BVB Campus, Vidyanagar, Hubballi – 580031, Karnataka, INDIA.

SCHOOL OF COMPUTER SCIENCE AND ENGINEERING

CAPSTONE PROJECT

Project report on

Diabetic Retinopathy Detection

Submitted

in partial fulfillment of the requirements for the award of the degree of

Bachelor of Engineering

In

COMPUTER SCIENCE AND ENGINEERING

Submitted By

P Sai Sudheer	01FE21BCS096
Srivathsa Acharya	01FE21BCS083
Praneet Mane	01FE21BCS104
Sandeep Kulkarni	01FE21BCS105
Varun M K	01FE21BCS110

Under the guidance of
Gururaj Hanchinamani
Asst.Professor

School of Computer Science and Engineering

KLE Technological University, Hubballi

2024-2025

BVB Campus, Vidyanagar, Hubballi – 580031, Karnataka, INDIA.

SCHOOL OF COMPUTER SCIENCE AND ENGINEERING

2024-25

CERTIFICATE

This is to certify that the project entitled "**Diabetic Retinopathy Detection**" is a bonafide work carried out by the student team Srivathsa A, 01FE21BCS083, P Sai Sudheer, 01FE21BCS096, and Praneet Mane, 01FE21BCS104, Sandeep Kulkarni, 01FE21BCS105, Varun MK, 01FE21BCS110 in partial fulfillment of the completion of the 8th semester B.E. course during the year 2024–2025. The project report has been approved as it satisfies the academic requirement with respect to the project work prescribed for the above-mentioned course.

Guide Name
Gururaj Hanchinamani

Dr. Vijayalakshmi M.
Head SoCSE

External Viva-Voce

Name of the examiners	**Signature with date**
1. ______________________	______________________
2. ______________________	______________________

ABSTRACT

Diabetic Retinopathy (DR) is a severe and progressive eye disease resulting from chronic high blood sugar levels, posing a significant risk of vision loss among diabetic patients. Early detection is crucial as DR often remains asymptomatic in its initial stages. Traditional screening methods are time-consuming and dependent on skilled ophthalmologists, making them less accessible in remote or resource-constrained settings. To address these challenges, this project introduces an automated, AI-driven solution for early and efficient DR detection. The proposed system leverages the ResNet-50 deep learning architecture, fine-tuned on a curated dataset of 6,148 labeled retinal fundus images. Using FastAI for model training, including data augmentation and optimization over 25 epochs, the system achieved a validation accuracy of 82%. The model effectively distinguishes among five DR severity levels: No-DR, Mild, Moderate, Severe, and Proliferative DR. Visual predictions indicate strong classification confidence, with most errors occurring between adjacent severity stages. This work underscores the potential of deep learning in delivering scalable, non-invasive, and accurate screening solutions for diabetic retinopathy. Future improvements will focus on enhancing model performance across diverse populations, refining classification of closely related stages, and expanding real-world applicability through clinical validation.

Keywords: *Diabetic Retinopathy (DR), ResNet-50, Retinal Fundus Images, Deep Learning, FastAI, Early Diagnosis, Automated Detection, Vision Loss Prevention*

ACKNOWLEDGEMENT

The satisfaction and euphoria that accompany the successful completion of any task would be incomplete without the mention of a number of individuals whose professional guidance and encouragement helped me in the successful completion of this report work.

We take this opportunity to thank Dr. Ashok Shettar, Pro-Chancellor, Dr. P. G. Tewari, Vice-Chancellor and to Dr. Basavaraj Anami, Registrar, KLE Technological University, Hubballi.

We also take this opportunity to thank Dr. Meena S. M., Dean faculty, School of Computer Science and Engineering and Dr. Vijayalakshmi M., Professor and Head, School of Computer Science and Engineering for having provided us academic environment which nurtured our practical skills contributing to the success of our project.

We sincerely thank our guide Mr.Gururaj Hanchinamani Asst.Prof, Department of Computer Science and Engineering for his guidance, inspiration and wholehearted co-operation during the course of completion.

