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OCULAR DISEASE RECOGNITION IN DEEP LEARNING

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Abstract— *There has always been a problem for clinicians to identify eye diseases using fundus images early enough. Ocular disease diagnosis by hand is an expensive task, prone to errors, and difficult. Automated computer system for detecting ocular diseases is needed to identify different eye illnesses utilizing fundus pictures. This research proposes a deep learning-based technique for focused ocular detection. Such a system is now an trouble-free because of deep learning algorithms that have enhanced picture categorization capabilities. For this, we classified the ODIR dataset, which includes 6000 photos of eight distinct fundus classes, using VGG-19, and ResNet50 image classification algorithms. Different ocular problems are characterized by these classifications. However, the dataset for these classes is somewhat erratic. This paper recommended using the same amount of photos for both categories and creating a binary classification challenge out of this multiclass classification problem to address this difficulty. This paper also uses the latest vision transformer method. The models are trained with actual data as well as with images after applying LBP(local binary pattern) on the image.*

KEYWORDS: *LBP, VGG-19 & ResNet50*

Introduction

Nearly 2.2 billion people around the world experience vision problems. The World Health Organization (WHO) estimates that there may have been a reduction in at least 1 billion of these incidents. Over time, there has been an increase in eye illnesses, with changes being one of the causes of a change in human behavior caused by technology and the creation of technological apparatus. That impact caused ocular diseases have had a significant impact on modern human life. Common eye diseases include glaucoma, diabetes, and hypertension.

Blindness is brought on by cataracts, pathological myopia, etc. could occur. Even though eye diseases' effects can be blindingly severe and result in early detection of the disorders can lessen the impact of the disease. Growing older and contact with certain substances, UV radiation, and genetic issues. With the prediction being digitized the model could be utilized for the analysis of the ocular disease. The disease should be accurately identified at all times. and effectiveness. One of the most important human organs is the eye. primarily vision aids in the recognition and detection of 3D objects. loss of one eyesight or both eyesight may cause a person to live an unsettling way of life because people make decisions based on what they observe in their daily lives. The effect of vision unsettling health can have an economic and personal impact. These symptoms are linked to a variety of eye illnesses. These include excruciating eye pain, an abrupt loss of vision in one or both eyes, fuzzy vision, red eyes, and droopy eyelids.

Given the serious effects of eye problems on people, to find eye diseases, this research was done on lifestyle with greater precision when using the fundus image. This study is primarily concerned with accurate recognition taking into account the Local Binary Pattern features (LBP) of ocular disease. It sights to create a variety of extracting features techniques and Neural Networks to distinguish typical visual disorders involving fundus photographs.

We discovered that eye illness identification using deep learning focuses on just one aberration in comparison to the prior methods. For various challenges, several designs were utilised in this paper, and the outcomes are fairly good. Thus, with accuracy more than 90% for each activity, illnesses including glaucoma, diabetic retinopathy, and cataract are adequately managed.

Dataset

We made use of the kaggle data collection for our research. In the dataset, we can find Diabetes, Glaucoma, Cataract, Related Macular Degeneration, Myopia, Hypertensive Retinopathy, and others.

The lens of your eye, which is typically straightforward, becomes clouded by a cataract.. Most cataracts grow slowly and don't initially impair your vision. However, cataracts will eventually obstruct your vision over time. Because of the white film it produces, it is one of the simplest abnormalities to spot. Figure 1 shows how a realistic depiction of a cataract appears in fundus images.

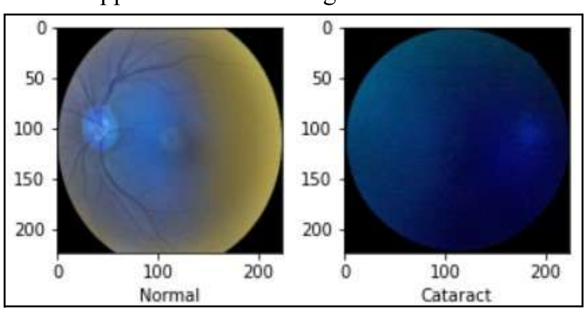

Fig.1: Normal Eye vs Cataract Eye

Image Preprocessing The quality of the image determines how well the entire model works, so it is essential to focus on the cornea's fundus.The classification model's accuracy is adversely impacted by the noise in the photos, though. When the image is turned into a grayscale, the fundus color also closely resembles the backdrop color. Because some of the photographs have white backgrounds, this impact leads the classifier astray. Therefore, in order to make it simpler to identify the interest points, the backgrounds of all photographs were manually eliminated as the first phase of pre-processing.

Feature Extraction The texture elements of the image are extracted using a technique called the local binary pattern. Each pixel in the picture has a value which the LBP receives, and the form of the LBP histogram distribution is used to determine the regularity of the image texture. The LBP is more efficient in computer vision operations due to its strong discriminative strength and computational simplicity. The field of medical image processing makes extensive use of LBP.

