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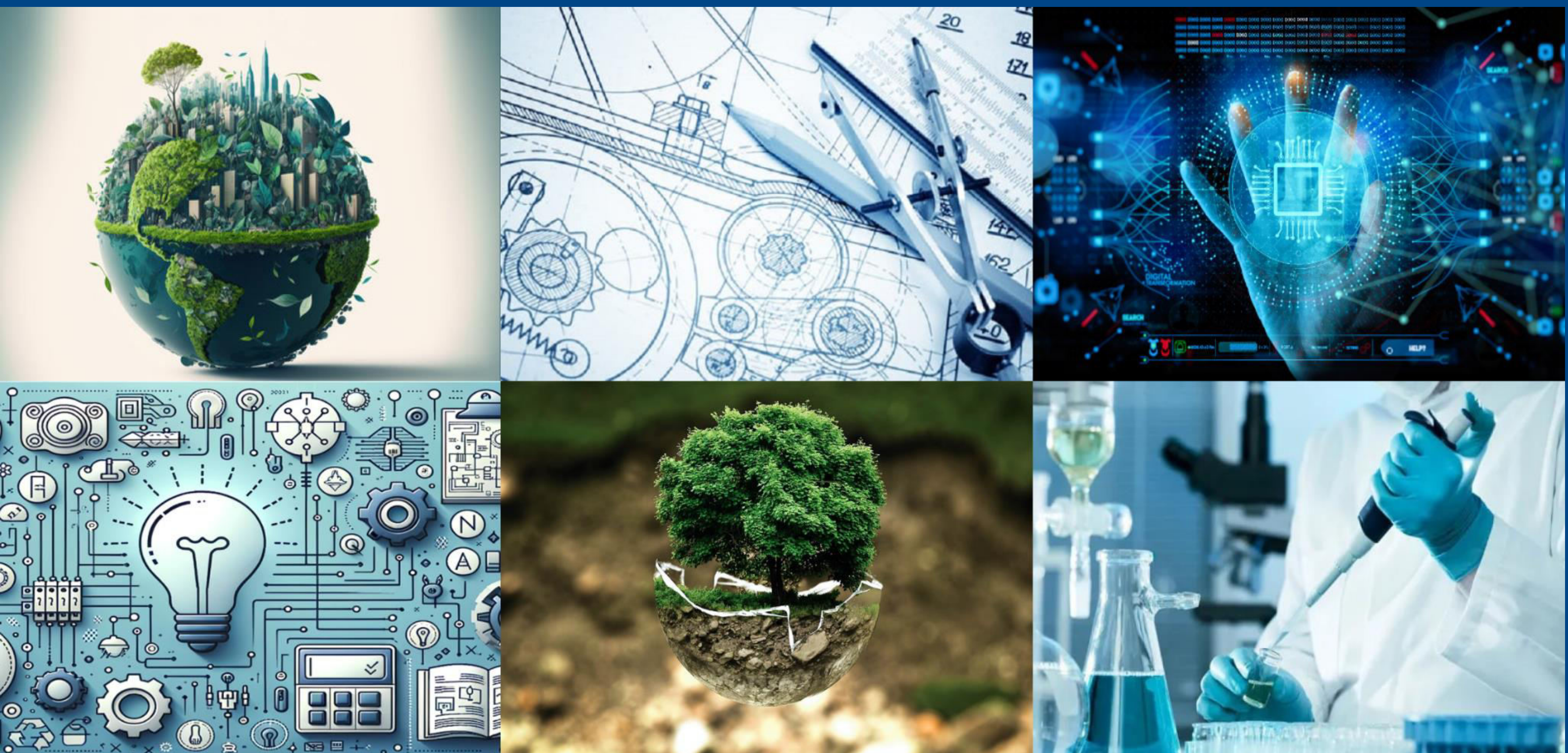

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Diabetic Retinopathy Classification using Resnet-50

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ABSTRACT: Diabetic retinopathy (DR) is a significant medical complication that arises due to prolonged elevated blood sugar, leading to retinal damage. Early diagnosis and timely treatment are vital since untreated DR can cause blindness, making diabetes the fifth leading global cause of vision loss. Traditional diagnostic approaches using image processing and simulation-based algorithms lack the precision and speed required for real-time clinical diagnosis. In response, deep learning techniques, particularly convolutional neural networks (CNNs), have shown superior performance in DR detection over conventional models. Although many CNN architectures exist for DR classification, continuous research is required to identify the optimal model. This paper investigates the application of the Residual Network (ResNet), a powerful pre-trained CNN, for identifying non-referable and various stages of diabetic retinopathy.

I. INTRODUCTION

Chronic hyperglycaemia, a result of unmanaged diabetes, is the main cause of diabetic retinopathy. As diabetes prevalence rises globally, DR has emerged as a major health concern. Projections indicate India alone could have 80 million diabetic patients by 2025-2030, while global DR cases may hit 592 million by 2025. The risk of DR increases with diabetes duration, affecting 21% of Type 1, 25% of Type 2, and up to 60% of mixed-type patients within a decade. Over a span of 30 years, up to 95% of diabetics may develop DR. Type 1 diabetes involves total insulin deficiency, while Type 2 leads to gradual insulin production impairment. Risk factors like obesity, pregnancy, high blood pressure, smoking, anemia, and lipid abnormalities can further accelerate DR progression.Despite its seriousness, a lack of awareness among one-third of the population and a limited number of eye care professionals (around 12,000 ophthalmologists and 3,500 retina specialists) contribute to underdiagnosis. The WHO and medical experts emphasize the urgency to enhance DR detection. This study highlights recent advancements in deep learning and the application of ResNet in identifying DR characteristics such as microaneurysms, hemorrhages, and exudates, aiming to boost detection accuracy and address current diagnostic challenges.

II. LITERATURE REVIEW

Diabetic retinopathy is a diabetes-related eye condition that can lead to blindness if not identified and managed early. Conventional diagnosis relies on retinal image analysis by ophthalmologists, which is time-intensive and may vary across observers. Deep learning has gained attention for its consistency and high accuracy in automating DR detection.
CNNs, including Inception-v3, VGG-19, and ResNet-50, have been explored extensively, with ResNet-50 standing out due to its deep architecture's ability to extract complex image features. Techniques like transfer learning, data augmentation, and ensemble models have been integrated to improve performance. Transfer learning uses models pre-trained on large datasets, while data augmentation enhances model generalization. Incorporating interpretability features aids clinicians in understanding disease indicators, thereby improving care. In summary, ResNet-50 and similar deep learning models hold great promise for automatic DR detection, with advanced methods boosting performance and clinical applicability.

III. TERMINOLOGY

DR involves retinal deterioration caused by blood vessel damage or fluid leakage into the retina, affecting vision. Early signs include blurry vision and trouble seeing in dim lighting, which may escalate to severe color vision loss, blind spots, or total blindness. DR stages include mild, moderate, and severe non-proliferative DR (NPDR), and proliferative

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DR (PDR), each with different symptoms and treatment strategies, such as lifestyle adjustments, laser therapy, or injections.

3.1 Features of DR

Key DR indicators involve analyzing retinal abnormalities like:

- **Microaneurysms**: Tiny, round bulges in capillaries.
- **Hemorrhages**: Bleeding spots indicating vessel rupture.
- **Exudates**: Yellow/white deposits due to lipid leakage.
- **Cotton Wool Spots**: White patches from inadequate blood flow.
- **Neovascularization**: Formation of abnormal new blood vessels.

Severity distinguishes NPDR from PDR, the latter being more critical due to vessel proliferation.

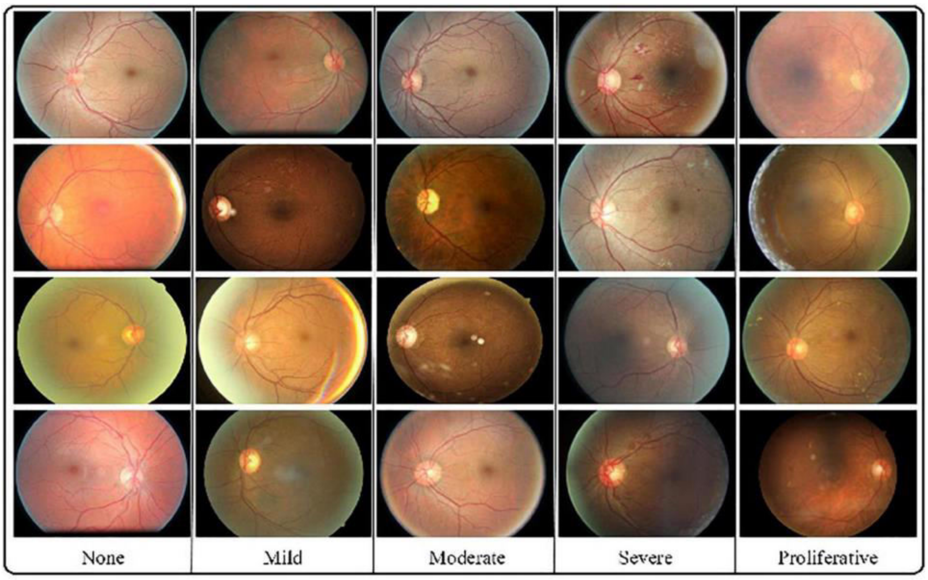
3.2 DR Classification

DR is categorized into:

- **NPDR (mild to severe)**: Microvascular occlusion without new vessel growth.
- **PDR**: Advanced stage involving new vessels causing leakage and vision loss.

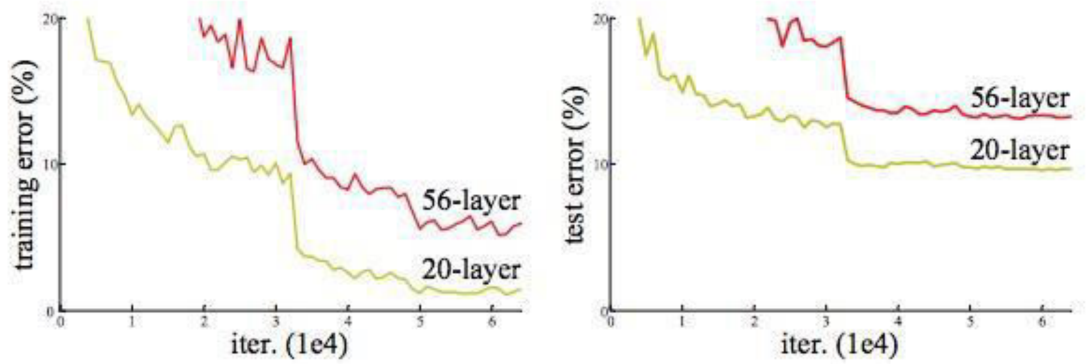
Fundus images help identify stages:

- **Grade 0**: No DR signs.
- **Grade 1**: Mild NPDR – at least one microaneurysm or hemorrhage.
- **Grade 2**: Moderate NPDR – more exudates and hemorrhages.
- **Grade 3**: Severe NPDR – meets any "4-2-1 rule" criteria (hemorrhages in all quadrants, venous beading in ≥2, or IRMA in ≥1 quadrant).
- **Grade 4**: PDR – two or more "4-2-1" features detected. This classification aids diagnosis and treatment planning.



IV. DESCRIPTION

CNNs evolved significantly after AlexNet's success, which inspired architectures like ZFNet, VGG16, and GoogleNet. However, deeper networks often resulted in increased errors. Microsoft addressed this with the **Residual Block**, allowing shortcuts that skip layers, forming the foundation of the ResNet model.Tests using the CIFAR-10 dataset showed that while deeper networks (like 56-layer CNNs) may suffer from performance issues, ResNet structures maintain efficiency due to skip connections that ensure smoother learning and better gradient flow.



4.1 Design Principles

ResNet-style networks, such as ResNet-34 and ResNet-50, are optimized with skip connections and 3x3 filters. VGG19, while having fewer layers, requires more operations (FLOPs) than ResNet-34. ResNet employs 1x1 convolutions to align dimensions between input and output when needed.

Smaller ResNet models (18, 34) use 2-layer blocks, while deeper versions (50+) integrate 3-layer blocks for better performance with minimal computational overhead.