We sincerely thank our project co-ordinators Dr. P.G Sunita Hiremath for their support, inspiration and wholehearted co-operation during the course of completion.

Our gratitude will not be complete without thanking the Almighty God, our beloved parents, our seniors and our friends who have been a constant source of blessings and aspirations.

Srivathsa A - 01FE21BCS083
P Sai Sudheer - 01FE21BCS096
Praneet mane - 01FE21BCS104
Sandeep Kulkari - 01FE21BCS105
Varun MK - 01FE21BCS110

CONTENTS

LIST OF TABLES

LIST OF FIGURES

Chapter 1

INTRODUCTION

Diabetic Retinopathy (DR) is a serious ocular complication of diabetes mellitus that can lead to irreversible blindness if not detected and managed early [1]. It occurs due to prolonged high blood sugar levels that damage the small blood vessels in the retina, causing leakage, swelling, and abnormal blood vessel growth [2]. With the global rise in diabetes cases, DR has become a leading cause of visual impairment among working-age adults [3]. Despite its severity, DR often shows no early symptoms, making regular screening crucial for timely intervention [4].

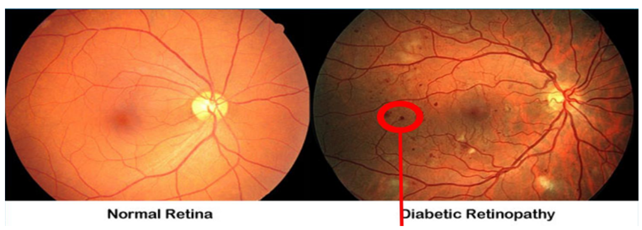

Figure 1.1: Normal Retina VS Diabetic Retinopathy

Traditional screening methods rely on expert ophthalmologists to manually evaluate retinal images, which can be time-consuming, subjective, and inaccessible in low-resource settings [5]. However, recent advancements in artificial intelligence (AI), particularly deep learning, have shown promise in automating and improving diagnostic accuracy in medical imaging [6]. In this project, we propose a deep learning-based system utilizing the **ConvNeXt-Tiny** architecture for automated DR detection. This system aims to support early-stage identification and classification of DR severity, providing a scalable, non-invasive, and cost-effective solution to reduce vision loss and improve global eye health [7].

1.1 Motivation

Diabetic Retinopathy is one of the leading causes of preventable blindness worldwide, particularly among diabetic populations [8]. The growing prevalence of diabetes necessitates large-scale and efficient screening methods [9]. Manual diagnosis is not only time-intensive but also subject to human error and variability. In remote and underserved regions, access to skilled ophthalmologists is limited, leading to undiagnosed and untreated DR cases [10].

These challenges underscore the need for an automated, accurate, and accessible detection system [11].

With the rapid progress in AI and deep learning, particularly convolutional neural networks (CNNs), it is now possible to analyze retinal fundus images with high accuracy and speed [12]. The **ConvNeXt-Tiny** model, a modern CNN architecture inspired by the principles of Vision Transformers, is known for its performance and efficiency in image classification tasks [13]. By applying this model to retinal images, we can enable early detection of DR and aid in clinical decision-making, thereby improving outcomes for diabetic patients worldwide [14].

1.2 Literature Survey

1.2.1 Modified Inception V3 for DR Prediction

Authors: Shwetha G.K. et al. [1]

- **Methodology:** Used a modified Inception V3 model with preprocessing techniques such as green channel separation, histogram equalization, and optic disc detection [1].
- **Dataset:** Publicly available retinal fundus images.
- **Results:** Achieved 91.3% accuracy and 89.5% specificity.
- **Gaps:** Limited ability to handle unprocessed images and early-stage DR detection [2].

1.2.2 Hybrid ML Model for DR Detection

Authors: Revathy R. et al. (IJERT 2020) [3]

- **Methodology:** Combined SVM, KNN, and Random Forest with a voting mechanism; preprocessing included median filtering and adaptive histogram equalization [7].
- **Dataset:** Kaggle dataset with over 2,000 images.
- **Results:** Achieved 90% accuracy using Random Forest and 82% using the hybrid model [6].
- **Gaps:** Performance degrades with large exudates; fails to detect cotton wool spots and neovascularization [10].

