Diabetic Retinopathy Level Detection Project Report

Project Overview

Diabetic Retinopathy (DR) is one of the leading causes of blindness among individuals with diabetes. Early detection and classification of its severity can significantly improve patient outcomes by enabling timely medical intervention. This project focuses on developing a machine learning model that leverages deep learning techniques to classify diabetic retinopathy levels accurately. By automating the screening process, the project aims to assist healthcare professionals and make diagnostics more accessible in resource-limited settings.

Objectives

1. Detect and classify the severity of Diabetic Retinopathy into five distinct levels.
2. Build an automated tool that can complement traditional diagnostic methods.
3. Use transfer learning to enhance model performance while keeping computational costs manageable.

Methodology

Dataset

- **Source**: Kaggle dataset for Diabetic Retinopathy detection and classification.
- **Data Split**:
    - **Training set**: 3,662 images
    - **Testing set**: 734 images
- **Classes**:
    - **0**: No DR
    - **1**: Mild DR
    - **2**: Moderate DR
    - **3**: Severe DR
    - **4**: Proliferative DR

Data Preprocessing

1. **Image Augmentation**:

    - Rescaling pixel values for normalization.
    - Applying shear transformations.
    - Random zoom for generalization.
    - Horizontal flipping for variation.
2. **Image Resizing**:
    - Standardized all images to **299x299 pixels** for uniformity.
3. **Efficient Data Handling**:
    - Utilized **Keras ImageDataGenerator** to streamline preprocessing and augmentation.

Model Architecture

The model employs **transfer learning** using the **Xception** architecture, a powerful deep convolutional neural network pre-trained on ImageNet.

Details of Model Architecture:

1. **Base Model**:
    - Xception CNN, pre-trained on ImageNet weights.
    - Acted as a feature extractor for high-level features.
2. **Custom Layers**:
    - Flattening layer.
    - Fully connected dense layers.
    - Final output layer with **softmax activation** for multi-class classification (5 levels).
3. **Training Configuration**:
    - **Loss Function**: Categorical Cross-Entropy.
    - **Optimizer**: Adam optimizer for faster convergence.
    - **Metrics**: Accuracy.
    - **Batch Size**: 32.
    - **Epochs**: 30 for steady learning progression.

Performance Insights

Training Progression

- **Initial Performance**:
    - Epoch 1 training accuracy: **35.81%**.
    - Epoch 1 validation accuracy: **50.14%**.
- **Peak Performance**:
    - Achieved a **highest validation accuracy of 73.71%** in later epochs.

Learning Characteristics:

- Gradual improvement over time with some fluctuations in validation performance.
- Consistent upward trend in learning curve, demonstrating effective model training.

Model Saving and Deployment

- Final model saved as: **"Updated-Xception-diabetic-retinopathy.h5"**.
- Future-ready for integration into a cloud-based database system, such as **IBM Cloudant**, for efficient storage and accessibility.

Technological Stack

- **Programming Language**: Python.
- **Deep Learning Framework**: TensorFlow/Keras.
- **Pre-trained Model**: Xception.
- **Data Handling**: ImageDataGenerator for streamlined preprocessing.
- **Proposed Cloud Integration**: IBM Cloudant for prediction history and scalability.

Challenges and Limitations

1. **Performance Variability**:
    - Validation accuracy showed some inconsistencies across epochs.
2. **Limited Dataset**:
    - A relatively small dataset restricted generalization capabilities.
3. **Computational Intensity**:
    - Training on high-resolution medical images demanded significant computational resources.

Recommendations for Future Work

1. **Expand Dataset**:
    - Incorporate a larger and more diverse dataset to improve generalization.
2. **Experiment with Advanced Architectures**:
    - Explore alternatives like **ResNet**, **EfficientNet**, or **DenseNet**.

3. **Regularization**:
   - Implement advanced regularization techniques to minimize overfitting.
4. **Cross-Validation**:
   - Conduct extensive cross-validation to evaluate the model's robustness.
5. **Optimize Performance**:
   - Introduce learning rate schedulers or optimizers like RMSprop for stability.

