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IN-DEPTH EVALUATION OF RETINAL IMAGE CLASSIFIERS:THE STRENGTHS AND DISTINCTIONS OF NEURAL NETWORK AND DEEP LEARNING APPROACHES

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Abstract

This research offers a complete investigation into the effectiveness of various neural networks and Deep learning algorithms for retinal image class, which is essential for Diabetic Retinopathy(DR)detection. To Facilitate the robust assessment, the proposed study leverages five different retinal image benchmark datasets – DRIVE, DIARETDB0, CHASEDB, STARE and MESSIDOR. The four different algorithms- Maximum Principal Curvature(MPC), Multilayer Perceptron(MLP), Dense Convolutional Neural Network(DCNN) and Discriminative CNN with 121 layers(Dis-CNN) are employed to examine the overall performance through different metrics, namely Accuracy, Sensitivity and Specificity. In this study, every algorithm is subjected to rigorous evaluation based on the unique characteristics of the dataset.The primary goal is to determine the algorithm's overall efficacy and identify the nuanced performance outcome of retinal images in the different datasets. This study outlines the strengths and differences of every set of algorithms in dealing with the facts of the retinal images. The selected algorithms include a range of approaches, from conventional techniques like Maximum Principal Curvature (MPC) to better neural network architectures along with MLP, Dense CNN, and a Discriminative CNN with 121 layers. The variety in algorithms and datasets ensures a comprehensive evaluation, providing precious insights into their suitability for real-world applications in Diabetic Retinopathy.Discriminative CNN with 121 layers is a better alternative algorithm across all datasets with accuracies ranging from 95.01% to 99.83%. This outstanding performance underscores the robustness of the Discriminative CNN, affirming its potential as a highly effective tool for the accurate DR classification and diagnosing abnormalities

Keywords: Deep Learning algorithms, DRIVE, DIARETDB0, CHASEDB, STARE, MESSIDOR, Maximum Principal Curvature, Multi-Layer Perceptron (MLP), Dense Convolutional Neural Network (DCNN), Discriminative CNN with 121 layers(Dis-CNN)

1.Introduction

Diabetes is a chronic illness that develops when the body either cannot use the insulin that the pancreas makes properly or does not create enough of it[1]. One hormone that controls blood sugar is insulin. Hyperglycaemia, sometimes called elevated blood glucose or blood sugar, is a frequent consequence of uncontrolled diabetes mellitus that eventually causes major harm to numerous bodily systems, particularly the blood vessels and neurons[2][3].

Diabetes affected person may have microvascular complications such as Diabetic Retinopathy(DR), nephropathy, and neuropathy and macro vascular complications like Cardiovascular diseases, including heart attacks and strokes[4].

Retinal image processing is the leading edge of identifying and diagnosing numerous ocular diseases using modern algorithms[5]. Diabetic Retinopathy is diagnosing the retinal abnormalities for the diabetic affected person. Serving as a unique window into systemic fitness, the retina presents worthwhile diagnostic insights, detecting early signs and symptoms, which includes diabetic retinopathy, glaucoma, and age-associated macular degeneration. [6]

In the area of diabetic retinopathy, a considerable public health concern, state-of-the-art imaging techniques like optical coherence tomography (OCT) and fundus image play a pivotal position in excessive-resolution retinal scans[7]. These techniques allow clinicians to visualize subtle changes within the retinal microstructure, including microaneurysms, Exudates and Haemorrhages and other vascular abnormalities.[8]

DR is typically classified into two main categories: Non-proliferative Diabetic Retinopathy (NPDR) and Proliferative Diabetic Retinopathy (PDR)[9]. NPDR is divided into Mild NPDR, Moderate NPDR and Severe NPDR. Mild NPDR is characterized by microaneurysms, small areas of retinal hemorrhage, and mild retinal swelling (edema). In Moderate NPDR stage, the number of microaneurysms and hemorrhages increases, affecting a larger area of the retina.Severe NPDR is marked by more pronounced retinal changes, including extensive hemorrhages, increased swelling, and the appearance of cotton wool spots. Severe NPDR indicates a higher risk of progressing to PDR[10].

Proliferative Diabetic Retinopathy (PDR) is divided into Early PDR, High risk PDR and advanced PDR.

In Early PDR there exist a growth of abnormal blood vessels called neovascularization on the surface of the retina or optic nerve head.

The presence of neovascularization and other high-risk features such as extensive neovascularization, vitreous hemorrhage, or both characterizes the High-risk PDR.

Advanced PDRis the most severe stage where there is significant neovascularization, extensive vitreous hemorrhage and the potential for complications such as tractional retinal detachment. Retinal detachment is an emergency when the retina, a thin layer of tissue at the back of the eye, separates from the blood vessels that supply and oxygenate it. Visual disturbances and floating are common symptoms of retinal detachment.

Although advanced imaging techniques have significantly increased our ability to identify and treat eye illnesses, it's important to understand their limitations. To ensure accurate and detailed diagnoses when going into retinal image processing, one must know the details of those techniques and their integral function in overall ocular healthcare[11].

1.1 Retinal Image Processing

A retinal fundus image captures the intricate details of the eye's interior surface, known as the fundus. This non-invasive imaging technique employs specialized and fundus or retinal cameras to acquire a comprehensive image of the retina, optic disc, macula, and blood vessels [12]. The retina, a light-sensitive layer at the back of the eye, plays a pivotal role in capturing light and converting it into electrical signals for interpretation by the brain. The retinal vascular structure is presented in the Figure 1. Comprising photoreceptor cells, nerve cells, and blood vessels, the retina is a crucial component of the fundus image. The optic disc, or optic nerve head, marks the point where the optic nerve exits the eye, appearing as a circular, slightly depressed area in the retinal fundus image[13]

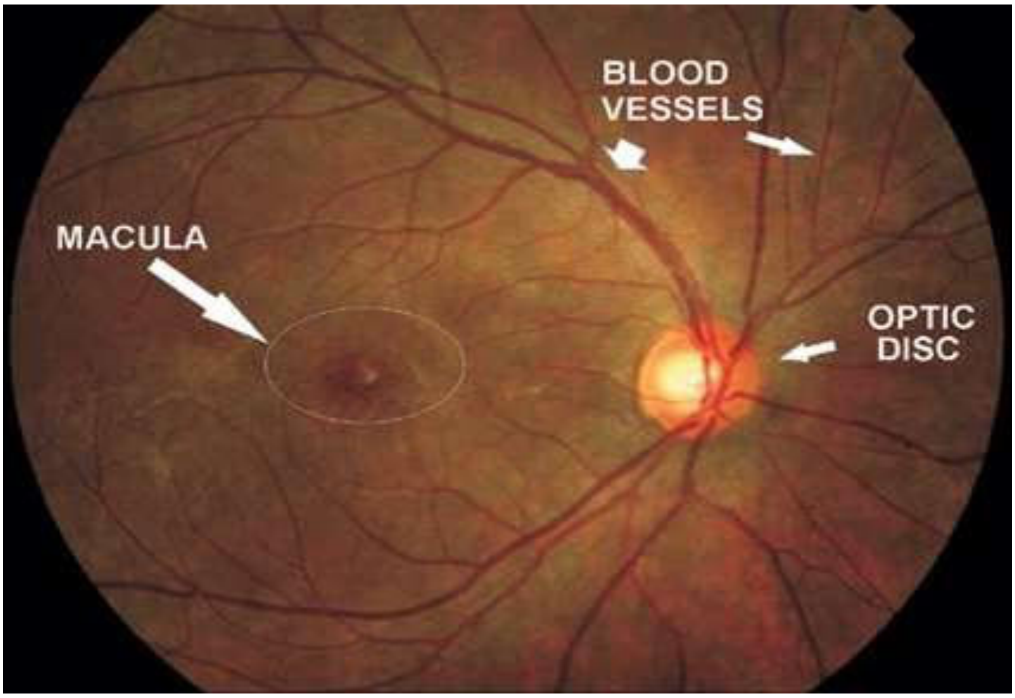

Figure 1: Fundus Image

The macula near the retina's center is responsible for essential vision tasks such as reading and recognizing faces. Additionally, the retinal blood vessels, depicted as branching patterns in the fundus image, provide oxygen and nutrients to the retina[14]. Retinal fundus imaging is integral in diagnosing and monitoring various eye conditions, including diabetic retinopathy, age-related macular degeneration, glaucoma, and hypertensive retinopathy. These images offer ophthalmologists valuable insights into the structural integrity of the retina, the presence of abnormalities, and the eye's overall health. With advancements in image processing and artificial intelligence, retinal fundus images have become increasingly valuable for early detection and management of eye diseases[15].

2.METHODOLOGY

2. 1Evaluation Of Retinal Image Classifiers

This study gives the comparative analysis of different neural network and deep learning algorithms to detect retinal abnormalities. The five different retinal fundus datasets used for retinal image analysis methodologies are the DRIVE, DIARETDB0, CHASEDB, STARE, and MESSIDOR. The dataset descriptions are given presented in the Table 1. Serving as benchmarks for numerous tasks within the realm of ophthalmic studies, these datasets are foundational for improving and validating algorithms associated with retinal vessel segmentation, diabetic retinopathy detection, fluid-filled area segmentation in OCT photos, and other vital aspects of retinal image processing. The overall process of disease identification is presented in t Figure 2, and Table 1 describes the different Retinal databases.