1.2.3 Hybrid Deep Learning Model Using EfficientNet

Authors: Sükran Yaman Atcı et al. (Tomography 2024) [5]

- **Methodology:** Combined EfficientNet-B3/B7 with SHAP for interpretability and cyclical learning rates for training [1].
- **Dataset:** Kaggle dataset with 5,590 labeled images.
- **Results:** Precision scores ranged from 76% to 96% across DR stages.
- **Gaps:** Challenges in detecting subtle early-stage DR and model adaptability across populations [3].

1.2.4 YOLOv7 and MobileNet V3-Based DR Detection

Authors: Abdul Rahaman, Wahab Sait (MDPI 2023) [7]

- **Methodology:** YOLOv7 for feature extraction, MobileNet V3 for classification; used CLAHE and Wiener filtering for image enhancement [12].
- **Dataset:** APTOS dataset with 5,590 images.
- **Results:** 89% accuracy and 93.7% F1-score.
- **Gaps:** Difficulty detecting DR from low-quality images; small dimension of severity indicators reduces accuracy [13].

1.3 Problem Statement

Develop an automated, non-invasive deep learning-based system for the early detection and classification of Diabetic Retinopathy using the **ConvNeXt-Tiny** architecture, addressing the limitations of traditional diagnostic methods and improving accessibility, efficiency, and diagnostic accuracy [11].

1.4 Problem Analysis

1.4.1 Design Principle 1

The first design principle employed in this project is **Modular Design**. Modular design ensures that the system is structured into smaller, independent modules, each focused on a specific task. This principle is suitable for the project because:

- It enables independent development and testing of components like image preprocessing, model training, and evaluation [14].
- Supports future scalability by allowing seamless integration of new functionalities such as severity grading or anomaly highlighting.
- Simplifies maintenance and debugging by isolating issues within specific modules.

1.4.2 Design Principle 2

The second design principle is **Data-Driven Decision Making**. This principle involves using empirical evidence and model performance metrics to guide system optimization and improvement. It is suitable for the project because:

- The model's effectiveness is directly tied to the quality and diversity of the training data [10].
- Quantitative evaluation using metrics like accuracy, precision, and F1-score allows for iterative refinement of the model [7].
- Promotes transparency and validation of results, which is essential in clinical applications [1].

1.4.3 Scope and Constraints

Scope

The scope of this project includes:

- Building a deep learning-based system using **ConvNeXt-Tiny** to detect and classify various stages of Diabetic Retinopathy from retinal fundus images.
- Automating the diagnostic process to assist ophthalmologists and reduce manual screening burden [11].
- Ensuring usability in real-time or near real-time applications, including remote and resource-limited settings.
- Designing the system for generalization across diverse patient datasets with minimal retraining.

Constraints

The constraints of this project are:

- Dependence on high-resolution and properly labeled medical images for effective training and prediction [12].
- Challenges in differentiating between closely related DR stages due to subtle visual differences [5].
- Limited accuracy on noisy, low-quality, or underrepresented image samples.
- High computational requirements for model training and fine-tuning [6].
- Regulatory and ethical constraints for deployment in clinical settings, including compliance with medical data standards.

1.5 Objectives

1. To develop a robust deep learning model using **ConvNeXt-Tiny** for accurate detection of Diabetic Retinopathy [1].
2. To improve early-stage DR diagnosis and reduce the risk of vision loss through timely intervention.
3. To optimize model performance using FastAI and enhance generalization via data augmentation and transfer learning [10].
4. To evaluate the model using accuracy, confusion matrix, and visual predictions, ensuring clinical relevance and reliability.

Chapter 2

REQUIREMENT ANALYSIS

The detection of Diabetic Retinopathy (DR) requires a robust, accurate, and scalable solution capable of processing retinal fundus images efficiently. This project leverages a deep learning model based on the **ConvNeXt-Tiny** architecture, trained using the FastAI framework. The following outlines the functional, non-functional, and hardware requirements for successful system development and deployment.