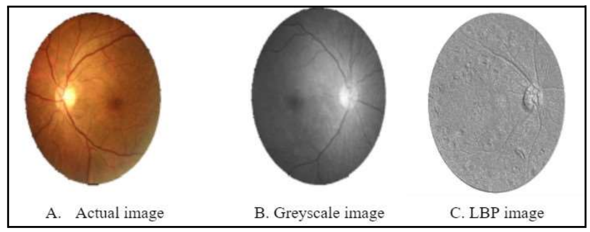

Fig.2: Actual image vs Greyscale image vs LBP image

Proposed Architecture

VGG-19

Advanced CNN-VGG19 has layers that have previously undergone training and has a solid understanding of the shape, colour, and structural aspects of a picture. For difficult classification tasks, the very deep VGG19 has been trained on an enormous variety of images.

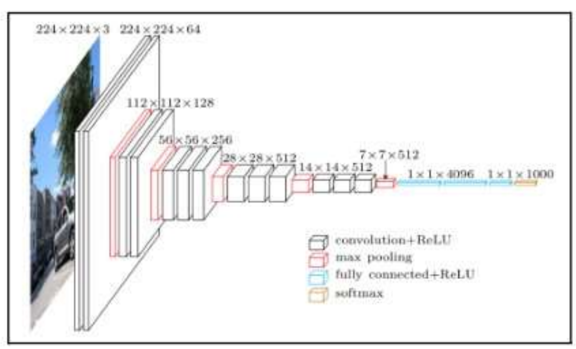

Fig.3: Architecture of VGG19

ResNet-50

Instead of attempting to learn specific characteristics, ResNet or Residual Network makes use of residual learning. Residual may be easily regarded as the feature learned from that layer's input subtracted. More than ResSNet50, there are other ResNet variations. Creating a shortcut connection that omits one or more levels is the fundamental concept behind ResNet. Glaucoma is another serious eye condition that can lead to blindness if not diagnosed and managed. ResNet-50 can be used for optic disc and cup segmentation in fundus images, which is crucial for glaucoma diagnosis. It can also be trained to classify images based on features indicative of glaucomatous damage.

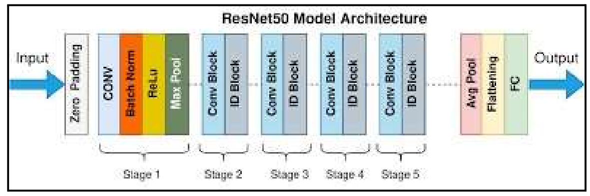

Fig.4: Architecture of ResNet50

Vision Transformer

The Vision Transformer, often known as ViT, is a classification system that employs a Transformer-like design in some portions of the image. By partitioning an image into fixed-size patches, linearly embedding each one, including location embeddings, and assembling the vectors, one may produce a series of vectors that can be fed into a standard Transformer encoder. The conventional way to conduct classification entails adding an extra "classification token" that may be learned to the sequence.

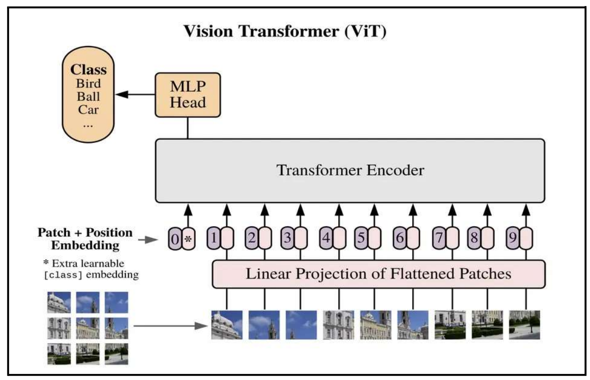

Fig.5: Architecture of Vision Transformer

Result

- **Without LBP**

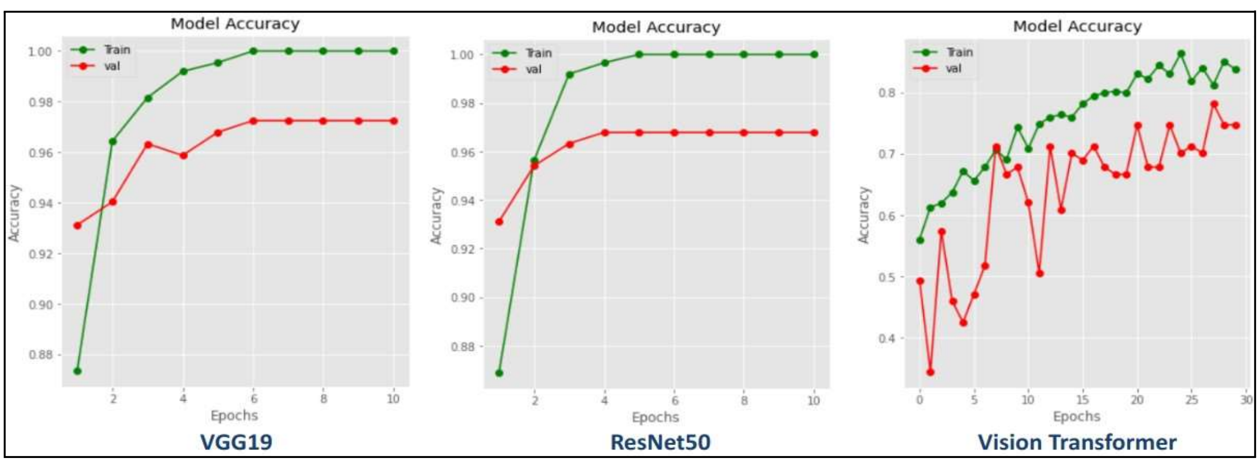

Fig.6 Model Accuracy vs Loss Curve

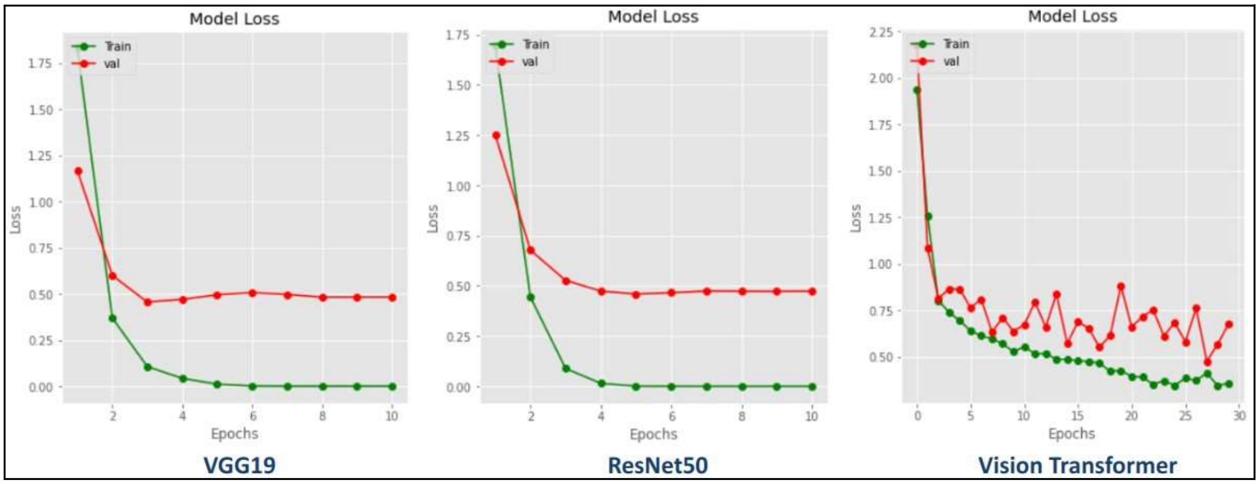

Fig.7: Model Loss vs epoch curve

Comparison table

The table shows that VGG19 performs very well with a validation accuracy of 99.08% and very less 0.08 validation loss. The vision transformer model performs very poorly compared to VGG19 and ResNet50.

	Model	Training_Accuracy	Training_Loss	Validation_Accuracy	Validation_Loss
1.	VGG19	0.996552	0.014352	0.990826	0.084891
2.	ResNet50	1.000000	0.000006	0.977064	0.131539
3.	Vision Transformer	0.863346	0.344338	0.781609	0.476366

Fig.8: Result Comparison of all models before using LBP

- **With LBP**

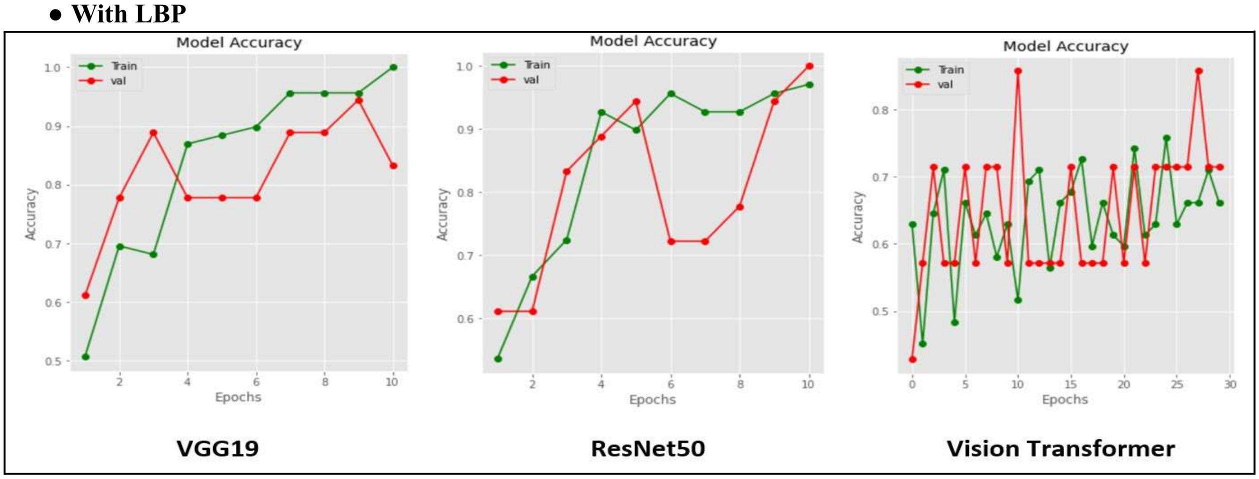

Fig.9: Model Accuracy vs Epoch Curve

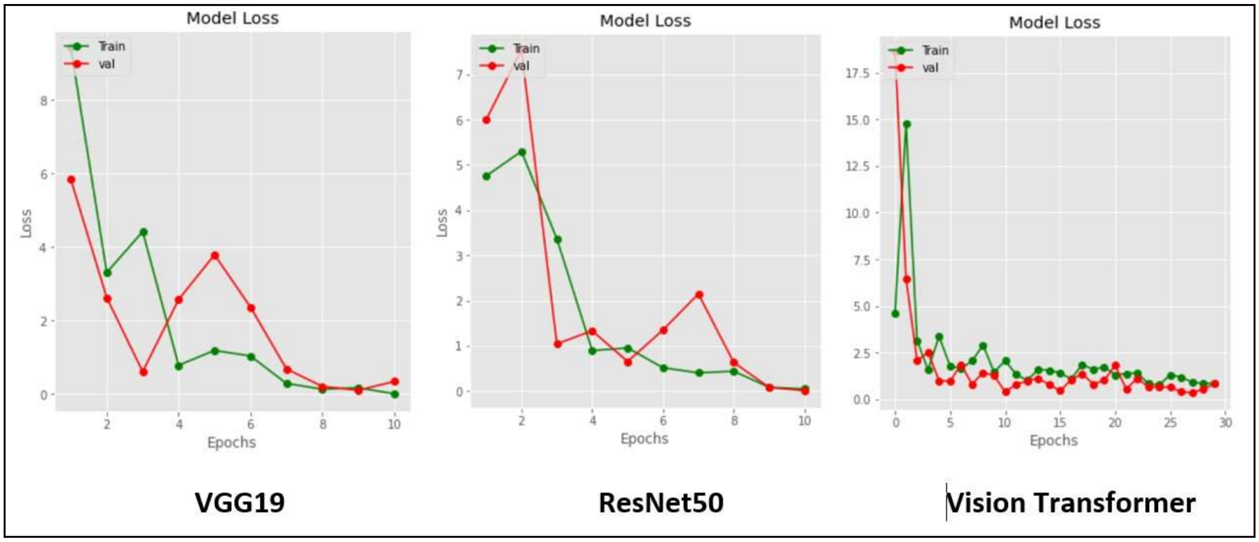

Fig.10: Model Loss vs epoch curve

Comparison table

Here VGG19 training accuracy is very good but validation accuracy is quite bad. ResNet50 model provided a validation accuracy of 100% and a validation loss of 0.008. The vision transformer here also performs very badly.

	Model	Training_Accuracy	Training_Loss	Validation_Accuracy	Validation_Loss
0	VGG19	1.000000	0.004897	0.944444	0.099631
1	ResNet50	0.971014	0.046032	1.000000	0.008169
2	Vision Transformer	0.758065	0.746540	0.857143	0.345332

Fig.11: Result Comparison of all models after using LBP

When we compare the model with the dataset after applying LBP and without LBP, then in both cases we cannot see any significant changes. One thing that we can notice is that the minimum validation loss in ResNet50 with LBP is very less as compared to models trained with the LBP image dataset.

Conclusion

The models VGG-19, ResNet50, and Vision Transformers were utilised in this work to categorise the different kinds of ocular disorders. These models are capable of predicting if a fundus is healthy or whether an eye has a disease. We found that models with the LBP dataset are performing very well giving high accuracy with minimum loss. To address the imbalance issue, we can employ generative adversarial networks (GANs) to generate comparable images of eye illness. A technology like this will also revolutionise the field of diagnosing eye diseases and be of great assistance to medical professionals. However, we believe that it can still be a useful model and that there are chances for improvement with additional research and investigation in the near future.

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