Layer Name	Output size	50-layer
Conv 1	112 x 112	7 x 7, 64, stride 2
Conv 2_x	56 x 56	3 x 3, max pool, stride 2
		3 x [1x1,64 3 x 3,64 1 x1,256]
Conv 3_x	28 x 28	3 x [1x1,64 3 x 3,64 1 x1,256]
Conv 4_x	14 x 14	3 x [1x1,64 3 x 3,64 1 x1,256]
Conv 5_x	7 x 7	3 x [1x1,64 3 x 3,64 1 x1,256]
	1 x 1	Average pool, 1000-d fc, softmax
FLOPs		3.8×10^9

4.2 Specifications

ResNet-50 consists of several convolutional blocks:

- **Conv1**: 64 filters (7x7), output size 112x112.
- Max pooling reduces size to 56x56.
- Subsequent blocks (Conv 2-x to Conv 5-x) follow a 1x1 → 3x3 → 1x1 convolution pattern.
- Shortcut connections bypass certain layers, improving training efficiency.
- Final layer applies SoftMax to generate classification results.

4.3 Performance

Using the Fastai library, ResNet models were retrained with transfer learning. Various models, including ResNet18, ResNet50, and ResNet101, were tested. Due to GPU constraints with ResNet101 and lower performance from ResNet34, ResNet50 was selected for optimization.

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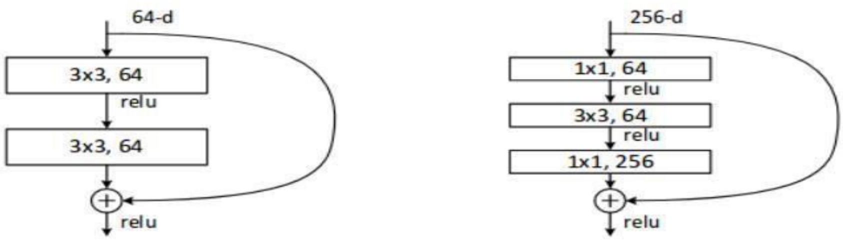
The experiments ran on an Nvidia K80 GPU with 12 GB memory. The final layers were adjusted to fit the target dataset's classification needs.



V. EXPERIMENTAL RESULTS AND ANALYSIS

This research assessed ResNet50's accuracy in:

1. **Binary Classification**: Detecting referable vs non-referable DR images.
2. **Multi-Class Classification**: Identifying the DR stage (0–4).

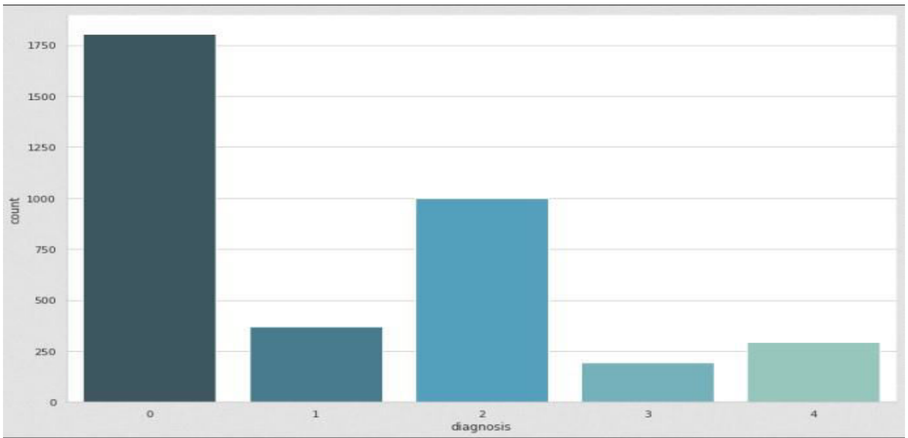
The dataset from Kaggle consisted of high-resolution retinal images with labels from ophthalmologists. Data was split 80/20 for training and validation.

Optimal parameters were:

- **Batch size**: 50
- **Epochs**: 5
- **Input image size**: Varied for multiclass experiments

Performance was evaluated using confusion matrices and accuracy metrics based on true/false positives/negatives.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$



VI. CONCLUSION

Diabetic retinopathy is a growing concern requiring prompt and accurate diagnosis to prevent vision impairment. This study showed that the ResNet architecture, particularly ResNet50, effectively classified both binary and multiple DR stages using the Kaggle dataset.The results confirm ResNet's robustness without heavy preprocessing. Future work should focus on benchmarking various ResNet versions, exploring alternative architectures, and incorporating

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preprocessing techniques to further enhance performance.This research underscores the vital role of deep learning in medical imaging and supports its potential to enhance DR diagnosis and patient care outcomes.

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