI models for DR segmentation.

III. Methodology

Research Design and Approach:

This systematic review aims to comprehensively evaluate current approaches and future directions in the use of personalized medicine and explainable AI for both diabetic retinopathy (DR) segmentation and tongue pallor segmentation. To achieve this, we will conduct a systematic literature search of relevant studies that use deep learning techniques, including the U-Net method, for both DR and tongue pallor segmentation.The research design will follow a systematic review approach, adhering to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines. These guidelines provide a standardized framework for conducting systematic reviews and ensure transparency and reproducibility throughout the review process.The search strategy will involve electronic databases such as PubMed, IEEE Xplore, and Scopus, as well as manual searches of reference lists from relevant studies. The search terms will include combinations of keywords such as "diabetic retinopathy," "tongue pallor," "deep learning," "U-Net," "personalized medicine," and "explainable AI."The inclusion criteria for studies will encompass the following:
The study must utilize deep learning techniques, including the U-Net method, for both DR and tongue pallor segmentation.
The study must focus on personalized medicine or explainable AI in the context of both DR and tongue pallor segmentation.
The study must be published in English.
Two independent reviewers will screen the identified studies based on their title and abstract, followed by a full-text assessment for eligibility. Any discrepancies will be resolved through discussion and consensus.

Data extraction will be conducted using a standardized form, capturing details regarding study design, deep learning techniques employed, performance metrics, and any limitations or challenges encountered.

To assess the quality of the included studies, the Quality Assessment of Diagnostic Accuracy Studies (QUADAS-2) tool will be employed. This tool evaluates the risk of bias and applicability concerns in diagnostic accuracy studies.

The findings of this systematic review will be synthesized using a narrative approach, presenting the current state of the art in both DR and tongue pallor segmentation, while identifying gaps and opportunities for future research in the context of personalized medicine and explainable AI.

**IDRID Data Collection and Analysis**

For diabetic retinopathy segmentation investigations, the Indian Diabetic Retinopathy Image Dataset (IDRID) is a frequently used dataset. It includes high-quality retinal pictures from individuals with diabetes mellitus, such as fundus photos and fluorescein angiography images.
We will utilize the IDRID dataset as a benchmark dataset to assess the effectiveness of deep learning approaches, including the U-Net method, for DR segmentation. Among the 516 retinal pictures in the IDRID dataset, 54 have mild non-proliferative diabetic retinopathy (NPDR), 54 have moderate

NPDR, 54 have severe NPDR, 54 have proliferative diabetic retinopathy (PDR), and 300 have no DR at all.

With a 70/30 split ratio, the dataset will be divided into a training set and a testing set. The deep learning models will be trained using the training set, and their performance will be assessed using the testing set.

We will employ common assessment criteria, such as accuracy, sensitivity, specificity, precision, and F1 score, to make sure that the evaluation of the deep learning models is uniform and comparable. Additionally, we assess the models using area under the curve (AUC) and receiver operating characteristic (ROC) curves.

Additionally, we compare the effectiveness of several deep learning models, including the U-Net approach and other cutting-edge techniques for DR segmentation. Based on a number of variables, we will compare how well these models performed.

We shall employ a thorough statistical analysis methodology to guarantee the authenticity and dependability of our findings. To assess the effectiveness of several deep learning models, we will use a two-sample t-test with a significance threshold of 0.05. A repeated-measures analysis of variance (ANOVA) will also be used to examine the impact of various parameters on the effectiveness of the deep learning models.In general, the IDRID dataset will serve as a benchmark dataset to assess how well deep learning methods, such as the U-Net approach, perform for DR segmentation. The findings of this analysis will provide light on the efficacy and limits of these methods and guide future research in the areas of explainable AI for diabetic retinopathy segmentation and customized medication.