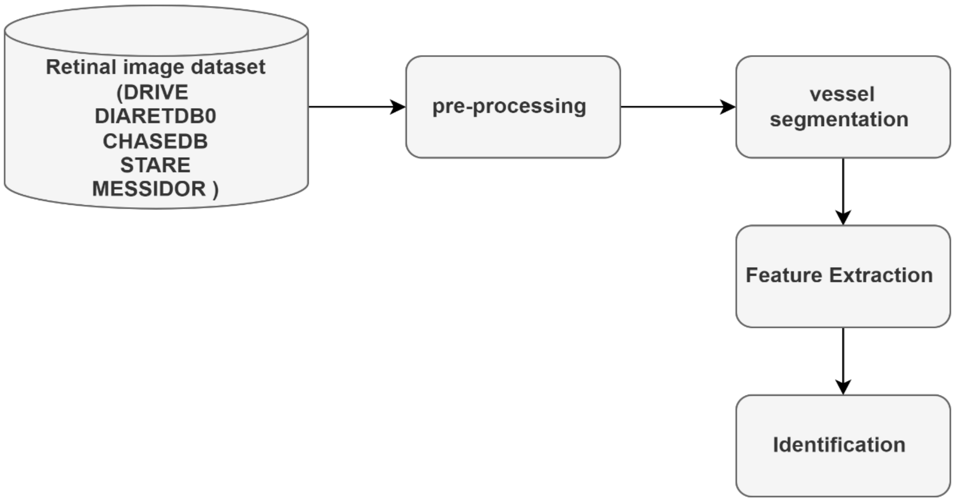

Figure 2: Process of DR identification

Dataset	Full Name	Description	Number of Images
DRIVE	Digital Retinal Images for Vessel Extraction	Benchmark dataset for retinal vessel segmentation algorithms. Consists of 40 color fundus images.[3]	40
DIARETDB0	Diabetic Retinopathy Database 0	Tailored for diabetic retinopathy research. Includes 130 fundus images captured using various digital fundus cameras. Suitable for developing and evaluating algorithms for detecting diabetic retinopathy.[4]	130
CHASEDB	Choroideremia Analysis from SD-OCT	Designed for evaluating algorithms related to segmenting fluid-filled regions in retinal optical coherence tomography (OCT) images. Consists of 28 B-scan images from 14 patients.[5]	28
STARE	Structured Analysis of the Retina	Features 20 color fundus images with a focus on normal retinas. Versatile for various retinal image analysis tasks, including vessel segmentation and feature extraction.[6]	20
MESSIDOR	MESSIDOR Database for Diabetic Retinopathy	Specifically crafted for diabetic retinopathy research. Comprises 1200 retinal images with varying resolutions, including both normal and pathological cases related to diabetic retinopathy.Three sets, every set is separated into four zipped subsets, each of which contains 100 TIFF photos.[7]	1200

Table 1: Five different Retinal Database

The following section describes the different methods such as Maximum Principal Curvature segmentation of blood vessels, classification of DR lesions using Multi layer Perceptron, Dense CNN and Discriminative CNN with 121 layers.

2.2Maximum Principal Curvature

Maximum Principal Curvature recommends a segmentation technique for extracting blood vessels in human retinal fundus pics, combining mathematical morphology and the concept of premier essential curvature[16]. The methodology objectives to enhance the accuracy and robustness of blood vessel segmentation in retinal images, crucial for diverse medical packages, including the early detection of sicknesses, including diabetic retinopathy. Leveraging mathematical morphology, which analyzes and manipulates the geometric shape of objects, and the gold standard important curvature, which captures vessel characteristics based on curvature analysis, our approach provides a complete solution for accurately delineating blood vessels. The technique applies to retinal fundus images, in which blood vessels exhibit elaborate styles and widths.

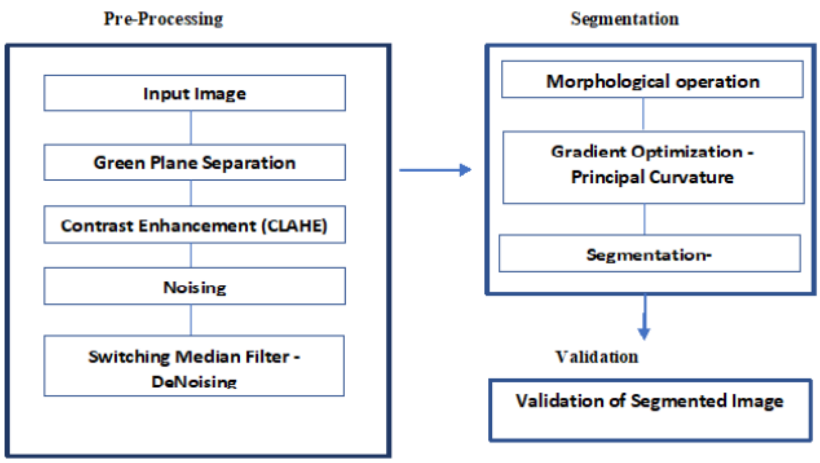

Figure 3: Different Steps for Vessel Segmentation

Integrating those techniques facilitates powerful vessel segmentation, contributing to the development of diagnostic procedures and advancing the field of clinical image analysis. The experimental results display the efficacy of our proposed approach, showcasing enhanced accuracy in blood vessel segmentation and its capacity effect on early disease detection and scientific decision-making in ophthalmology. The Figure 3 describes the methods used in this work[17].

2.3 Multi-Layer Perceptron,

In Diabetic Retinopathy Lesions Identification in the Color Fundus Images using Multi-Layer Perceptron, responsiveness at the identification of diabetic retinopathy lesions in coloration fundus images thru the model of a Multi-Layer Perceptron (MLP) neural community. Diabetic retinopathy is a familiar hassle of diabetes, and early identification of associated lesions is essential for well-timed intervention and effective management. Our proposed methodology employs a Multi-Layer Perceptron, a sort of artificial neural community able to learning algorithms of complicated styles and relationships within records, to research colour fundus images for the presence of diabetic retinopathy lesions. Figure 4 represents the different process of the MLP classification[18].

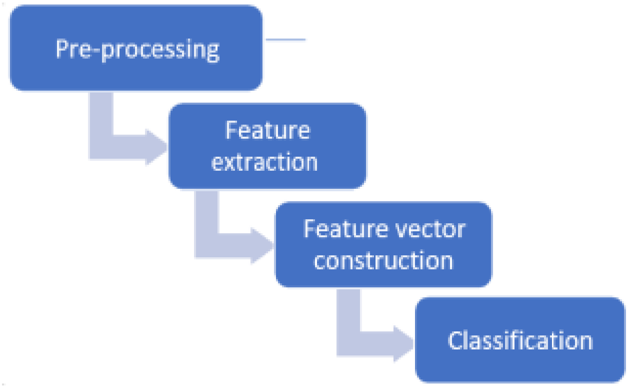

Figure4: MLP Classification Process

The network is trained on various datasets, encompassing several retinal images depicting varying degrees of diabetic retinopathy. The intention is to enable the MLP to autonomously pick out and classify one of a kind varieties of lesions, such as microaneurysms, hemorrhages, and exudates, contributing to the automatic screening and diagnosis of diabetic retinopathy. The efficacy of the Multi-Layer Perceptron in appropriately figuring out diabetic retinopathy lesions in coloration fundus photos, showcasing its ability as a treasured tool for ophthalmic diagnostic applications.

2.4 Dense Convolution Neural Network

In Dense Convolution Neural Network for Automated Diabetic Retinopathy Detection, advise using a Dense Convolutional Neural Network (Dense CNN) to automatically detect diabetic retinopathy. The Dense CNN structure, acknowledged for its potential to seize involved functions in images through dense connections among layers, is implemented to research retinal images and determine pathological symptoms associated with diabetic retinopathy. The model is trained on a diverse dataset comprising images with various stages of retinopathy severity.[10]. Figure 5 represents the overall process of Dense Convolutional Neural Network.

By leveraging the dense connectivity and feature reuse characteristics of Dense CNN, our approach aims to enhance the network's ability to discern subtle patterns indicative of diabetic retinopathy lesions. The study evaluates the performance of the proposed Dense CNN in automated diabetic retinopathy detection, showcasing its potential as an advanced tool for efficient and reliable screening in DR diagnosis[19].

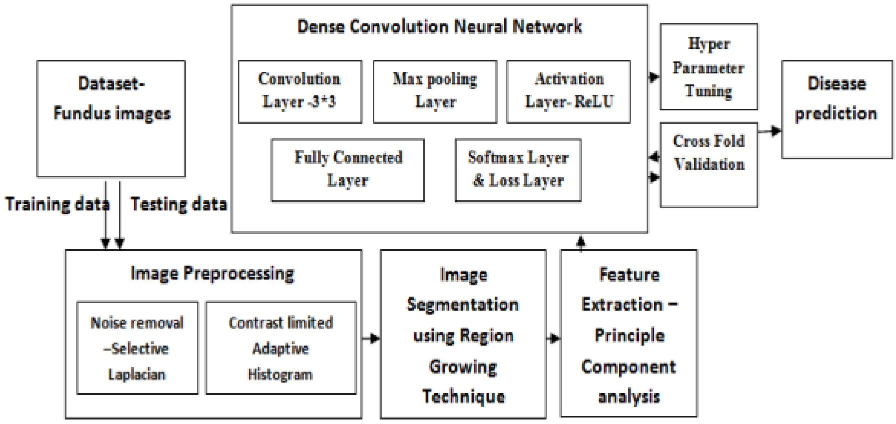

Figure 5: Dense CNN Classification

2.5 121-Layers Convolutional Neural Network with Discriminative Features

In Diabetic Retinopathy Lesions Identification And Classification Using 121-Layers Convolutional Neural Network with Discriminative Features, recent an advanced approach

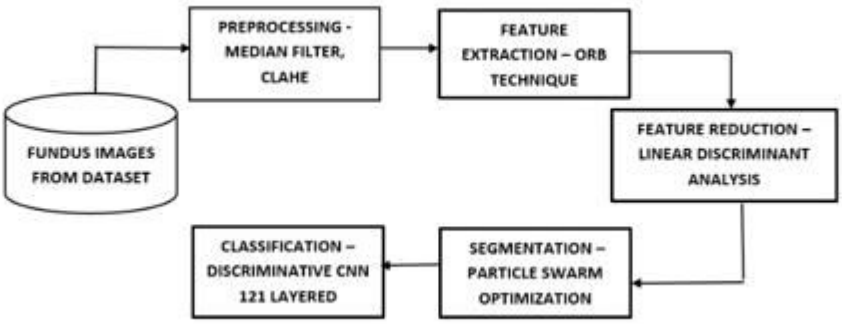

Figure 6: Discriminative CNN with 121 layers Classification

For identifying and classifying diabetic retinopathy lesions utilizing a 121-Layers Convolutional Neural Network (CNN) enriched with discriminative features. Our proposed CNN architecture includes 121 layers, is designed to analyse retinal images, capturing intricate features crucial for lesion identification. The network is trained on a diverse dataset, encompassing various manifestations of diabetic retinopathy lesions. Figure 6 represents the overall process of 121 layered Discriminative Convolutional Neural Network with discriminative features[20].

We integrate discriminative features into the CNN, elevating its ability to distinguish subtle characteristics indicative of different lesion types. This innovative approach streamlines the identification process and facilitates the classification of lesions such as microaneurysms, hemorrhages, and exudates. The study showcases the effectiveness of the 121-Layers CNN with discriminative features in accurately identifying and classifying diabetic retinopathy lesions, thereby contributing to the advancement of automated and precise diagnostic tools in ophthalmology.

3. RESULTS AND ANALYSIS

The research presents a detailed investigation into the efficacy of various neural network and deep learning algorithms for retinal image classification, focusing on disorder detection. Leveraging five well-known retinal image datasets—DRIVE, DIARETDB0, CHASEDB, STARE, and MESSIDOR—the study employs four distinct algorithms: Maximum Principal Curvature, Multi-Layer Perceptron (MLP), Dense Convolutional Neural Network (CNN), and a Discriminative CNN with 121 layers. Key metrics such as accuracy, sensitivity, and specificity are assessed to evaluate the performance of each algorithm. The research aims not only to determine the overall effectiveness of the algorithms but also to analyze their nuanced performance across different retinal image datasets. With a focus on disease detection, the study delineates the strengths and weaknesses of each algorithm in handling the complexities of retinal images.

The chosen algorithms encompass a diverse spectrum, ranging from traditional methods like Maximum Principal Curvature to advanced neural network architectures such as MLP, Dense CNN, and a Discriminative CNN with 121 layers. This diversity ensures a comprehensive evaluation, providing valuable insights into the suitability of these algorithms for real-world applications in DR detection. The research contributes to understanding how different algorithms perform under various conditions and datasets, facilitating informed decisions for implementing retinal image classification systems in clinical settings.

Accuracy Analysis:

Accuracy is calculated by dividing the number of correct predictions by the total prediction value.[11].

Dataset	**Maximum Principal Curvature**	**Multi-Layer Perceptron (MLP)**	**Dense CNN**	**Discriminative Convolution Neural Network 121 layer**
DRIVE	0.965	100	97.35	98.71
DIARETDB0	0.935	100	98.89	99.28
CHASEDB	0.902	98	97.91	95.01
STARE	0.925	98	98.38	97.13
MESSIDOR	0.929	95	98.90	99.83

