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Detection of Diseases Using Retinal Imaging

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ABSTRACT

Retinal Imaging is a powerful tool for detecting and managing a range of eye and systemic diseases. This project focuses on developing an automated system that uses advanced image processing and machine learning techniques to ana- lyze retinal features, such as blood vessels and the optic nerve, for early disease detection. The system is designed to be non-invasive, improving accessibility and facilitating timely diagnosis. Key diseases targeted include Diabetic Retinopa- thy (DR), Glaucoma, Hypertension, and Cataracts. For Diabetic Retinopathy, the system detects early changes in retinal blood vessels to prevent progression to blindness [1]. Glaucoma is identified by analyzing structural changes in the optic nerve, while hypertension-related damage is detected by examining retinal blood vessel abnormalities[2,3]. Cataract effects, though primarily impacting the lens, are assessed indirectly through their influence on retinal image quality, using techniques like Optical Coherence Tomography (OCT)[4]. The system integrates preprocessing techniques for image clarity and employs advanced algorithms to segment and extract critical features. These features enable automated, accurate detection of abnormalities, minimizing false positives and improving efficiency. By streamlining the diagnostic process, the system aims to make high-quality eye care accessible even in underserved areas, reducing dependence on specialized expertise. This project demonstrates the potential of combining retinal imaging with artificial intelligence to transform disease detection. By prioritizing early intervention and accessibility, the system can help prevent vision loss and improve health outcomes for patients worldwide.

Keywords: Retinal Imaging, Disease Detection, Image Processing, Machine Learning, Diabetic Retinopathy (DR), Glaucoma, Hypertension, Cataracts, Optical Coherence Tomography (OCT), Artificial Intelligence (AI), Early Diagnosis, Accessibility, Vision Loss Prevention.

1. INTRODUCTION

Retinal imaging has become a critical tool in the diagnosis and management of a variety of ocular and systemic diseases, including Diabetic Retinopathy, Glau- coma, Hypertension, and Cataracts. These conditions are the main contributors to preventable blindness and often serve as indicators of other health issues such as cardiovascular and metabolic disorders. Early detection and timely interven- tion are essential to prevent irreversible damage, yet conventional diagnostic methods, such as fundus photography, remain limited due to their dependence on expert interpretation, high costs, and specialized equipment. This project addresses these challenges by leveraging advancements in AI and image process- ing to develop an automated retinal diagnostic system. By improving the quality of retinal images through preprocessing techniques like noise reduction and his- togram equalization, the system ensures that subtle but critical features, such as blood vessel morphology and optic nerve anomalies, are captured with clar- ity. These features are analyzed using convolutional neural networks (CNNs) to detect abnormalities indicative of early-stage diseases. The system reduces the reliance on human expertise, mitigates subjectivity, and provides faster, more accurate diagnoses. Designed to be accessible and scalable, the proposed solu- tion is particularly impactful for underserved regions where specialized care is often unavailable. By automating the diagnostic process, the system democra- tizes access to advanced eye care, enabling early intervention and improving patient outcomes. The integration of privacy safeguards further enhances trust and adaptability, making the system a robust and efficient tool to tackle the growing burden of vision-related diseases worldwide. This approach exempli- fies the transformative potential of combining artificial intelligence with retinal imaging to improve accessibility and efficacy in healthcare.

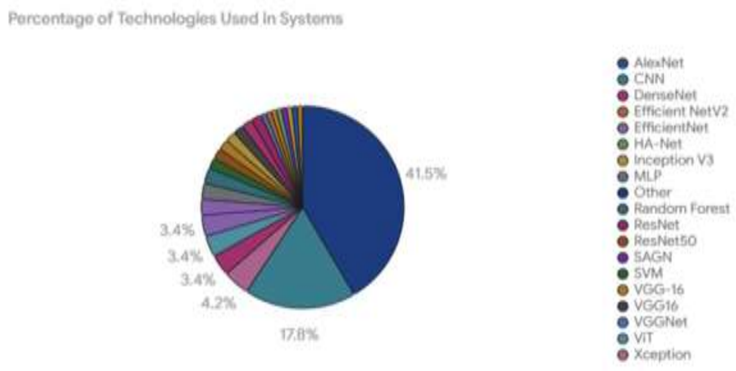

Figure 1: Technologies and methodologies adapted by existing systems

Figure 1 provides a clear overview of the adoption rates of various technolo- gies in system implementations. Each slice of the chart represents a technology, with its size corresponding to the percentage of systems utilizing it. The distinct colors assigned to each slice make it easy to distinguish between technologies, while the order of slices highlights the most widely used options.

Convolutional Neural Networks (CNNs) dominate the chart, accounting for 17.8% of system use, underscoring their central role in modern technol- ogy applications. Vision Transformers (VIT) and EfficientNet follow, with 6.7% and slightly less than 6.7% usage, respectively. Several technologies, includ- ing Pulse Coupled Neural Network (PCNN), Boltzmann Machines, Artificial Neural Network (ANN), Region-based Fully Convolutional Network (R-FCN), Inception-v4, Visual Geometry Group (VGGNet), and Bags of Visual Words, appear as the least adopted, each comprising only 0.8% of the systems. This distribution highlights the significant preference for CNNs while reflecting the niche application of other technologies.

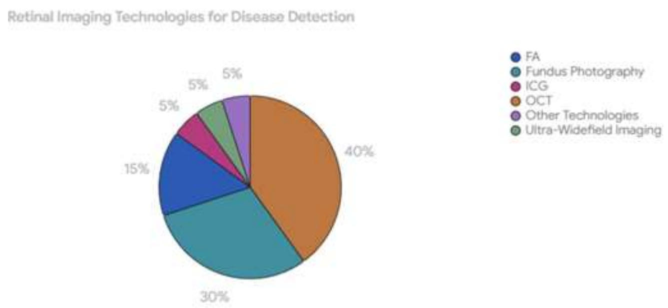

Figure 2: Traditional methodologies

Figure 2 showcases the use of different imaging techniques in retinal diagnos- tics. OCT leads with a 40% share, offering detailed cross-sectional images of the retina to detect and monitor conditions such as macular degeneration and DR. Close behind, Fundus Photography holds a 30% share, capturing comprehen- sive two-dimensional images of the retina, optic nerve, and blood vessels. These two techniques dominate due to their accuracy, ease of use, and effectiveness in tracking disease progression and treatment response.

Other technologies, though less prominent, play essential roles in specific scenarios. Fluorescein Angiography (FA) (15%) and Indocyanine Green Angiog- raphy (ICG) (5%) help visualize blood flow and detect vascular abnormalities, such as leakage and blockages. Ultra-Widefield Imaging (5%) broadens the diagnostic view by capturing peripheral retinal details often missed by tradi- tional methods. The final 5% represents emerging or niche imaging modalities, which contribute to advancing the field. Together, these technologies provide a comprehensive toolkit for diagnosing and managing a wide range of retinal diseases.

1.1 PROBLEM STATEMENT

The increasing prevalence of vision-related diseases like Diabetic Retinopathy, Glaucoma, Hypertension, and Cataracts presents a major global health chal- lenge, as these conditions are leading causes of preventable blindness. Often progressing without symptoms until significant damage occurs, they not only threaten vision but can also signal underlying systemic health issues, includ- ing cardiovascular and metabolic disorders. Timely diagnosis and intervention are crucial, but current diagnostic methods like fundus photography and Opti- cal Coherence Tomography (OCT) rely heavily on skilled ophthalmologists and expensive equipment, limiting accessibility, especially in underserved regions. Manual analysis is time-consuming, subjective, and prone to variability, lead- ing to delays and inconsistencies in diagnosis. These challenges are amplified in resource-poor settings, where a lack of professionals and infrastructure fur- ther hinders timely treatment. To address these issues, there is a growing need for solutions that leverage advanced image processing and artificial intelligence to automate retinal disease detection, enabling early and accurate diagnosis regardless of location or resources.

1.2 MOTIVATION

There is an ever-growing and pressing need to combat the growing prevalence of vision-threatening diseases like Diabetic Retinopathy, Glaucoma, Hyperten- sion, and Cataracts, which have a profound impact on global health, across the world. Beyond causing preventable blindness, these conditions often signal broader health issues, such as cardiovascular and metabolic disorders, making early detection crucial. However, traditional diagnostic methods depend heavily on specialists, are time-consuming, and remain out of reach for many due to high costs and limited infrastructure, especially in underserved areas. This project aims to bridge this gap by harnessing the power of advanced retinal imaging, image processing, and artificial intelligence. By automating critical processes like image enhancement, feature extraction, and disease classification through convo- lutional neural networks, the system seeks to make diagnostics more accessible, accurate, and efficient. This innovation not only empowers healthcare providers but also ensures timely interventions, offering a transformative approach to preserving vision and improving health outcomes worldwide.

2. RELATED WORKS

The field of disease detection using Retinal Imaging has seen significant evolu- tion, progressing from traditional image processing techniques to the forefront of deep learning. Early approaches focused on analyzing fundus images using methods like image enhancement, vessel segmentation, and exudate detection. These techniques, while foundational, often faced limitations in accurately cap- turing the intricate patterns associated with DR severity [1]. The emergence of deep learning, particularly Convolutional Neural Networks (CNNs), marked a turning point in DR detection. CNNs have the remarkable ability to automati- cally learn hierarchical features from raw image data, revolutionizing the field. Numerous studies have demonstrated the superior performance of deep learning models in classifying DR severity, surpassing traditional methods [1,2,3,4].