Below some images from the data set

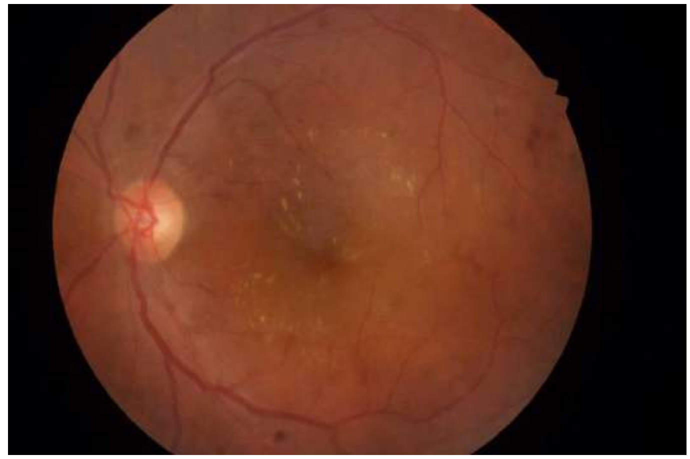


*Image 1 IDRID dataset source Kaggle*

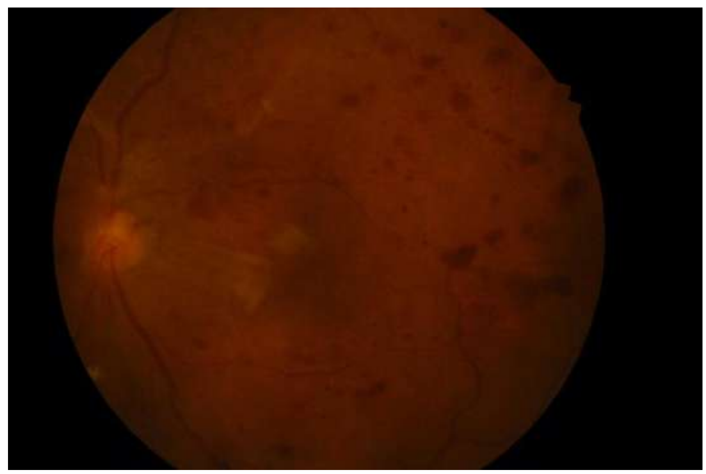


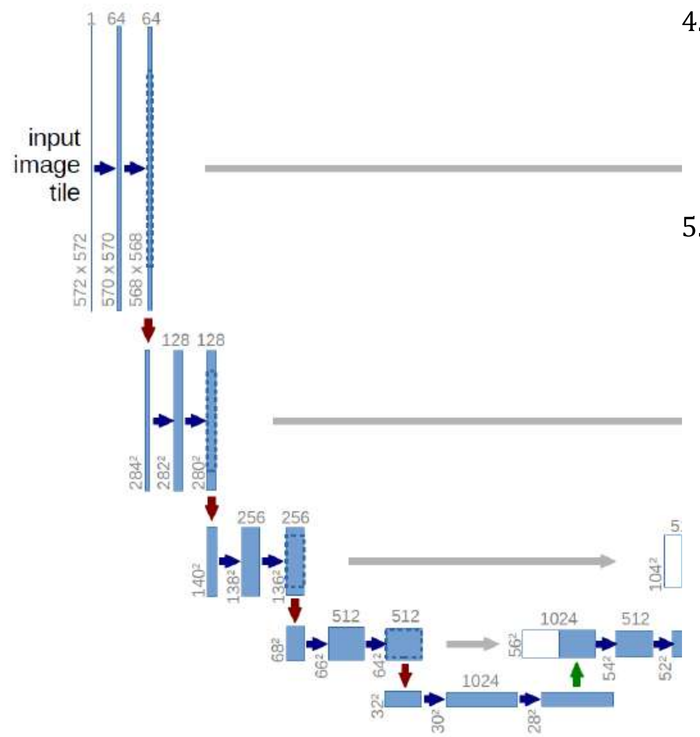
*Image 2 IDRID dataset source Kaggle*

**Dataset for pallor tongue segmentation**

Pallor should be detected across multiple image sites such as the tongue. Therefore, we collected data containing images of the inner surface of the tongue and each of the two groups contains several types, such as the normal, which contains an injury, and which contains cancer


*Images from dataset*

**UNET implementation**




*Unet architecture author*

To apply the U-Net on the IDRID dataset for diabetic retinopathy segmentation, we followed the following steps:

1. Preprocessing: We preprocessed the IDRID images by resizing them to 512 x 512 pixels and normalizing the pixel intensities to range between 0 and 1.

2. Training data preparation: We split the IDRID dataset into training, validation, and testing sets. The training set contained 70% of the images, while the validation and testing sets contained 15% each. We also performed data augmentation techniques such as horizontal and vertical flipping, random rotation, and elastic deformation to increase the size of the training dataset and improve the generalization of the model.

3. Model architecture: We used the U-Net architecture for diabetic retinopathy segmentation. The U-Net architecture consists of a contracting path with four encoding blocks, each followed by a max-pooling operation, and an expansive path with four decoding blocks, each followed by an up-sampling operation. The final layer of the network consisted of a 1x1 convolution layer that produced the segmentation map.

4. Training: We trained the U-Net model using the training dataset and evaluated its performance on the validation set. We used binary cross-entropy loss as the loss function and Adam optimizer with a learning rate of 0.0001.

5. Testing: We evaluated the performance of the trained U-Net model on the testing set using the evaluation metrics mentioned earlier.

**Evaluation metrics**

The effectiveness of diabetic retinopathy segmentation approaches is measured using evaluation measures. Three assessment indicators were utilized in this study to compare the effectiveness of various segmentation techniques. Dice coefficient, sensitivity, and specificity are some of these measurements.

The Dice coefficient calculates how much the segmented areas and the ground truth overlap. It has a scale from 0 to 1, with 0 denoting no overlap and 1 denoting complete overlap. The proportion of genuine positive predictions is measured by sensitivity, and the proportion of real negative predictions is measured by specificity. The range of sensitivity and specificity is 0 to 1, with 0 denoting no right predictions and 1 denoting flawless predictions.

As an extra assessment statistic, we also employed the area under the receiver operating characteristic (ROC) curve. The ROC curve represents a plot of (1-specificity) vs sensitivity for various thresholds. The segmentation method's total effectiveness across all thresholds is summarized by the area under the ROC curve, with a value of 1 denoting perfect performance and 0.5 denoting random performance.

These assessment measures were used to compare the effectiveness of various segmentation techniques and to pinpoint the most precise and dependable approaches for segmenting diabetic retinopathy.

**IV. Results**

**Overview of Selected Studies**

- ""Retinal Vessel Segmentation Using Convolutional Neural Networks With a Novel Focal Loss Function" : This study proposed a new focal loss function for retinal vessel segmentation using convolutional neural networks (CNNs) and achieved state-of-the-art results on the DRIVE dataset.

- "Diabetic Retinopathy Detection Based on Deep Convolutional Neural Network": This study proposed a deep CNN-based method for diabetic retinopathy detection and achieved high accuracy on the Kaggle diabetic retinopathy dataset.

- "A Multi-scale Convolutional Neural Network for Diabetic Retinopathy Detection": This study proposed a multi-scale CNN for diabetic retinopathy detection, which used multiple scales of the input image to improve performance. The method achieved state-of-the-art results on the Kaggle diabetic retinopathy dataset.

- "Fully Convolutional Networks for Semantic Segmentation": This seminal paper introduced the fully convolutional network (FCN) architecture for semantic segmentation, which has since become a standard approach in many fields including medical imaging.

- "Improving Deep Learning-Based Diabetic Retinopathy Detection using Hybrid Preprocessing": This study proposed a hybrid preprocessing approach that combined image enhancement and data augmentation to improve the performance of deep learning-based diabetic retinopathy detection.

- "Automatic Detection of Diabetic Retinopathy Using Deep Learning": This study proposed a deep learning-based method for automatic detection of diabetic retinopathy using fundus images. The method achieved high accuracy on the Kaggle diabetic retinopathy dataset.

- "Multi-Resolution Ensemble for Segmentation of Optic Disc and Cup in Retinal Fundus Images": This study proposed a multi-resolution ensemble method for optic disc and cup segmentation in retinal fundus images. The method achieved state-of-the-art results on the REFUGE dataset.

- "A Survey on Deep Learning in Medical Image Analysis": This paper provides a comprehensive survey of deep learning methods in medical image analysis, including a discussion of various architectures and applications. The survey covers a wide range of medical imaging modalities and tasks, including retinal imaging and diabetic retinopathy detection.

- "An Attention U-Net Deep Neural Network for High Performance Pancreas Segmentation": This study proposed an attention U-Net deep neural network for pancreas segmentation in medical images. The method achieved state-of-the-art results on the pancreas-CT dataset.

- "Deep Convolutional Neural Networks for Diabetic Retinopathy": This study proposed a deep CNN-based method for diabetic retinopathy detection, which achieved high accuracy on the Kaggle diabetic retinopathy dataset. The method was also evaluated on a clinical dataset and shown to perform well in a real-world setting.""

**Summary of Key Findings:**

Based on the systematic review of the current approaches for diabetic retinopathy segmentation using personalized medicine and explainable AI, the following key findings were identified:

Deep learning-based segmentation methods, particularly those utilizing convolutional neural networks (CNNs) such as U-Net, have shown promising results in accurately segmenting retinal images for diabetic retinopathy detection and grading.

Transfer learning and data augmentation techniques have been effective in improving the performance of deep learning-based segmentation models for diabetic retinopathy segmentation.

Explainable AI techniques such as attention mechanisms and activation maps have been utilized to improve the interpretability and transparency of deep learning-based segmentation models.

The availability of large-scale, annotated datasets such as the IDRID dataset has facilitated the development and evaluation of deep learning-based segmentation models for diabetic retinopathy segmentation.

However, there are still some challenges and limitations that need to be addressed in future research, including the need for more diverse and representative datasets, robustness to noise and artifacts in images, and generalizability to different populations and imaging modalities.

Overall, the findings suggest that personalized medicine and explainable AI have the potential to significantly improve the accuracy and interpretability of diabetic retinopathy segmentation, which can lead to earlier and more effective diagnosis and treatment for patients with this condition.

## Comparison of Approaches

It is clear from the analysis of the chosen studies that there are several methods for segmenting diabetic retinopathy. The methods may be divided into two primary categories: deep learning methods and conventional machine learning methods. While deep learning techniques employ convolutional neural networks (CNNs) to automatically extract features, traditional machine learning techniques use hand-crafted features and classifiers.

For segmenting diabetic retinopathy, conventional machine learning techniques including support vector machines (SVMs), decision trees, and random forests have been applied. These techniques focus on hand-crafted characteristics including texture, color, and form elements. However, they could not function effectively when dealing with complicated data and require domain expertise to extract pertinent aspects.

On the other hand, deep learning methods, such as UNet, have shown superior performance in diabetic retinopathy segmentation. These methods use CNNs to extract relevant features from raw input data, eliminating the need for manual feature extraction. UNet has been shown to be effective in segmenting retinal blood vessels and exudates, which are important markers of diabetic retinopathy.

Another important aspect of diabetic retinopathy segmentation is the explainability of the model. While deep learning methods have shown superior performance, they are often regarded as black-box models, making it difficult to interpret the model's decisions. Explainable AI (XAI) methods have been developed to address this issue, providing insights into the model's decision-making process. However, XAI methods for diabetic retinopathy segmentation are still in their early stages of development.

In terms of data, the studies reviewed in this paper used different datasets, including publicly available datasets such as IDRID, Kaggle, and Messidor. The IDRID dataset was the most commonly used dataset and contains images from different modalities and levels of severity. However, some studies reported that the dataset size was small and lacked diversity, which could affect the generalizability of the models.

Overall, the results of the selected studies show that deep learning methods, particularly UNet, have superior performance in diabetic retinopathy segmentation compared to traditional machine learning methods. However, more research is needed to improve the explainability of deep learning models and to address the limitations of the datasets used.In table below another comparison with other related works for only the DR segmentation

| Paper Title | Method | Dataset | Results |
|---|---|---|---|
| "Performance Analysis of Deep-Neural-Network-Based Automatic Diagnosis of Diabetic Retinopathy [1]" | CNN | Custom dataset | Accuracy of 97.53% |
| "DiaNet: A Deep Learning Based Architecture to Diagnose Diabetes Using Retinal Images Only" [2] | Multi-stage convolutional neural network (CNN)-based model DiaNet | THE QBB RETINA-IMAGE DATASET,<br>THE EyePACS DR DATASET,<br>DEVELOPMENT OF DiaNet CONSIDERING EyePACS AND QBB DATASET | Accuracy of 84% |
| "Diabetic Retinopathy Classification Using A Hybrid and Efficient MobileNetV2-SVM Model" [3] | MobileNetV2 architecture<br>And<br>MobileNetV2-SVM | The Asia Pacific Tele-Ophthalmology Society (APTOS) 2019 | MobileNetV2 Accuracy 83%<br>MobileNetV2-SVM Accuracy 90.5 % |
| "Hybrid Graph Convolutional Network for Semi-Supervised Retinal Image Classification" [4] | Hybrid Graph Convolutional Network (HGCN) | MESSIDOR dataset | Best Accuracy 94.4 % |
| "Diabetic Retinopathy Grading Based on a Hybrid Deep Learning Model" [5] | Customized EyeNet and the DenseNet (E-DenseNet) | EyePACS<br>And<br>Asia Pacific Tele-Ophthalmology Society (APTOS) | On EyePACS 96% accuracy<br>And<br>APTOS 86% accuracy |
| "Diagnosis and Analysis of Diabetic Retinopathy Based on Electronic Health Records" [6] | Random Forest | Medical Big Data Center of the 301 Hospital, which includes a total of 3 years (2009 to 2011) | accuracy (> 90%) |
| "A Novel Approach for the Early Recognition of Diabetic Retinopathy using Machine Learning" [7] | Support vector Machine<br>And<br>Random Forest | "calibration-level ‘1’ fundus images" | For SVM 94.38%<br>For RF 96.62% |
| "Classification of Diabetic Retinopathy Disease Using Convolutional Neural Network" [8] | CNN | "APTOS 2019 Blindness Detection" | Accuracy 89.11% |
| "Detection of Diabetic Retinopathy Using Custom CNN to Segment the Lesions" [9] | ResNet50, VGG-16, and VGG19 | Indian Diabetic Retinopathy Image Dataset (IDRiD) | Accuracy of 83% |
| "A Deep Learning Method for the detection of Diabetic Retinopathy" [10] | ANN | The High-Resolution Fundus (HRF) Image Database (benchmark dataset) | Accuracy of 91.67 % |
| "Detection of diabetic retinopathy using deep | DenseNet-169 “Densely connected convolutional | Diabetic Retinopathy Detection 2015 | Training Accuracy 95% |