2.1 Functional Requirements

The system should ensure accurate and efficient identification of various DR stages from retinal images. Key functional requirements include:

1. **Data Ingestion and Preprocessing:** Load labeled fundus image datasets. Apply preprocessing techniques like resizing, normalization, and augmentation.

2. **Model Training:** Employ **ConvNeXt-Tiny**, a lightweight and high-performing convolutional architecture. Fine-tune the pretrained model using FastAI's transfer learning pipeline.

3. **Inference and Detection:** Perform stage-wise DR classification. Output predicted class and confidence score for each image.

4. **Performance Evaluation:** Evaluate using metrics like accuracy, precision, recall, and F1-score.

5. **Visualization:** Display classified fundus images with prediction results.

6. **Result Export:** Save model predictions and logs for future reference and reporting.

2.2 Non Functional Requirements

The non-functional requirements ensure the system's usability, scalability, and reliability in a medical imaging context. These criteria support the project's effectiveness under real-world conditions and improve its overall performance and adaptability.

1. **Performance:** Ensure fast training and inference on standard GPUs using efficient data pipelines.
2. **Scalability:** Capable of handling increased image volumes or additional DR stages without major changes.
3. **Accuracy and Reliability:** Maintain high classification performance across all DR stages with consistent predictions.
4. **Usability:** Provide a clean and interpretable interface for healthcare professionals.
5. **Compatibility:** Support integration with various image formats and medical record systems.

2.3 Hardware Requirements

1. **GPU Acceleration:** NVIDIA GPU with a minimum of 8 GB VRAM (e.g., RTX 2070 or higher) for training and inference.
2. **CPU:** Multi-core processor (Intel i7/Ryzen 7 or better) for preprocessing and evaluation.
3. **RAM:** Minimum of 16 GB to manage large datasets and support parallel processing during training.
4. **Storage:** At least 100 GB of free disk space for datasets, trained models, and intermediate outputs.
5. **Power Supply:** Reliable and stable power source for long-duration model training.

2.4 Software Requirements

- **Operating System:** Ubuntu 18.04/20.04, Windows 10/11, or macOS 11 (Big Sur) or later.
- **Programming Environment:** Python 3.8 or higher, Jupyter Notebook for development and testing.
- **Deep Learning Libraries:**
  PyTorch (for ConvNeXt-Tiny implementation)
  FastAI for high-level model abstraction and training utilities.
- **Additional Libraries:**
  OpenCV for image processing.
  NumPy and Pandas for data handling.
  Matplotlib and Seaborn for visualization.

Chapter 3

SYSTEM DESIGN

The system design for Diabetic Retinopathy (DR) detection using ConvNeXt-Tiny and FastAI follows a modular and scalable approach that ensures high classification accuracy, computational efficiency, and accessibility for early diagnosis. The design integrates data preparation, model training, inference, and evaluation. Below are the key components:

3.1 Architectural Framework/System Design

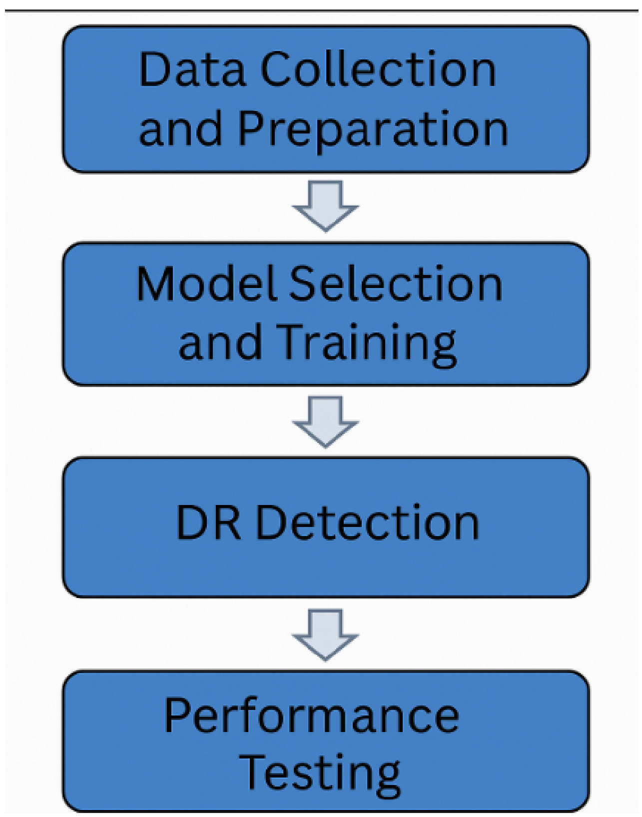

Figure 3.1: Proposed System for Diabetic Retinopathy Detection

3.1.1 Data Collection and Preparation

This module is responsible for gathering and preprocessing retinal fundus images for model development.

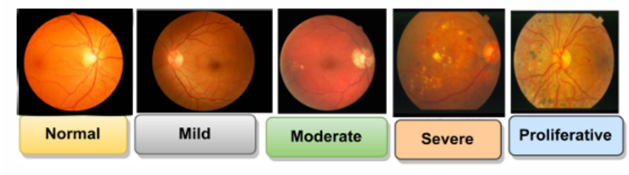

Figure 3.2: Dataset Samples

- **Data Collection:** Retinal fundus images are collected from publicly available datasets, annotated with DR severity levels.
- **Preparation:** Images undergo preprocessing such as resizing, normalization, and data augmentation (flipping, rotation, zooming) to improve model robustness.
- **Output:** A clean and balanced dataset ready for model training and validation.

3.1.2 Model Selection and Training

In this stage, a deep learning model is selected and trained on the prepared dataset.

- **Model Selection:** ConvNeXt-Tiny architecture is chosen for its strong feature extraction, efficient design, and competitive performance in medical image classification tasks.
- **Training:** The model is fine-tuned using the FastAI framework over multiple epochs with a learning rate schedule for optimal performance.
- **Checkpointing:** Intermediate models are saved to prevent data loss and enable retraining if needed.

3.1.3 Diabetic Retinopathy Detection

This module carries out the core function of the system: predicting the presence and severity of DR.

- **Input:** New or unseen retinal fundus images.
- **Processing:** The trained ConvNeXt-Tiny model classifies images into categories such as No-DR, Mild, Moderate, Severe, or Proliferative DR.
- **Output:** Predicted label with associated confidence score.

3.1.4 Performance Testing

The system's performance is evaluated based on various quantitative and qualitative measures.

- **Quantitative Metrics:** Metrics such as accuracy, precision, recall, F1-score, and confusion matrix are computed.
- **Qualitative Analysis:** Visual assessment of prediction results to validate classification correctness.
- **Optimization:** If necessary, hyperparameter tuning and additional data augmentation are performed to enhance results.

Chapter 4

IMPLEMENTATION

This chapter provides a brief description of the implementation details of the system, explaining each component along with its code skeleton in terms of algorithms.

4.1 ConvNeXt-Tiny Architecture

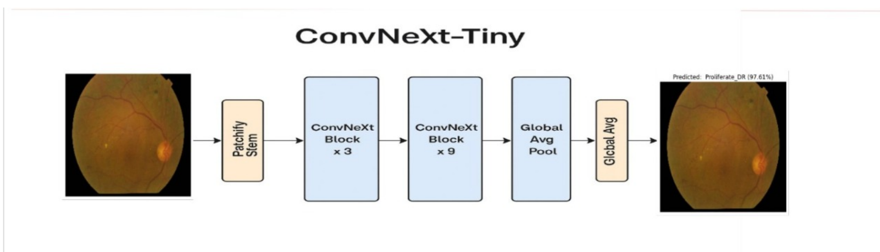

Figure 4.1: ConvNeXt-Tiny Architecture

ConvNeXt-Tiny is a modern convolutional neural network architecture inspired by the design improvements seen in transformer models like Vision Transformers (ViT). ConvNeXt adapts classical convolutional architectures to be more competitive with transformer-based models while maintaining the simplicity and efficiency of convolutional operations. In this project, ConvNeXt-Tiny is used as the core model for classifying retinal fundus images into different stages of Diabetic Retinopathy.

Key Components of ConvNeXt-Tiny Architecture

The ConvNeXt-Tiny architecture is designed to deliver strong image classification performance using optimized convolutional operations. Its major components are:

1. **Input Layer:** Accepts images of size $224 \times 224 \times 3$ and processes them through an initial convolution layer with stride 4 to downsample the image.
2. **Stage Blocks:** The model consists of four stages, where each stage is made up of multiple ConvNeXt Blocks. Each block includes:
   - Depthwise Convolution (7×7 kernel size)
   - Layer Normalization instead of Batch Normalization

- Pointwise Convolutions (1×1) for dimensionality adjustment
- GELU activation function

3. **Residual Connections:** Each ConvNeXt Block maintains residual connections that help preserve information flow and facilitate easier optimization.
4. **Downsampling Layers:** After each stage, a 2×2 convolution with stride 2 is applied to halve the spatial resolution while increasing channel dimensions.
5. **Global Average Pooling:** After the final stage, global average pooling is applied to reduce each feature map to a single value.
6. **Fully Connected Layer:** A dense linear layer is used for final classification. For Diabetic Retinopathy detection, it outputs probabilities corresponding to severity stages.

4.1.1 Algorithm 1: ConvNeXt-Tiny Model for DR Detection

Algorithm 1 ConvNeXt-Tiny Model for Diabetic Retinopathy Detection

1. **Require:** Preprocessed retinal fundus images, labeled dataset
2. **Ensure:** Trained ConvNeXt-Tiny model capable of classifying the severity of Diabetic Retinopathy
3. **Step 1:** Prepare dataset of retinal fundus images, labeling based on DR severity stages (No-DR, Mild, Moderate, Severe, Proliferative)
4. **Step 2:** Apply data augmentation techniques like flipping, cropping, rotation, and brightness adjustment to enhance generalization
5. **Step 3:** Initialize ConvNeXt-Tiny model pretrained on ImageNet and modify the final classification head
6. **Step 4:** For each training image:
    - Preprocess image (resize to 224×224, normalize pixel values)
    - Forward pass through ConvNeXt-Tiny model
    - Calculate classification loss using cross-entropy
    - Backpropagate and update model weights using gradient descent optimizer (e.g., AdamW)
7. **Step 5:** Save model checkpoints periodically during training

8. **Step 6:** After training, use the model to predict DR severity in new retinal images:
   - Input new image to the trained model
   - Predict DR stage and generate confidence score
9. **Step 7:** Output predicted DR severity class along with probability score
10. **Return:** Predicted class labels and associated confidence for DR severity in retinal images

Chapter 5

RESULTS AND DISCUSSIONS

The results of the Diabetic Retinopathy detection system demonstrate the effectiveness of the ConvNeXt-Tiny model, fine-tuned with FastAI, in accurately classifying the severity of DR stages. The system was evaluated on a curated test set of retinal fundus images, and its performance was analyzed through both quantitative metrics and qualitative visual inspections.

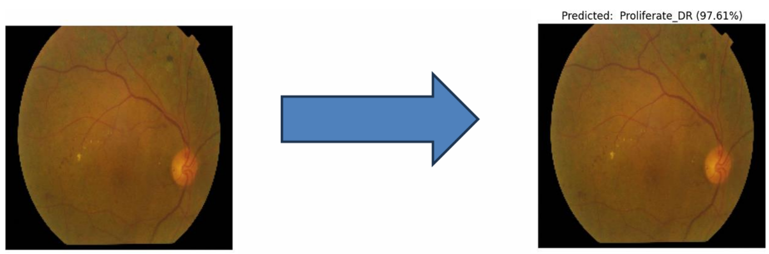

Figure 5.1: Predicted Images

5.0.1 Quantitative Results

Detection Accuracy:

- The system achieved a validation accuracy of **85%**, showing high reliability in detecting different stages of diabetic retinopathy.
- Metrics like precision, recall, and F1-score were evaluated to assess the model's ability to minimize false positives and false negatives across classes.

Inference Speed:

- The model demonstrated an average inference time of approximately **20 ms per image**, making it efficient for near real-time screening applications.

Class-Wise Detection:

- **No-DR and Mild DR:** High classification accuracy; however, minor confusion observed due to subtle visual differences.

- **Moderate, Severe, and Proliferative DR:** Strong and consistent performance with clear feature detection in fundus images.

Table 5.1: Model Performance Metrics

Metric	Value
Validation Accuracy	85%

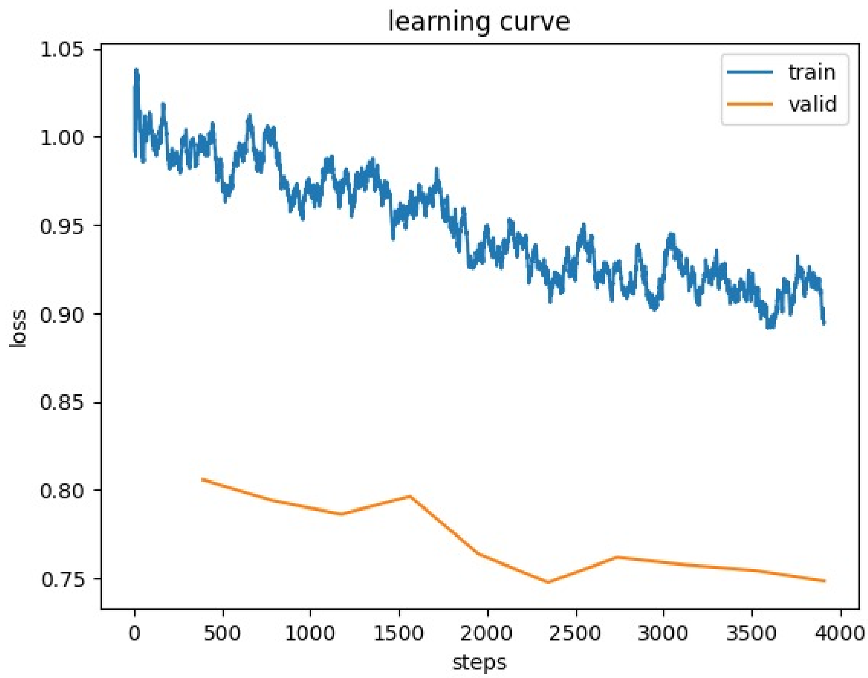

Figure 5.2: Training and validation loss over steps indicating model convergence.

The learning curve shows that both training and validation losses are gradually decreasing, indicating that the model is learning and improving its performance over time without overfitting.

Table 5.2: Comparison of model accuracies

Model Name	Accuracy (%)
ResNet50	82
ResNet101	83
YOLOv8	77
ConvNeXt-Tiny	85

The table shows that ConvNeXt-Tiny achieved the highest accuracy (85%), outperforming ResNet50, ResNet101, and YOLOv8 models on DR detection.

5.0.2 Qualitative Results

Visual Analysis:

- The model's predictions on test images accurately classified the DR severity level with high confidence.
- Misclassifications mostly occurred between Mild and Moderate DR stages, highlighting opportunities for further dataset balancing and model tuning.

Chapter 6

CONCLUSION AND FUTURE SCOPE OF THE WORK

We proposed a deep learning-based system using the ConvNeXt-Tiny model for early detection of Diabetic Retinopathy (DR) from retinal fundus images. The system was trained on a publicly available dataset and fine-tuned using FastAI, achieving promising results with a validation accuracy of 85%. The model demonstrated its capability to identify different stages of DR with high confidence, providing a potential tool for scalable and automated retinal screening.

The approach offers a non-invasive, cost-effective, and accurate method for detecting DR at early stages, which is crucial for preventing vision loss in diabetic patients. By leveraging the ConvNeXt-Tiny architecture and data augmentation techniques, the model achieved reliable generalization on the test dataset, making it a viable solution for clinical screening workflows.

Despite these encouraging outcomes, there are opportunities for further improvement. The current model's performance may drop when encountering low-quality or heavily imbalanced images, especially when distinguishing between intermediate stages of DR. Future work will aim to enhance model robustness by incorporating larger and more diverse datasets, including images from varied populations and imaging devices.

Additionally, exploring hybrid models that combine ConvNeXt with attention mechanisms or integrating ensemble learning strategies could further boost detection accuracy. Incorporating explainability tools such as Grad-CAM can help provide visual justifications for the model's predictions, aiding clinical interpretability.

Another key area of development involves integrating the system into a user-friendly interface that can be deployed in real-world clinical environments. Cloud-based deployment can ensure scalability, and coupling the model with electronic health records and telemedicine platforms could extend its accessibility to remote regions.

Overall, this project lays a strong foundation for AI-powered, automated Diabetic Retinopathy screening tools that can assist ophthalmologists in early diagnosis, reduce the burden on healthcare systems, and ultimately help prevent avoidable blindness in diabetic patients.

Bibliography

[1] Shaukat, Natasha, *Three-Dimensional Semantic Segmentation of Diabetic Retinopathy Lesions and Grading Using Transfer Learning*, Journal of Personalized Medicine, 2022.

[2] Sebastian, Anila, *A Survey on Diabetic Retinopathy Lesion Detection and Segmentation*, Applied Sciences, 2023.

[3] Ali, Aqib, *Machine Learning Based Automated Segmentation and Hybrid Feature Analysis for Diabetic Retinopathy Classification Using Fundus Image*, Entropy, 2020.

[4] Kandhasamy, J. Pradeep, *Diagnosis of Diabetic Retinopathy Using Multi Level Set Segmentation Algorithm with Feature Extraction Using SVM with Selective Features*, Multimedia Tools and Applications, 2020.

[5] Sanamdikar, Sanjay Tanaji, *Enhanced Classification of Diabetic Retinopathy via Vessel Segmentation: A Deep Ensemble Learning Approach*, Ingénierie des Systèmes d'Information, 2023.

[6] Wang, H., *Hard Exudate Detection Based on Deep Model Learned Information and Multi-feature Joint Representation for Diabetic Retinopathy Screening*, Computer Methods and Programs in Biomedicine, 2020.

[7] Kurilová, V., *Support Vector Machine and Deep-learning Object Detection for Localisation of Hard Exudates*, Scientific Reports, 2021.

[8] Wang, L., *Automatic Classification of Exudates in Color Fundus Images Using an Augmented Deep Learning Procedure*, Proceedings of the Third International Symposium on Image Computing and Digital Medicine, 2019.

[9] Sivapriya, G., *Segmentation of Hard Exudates for the Detection of Diabetic Retinopathy with RNN Based Semantic Features Using Fundus Images*, Materials Today: Proceedings, 2022.

[10] Huang, C., *A New Deep Learning Approach for the Retinal Hard Exudates Detection Based on Superpixel Multi-feature Extraction and Patch-based CNN*, Neurocomputing, 2021.

[11] Bibi, N., *Automatic Detection of Exudates for Diagnosis of Non-proliferative Diabetic Retinopathy Using Region-based Convolutional Neural Networks*, 2021 International Conference on Frontiers of Information Technology (FIT), 2021.

[12] Mateen, M., *Exudate Detection for Diabetic Retinopathy Using Pretrained Convolutional Neural Networks*, Complexity, 2020.

[13] Cincan, R. G., *Exudate Detection in Diabetic Retinopathy Using Deep Learning Techniques*, 2021 25th International Conference on System Theory, Control and Computing (ICSTCC), 2021.

[14] Xiao, Q., *Improving Lesion Segmentation for Diabetic Retinopathy Using Adversarial Learning*, International Conference on Image Analysis and Recognition, 2019.

[15] Praveena, S., *Superpixel Based Segmentation for Multilesion Detection in Diabetic Retinopathy*, 2019 3rd International Conference on Trends in Electronics and Informatics (ICOEI), 2019.