A study employed deep learning models to detect DR, leveraging CNNs for fundus image analysis. The proposed approach demonstrated significant accu- racy in identifying retinal anomalies and effectively handling diverse datasets. The researchers utilized pre-trained models to extract deep features, which were fine-tuned for DR-specific classifications. The system was robust against noise and variability in fundus images, making it a benchmark for further studies in scalable DR detection systems [1].

Another investigation reviewed classification-based deep learning methods tailored for DR diagnosis. By analyzing the performance of various architec- tures, including ensemble techniques, this study highlighted how hybrid models can distinguish between multiple DR stages with improved reliability and adapt- ability. It also discussed the use of transfer learning to mitigate the challenge of limited labeled datasets and presented a comparative analysis of commonly used loss functions for optimizing classification performance [2].

One work focused on preprocessing and augmentation techniques to address dataset imbalances in DR detection. The methodology included advanced data augmentation strategies such as geometric transformations, contrast adjust- ments, and synthetic data generation. These techniques enhanced the robustness of deep learning systems by mitigating biases, ensuring applicability in real- world settings with variable data quality. The study demonstrated significant improvements in model generalization when trained on augmented datasets [4].

A comprehensive review on AI-assisted retinal imaging explored applications in systemic diseases, emphasizing DR detection. It discussed the integration of AI systems into clinical workflows, highlighting challenges such as interpretabil- ity, scalability, and regulatory compliance. The review also analyzed case studies where AI models reduced diagnostic time and improved accuracy in clinical settings, particularly in under-resourced regions [5].

AI-enabled diagnostic systems for retinal conditions, including glaucoma and DR, were systematically developed in another study. This research under- scored the importance of validating AI models across diverse demographics and demonstrated cross-domain applicability of these technologies. The study pro- vided insights into optimizing hyperparameters for multi-condition detection and highlighted the role of federated learning in enhancing data privacy [6].

An innovative approach utilized Vision Transformer models to predict DR severity from fundus photographs. By implementing self-attention mechanisms, the model captured complex contextual details, resulting in improved classifi- cation accuracy and scalability. The study also introduced a novel positional encoding technique to better model spatial relationships in retinal images, further improving prediction robustness [7].

A review on deep learning approaches for DR diagnosis outlined key research challenges, including dataset limitations and the need for explainable AI. This study emphasized the significance of integrating advanced techniques to over- come barriers to clinical adoption. It included a detailed discussion on using saliency maps and Grad-CAM visualizations to enhance the interpretability of model predictions [8].

Another study introduced a multitasking deep learning framework capa- ble of identifying all five DR stages. This system used task-specific layers for simultaneous disease stage classification and severity grading, offering a holistic solution for clinical diagnostics. The framework incorporated weighted loss func- tions to address class imbalances and demonstrated high accuracy in multi-label classification tasks [9].

A lightweight CNN-based system was proposed for DR detection, focus- ing on computational efficiency without compromising accuracy. This design ensures accessibility in resource-constrained environments, making it suitable for wider deployment. The study also explored the use of quantization tech- niques to reduce model size and inference time while maintaining diagnostic performance [10].

Lastly, a detailed comparative analysis of deep learning techniques revealed the transformative potential of modern architectures over traditional meth- ods. The study highlighted advancements in diagnostic precision and processing speed, paving the way for enhanced DR detection. It also explored the integra- tion of multi-modal data, combining fundus images with patient metadata to achieve superior classification outcomes [11].

3. TECHNOLOGIES USED

3.1 DEEP LEARNING ALGORITHMS

Deep learning plays a pivotal role in medical imaging diagnostics, especially in identifying DR through advanced neural network architectures. CNNs are widely used to analyze images of the retinal fundus, extract intricate patterns, and classify stages of DR. These networks specialize in spatial feature analysis, enabling accurate detection of micro aneurysms, hemorrhages, and exudates. Additionally, Vision Transformers (ViTs) have emerged as a novel approach, excelling in severity prediction through their ability to model global relationships within high-resolution fundus images. Another innovative application includes multitasking deep learning models, which enable simultaneous detection and classification across multiple stages of DR. Hybrid architectures like CNN-LSTM models extend the capabilities of CNNs by incorporating temporal dependencies, making them suitable for longitudinal data analysis.

3.2 FEATURE SELECTION AND EXTRACTION TECHNIQUES

Efficient feature selection and extraction techniques are essential to improve model performance and interpretability in DR detection. Recursive Feature Elimination (RFE) is commonly employed to identify the most critical fea- tures from extensive datasets, ensuring computational efficiency while retaining diagnostic accuracy. For dimensionality reduction in high-dimensional datasets, auto- encoders are utilized to transform raw imaging data into meaningful, com- pact representations. These methods not only reduce computational costs but also enhance model generalization, addressing the challenges of limited datasets by focusing on salient image features.

3.3 NEUROIMAGING AND ANALYTICAL TOOLS

Neuroimaging and analytical tools provide insights into the neural underpin- nings of systemic diseases like DR. Functional MRI (FMRI) is used to examine connectivity patterns in neural networks, helping to identify biomarkers asso- ciated with disease progression. Coupled with machine learning, fMRI data is analyzed for classification tasks, offering a holistic understanding of systemic implications. General Linear Model (GLM) analysis, commonly employed in task-based fMRI studies, extracts parameters like brain activity signals, sta- tistical maps, and connectivity patterns. These parameters are then processed using machine learning models to identify correlations between neural activity and the severity of DR.

3.4 MACHINE LEARNING MODELS

Machine learning models form the foundation of automated DR detection sys- tems. Support Vector Machines (SVMs) are highly effective for binary and multi class classification tasks, particularly in handling high-dimensional imag- ing data [14,15]. Random Forest and Gradient Boosting techniques enhance predictive accuracy by combining ensemble learning approaches, making them robust against overfitting. Graph Convolutional Networks (GCNs) are increas- ingly applied to analyze graph-based representations of retinal structures or neural connectivity, offering a unique perspective on complex patterns in medical imaging datasets.

3.5 MULTIMODAL FRAMEWORKS

Multimodal frameworks integrate diverse data types, including imaging, behav- ioral, and neuroimaging datasets, to improve the diagnostic accuracy of DR detection systems. These frameworks leverage the complementary strengths of different modalities, enabling a comprehensive understanding of disease pro- gression. For instance, combining retinal image analysis with patient behavioral data can enhance predictions by contextualizing imaging findings. Similarly, incorporating neuroimaging biomarkers alongside fundus photography allows for the [12] detection of systemic effects, bridging the gap between local and systemic diagnostics[12]. Such integrated approaches, although computationally intensive, demonstrate superior performance in real-world diagnostic scenarios.

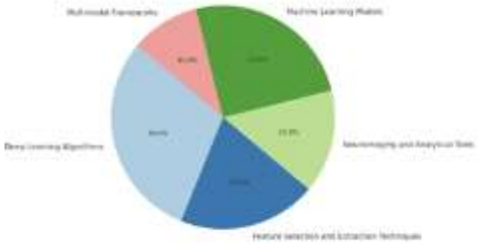

Figure 3: Pie Chart representing the distribution of technologies used in Disease Detection through Retinal Imaging

4. METHODOLOGIES

4.1 DETECTING DISEASES USING DEEP LEARNING

Emphasizes the use of deep learning techniques for analyzing retinal images to detect diseases, specifically DR. It employs CNNs to extract features from the retinal images, enabling classification into normal or affected categories. The approach involves multiple stages, such as preprocessing the retinal images to remove noise and enhance clarity, applying CNNs for hierarchical feature learning, and using dense layers for final classification. The model's performance is assessed using metrics like accuracy, sensitivity, and specificity [1].

```
# Step 1: Import Libraries
Import OpenCV, NumPy, TensorFlow/Keras, Matplotlib, Scikit-
    learn

# Step 2: Load Dataset
Load retinal images and labels from Kaggle dataset (
    ILOVESCIENCE).

# Step 3: Preprocess Data
FOR each image:
    Crop black frames and corners.
    Resize to (64, 64), convert to grayscale.
    Segment blood vessels using edge detection.
Split data into training (80%) and validation (20%).

# Step 4: Define Custom CNN
model = Sequential([
    Conv2D(32, (3, 3), activation='relu', input_shape=(64,
        64, 1)),
    MaxPooling2D((2, 2)),
    Conv2D(64, (3, 3), activation='relu'), MaxPooling2D((2,
        2)),
    Conv2D(128, (3, 3), activation='relu'), MaxPooling2D((2,
        2)),
    Conv2D(256, (3, 3), activation='relu'), MaxPooling2D((2,
        2)),
    Flatten(), Dense(512, activation='relu'), Dropout(0.5),
    Dense(5, activation='softmax')
])

# Step 5: Compile and Train
model.compile(optimizer=SGD(learning_rate=0.01),
              loss='categorical_crossentropy',
              metrics=['accuracy'])
history = model.fit(X_train, y_train,
                    validation_data=(X_val, y_val),
                    epochs=300, batch_size=32)

# Step 6: Evaluate and Predict
metrics = model.evaluate(X_val, y_val)
Print("Validation Accuracy:", metrics['accuracy'])
FOR test_image IN test_set:
    prediction = model.predict(Preprocess(test_image))
    predicted_class = ArgMax(prediction)

# Step 7: Post-Processing and Comparison
Generate confusion matrix and classification report.
Compare performance (accuracy, time) with ResNet50,
    DenseNet202, etc.

# Step 8: Save and Deploy
model.save("custom_cnn_dr_model.h5")
Deploy model via Flask/FastAPI for real-time predictions.
```

Listing Pseudocode for Custom CNN Model

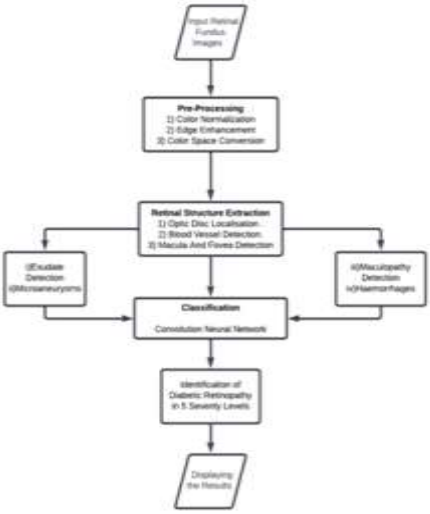

Figure 4: [1] Block diagram

4.2 DEEP LEARNING MODEL FOR CLASSIFICATION

Explores classification models for DR detection using supervised learning. The primary steps include collecting labeled retinal image datasets, applying prepro- cessing techniques such as normalization and augmentation, and training deep

Figure 5:[2] Overall Architecture for the system

learning models like CNNs or RNNs. The process integrates layers for detecting intricate patterns in the images, which are critical for accurate classification. Ensemble methods and cross-validation are used to improve model robustness. This study also compares the efficiency of different classification algorithms for this medical application [12].

The MAP Concordance Regressive Camargo's Index-Based Deep Multilayer Perceptive Learning Classification (MAPCRCI-DMPLC) is a deep learning-based technique for early detection of DR. The method consists of three key steps: (1) pre- processing using MAP-estimated local region filtering to enhance image quality by removing noise, (2) feature extraction via ROI extraction, Concordance Correlative Regression, and color space transformations, and (3) classification into DR stages using a Swish activation function. The model ensures high accuracy, low computational complexity, and robustness against noisy data.

```
# Input: Retinal fundus images {FI1, FI2, ..., FIn} from dataset
# Output: Classification of DR stages {Normal, Mild, Moderate,
    Severe, Proliferative}

# Step 1: Data Collection and Initialization
Load retinal fundus images from dataset.
Initialize model parameters (weights, biases) for input, hidden,
    and output layers.

# Step 2: Preprocessing (First Hidden Layer)
FOR each image FIi:
    - Apply MAP-estimated local region filtering:
        - Arrange pixels in ascending order within a filtering
          window.
        - Identify and remove noisy pixels based on pixel
          likelihood.
    - Output: Enhanced image with reduced noise.

```

```
# Step 3: ROI Extraction and Feature Extraction (Second Hidden
    Layer)
FOR each preprocessed image:
    - Apply Camargo's index for ROI extraction:
        - Identify infected regions using pixel similarity
          measures.
    - Extract texture features using Concordance Correlative
      Regression:
        - Calculate spatial relationships and texture
          characteristics.
    - Extract color features:
        - Transform RGB to HSV and extract hue, saturation, and
          value components.

# Step 4: Classification (Output Layer)
FOR each feature vector:
    - Apply Swish activation function:
        - Compute output using extracted features and weights.
        - Classify into DR stages based on activation thresholds

# Step 5: Optimization
- Compute classification error (er) using Mean Squared Error.
- Update weights using the Steepest Descent function to minimize
  error.

# Step 6: Evaluation
Evaluate model performance using metrics:
    - Accuracy
    - False Positive Rate (FPR)
    - Peak Signal-to-Noise Ratio (PSNR)
    - Time Complexity

# Step 7: Output
Output classification results and performance metrics.
```

4.3 AI-ASSISTED RETINAL IMAGING APPLICATIONS

Integrates AI techniques into retinal imaging systems for diagnosing systemic diseases, including DR, Glaucoma, Hypertension and Cataract. Automated image segmentation is used to identify regions of interest in the retina, followed by pattern recognition algorithms to detect abnormalities. The use of pre-trained AI models, fine-tuned with domain-specific datasets, enhances the diagnostic accuracy. This methodology also emphasizes real-time processing capabilities to support clinical decision-making[5].

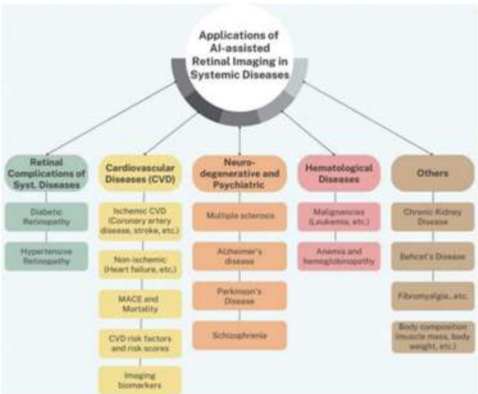

Figure 6:[5] Application of AI assisted Retinal Imaging in Systemic Diseases

4.4 VIT FOR SEVERITY PREDICTION

The VIT model is employed to predict the severity of DR from fundus images. This methodology takes advantage of self-attention mechanisms in transformers to analyze global and local patterns in images. The process includes training the model on a large dataset of labeled images, fine-tuning with specialized loss functions to handle imbalanced datasets, and validating performance using visual attention maps. The ViT model is shown to outperform traditional CNNs in capturing subtle differences between severity levels[7].

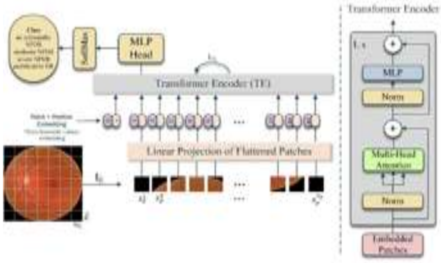

Figure 7: [7] ViT Architecture ; MLP is for Multi-Layer Perceptron

```
# Vision Transformer (ViT) Pipeline for Diabetic Retinopathy
    Severity Detection

# Step 1: Data Preprocessing
load_dataset(dataset_path)
normalize_images() # Normalize pixel values to ensure
    consistency
split_data(train=80%, validation=10%, test=10%)  # Split dataset

# Step 2: Data Augmentation
apply_augmentations(augmentations=[
    "horizontal_flip", "vertical_flip", "random_rotation",
    "brightness_adjustment", "contrast_adjustment", "
        saturation_adjustment"
])

# Step 3: Data Balancing
calculate_class_weights() # Assign weights to handle class
    imbalance
apply_label_smoothing() # Smooth labels to prevent
    overconfidence

# Step 4: Initialize ViT Model
initialize_ViT(patch_size=32, pretrained_weights="ImageNet21k")
add_dense_layers(layers=[128, 64, 32]) # Extra classifier layers
configure_hyperparameters(learning_rate=3e-4, optimizer="AdamW",
    epochs=100)

# Step 5: Model Training
for epoch in range(epochs):
    train_on_batch(train_data, loss_function="focal_loss",
        class_weights=calculated_weights)
    validate_on_batch(validation_data)
    log_metrics(epoch, accuracy, F1_score, etc.)

# Step 6: Testing and Evaluation
evaluate_model(test_data, metrics=["accuracy", "F1_score", "
    precision", "recall"])
generate_confusion_matrix(test_data)  # Visualize results

# Step 7: Explainability (Attention Maps)
generate_attention_map(test_image)# Highlight regions
    influencing predictions

#        End
save_trained_model(model_path)
```

Listing 1 ViT Pipeline for Diabetic Retinopathy Detection

5 RESULTS AND DISCUSSION

5.1 PERFORMANCE ANALYSIS

Table 1 provides a detailed performance analysis of various methods for detecting and analyzing DR using retinal imaging. It highlights key metrics like accuracy, sensitivity, specificity, and computational efficiency across models such as Decision Trees, CNNs, and Vision Transformers. Each approach's strengths—like enhanced feature extrac- tion, reduced false positives, and improved handling of data imbalances—are compared to alternative techniques, addressing challenges like dataset limitations and real- time implementation. While these models show promise, gaps remain in scalability, broader disease coverage, and computational demands, guiding future advancements in automated retinal disease detection[12].

Title	**Quantitative Analysis**	**Qualitative Analysis**	**Comparison with Alternatives**
Detecting Diabetic Retinopathy using Deep Learning	Decision Tree achieved 99.9% accuracy for grading microaneurysms.	Focused on decision tree, SVM, and KNN methods with image processing for lesion detection.	More specific lesion focus compared to others but lacks broader feature consideration.
Deep Learning Approach to Diabetic Retinopathy Detection	Achieved 94.45% accuracy (ILOVE-SCIENCE dataset); reduced computational complexity.	Utilized 3-layer CNN with hyperparameter tuning and feature extraction techniques.	Better computational efficiency but limited external dataset validation.
Deep learning model using classification for diabetic retinopathy detection: an overview	Reduced False Positive Rate by 35%-54%.	Focused on MAP Concordance Regressive Camargo's Index for classification with improved sensitivity and specificity.	Improved sensitivity but lacks real-time implementation capabilities.
Applications of AI-assisted retinal imaging in systemic diseases	Highlights accurate systemic disease detection but lacks metrics for performance.	Synthesized AI applications for systemic disease detection like kidney and cardiovascular risks.	Broader disease coverage but faces challenges in clinical validation and patient trust.
Systematic Development of AI-Enabled Diagnostic Systems for Glaucoma and Diabetic Retinopathy	Improved vessel segmentation accuracy and reduced computational complexity.	Explored image preprocessing and vessel segmentation with modified ColonSegNet model.	Focused on thin vessel detection but remains challenging in sparse annotated datasets.
Vision Transformer Model for Predicting the Severity of Diabetic Retinopathy	Achieved superior results using FGADR dataset with better severity classification.	Vision Transformer (ViT) model showcased enhanced feature extraction compared to conventional methods.	Requires large datasets for optimal performance; less accessible computationally.
Deep Learning for Diabetic Retinopathy Analysis: A Review	Improved image quality and algorithm optimization.	Provided insights into CNNs and inception models for DR detection with a focus on subtle disease features.	Rural implementation remains a challenge due to cost and dataset limitations.
Multitasking Deep Learning Model for Detection of Five Stages of Diabetic Retinopathy	Weighted Kappa scores: 0.90 (APTOS dataset), 0.88 (EyePACS dataset).	Combines classification and regression models for better handling of imbalanced datasets.	Multitasking capability outperforms traditional models but with higher training times.
Diabetic Retinopathy Diagnosis based on Convolutional Neural Network	Accuracy: 100% on DiaretDB0, 99.495% on DiaretDB1, 97.55% on DrimDB.	Employed CNN with preprocessing via CLAHE for enhanced visibility of retinal features.	Achieved high accuracy but lacks coexisting disease considerations and real-time deployment.
Diabetic Retinopathy Detection through Deep Learning Techniques: A Review	CNN architectures achieved superior accuracy but highlighted transfer learning limitations.	Discussed CNN architectures and transfer learning effectiveness.	Transfer learning is useful for small datasets but custom CNNs provide higher accuracy when datasets are available.

Table 1 Performance analysis of various methodologies for Diabetic Retinopathy detection.

6. COMPARATIVE ANALYSIS

Table 2 compares various technologies for DR detection, each with its own strengths and limitations. The VIT model excels in capturing long-range dependencies and addressing imbalanced datasets, but has high computational cost. The Multitasking Deep Learning Model (MXception) introduces a novel approach using both classifi- cation and regression, improving accuracy but limited by training time. The Tandem PCNN with Deep Learning-based SVM (DLBSVM) efficiently extracts blood vessels and boasts high accuracy, but requires parameter tuning. The Custom CNN with 4 Layers achieves high accuracy with low complexity, yet potential for generaliza- tion exists. The CNN for Diabetic Retinopathy Diagnosis demonstrates high accuracy in binary classification, but its evaluation metrics and dataset diversity are limited. Zoom-in-Net effectively diagnoses DR and highlights suspicious regions, but the res- olution of attention maps can be improved. AI-assisted Retinal Imaging for Systemic Diseases provides a non-invasive and effective tool for diagnosis, but data limitations need to be addressed. The Modified ColonSegNet for Retinal Vessel Segmentation offers high accuracy and low complexity, but detecting very thin vessels remains a challenge[10].

Technology	Accuracy	Sensitivity	Specificity	Strengths	Limitations
Vision Transformer (ViT).	0.825	0.825	0.956	Captures long-range dependencies in images, addresses imbalanced datasets, validated on unseen test data, compared against state-of-the-art models.	High computational cost.
Multitasking Deep Learning Model (MXception).	0.86 (APTOS), 0.82 (EyePACS)	0.76 (APTOS), 0.64 (EyePACS)	Not reported	Novel approach using multitasking (one classification and one regression model), improved accuracy compared to single-task models.	Limited by dataset comprehensiveness and training time.
Tandem PCNN and Deep Learning-based SVM (DLB-SVM).	0.9949	0.8061	0.9954	Efficiently extracts blood vessels from pathological fundus images, high accuracy, fast execution.	Limited by the need for parameter tuning and potential for improvement in handling tiny vessels.
Custom CNN with 4 Layers.	0.9445	0.9351	0.943	High accuracy, low computational complexity, fast training and testing.	Potential for improvement as a more generalized model by training on diverse datasets.
CNN for Diabetic Retinopathy Diagnosis.	0.9755 to 100.	Not reported	Not reported	High accuracy in detecting and classifying healthy and unhealthy retina images.	Limited evaluation metrics and potential for improvement by training on more datasets.
Zoom-in-Net.	Up to 0.957 (AUC)	Not reported	Not reported	Simultaneously diagnoses diabetic retinopathy and highlights suspicious regions, high accuracy, good localization ability.	Limited by the resolution of attention maps and potential for improvement in localization precision.
AI-assisted Retinal Imaging for Systemic Diseases.	Variable, up to 0.98 (AUROC)	Variable	Variable	Non-invasive, effective in diagnosing and managing systemic diseases with retinal involvement, early identification of individuals at risk.	Limited by data poverty and potential for diagnostic inaccuracies and suboptimal treatment plans.
Modified ColonSegNet for Retinal Vessel Segmentation.	0.9669 to 0.9723	0.8391 to 0.8671	0.9792 to 0.9812	High accuracy, lightweight deep neural network model, effective in detecting thin vessels, low computational complexity.	Potential for improvement in accurately detecting very thin vessels.

Table 2 Comparison of technologies based on accuracy, sensitivity, specificity, strengths, and limitations.

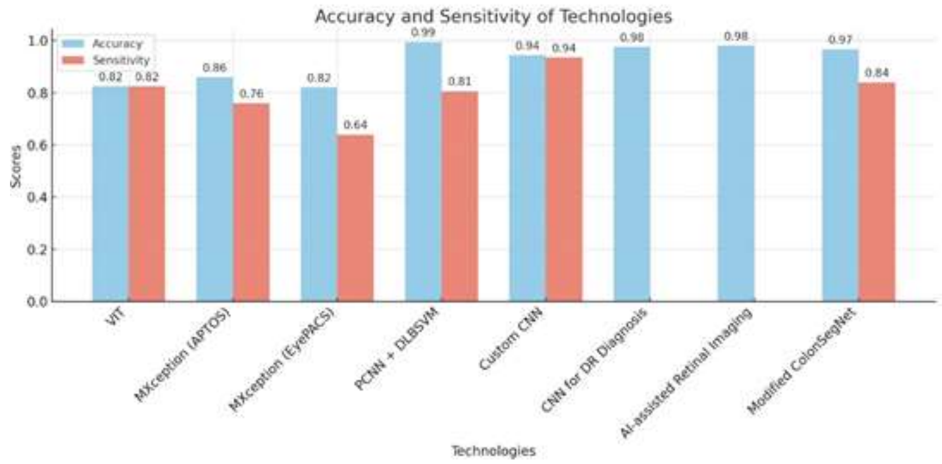

Figure 8: Comparing various technologies to Detect Diseases through eyes

6.1 CHALLENGES AND LIMITATIONS

The reviewed literature highlights significant advancements in applying deep learning and artificial intelligence to retinal disease detection, showcasing innovative method- ologies such as CNNs, Vision Transformers, and multitasking models. While these approaches demonstrate promising accuracy and efficiency, common challenges persist, including limited dataset diversity, lack of external validation, computational com- plexity, and difficulties in real-world implementation. Issues like thin vessel detection, subtle feature recognition, and generalization across diverse clinical settings further constrain their applicability. Addressing these limitations requires robust datasets, enhanced algorithmic frameworks, and practical deployment strategies to bridge the gap between theoretical research and clinical utility.

The literature on retinal disease detection showcases significant advancements in leveraging Artificial Intelligence (AI) and Machine Learning (ML) techniques for diag- nosing conditions like Diabetic Retinopathy (DR) and Glaucoma. A custom 3-layer CNN model achieved 94.45% accuracy, although its reliance on a single dataset and lack of external validation limit its generalizability [1]. Similarly, a classification model based on MAP Concordance Regressive Camargo's Index demonstrated reductions in false positives but faced challenges with larger datasets and real-time applications [2]. Traditional ML algorithms such as Support Vector Machines and Decision Trees achieved high accuracy in detecting specific lesions, but these approaches struggled to incorporate diverse pathological features and adapt to real-time systems [3].

Advanced methods also revealed potential and challenges. AI applications in retinal imaging highlighted the need for greater clinical validation, data diversity, and accep- tance in clinical practice [5]. Enhanced image segmentation techniques using modified ColonSegNet showed promise, though issues such as thin vessel detection and limited annotated data persist [6]. The Vision Transformer model demonstrated effectiveness with detailed datasets but requires further optimization for diverse settings [7]. While multitasking deep learning models improved detection accuracy, they encountered difficulties with training time and generalization across datasets [9]. Other studies emphasized the necessity of broader dataset coverage and consideration of multi-disease detection for improved clinical applicability [10,11]. Collectively, these findings underline the transformative potential of AI in retinal diagnostics while emphasiz- ing critical areas for improvement, such as dataset diversity, clinical validation, and deployment scalability.

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