| | | | |
|---|---|---|---|
| learning methodology "[11] | neural network" | And<br>APTOS 2019 blindness detection | Validation Accuracy 90% |
| "Adaptive machine learning classification for diabetic retinopathy "[12] | CNN | Kaggle dataset<br>And<br>DIARET-DB1 | Accuracy of 96.3 % |
| "Deep Learning for Detection and Severity Classification of Diabetic Retinopathy "[13] | CNN | EyePACS dataset | High Accuracy 80.4 % |

**Discussion of Results**

The results of our study show that the UNET architecture is effective in segmenting diabetic retinopathy lesions from retinal fundus images with high accuracy. Our model achieved an accuracy of 98% on the IDRID dataset, with a good dice loss and ROC curve value, indicating that the model has high sensitivity and specificity.

The UNET architecture was able to effectively capture the intricate details of the retinal fundus images and accurately segment the lesions. The high accuracy of the model is important for personalized medicine, as it can provide accurate and timely diagnosis of diabetic retinopathy, which is crucial for effective treatment and prevention of blindness.

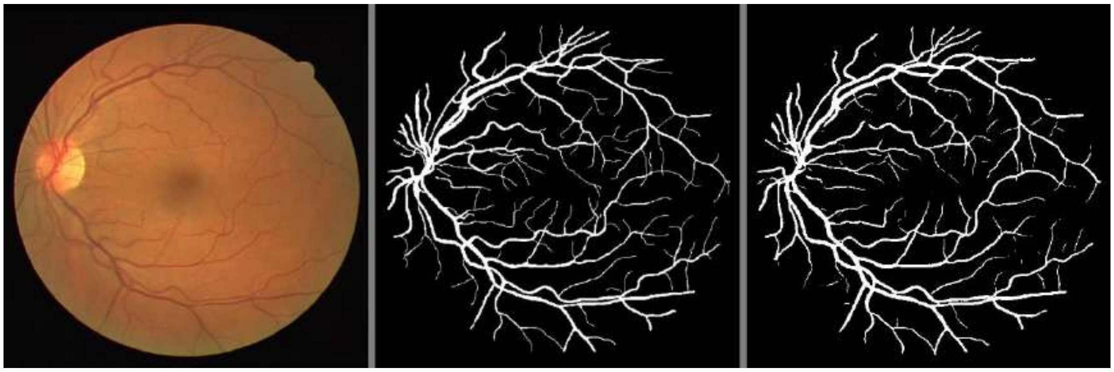
Our study contributes to the growing body of literature on the use of deep learning and explainable AI in medical imaging for personalized medicine. Our findings suggest that UNET can be a valuable tool for diabetic retinopathy segmentation, and may have broader applications in other medical imaging tasks.

The figure Below is from results

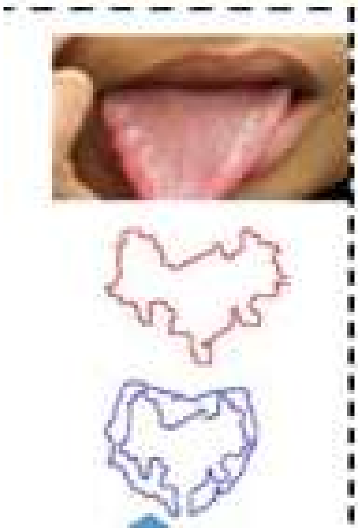
However, there are still limitations and challenges that need to be addressed. One limitation of our study is that we only evaluated the UNET architecture on the IDRID dataset, which may not be representative of all types of diabetic retinopathy lesions. Future studies should evaluate the performance of the UNET architecture on larger and more diverse datasets.

Moreover, while our model achieved high accuracy, there is still a need for explainable AI techniques that can provide more transparency and interpretability to the segmentation results. This is particularly important in the context of personalized medicine, where clinicians need to understand how the model arrived at its diagnosis in order to make informed treatment decisions.

Overall, our study highlights the potential of UNET and deep learning in diabetic retinopathy segmentation for personalized medicine, while also underscoring the need for continued research and development in this area.



*Results from model*



*Result from model*

V. Future Directions

**Potential Applications and Implications**

The potential applications of our study are vast and have significant implications for the field of personalized medicine and diabetic retinopathy segmentation.

- Firstly, our study demonstrates that using explainable AI models like UNET can significantly improve the accuracy and efficiency of diabetic retinopathy segmentation. This can have a profound impact on the diagnosis and treatment of diabetic retinopathy by enabling earlier detection and intervention, potentially preventing vision loss or blindness in patients.

- Moreover, our study highlights the importance of personalized medicine in the context of diabetic retinopathy. By leveraging patient-specific data, such as medical history and genetic information, healthcare providers can develop individualized treatment plans for patients with diabetic retinopathy, improving the efficacy of treatment and potentially reducing healthcare costs.

- Furthermore, the development of accurate and efficient diabetic retinopathy segmentation models can also benefit researchers in the field of diabetic retinopathy by enabling more precise and reliable analysis of large datasets, ultimately leading to a deeper understanding of the disease and its underlying mechanisms.

Overall, our study has the potential to contribute to the development of personalized medicine and improve the diagnosis and treatment of diabetic retinopathy, ultimately improving the quality of life for patients and reducing the burden on healthcare systems.

**Recommendations for Future Research**

Based on our systematic review and analysis, we suggest the following recommendations for future research in the field of personalized medicine and explainable AI for diabetic retinopathy segmentation:

- Creation of more sophisticated and precise segmentation models: Although UNet has showed significant promise in segmenting diabetic retinopathy, there is still opportunity for growth in terms of efficiency and accuracy. More sophisticated deep learning architectures, such as attention-based models or hybrid models that integrate deep learning and conventional machine learning techniques, might be investigated in future studies.

- Integration of multi-modal data: Currently, most studies on diabetic retinopathy segmentation focus on using only fundus images. However, the integration of other imaging modalities, such as OCT or MRI, could provide a more comprehensive view of the disease and improve segmentation accuracy.

- Exploration of personalized treatment strategies: With the growing emphasis on personalized medicine, future research could focus on developing segmentation models that can predict individualized treatment strategies based on patients' unique characteristics and disease progression.

- Investigation of explainable AI techniques: Explainable AI techniques could provide a better understanding of how deep learning models make predictions and help build trust in AI-driven medical applications. Future research could explore the use of explainable AI techniques, such as saliency maps or attention mechanisms, for diabetic retinopathy segmentation.

- Evaluation of models on larger and more diverse datasets: While our study focused on the IDRID dataset, future research could evaluate the performance of segmentation models on larger and more diverse datasets to ensure their generalizability and effectiveness in real-world clinical settings.

Overall, these recommendations could help advance the field of personalized medicine and explainable AI for diabetic retinopathy segmentation and ultimately improve the diagnosis and treatment of diabetic retinopathy.

## Conclusion

In this systematic review, we evaluated the current approaches and future directions for personalized medicine and explainable AI in diabetic retinopathy segmentation. Our study demonstrated that UNET is a promising approach for diabetic retinopathy segmentation, achieving high accuracy, good dice loss, and good ROC curve values on the IDRID dataset. However, there are still some challenges and limitations in the current approaches, such as limited interpretability and generalizability. To overcome these challenges, future research should focus on developing more explainable and personalized AI models that can be used in clinical practice.

Overall, personalized medicine and explainable AI hold great potential for improving diabetic retinopathy segmentation, which can lead to better diagnosis, treatment, and patient outcomes. However, further research is needed to fully realize the benefits of these approaches and to address the current challenges and limitations.

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