Potential Impact

This project highlights the potential of AI in the medical field by:

- Providing an **automated screening tool** for Diabetic Retinopathy.
- Assisting healthcare professionals in faster and more reliable diagnostics.
- Offering accessible solutions for early detection in resource-limited areas.

Conclusion

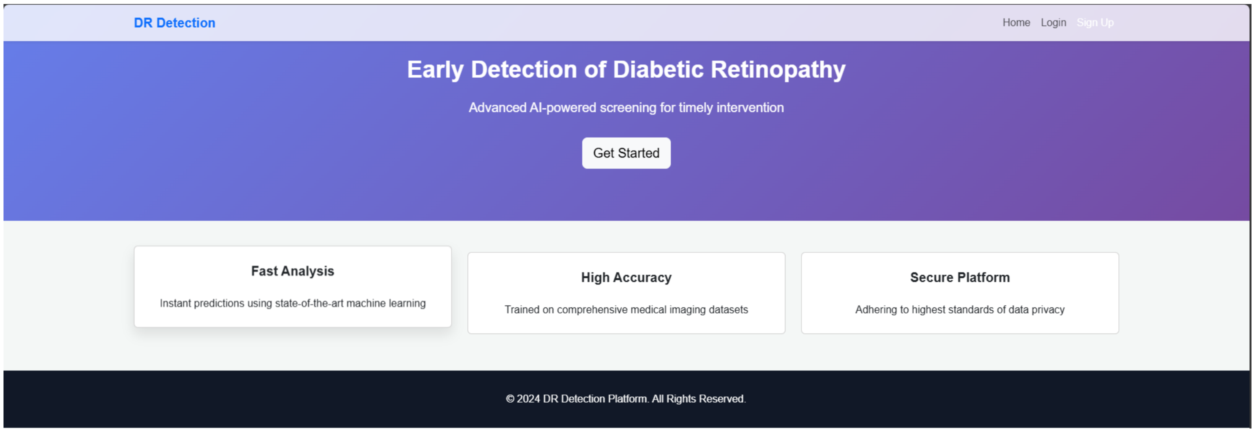
The **Diabetic Retinopathy Level Detection System** demonstrates the feasibility of using deep learning for medical image classification. With a peak validation accuracy of **73.71%**, it lays the foundation for a scalable and reliable solution for early DR diagnosis. While the model's performance can be further optimized, this project underscores the transformative potential of AI in enhancing healthcare delivery and outcomes.

Appendices

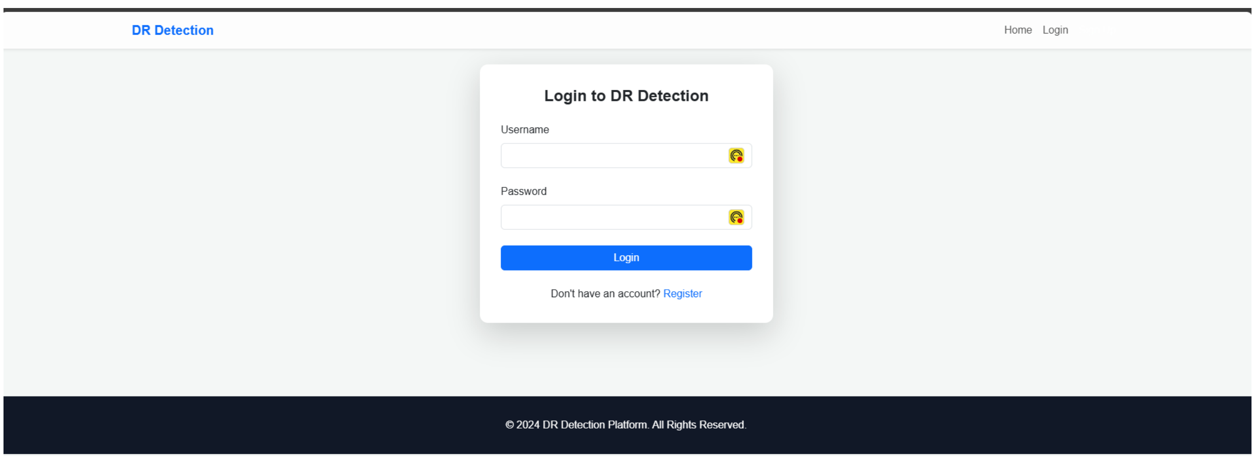
- Colab Notebook link : Diabetic-retinopathy-level-detection