Table 2 : Accuracy Analysis

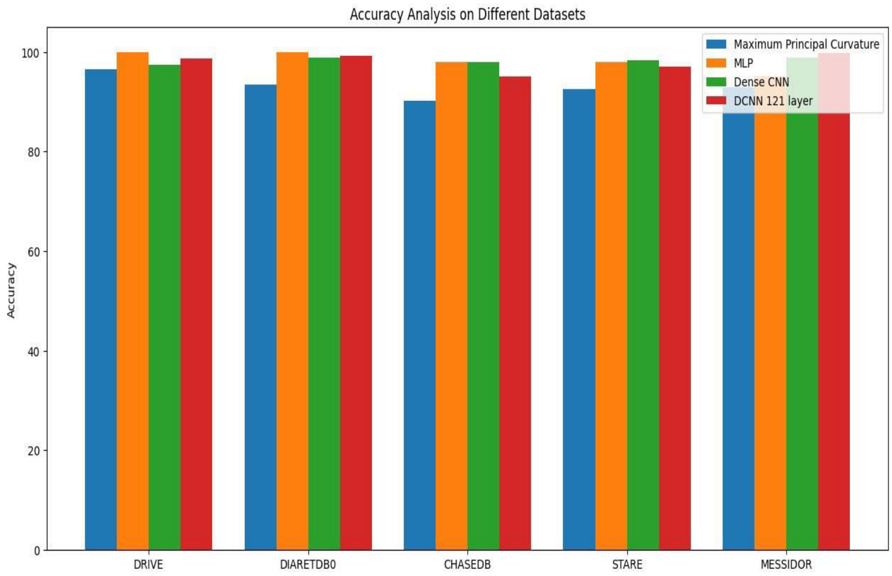

Figure 7: Accuracy Analysis

The accuracy analysis across multiple retinal image datasets underscores the significance of algorithm choice in achieving effective classification. In the DRIVE dataset, Maximum Principal Curvature showcases commendable performance with an accuracy of 96.5%, while the Discriminative Convolution Neural Network with 121 layers outshines others, achieving an impressive accuracy of 98.71%. The Dense CNN also delivers noteworthy results at 97.35%, and the Multi-Layer Perceptron (MLP) attains a perfect accuracy of 100%. Moving to the DIARETDB0 dataset, the Discriminative Convolution Neural Network with 121 layers emerges as the top performer with an accuracy of 99.28%. Dense CNN also proves to be competitive, achieving an accuracy of 98.89%. Remarkably, Maximum Principal Curvature and Multi-Layer Perceptron (MLP) attain perfect accuracies of 100%. Table 2 and Figure 7 describes the accuracy analysis of different classification models for different datasets.

In the CHASEDB dataset, the Discriminative Convolution Neural Network with 121 layers leads with an accuracy of 95.01%, closely followed by Maximum Principal Curvature at 90.2%. The Multi-Layer Perceptron (MLP) achieves a robust accuracy of 98%, and the Dense CNN exhibits strong performance with an accuracy of 97.91%. The STARE dataset sees the Discriminative Convolution Neural Network with 121 layers securing the highest accuracy at 97.13%, followed closely by Dense CNN at 98.38%. Maximum Principal Curvature and Multi-Layer Perceptron (MLP) achieve 92.5% and 98% accuracy, respectively. Finally, in the MESSIDOR dataset, the Discriminative Convolution Neural Network with 121 layers demonstrates exceptional accuracy, reaching an outstanding 99.83%. Multi-Layer Perceptron (MLP) performs well with an accuracy of 95%, while Maximum Principal Curvature and Dense CNN achieve 92.9% and 98.9%, respectively.The consistent superiority of the Discriminative Convolution Neural Network with 121 layers across diverse datasets underscores its robustness in handling the complexities of retinal image classification tasks. These results emphasize the critical role of algorithm selection in achieving accurate and reliable outcomes, demonstrating the potential of advanced neural network architectures in this medical imaging domain.

SensitivityAnalysis :

Sensitivity defines the measurement of correctly identified parts from the actual positives, also known as the True Positive rate [12]

Dataset	Maximum Principal Curvature	Multi-Layer Perceptron (MLP)	Dense CNN	Discriminative Convolution Neural Network 121 layer
DRIVE	0.752	100	94.12	98
DIARETDB0	0.723	100	97.60	99.45
CHASEDB	0.710	97	96.15	98
STARE	0.720	98	95.14	98
MESSIDOR	0.721	94	97.5	99.91

Table 3 :Sensitivity Analysis

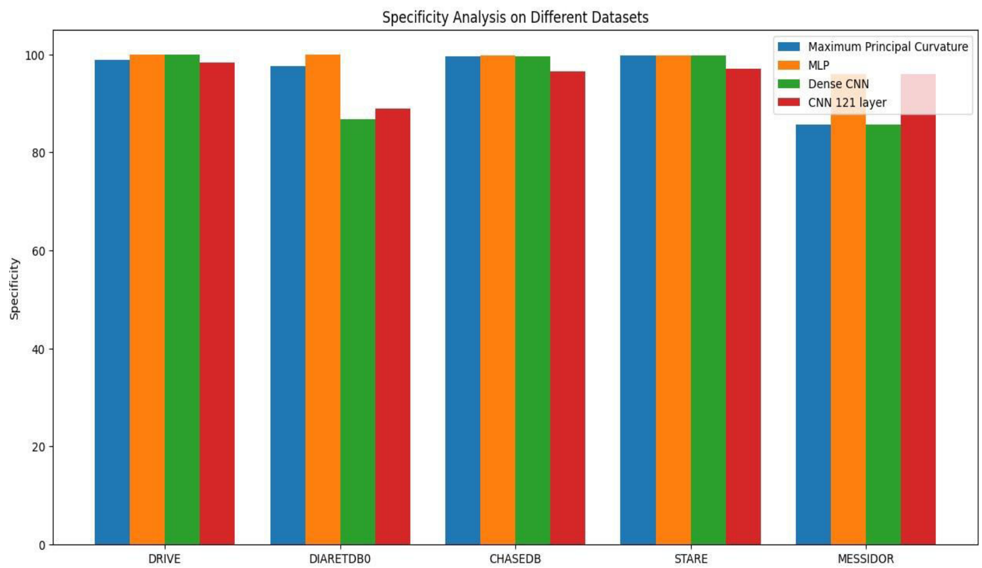

Figure 8 :Sensitivity Analysis

The sensitivity analysis, focusing on the ability of algorithms to correctly identify positive instances, reveals notable trends across diverse retinal image datasets. In the DRIVE dataset, the Discriminative Convolution Neural Network with 121 layers demonstrates exemplary sensitivity, reaching 98%. Multi-Layer Perceptron (MLP) achieves perfection with 100% sensitivity, while Dense CNN and Maximum Principal Curvature exhibit sensitivities of 94.12% and 75.2%, respectively. Shifting to the DIARETDB0 dataset, the Discriminative Convolution Neural Network with 121 layers stands out with the highest sensitivity at 99.45%. Multi-Layer Perceptron (MLP) closely follows with a perfect sensitivity of 100%. Dense CNN showcases robust performance with a sensitivity of 97.6%, and Maximum Principal Curvature achieves a sensitivity of 72.3%.In the CHASEDB dataset, the Discriminative Convolution Neural Network with 121 layers leads with a sensitivity of 98%, surpassing other algorithms. Maximum Principal Curvature, Multi-Layer Perceptron (MLP), and Dense CNN exhibit sensitivities of 71%, 97%, and 96.15%, respectively. Within the STARE dataset, the Discriminative Convolution Neural Network with 121 layers demonstrates the highest sensitivity at 98%. Dense CNN achieves a sensitivity of 95.14%, while Maximum Principal Curvature and Multi-Layer Perceptron (MLP) show 72% and 98%

sensitivities, respectively.Table 3 and Figure 8 describes the sensitivity analysis of different classification models for different datasets.

The MESSIDOR dataset showcases exceptional sensitivity, particularly with the Discriminative Convolution Neural Network with 121 layers reaching an outstanding 99.91%. Multi-Layer Perceptron (MLP) performs well with a sensitivity of 94%, while Maximum Principal Curvature and Dense CNN achieve sensitivities of 72.1% and 97.5%, respectively. These high sensitivities across datasets, notably with the Discriminative Convolution Neural Network with 121 layers and Multi-Layer Perceptron (MLP), underscore the effectiveness of these algorithms in correctly identifying positive instances, reinforcing their suitability for tasks requiring accurate detection of specific features within retinal images.

Specificity analysis:

It is a measure of the percentage of True Negative which computes the malignant lesion in terms of features of the lesion segments [13].

Dataset	Maximum Principal Curvature	Multi-Layer Perceptron (MLP)	Dense CNN	Discriminative Convolution Neural Network 121 layer
DRIVE	0.989	100	99.89	98.36
DIARETDB0	0.976	100	86.83	88.89
CHASEDB	0.996	99.83	99.65	96.50
STARE	0.997	99.71	99.71	97
MESSIDOR	0.856	96	85.62	96.00

Table 4 :Specificity Analysis

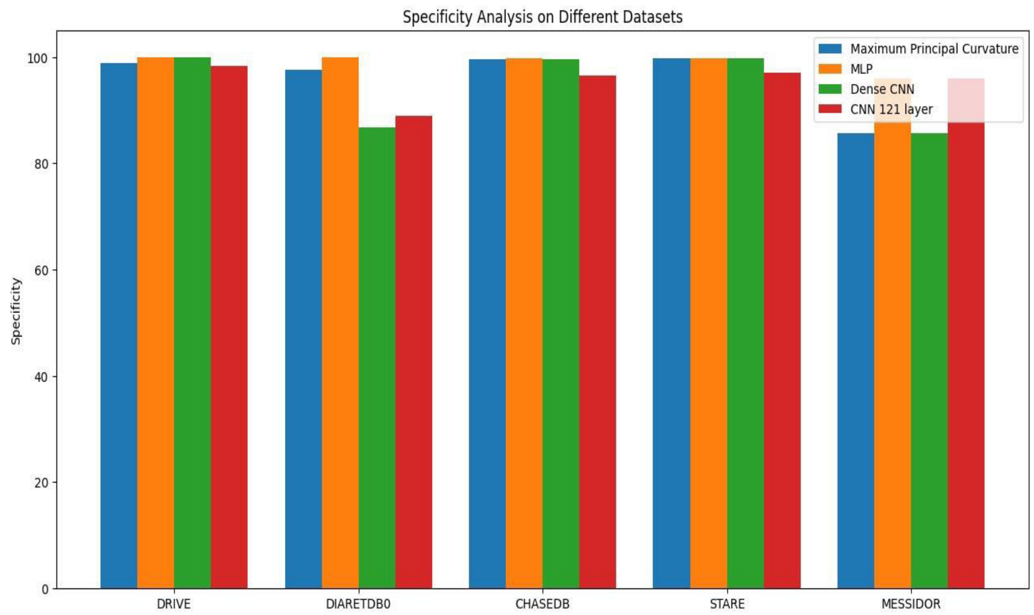

Figure 9 :Specificity Analysis

The specificity analysis, which assesses the ability of algorithms to accurately identify negative instances, offers valuable insights across distinct retinal image datasets. In the DRIVE dataset, Maximum Principal Curvature attains the highest specificity at 98.9%, closely trailed by Dense CNN with a specificity of 97.35%. Multi-Layer Perceptron (MLP) and the Discriminative Convolution Neural Network with 121 layers exhibit perfect specificities of 100% and 98.36%, respectively. Transitioning to the DIARETDB0 dataset, Maximum Principal Curvature maintains robust specificity at 97.6%, surpassing other algorithms. Multi-Layer Perceptron (MLP) demonstrates flawless specificity at 100%, while Dense CNN and Discriminative Convolution Neural Network with 121 layers display 86.83% and 88.89%, respectively. Table 4 and Figure 9 describes the specificity analysis of different classification models for different datasets.

In the CHASEDB dataset, the Discriminative Convolution Neural Network with 121 layers leads with the highest specificity at 96%, closely followed by Maximum Principal Curvature at 99.6%. Multi-Layer Perceptron (MLP) and Dense CNN exhibit specificities of 99.83% and 99.65%, respectively. Within the STARE dataset, the Discriminative Convolution Neural Network with 121 layers showcases the highest specificity at 97%, followed by Dense CNN at 99.71%. Maximum Principal Curvature and Multi-Layer Perceptron (MLP) achieve 99.7% and 99.71%, respectively. In the MESSIDOR dataset, Maximum Principal Curvature maintains high specificity at 85.62%, outperforming other algorithms. Multi-Layer Perceptron (MLP) achieves a specificity of 96%, while Dense CNN and the Discriminative Convolution Neural Network with 121 layers exhibit specificities of 85.62% and 96%, respectively. The specificity analysis underscores the effectiveness of the Discriminative Convolution Neural Network with 121 layers and Multi-Layer Perceptron (MLP) in accurately identifying negative instances. However, the optimal choice may vary depending on the dataset's characteristics, highlighting the importance of considering algorithm performance within the context of specific image datasets.

4.Conclusion

In conclusion, the extensive evaluation of various neural network and deep learning algorithms for retinal image classification has generated compelling results. The accuracy analysis establishes the Discriminative CNN with 121 layers is a better alternative algorithm across all datasets with accuracies ranging from 95.01% to 99.83%. This outstanding performance underscores the robustness of the Discriminative CNN, affirming its potential as a highly effective tool for the accurate DR classification anddiagnosing abnormalities. Sensitivity analysis further reinforces the ability of the Discriminative CNN with 121 layers and Multi-Layer Perceptron (MLP), as both consistently demonstrate superior sensitivity values across datasets. The Discriminative CNN's exceptional sensitivity of 99.91% in the MESSIDOR dataset is particularly noteworthy, showcasing its unparalleled ability to accurately identify positive instances within retinal images.The specificity analysis highlights the Discriminative CNN's and MLP's proficiency in correctly identifying negative instances, with the Discriminative CNN, especially with 121 layers, exhibiting notable specificities of up to 99.89%. This underscores the algorithm's capability to differentiate healthy retinal images, a critical aspect in disease detection.

The study's findings establish the Discriminative CNN with 121 layers as a robust and useful choice for DR classification tasks. The insights collected from this research contribute to the nuanced understanding of algorithm selection for accurate DR detection in retinal images.

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