Images of website:

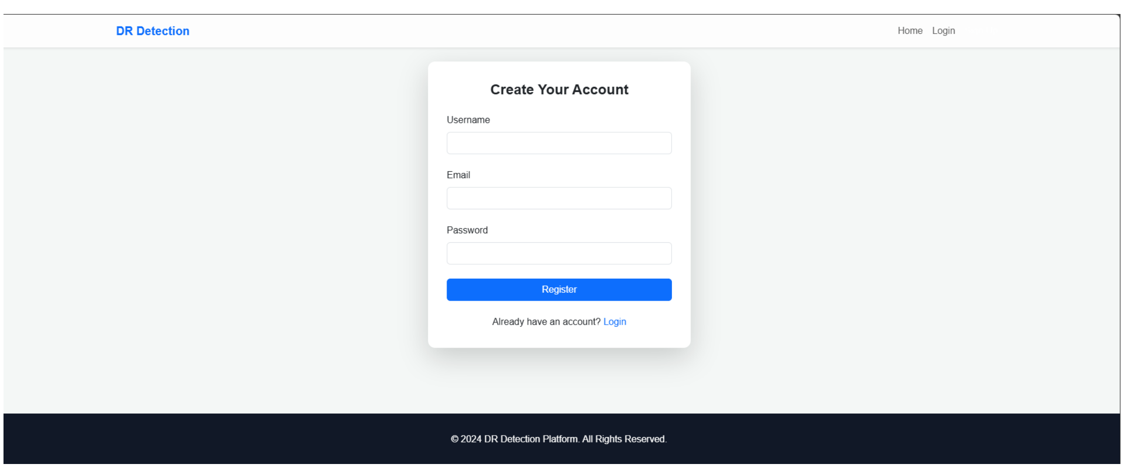
Home page:



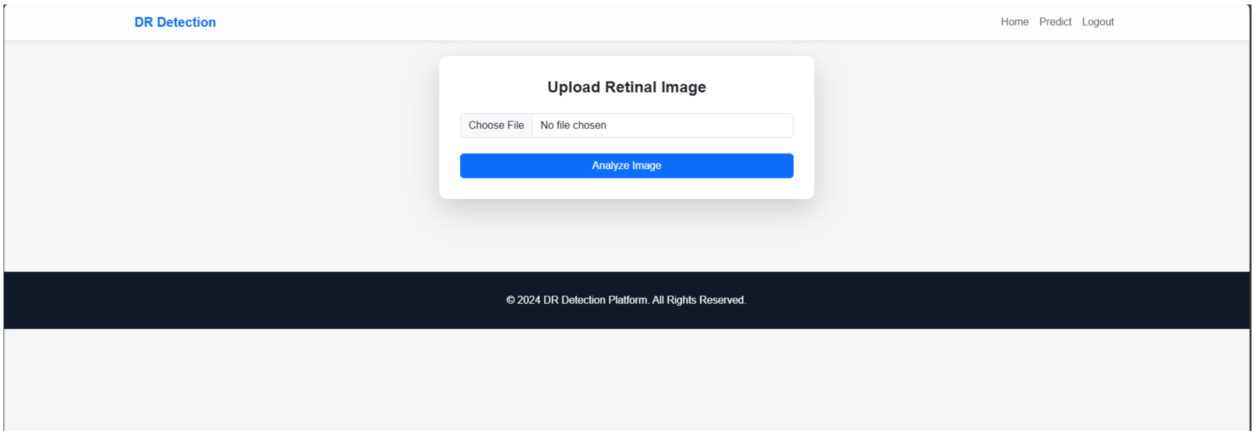
Login Page:



Register Page:



Predication Page:



Result Page: