International Journal of Computing and Digital Systems
ISSN (2210-142X)
Int. J. Com. Dig. Sys. 16, No.1 (Aug-24)

DOI:http://dx.doi.org/10.12785/ijcds/160168

Application of Optimized Deep Learning Mechanism for Recognition and Categorization of Retinal Diseases

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Received 24 Feb. 2024, Revised 6 May 2024, Accepted 7 May 2024, Published 10 Aug. 2024

Abstract: Retinal disorders are one of the common eye problems and its complication affects the eyes. In some cases, the retinal diseases would not cause any symptoms, or they only show mild vision impairments. Finally, it causes no vision or blindness. So, earlier recognition of symptoms could help to avoid blindness. Routine screening is one of the methods for early diagnosis of retinal disease. Another common way to identify retinal disease is to have an expert evaluate and rate eye photographs for the existence and severity of the illness. Unfortunately, in many parts of the world where retinal disease is common, the medical specialists capable of recognizing DR are scarce. Hence, a novel optimized African Buffalo-based deep Convolutional Neural Network (AB-DCNN) deep learning model is introduced in this article, which could detect the retinal disorders in the earlier stage from the fundus retinal image datasets and classify its stages. The proposed mechanism could detect diseases like Central Serous Retinopathy (CSR), Age-related Macular Degeneration (AMD), Diabetic Retinopathy (DR) and Macular hole (MH) and classify its stages as Severe, Moderate, Mild NPDR, PDR, and normal case. Depending upon the clinical importance, the impact of uncertainty on system performance and the relation between explained ability and uncertainty are examined. The uncertainty evidences make the system more reliable for usage in clinical environments. The proposed methodology increases the operational speed and lessens the computation time of the algorithm. It also reduces the losses and enhances classification accuracy.

Keywords: Retinal disease; Deep learning; African Buffalo optimization; Classification.

1. INTRODUCTION

As per the WHO's first World Report on Vision, approximately 2.2 billion people worldwide suffer from impaired vision or blindness. Furthermore, the world population's increase and changes in its age structure are leading this quantity to grow at a faster rate. The detection and prognosis of various eye illnesses from the muscle area is a critical issue for ophthalmologists [1]. As a result, illness progression is tracked and addressed through small vessel identification and structural and functional evaluation. Furthermore, the microvascular networks and the retinal analysis structure are used to diagnose eye diseases for example macular edoema, glaucoma, and AMD. If retinal disease is detected earlier, it could be treated; otherwise, it might result in irreparable blindness. As a result, routine screening is critical for early diagnosis of retinal disease [2]. Unfortunately, in various regions of the world wherein diabetes is more common, medical specialists capable of recognizing Diabetic Retinopathy disorder are scarce. There is enough data to suggest that retinal screening and diagnosis could help reduce unnecessary blindness.

One of the simplest ways to identify retinal disorders is having an expert evaluate and rate eye photographs for the existence and severity of the illness. Fundus cameras are already accessible in clinics, which provide decent quality images, although they are typically big and expensive [3], [4]. As a result, there have lately been major efforts to make use of recent advances in telecommunications and smartphone techniques to develop convenient, cost-effective fundus cameras for ophthalmic screening in remote places. Fundus images could reveal and detect various critical retinal locations such as the Optic Disk, Ocular Centre, retinal vessel and Optic nerve head (ONH). Age-related macular degeneration (AMD), Diabetic retinopathy (DR), glaucoma, cataracts, and myopia everything could be detected with a fundus camera colour imaging approach, which is simple to set up. Early diagnosis of the disorder is vital in preventing visual impairments in patients [5]. DR has been identified as a universal public healthcare issue, and diabetics-based vision damage must be treated quickly to be avoided.

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According to an epidemiological study, one for every 3 diabetics exhibits indications of DR, and a third of that may have eyesight retinal, which is classified as serious non-proliferative eye problems or diabetic maculae edoema [6].

Slight Non-Proliferative Diabetic Retinopathy (NPDR), Severe and Moderate NPDR, and Proliferative Diabetic Retinopathy (PDR) are the four types of diabetic retinopathy (PDR). NPDR will be the first phase of diabetic retinopathy, which is characterised by a microscopic aneurysm (MA), which is the smaller region of bulging in the retinal blood vessels. There seems to be no excessive bleeding in the retinal nerve, and if DR is discovered early enough, it may be possible to save the patient's vision with appropriate healthcare therapy. Slight NPDR escalates to a severe state if blood leaks from the clogged retina arteries if untreated. That's the Severe NPDR stage [7]. The fundus images of a healthy and an impaired eye are illustrated in Figure 1.

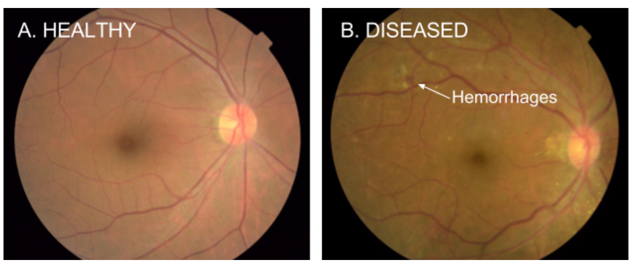

Figure 1. Healthy and diseased fundus eye images

Artificial intelligence (AI) is important and viable for automated screening of eye disease or detection based upon colour retinal fundus images, due to the advancement of Artificial Intelligence in medicine throughout the last decades. In recent years, the learning-based approach has aimed to build a model based upon a set of attributes to recognize or categorize the outcome into various categories [8], [9]. To overcome the DR challenges, sophisticated deep learning methods like CNN and Squeeze Net are used. Therefore, the more data we use, the more accurate will be the outcome. Deep learning, on the other hand, extracts feature automatically and feeds them to the network to match with the item of interest. It an essential part of the rapidly expanding discipline of data science. It establishes a rigorous conceptual framework for interpreting data and making decisions in diagnosis and management. Figure 2 represents the application of Deep Learning mechanisms in the healthcare industry from the year 2008 to till date [10].

A. *Motivation*

Although DL-based techniques in healthcare are fast evolving, and several observational studies have shown that AI can function on pace with healthcare specialists, the majority of such techniques have yet to be examined in designed clinical predictive research [11]. Many impediments, such as algorithmic accessibility, document management, confidentiality, and information standardization, impede actual deployment in patient-care situations. Furthermore, DL techniques are particularly 'data hungry,' necessitating vast amounts of health information to undertake huge investigations [12]. Considering AI's quick and spectacular advancement, the healthcare industry is extremely hopeful that AI will eventually provide greater and lesser care [13]. Deep learning systems with economically comparable results have been established in ophthalmology for a variety of end tasks, such as the detection of various eye illnesses like DR, AMD and glaucoma [14]. Yet, substantial, diversified, and precisely labelled data is required for the future growth, training, and evaluation of deep learning techniques. It's difficult since fine-tuning a pre-trained deep convolutional neural networks framework on Diabetic Retinopathy images may produce comparable findings. As a result, the problem must be met by choosing a proper technique for designing and building for DR image categorization. As a result, in the paper, an optimised deep learning architecture is given, in which the optimizing method addresses the obstacles in previous literature and produces a dependable result.

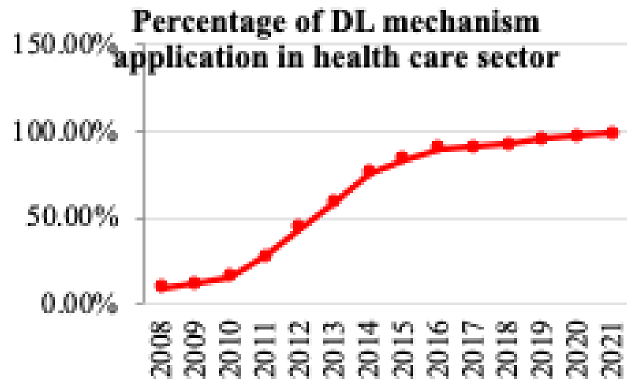

Figure 2. Application of DL mechanism from 2008 to till date

B. *Contributions*

The contributions of this paper are stated as follows:

- Fast and Effective Deep Learning Model: we proposed a fast and effective deep learning model called an optimized African Buffalo-based deep Convolutional Neural Network (AB-DCNN) for retinal disease recognition by detecting the retinal disorders in the earlier stage from the fundus retinal image datasets and classifying its stages.
- Deep Learning Integration: we proposed an integrated DL-based assistance diagnostics to analyze input retina photos and categorize diabetic retinopathy stages using an optimum pre-trained DL-CNN model with different amounts of variables and tiers. Several key responsibilities in diagnosing and interpreting retinal disorders include separation of the optic disc (OD), retinal blood vessel, and optic cup (OC) using

fundus images and retina layers in OCT images.

- Extensive Evaluation: we used real-world datasets to verify the efficiency and effectiveness of the proposed retinal disease recognition model.

The rest of this paper is organized as follows: Section 2 examines prior deep learning-based research on the recognition of retinal disorders, whereas Section 3 discusses the issues in the retinal disease detection process, and Section 4 discusses the present research's proposed techniques, including algorithms and schematic explanations. The experimental results and discussion are described in Section 5, and Section 6 provides the conclusion.

2. Related Works

Some of the recent literature that discusses the detection of retinal disease is explained below and few of the existing literature on the detection of diabetic retinopathy disorder are framed in Table I

A. *Detection of Retinal Disease Models*

A customized Convolutional Neural Network mechanism was introduced in [15] to distinguish between referable and non-referable Diabetic Retinopathy images. On the Messidor-2 dataset, the CNN was trained on Kaggle and attained an Area under ROC of 98.21 percent. [16] utilized three pre-trained Convolutional Neural Network models, Inception V3, Resnet152, and Inception-Resnet-V2 to categorize Diabetic Retinopathy images as referable Diabetic Retinopathy or not. To categorise referable Diabetic Retinopathy images in a private dataset, a weighted pathways Convolutional Neural Network termed WP-CNN was constructed [17]. Two separate Convolutional Neural Network models were suggested to identify images as normal or Diabetic Retinopathy [18]. On the DIARETDB1 dataset, their Convolutional Neural Network model has achieved an accuracy of 98.7 percent.

For the semi-supervised data, a Multi-Instance Learning technique employing multiple kernels (MK-MLI) was suggested in [19] for predicting Haemorrhage-Microaneurysm (HMA) on the region of interest of fundus images acquired from the Messidor dataset. This approach has 91.6 percent accuracy, but it has several drawbacks, like difficulties finding information hidden beneath complicated structures and instantly collecting higher-order data. The candidate identification procedure in sparse Bayesian classification is a difficult operation to accomplish in a complex image. The Arteriolar-to-venular realistic identification technique was proposed in [20]. The efficient method of Super Resolution (SR) revival was discussed in [21]. The micro-motion connectivity between hyperacuity and the human eye's retina is more accurate. There are several other forward-improving approaches with noise-suppression capabilities in it.

Recently, reviewed retinal image improvement literature focused either on image de-blurring or image super-resolution. Various techniques for eliminating motion blur, improving contrast, and improving the brightness of retinal fundus images have currently been presented. Contrast enhancement adaptive histogram equalisation (CLAHE) and Luminance gain matrix techniques have been offered as ways for enhancing luminosity and contrast [22]. To decrease the transparency and improve the sharpness of fundus images, the CLAHE and Fourier transform approach was employed [23]. The blurriness-removing function was conducted in [24] by calculating the transmission map and backdrop illumination level. The previously disclosed approaches were confined to extremely particular scenarios since they required estimating the deterioration model. A hierarchical CNN-based system was suggested in [25] for classifying blurry and non-blurry photos, followed by image restoration. None of these strategies took spatial resolution into account as a degradation mechanism, nor could they test various types of blurring difficulties. Various fundus imaging super-resolution activities, on the other hand, have been completed.

A novel innovation of a low-cost Mobile phone effective process with a microscopic lens as described in [26], which enables people in remote and inaccessible places to continue receiving eye checkups and illness diagnoses. A Generated Adversarial Network methodology with retinal fundus imaging super-resolution was developed in [27], which integrates saliency reduction for improved super-resolved photo quality. A progressively generative adversarial model was utilised to elevate the fundus image database in a future review [28]. Additional image-degrading models were not considered in such super-resolution studies. As could be observed, every one of those studies focused on a different aspect of image super-resolution or blurs, and thus cannot be generalised for potential implementation.

The area identification structure for the registrations of retinal fundus images with greater resolution was described by [4]. In terms of consistency, rotational change, substance modification, and limited scale adjustment, the strategy provides good experimental findings. Nonetheless, multimodal identification of retinal images is not ever included. The retinal images including their blood vessels are segregated to use the segmentation. As a result, this technique is preferred to physiologic and pathologic retinal images, but it has a higher computing complexity. An RF-based classifier was introduced in [5] to detect retinal abnormalities and provide doctors with a useful tool. To avoid the computation time of the SVM, the researcher forecasted the Diabetic Retinopathy by assessing the microaneurysm and region of the fundus images utilizing Twin-SVM (TSVM) instead of a solo SVM [29]. The TSVM is 4 times as quick as the standard SVM. The only factor influencing the TSVM's effectiveness is the amount of noise within the database. [30] used an NB classification to tackle the DR problems by extracting textural properties in fundus images and classified them into 3 categories with a 93.44 percent ACC. Nevertheless, one drawback of this method is that it has low predictive accuracy when used with a limited database. To diagnose eye illnesses, a Bayesian classification based on colour characteristics was used in [7]. They employed a complicated technique that integrated a lighting adjusting technique with classification tasks and a validation approach depending on local windows. The method had a decent rate of precision, but it required a lot of computational power. A multi-layer Neural Network was described for the identification of diseases in grey-scale retinal images [31]. The researcher analyzed the influence of an autonomous artificial intelligence model for Diabetic Retinopathy detection and sight threatening Diabetic Retinopathy identification and evaluated a mobile phone fundus photographic method for DR screening [32].

The author in [8] looked at how well the DL technology (Inception-V3) worked in patient healthcare. The classifier was tested using 30,000 photos from the public sphere (EyePACS, DiaRetDB1, and the Australian Tele-eye care Diabetic Retinopathy database), with ICDRSS criterion used to assess the degree of DR. A maximum of 193 diabetic patients were enrolled and 386 images were evaluated at a primary healthcare clinic in Western Australia. The analysis revealed that the specificity was 92 percent. In [33], retina images from diabetic patients taking part in a countrywide screening programme were used to evaluate the effectiveness of the algorithm.

A deep learning approach was used in [34] to show the potentiality of AI in a Zambian setting. In the retinal fundus images from diabetic participants who took part in the SDRP, the group developed an ensemble of DL models (VGGNet and ResNet). A maximum of 4504 retinal fundus images was collected from 3093 pupils of 1574 Zambians having diabetic disease. For pre-training DR, the area under ROC of the Deep learning method was 0.973, with sensitivities of 92 percent and specificity of 89 percent. The diagnostic accuracy of vision-threatening DR was 99 percent, while DME sensitivities were 97 percent. A machine learning software was utilized in [35] to recognize sight-threatening Diabetic Retinopathy (moderate to severe Diabetic Retinopathy, and DME) in 6788 fundus images (3460 individuals) from the Nakuru Eye Study in Kenya.

The ImageNet database was used in [36] for training InceptionNet V3 for five-class classifications using pre-training and obtained 90.9 percent accuracy. ImageNet pre-train was used in [37] for training ResNet50, Xception Nets, DenseNets, and VGG and attained 81.31 percent accuracy. Two research groups used databases provided by APTOS and Kaggle. The authors in [38] retrieved the characteristics from the full image to use a 2-D wavelet transform and fed them into a neural network for training. They tested 45 photos from the HRF dataset and found that 95.8% of them were correct. The wavelet technique was used in [39]. The RIM-ONE database revealed an accuracy of 81.3 percent. U-net is used in [40] for separating the Optical Disk and Optical Cup regions, then retrieved 8 morphologic characteristics and submitted it to an RF classifier as an input. They used the ORIGA dataset to test and got an accuracy of 76.9% and an AUC of 83.1 percent. The Hough transform was utilized in [41] to determine the OD region.

A Deep Learning method (Inception-V3) was used in [1] for the diagnosis of eyesight Diabetic Retinopathy. The authors in [42] suggested utilizing colour fundus images. On a test set of 250 photos, they were able to extract attributes from the original image utilizing image processing mechanisms and feed it into the support vector machine classifier for binary categorization, with accuracy, specificity and sensitivity of 97.6 percent, 96 percent, and 98 percent respectively. In [43], the authors used a three-step process to place and retrieve the Optic Disk region: first, a region proposal system was used to create a random number of rectangle objects, then the filtration images were given to a Convolutional Neural Network for discovering the objects with the best rating.

The DRISHTI-GS database was used in [44] to estimate CDR after employing a U-net algorithm. Disk and optic nerve face were evaluated using superpixel segmented in [45]. The simple linear popular technique superpixels were used in [46] to separate the Optic cup and Optic Disk regions after pre-processing the images to eliminate noise and improve contrasts.

The authors in [6] manually clipped the region of the Optic Disk before capturing the blood vessels and enhancing the contrast. Five Convolutional Neural Network models based upon typical Convolutional Neural Networks—ResNet50, VGG19, GoogleNet and DENet, of which VGG19 scored well for the RIM-ONE dataset was presented in [47], which has a sensitivity of 87 percentage, a specificity of 89 percentage, and Area under ROC of 94 percent. MI-GAN was proposed by [48] for producing different medical images and associated segmentation coverings from a small amount of training data. The entire retinal images for pre-training the network based upon the ResNet framework were used in [49]. Employing 1768 normal eye images and 1364 glaucoma images from a local dataset, researchers were able to get an area under ROC of 94.8 per cent. Deep CNN ensembles have been proven to be more accurate and efficient than single Convolutional Neural Network ensembles. A two-stage pipeline was suggested in [50].

A hybrid algorithm was proposed in [51] to identify and classify diabetic retinopathy disorders that used image processing and deep learning mechanisms. The framework was tested utilizing the MESSIDOR database's retinal fundus dataset, which consisted of 400 images and yielded positive results. A computer-aided screening method was used [52] which facilitated the analysis of fundus images with various lighting and angles. Machine Learning models were used to help identify the severity levels of Diabetic Retinopathy disorder in this investigation.

For discovering the blood vessel, [52] offers median filtering operation and morphological processes. The processes of region growing and thresholding are simple, but choosing region seed points, threshold values, and stopping criteria might be tricky. A median filter was employed in [14] for eliminating the noise, thresholding for segmenting the brighter and darker lesions, region growing operation, and Mahalanobis, Bayesian, and nearest neighbour classifiers for the detection of exudates regions. In low-quality photos, the technique failed in exudate identification. The researchers in [53] suggested a technique for the classification of hyperspectral images that uses a Convolutional Neural Network and real capsule architectures such as a 1D deep capsule architecture and a 3D deep capsule architecture. Recently, deep learning models have been developed for the early identification and categorization of retinal diseases, including diabetic retinopathy (DR). The studies [54] and [55] both demonstrate that their models are effective at detecting and classifying DR, with ManojS 2024 earning a high quadratic weighted kappa score and P 2023 achieving an average accuracy of 97.86%. The study [56] uses a multiclass model to overcome data bias and class imbalance in retinal illness recognition, resulting in an overall accuracy of 80.46%. Sundar 2023 proposes a graph convolutional neural network (GCNN) for categorization of DR illness levels that outperforms other cutting-edge methods. This research illustrates deep learning's promise for improving the early detection and management of ocular diseases. The transfer learning is used to construct a VGG-19 architectural model [57] with a classification accuracy of 99.17% for disorders such as diabetic macular edema and choroidal neovascularization.

B. *Strengths and Weaknesses of Exiting Works*

Table I discusses the methods and drawbacks of recent works on retinal disease detection. Most of the literature on the subject divides the condition into two categories: healthy eyes and diabetic retinopathy-defective eyes. While the abovementioned methods have significantly benefited retinal disease detection, addressing their inherent shortcomings is crucial. Existing works on retinal disease recognition exhibit numerous drawbacks, particularly regarding accuracy and efficiency. These limitations emphasize the pressing need for improved approaches, especially in identifying intricate patterns.

The goal of this paper is to distinguish between the non-proliferative and proliferative phases of diabetic retinopathy. Normal (Healthy) eyes, mild, moderate, and severe NPDR, and PDR are the five types of eyes. Furthermore, one of the best scopes that have been explored in this paper is retrieving manually made features from real photos after various processing:

- At first, the data set is trained in the proposed AB-DCNN model.
- Consequently, the pre-processing is accomplished through the Gaussian filter for noise removal enhancing the image and making it suitable for further processing steps.
- The AB-DCNN mechanism extracts the relevant attributes accurately from the pre-processed image detects the retinal disorder and classifies the stages of DR disorder more precisely.
- The anatomy of the retina blood vessels alters when illnesses like DR are present. Because of the existence of glaucoma, the cup-to-disc proportion is modified. After separation, the density of retina layers can also be used to detect glaucoma.
- Disease parameters are estimated, including glaucoma diagnosis, DR stage grading, and AMD identification. The appearance of red lesions in the fundus images (micro-aneurysms, haemorrhage) is a helpful indicator for Diabetic Retinopathy grading.
- Image enhancement evaluation, colour reproduction progression (deblurring, denoising of OCT images, super-resolution of fundus images), digital image generation.

3. Problem Statement

Since before the Deep Learning era, synthesizing accurate images of the ocular fundus has been a difficult undertaking. Recently, technological advancements have resulted in significant processing capacity, allowing Machine learning to progress to Neural networks with deep architectures. The quick improvement of the Deep learning mechanism aided in the creation of realistic-looking images, resulting in a technically stable and visually acceptable colored retinal fundus image. Screening for glaucoma in its earlier phases is difficult because it consumes more time, is subjective, and labor-demanding, and there aren't enough eye experts [63]. Prior literature had excellent performance in recognizing Diabetic Retinopathy, but they didn't account for the 5 stages of DR and the varied lesions [60]. The binary classification method's fundamental flaw is that it only categorizes DR images into two groups, ignoring the five stages of DR [64]. According (Kumar, Chatterjee, and Chattopadhyay 2021), since it uses cross datasets, it would take a larger computation time and a hybrid DL mechanism makes the model more complex.

The study's purpose is to create a model that could categorise DR images into five categories and have great results. Color fundus photos from five separate databases were used. The following are the major challenges: It achieved excellent outcomes when the image had a high resolution. While developing the models, though, it necessitated a lot of computing power. Utilizing low-resolution photos, on either hand, resulted in poor simulation results. Additionally, photos with distortion and a wider availability among classifications may have an impact on the model's effectiveness. Multiple image classification techniques led to substantial improvements when used with certain databases, but applying a similar approach to different areas and databases was a hurdle in machine learning and image analysis. The determination of the exact eye disease is significant for choosing an appropriate treatment process and for the prevention of retinal deterioration. The use of deep learning mechanisms is significantly reduced due to the models' ambiguity and vulnerability in making incorrect decisions in complex situations [65]. To address all of these concerns, several changes were made to the deep learning framework, which are described in detail below.

TABLE I. Existing literature of research on retinal disease detection

Reference	Year	Method	Drawback
[58]	2016	Convolutional Neural Network	The network found it difficult to learn deep sufficient attributes to recognize some more complex components of DR
[59]	2017	Support Vector Machine	It will not detect soft exudates and so the reduced accuracy
[60]	2018	Binary classification method	It only categorizes as DR or not DR but not all the five stages of DR
[61]	2019	Generative Adversarial Networks	As GAN could only handle retinal images with resolutions often lesser than those supplied by existing retinal fundus imaging, the synthesized datasets may be of bad quality
[62]	2021	GAN	The output images have blurry and discontinuous edges which are not similar to that of the real fundus image dataset
[2]	2020	PCA + Firefly algorithm + Deep Neural Network	It will not provide the optimal solution for better classification accuracy

Research Questions:
1. How can the deep learning process be improved to lower the decision of making a mistake in challenging situations?
2. What is the framework to categorise the retinal image with accurate results?
3. What are the changes made to deep learning mechanisms to solve the issues of computation burden and time consumption?

4. Proposed AB-DCNN Methodology

The work represents the construction of a convolutional neural network that can diagnose retina illness and phases of diabetes retinopathy using colour fundus images as input. The proposed method uses an optimization mechanism along with the deep learning approach to make the design free from the aforementioned problems. The proposed mechanism's processing steps contain 4 phases namely, Data gathering, Pre-processing, Feature extraction, and categorization followed by the performance evaluation. It utilizes a novel African Buffalo optimization mechanism based on deep CNN (AB-DCNN). The ABO mechanism accomplishes the feature extraction operation followed by classification using the deep neural network model.

A. *Working of AB-DCNN mechanism*

The approach for establishing and verifying the suggested AB-DCNN technique and its various processing stages are depicted in Figure **??**. The initial step was to gather fundus photos from multiple resources into a huge database that included both publicly available databases and a unique database. The fundus photographs were then pre-processed, which included manually removing fundus images that were not suitable for diagnosis due to poor quality, as well as reducing images from various providers to a suitable size. The AB-DCNN methodology was built on the training and validation data in the third phase. The training dataset was used to optimise the model's learnable parameters, while the validating dataset was utilised to identify the best configurations of the hyper-parameters (such as training data, batch size, and velocity) using a randomized selection method. The ideal hyper-parameters are a set of hyper-parameters that allow the AB-DCNN modelling to get the best Area under the curve on the testing dataset. In the final step, it is examined the completed model's potential to recognize 6 prevalent ocular diseases, varying severity levels of DR, and 36 various kinds of fundus aberrant abnormalities or disorders using internal and primary exterior testing datasets. The various stages and their severity levels of Diabetic retinopathy disease are shown below in Table II.

1) Data collection

The retinal fundus images are gathered from the online datasets. Datasets are utilized for training the model for detecting the referable retinal disorder. Four publicly available datasets namely, Optical Coherence Tomography Image Database (OCTID), Retinal Fundus Multi-Disease Image Dataset (RFMiD), STARE dataset, and Indian Diabetic Retinopathy Image Dataset (IDRiD) are utilized for training and validating the proposed model. In total, 574 retinal fundus images are taken for analysis. Among these, 460 images are utilized for training the residual of which are utilized for testing. Both the divisions comprise normal

TABLE II. Classifying the stages of Diabetic retinopathy disorder

Severity level	Stage
Mild NPDR	the initial stage of DR
Moderate NPDR	progressive stage of DR
Severe NPDR	Severe stage of DR
PDR	Advanced stage of DR
Normal	

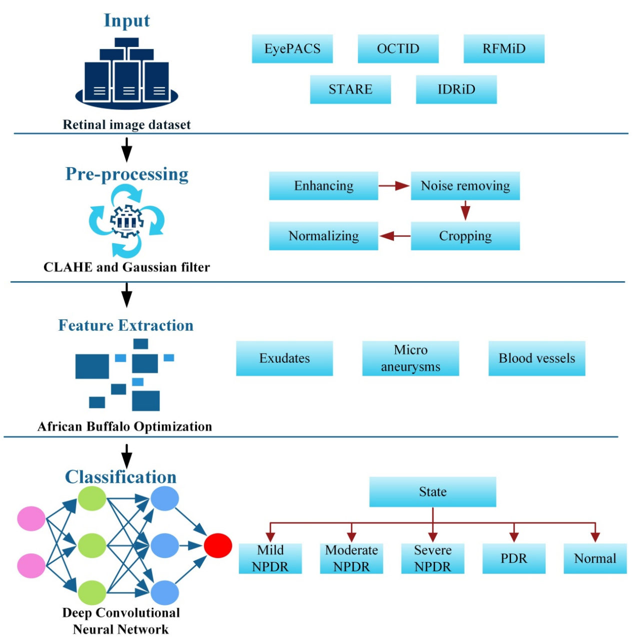

Figure 3. Processing phases of AB-DCNN model

fundus images as well as diseased images like Macular hole (MH), Age-related Macular Degeneration (AMD), Central Serous Retinopathy (CSR), and Diabetic Retinopathy (DR). The total number of training and testing data for five cases is illustrated in Table III.

2) Pre-processing

Pre-processing is an essential phase for the enhancement of the retinal image quality and proceeds to the successive phases with improved performance. The contrast of the fundus image is improved through pre-processing. The datasets came from a variety of real-world sources, and their properties represent that some photographs are out of focus and have incorrect illumination, or contain noise and distortions that are irrelevant to the analysis. Such poor-quality fundus images must be removed from those approaches to guarantee that they are not mistaken for abnormal images.

Pre-processing was carried out in two stages. The first is generic pre-processing, which is implemented in all of the dataset's images. The subsequent procedure is to accomplish specialised pre-processing based on the attributes that will be retrieved. Green channel extraction, Resizing, and Contrast Limited Adaptive histogram equalization (CLAHE) are all part of the basic pre-processing stage. The real images are 1024x1024 pixels in size. Because the dataset is large, the photos are saved in.jpeg format with a resolution of 300×300 pixels to reduce computing time. The retinal vessels are visible as well; however, they have lower contrast than the green channel. The blue channel is noisy and lacks information. For contrast enhancement, CLAHE (Contrast limited adaptive histogram equalisation) is applied. It makes various image histograms and utilizes them to reassign the image's pixel intensity. As a result, CLAHE is better at improving edge improvement and regional contrast in every image region. The morphological procedure, median filter operation, and thresholding are used to accomplish particular pre-processing for the detection of exudates. The discovery of blood vessels and microaneurysms comes next.

3) Detection of Exudate

Morphological dilation is accomplished through a 6x6 elliptical-shaped structural component. For the reduction of noise, a non-linear median filter is utilized. The exudate intensity is much higher. Therefore, thresholding was utilized for extracting it. Following this pre-processing operation, the pixels with a luminance higher than 235 are converted to 255, and the residuals are changed to 0. Then the region of exudates is found by the image traversing function.

4) Detection of Blood Vessel

The blood vessel is one of the most significant criteria for identifying diabetic retinopathy stages. After capturing the green channel image and improving the image contrast, a variety of strategies have been used to eliminate blood vessels. In the image, alternative sequential filtering is used, with ellipse-shaped and 3 distinct-sized structural elements (5×5, 11×11, and 23×23). The generated image is then deducted from the actual one. There are numerous minor sounds in the deducted image. Area parameter noise removal is utilized for eliminating such turbulences. The find contours () function is used for discovering the contours of every element, such as sounds, and the contour area () function is used for calculating the contour area and eliminating noises with an area equal to or greater than 200 pixels. The image is then binarized by applying a threshold

TABLE III. Datasets used for retinal disease detection.

Dataset	DR	CSR	AMD	MH	Normal	Total
Training	45	81	85	83	166	460
Testing	12	19	20	21	42	114
Total	57	100	105	104	208	574

value. Finally, the no. of pixels required to cover the area of blood vessels is evaluated.

5) Detection of Microaneurysm

Microaneurysms are extracted from the green region of the RGB value. CLAHE is utilised for improving contrast. The noise would then be discarded utilizing a median filter. For morphological operation, a 7×7 elliptical-shaped parametric model is utilized. After the application of the morphological erosion process, the image is inverted. Morphological closing operation is utilised to link the discontinuous portions of the blood artery. Subsequently, the image was binarized. As the haemorrhage, blood vessel, and microaneurysm all have nearly similar intensities, the binarized image would identify all three elements simultaneously. As the microaneurysms are minor, the contour area was utilized for extracting them.

The LBP texture descriptor is based on two attributes: shape and blood vessels. For the detection of shape, the subsequent pre-processing procedures are utilized: Converting a colour image into a grayscale image is the starting stage. The grayscale image is then filtered with a median filter in the next stage. The filtered image is then applied with an adaptive histogram equalisation mechanism called the CLAHE [22]. The image is then normalised, and the blood vessels can be observed using the morphological approach.

B. Feature Extraction and Classification

Feature extraction is used to extract the essential features for categorization purposes. The primary concept behind feature extraction is to capture significant features or characters like shape, colour boundaries, etc. Extraction of features could be accomplished using the African Buffalo Optimization mechanism [66]. In the final part of the AB-DCNN model, the African buffalo optimization mechanism is used as an optimizer. The ABO mechanism attracts its inspiration from the African buffalo's characteristics in the wide savannah regions and the African forests. They search and trace the lush green pastures in different parts of Africa to satisfy their large appetites. Likewise, this mechanism traces the location of the affected parts in the retinal image using their fitness function. Some of the important features that need to be identified for classifying diabetic retinopathy disorder are the Area of Exudates, Area of Micro aneurysms, and Area of Blood vessels. It has been discovered through research into related studies that using deep learning-based classifiers for hand-crafted characteristics from unprocessed photos yields better accurate forecasting. An optimization strategy implemented in a deep convolutional neural network model was chosen for the research depending upon the findings.

1) African Buffalo Optimization (ABO) Mechanism

The ABO is a stochastic optimization method that draws inspiration from the behaviour and attitude of African buffalos. These wild cows, similar to domestic cows, travel in large herds of up to a hundred buffalos, covering thousands of kilometres through African tropical rainforests and scrubland. They achieve this by travelling together. They are travelling in search of ample grazing grounds. They tend to migrate towards areas with rainy weather to locate plentiful grazing meadows. Due to the geographical diversity of Africa, buffalos are always in motion as they seek their favourite grasslands. The ABO algorithm is specifically designed to analyze the many kinds of communication utilized by buffalos to organize themselves. They have employed several auditory signals to signify the hazardous areas, favourable and unfavourable regions of grazing areas, and to motivate their herds to remain and take advantage of the available resources. The vocalization of the 'waa' sound serves as a signal to the buffalos, informing them of the presence of assailants or a scarcity of pastures. This prompts the herds to relocate to safer areas or portions of the grassland that offer better resources. After the cry is given, the animals are directed to stay alert and locate a safe or more well-fed pasture. The 'maa' noises, in contrast, are employed to encourage buffalos to unwind as there are ample grazing meadows nearby and the surroundings are conducive to grazing. The herds can effectively meet their need for food sources by utilizing these signals.

Furthermore, its learning factors assist in processing the buffalo movement. The helpful behavior of buffalo is upgraded through $le_1(\beta_p^{targ} - w_f)$, and the buffalo's intelligence is denoted by $le_2(b_{pmax.f} - w_f)$. Also, the fitness value is computed through eqn. 1.

Furthermore, its learning factors assist in processing the buffalo movement. The helpful behavior of buffalo is upgraded through $le_1(\beta_p^{targ} - w_f)$, and the buffalo's intelligence is denoted by $le_2(b_{pmax.f} - w_f)$. Also, the fitness value is computed through Eq. 1.

$$m_{f+1} = m_f + le_1(\beta_p^{trag} - w_f) + le_1(b_{pmax.f} - w_f) \quad (1)$$

Here m_{f+1} denotes the next feature, and also m_f represents

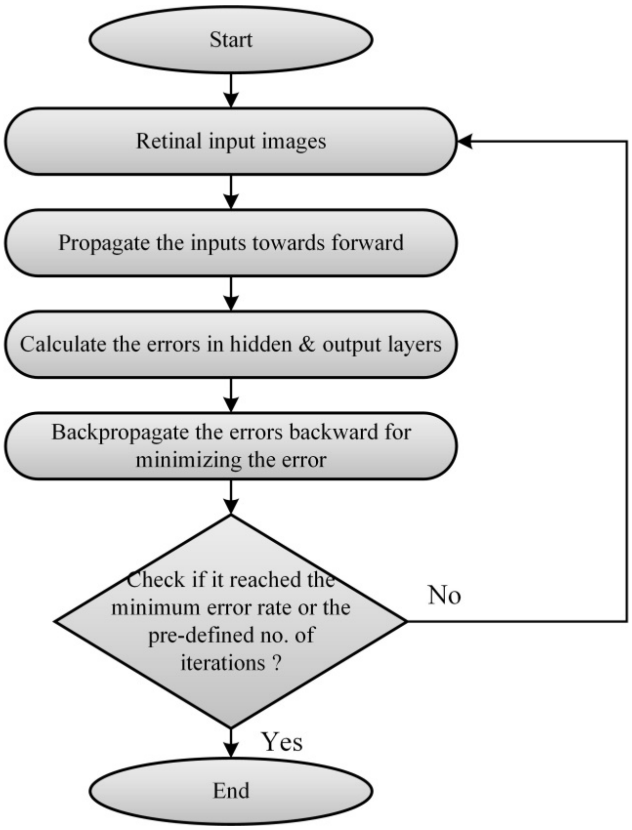

Figure 4. Flowchart for training AB-DCNN model

the current feature value. In addition, new feature update is deliberated using Eq. (2).

$$w_{f+1} = \frac{w_f + m_f}{\lambda^*} \tag{2}$$

Where w_f and m_f indicate the respective exploration and exploitation fitness of f.

λ^* indicates the random number that takes any value between 1 and 1 depending on the problem being solved

hereby, it provides the best optimal feature set for making the classification accuracy higher. The Pseudo code of the African buffalo optimization mechanism is discussed below in algorithm 1.

The classification of diabetic retinopathy is accomplished through the Deep Convolutional Neural Network mechanism. The delicate features included in the categorization tasks such as exudates, micro-aneurysms, and hemorrhages on the retina could be identified using a deep convolutional neural network model resulting in an automated assessment. CNNs could be trained to recognize the symptoms of Diabetic Retinopathy in fundus images. The flowchart for detecting the retinal disease is represented below in Figure 4.

The working of the proposed AB-CNN mechanism is represented below in algorithm 2.

Initially, the input retinal Image dataset is trained in the system. Subsequently, the images are imported to the preprocessing layer in which the image quality is enhanced for further processing. Following this, the preprocessed images are imported into the core important layer called the feature extraction layer to perform the extraction process. It is accomplished through African Buffalo Optimization (ABO) mechanism. Finally, the feature-extracted images are imported into the classification process to categorize the stages of Diabetic Retinopathy. It is accomplished through the Deep Convolutional Neural Network mechanism. The novel mechanism could offer an automated system for DR detection with Very high accuracy, instantaneous reporting of results, and Consistency of interpretation (the algorithm will make the same prediction on a specific image every time).

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5. Result and Discussion

This section discusses the experimental results of our proposed model for the recognition and categorization of retinal diseases using deep learning. We conducted extensive experiments using diverse real medical image datasets.

A. *Steps for performance evaluation*

1) Split the examples into training set X and test set Y randomly.
2) Use training set X to learn the model.
3) Evaluate using the testing set Y.

The suggested methodology is dependent on the design of a Convolutional neural network. The design is comprised of convolutional layers that convolute the input before passing it on to the pooling layer. The technique is repeated hundreds to thousands of times for feature extraction. As a result, the model is capable of extracting several characteristics from each input. The retinal image is transformed into a grayscale image and then pre-processed to retrieve the characteristics using the developed model. The African Buffalo Optimization algorithm is utilized to detect the attributes. Deep Convolutional Neural Networks are utilized for classifying the data. A total of 574 photos are taken, with 114 images being used for tests and the rest being used for training. The testing process takes longer than the training stage. The rate of learning is assumed to be 0.1. MATLAB was used to generate the simulation findings. Table IV shows the comparison of datasets in existing deep-learning mechanisms for classifying retinal diseases.

B. *Performance evaluation*

Performance criteria like accuracy, recall, precision, F1-score, sensitivity, and specificity are utilized for calculating the suggested technique's effectiveness and reliability.

1)Accuracy

Algorithm 1: African Buffalo Optimization Mechanism
Function $f(n) = (f_1, f_2, \ldots, f_n)^k$
Place buffaloes in the solution path
Input fitness values using Eq. (1)
Location Update β_p^{trag} and using equation (2)
If $b_{pmax.f}$ provides Yes, then proceed
If $b_{pmax.f}$ provides No, then back to initial step
Stopping procedure not performed, and then starts with fitness step
Get Output

Algorithm 2: Working of AB-DCNN mechanism

Input: Input retinal image
Output: Classification of DR classes
Import the data in the AB-DCNN model
Data is pre-processed
- Image enhancing (CLAHE)
- Noise removal (Gaussian filter)
- Cropping
- Normalizing

Feature extraction by African Buffalo Optimization mechanism
- Area of Exudates
- Area of Microaneurysms
- Area of Blood vessels

Classifying the stage of DR by Deep CNN
- Mild NPDR
- Moderate NPDR
- Severe NPDR
- PDR
- Normal

Classify the retinal disease as AMD, MH, DR, CSR
Performance Evaluation

TABLE IV. Comparison of datasets in existing deep learning mechanisms for classifying retinal diseases

References	Dataset used	Lesion detection
[67]	Kaggle	No
[68]	Private dataset	No
[69]	Private dataset	Red lesion
Proposed AB-DCNN model	5 datasets	Yes

The simplest intuitive performance metric is accuracy, which is expressed to be the proportion of precisely predicted observations to all observations.The proportion of precisely categorized patterns to the total no. of classified patterns is known as accuracy. It is calculated using Eq. (3) as follows,

$$Accuracy = \frac{tp + tn}{tp + fp + tn + fn} \tag{3}$$

Table IV represents the accuracy comparative analysis of the prevailing and the proposed approaches and its graphical representation is shown in Figure **??** The revised AB-DCNN methodology has advantages in accuracy over Random Forest, VGG16, AlexNet and SVM methods in recognition and categorization of retinal disease.

2) Precision

Precision is measured by the amount of positive class predictions that belong to the positive class. Precision is expressed to be the ratio of the rate of correct classification of events among every detected event. It is computed using eqn.(4) as,

$$precision = \frac{tp}{tp + fp} \tag{4}$$

TABLE V. Accuracy Comparison of existing deep learning mechanisms for classifying retinal diseases

Methods	Accuracy
Random forest	94.2%
VGG16	99.17%
AlexNet	98.32%
SVM	88.25%
Proposed AB-DCNN model	99.82%

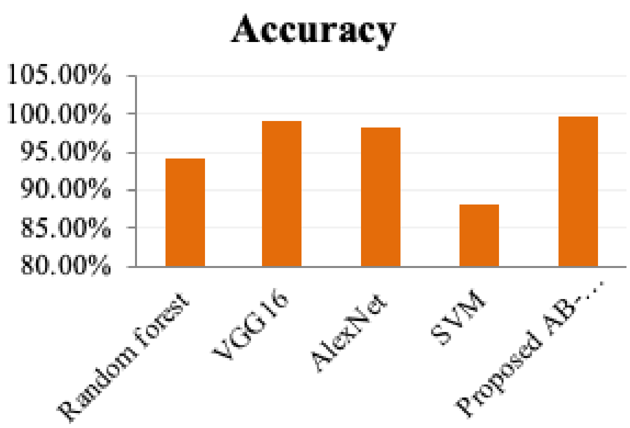

Figure 5. Comparison of Accuracy

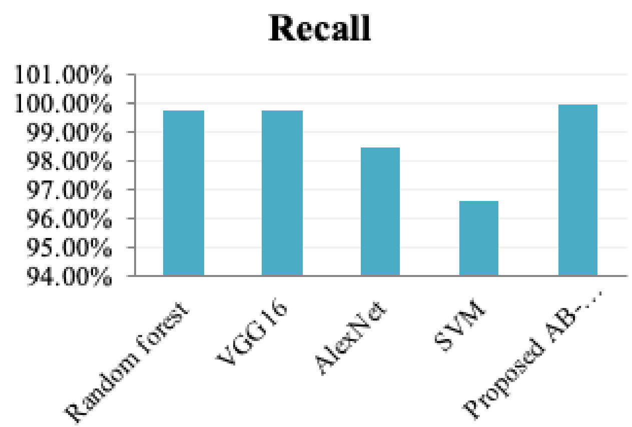

Figure 7. Comparison of Recall

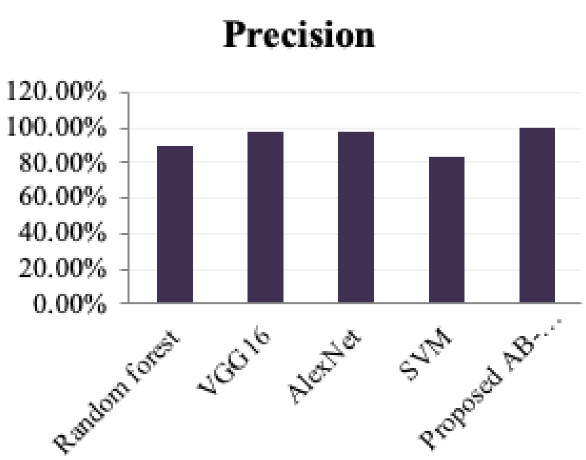

Figure 6. Comparison of Precision

The projected technique Combined novel African Buffalo-based deep Convolutional Neural Network achieves a higher precision of 99.67% when compared to the existing retinal disease recognition and categorization methods such as Random Forest, VGG16, AlexNet and SVM classifier. Table VI represents the precision comparative analysis of the prevailing and the proposed approaches and its graphical representation is shown in Figure 6.

3) Recall (or) Sensitivity

The recall is described as the amount of positive class predictions that are made out of all positive examples in the dataset. The fraction of right events among all events is known as recall. It is calculated using eqn.(5) as follows,

$$recall = \frac{tp}{tp + fn} \tag{5}$$

Table VII represents the recall comparative analysis of the prevailing and the proposed approaches and its graphical illustration is shown in Figure 7. The proposed strategy when compared to the current techniques for categorizing and recognising retinal diseases, such as Random forest, VGG16, AlexNet, and SVM classifier, the combined novel African Buffalo-based deep Convolutional Neural Network gets an enhanced level of recall of 100%.

4) F-measure F-measure is the degree of harmonic mean among recall and precision. It is the statistical degree utilized to rate the performance. F1-score is formulated in eqn.(6) as,

$$F - measure = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{6}$$

TABLE VI. Precision Comparison of existing deep learning mechanisms for classifying retinal diseases

Methods	Precision
Random forest	89.4%
VGG16	98.32%
AlexNet	98.32%
SVM	83%
Proposed AB-DCNN model	99.67%

TABLE VII. Recall comparison of existing deep learning mechanisms for classifying retinal diseases

Methods	Recall
Random forest	99.80%
VGG16	99.79%
AlexNet	98.5%
SVM	96.63%
Proposed AB-DCNN model	100%

TABLE VIII. F1-score Comparison of existing deep learning mechanisms for classifying retinal diseases

Methods	F1-score
Random forest	94.4%
VGG16	99.2%
AlexNet	98.42%
SVM	89.24%
Proposed AB-DCNN model	99.71%

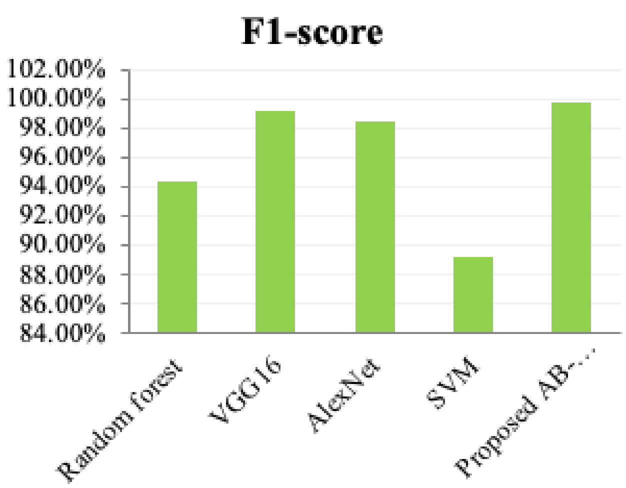

Figure 8. Comparison of F1-score

The combined novel African Buffalo-based deep Convolutional Neural Network achieves an improved degree of F1-score of 99.71% when compared to the existing methods for classifying and identifying retinal diseases, such as Random Forest, VGG16, AlexNet, and SVM classifier. Table VIII represents the precision comparison of the prevailing and the proposed approaches and its graphical illustration is shown in Figure 8.

5) Specificity

Specificity is described as the amount of negative class predictions that are made out of negative examples in the dataset. It's the probability that the screening process would accurately determine a disease-free person. It is calculated using eqn.(7) as follows,

$$Specificity = \frac{tn}{tn + fp} \quad (7)$$

Table IX represents the precision comparison of the existing and the proposed approaches and its graphical representation is shown in Figure 9. Comparing the suggested approach to existing methods for classifying and identifying retinal diseases, such as Random Forest, VGG16, AlexNet, and SVM classifier, the combined novel African Buffalo-based deep Convolutional Neural Network obtains an increased level of specificity of 99.43

C. *Discussion*

Due to its significance in supporting ophthalmologists in screening glaucoma illness more simply and cheaply, a computerized retinal disease diagnosis system is an important function in saving people's vision. Due to the usage of diverse datasets and the absence of a consistent system for comparisons, the analyzed outcome is not always the greatest when compared to the preceding techniques. To

TABLE IX. Specificity comparison of existing deep learning mechanisms for classifying retinal diseases

Methods	Specificity
Random forest	88.74%
VGG16	98.38%
AlexNet	98.43%
SVM	80.51%
Proposed AB-DCNN model	99.43%

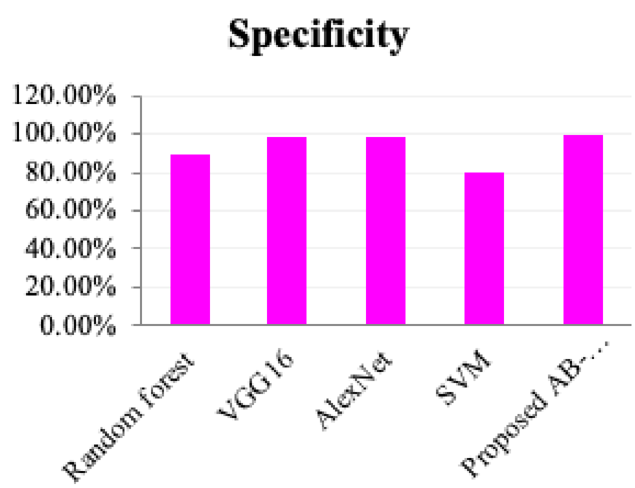

Figure 9. Comparison of Specificity

make the verification requirements easier, all of the suggested methodologies' findings and results were matched to those of other studies and used similar experimental results. Due to parameter sharing and reduced connectivity, the Convolutional Neural Network detects straight from image pixels with minimal pre-processing and the greatest result utilising small parameters. The research offered a Deep learning model for retinal diagnosis that is both ambiguous and understandable. The end-user can deduce which areas the system examined and how confident the algorithm is in its projections before making a final decision. Splitting situations with higher levels of uncertainty for referrals might also aid predictive accuracy and establish credibility.

These charts show how effective uncertain data is. Rather than misidentifying, reporting unclear images to a doctor can improve patient safety by improving assurance in the operating platform. Several broad conclusions concerning the link between ambiguity and the traits emphasized by solutions could also be reached. Cases with more variation between the components appear to be categorized more accurately. Clinicians also take into account the darkened areas, such as fluid build-up and new blood vessel shadowing. Ultimately, there is a link between a deep learning model's uncertainties, justifications, and reliability for retina OCT images. The work is a preliminary analytical study that results in various subjects for additional investigation.

6. Conclusion

On the premise of fundus images, the suggested methodology obtains greater precision, sensitivity, and specificity scores in identifying retinal disorders. It also overcomes all the limitations in the existing model and it effectively detects and classifies the stages of DR disorder. The present work offers an efficient complete automatic screening model for assisting in the diagnosis of retinal disorders and it is cost-effective and lessens the computational burden. The technique is more accurate than previous machine learning algorithms and takes less time. It also consumes massive volumes of information and works admirably, necessitating less image pre-processing in the presence of noisy data. It suggests that such a model could be a useful and cost-effective tool for ophthalmologists to improve existing clinical pathways for identifying retinal illness phases less affordably and more quickly. However, the suggested technique does not successfully encode the location and orientation of affected regions and requires a large amount of training data to be efficient. Future research is required to assess the usefulness of the Deep Learning approach in retinal illness screenings employing hybrid optimization techniques to enhance the program's reliability and efficiency.

Future research could extend the technique to a wider range of topics to improve deep neural networks for practical uses. This data could be utilized to improve the resilience of a model by changing the characteristics it learns. An additional approach might be to measure diseased traits like the light and density of the retinal pigment epithelium then link these to explanation and uncertainties. The fundamental impediments to the acceptability of deep learning approaches in numerous areas, particularly medical diagnosis, could be overcome by developing uncertainty-conscious and understandable systems.

References

[1] M. D. Abràmoff, P. T. Lavin, M. Birch, N. Shah, and J. C. Folk, "Pivotal trial of an autonomous ai-based diagnostic system for detection of diabetic retinopathy in primary care offices," *NPJ digital medicine*, vol. 1, no. 1, p. 39, 2018.

[2] T. R. Gadekallu, N. Khare, S. Bhattacharya, S. Singh, P. K. R. Maddikunta, I.-H. Ra, and M. Alazab, "Early detection of diabetic retinopathy using pca-firefly based deep learning model," *Electronics*, vol. 9, no. 2, p. 274, 2020.

[3] L. A. Yannuzzi, M. D. Ober, J. S. Slakter, R. F. Spaide, Y. L. Fisher, R. W. Flower, and R. Rosen, "Ophthalmic fundus imaging: today

and beyond," *American journal of ophthalmology*, vol. 137, no. 3, pp. 511–524, 2004.

[4] Z. Ghassabi, J. Shanbehzadeh, and A. Mohammadzadeh, "A structure-based region detector for high-resolution retinal fundus image registration," *Biomedical signal processing and control*, vol. 23, pp. 52–61, 2016.

[5] A. R. Chowdhury, T. Chatterjee, and S. Banerjee, "A random forest classifier-based approach in the detection of abnormalities in the retina," *Medical & biological engineering & computing*, vol. 57, pp. 193–203, 2019.

[6] J. I. Orlando, E. Prokofyeva, M. del Fresno, and M. B. Blaschko, "Convolutional neural network transfer for automated glaucoma identification," in *12th international symposium on medical information processing and analysis*, vol. 10160. SPIE, 2017, pp. 241–250.

[7] H. Wang, W. Hsu, K. G. Goh, and M. L. Lee, "An effective approach to detect lesions in color retinal images," in *Proceedings IEEE Conference on Computer Vision and Pattern Recognition. CVPR 2000 (Cat. No. PR00662)*, vol. 2. IEEE, 2000, pp. 181–186.

[8] Y. Kanagasingam, D. Xiao, J. Vignarajan, A. Preetham, M.-L. Tay-Kearney, and A. Mehrotra, "Evaluation of artificial intelligence–based grading of diabetic retinopathy in primary care," *JAMA network open*, vol. 1, no. 5, pp. e182 665–e182 665, 2018.

[9] D. Kavitha and S. S. Devi, "Automatic detection of optic disc and exudates in retinal images," in *Proceedings of 2005 International Conference on Intelligent Sensing and Information Processing, 2005.* IEEE, 2005, pp. 501–506.

[10] S. Srivastava, S. Soman, A. Rai, and P. K. Srivastava, "Deep learning for health informatics: Recent trends and future directions," in *2017 international conference on advances in computing, communications and informatics (ICACCI).* IEEE, 2017, pp. 1665–1670.

[11] A. Lee, P. Taylor, J. Kalpathy-Cramer, and A. Tufail, "Machine learning has arrived!" *Ophthalmology*, vol. 124, no. 12, pp. 1726–1728, 2017.

[12] J. He, S. L. Baxter, J. Xu, J. Xu, X. Zhou, and K. Zhang, "The practical implementation of artificial intelligence technologies in medicine," *Nature medicine*, vol. 25, no. 1, pp. 30–36, 2019.

[13] W. W. Stead, "Clinical implications and challenges of artificial intelligence and deep learning," *Jama*, vol. 320, no. 11, pp. 1107–1108, 2018.

[14] B. M. Ege, O. K. Hejlesen, O. V. Larsen, K. Møller, B. Jennings, D. Kerr, and D. A. Cavan, "Screening for diabetic retinopathy using computer based image analysis and statistical classification," *Computer methods and programs in biomedicine*, vol. 62, no. 3, pp. 165–175, 2000.

[15] R. Pires, S. Avila, J. Wainer, E. Valle, M. D. Abramoff, and A. Rocha, "A data-driven approach to referable diabetic retinopathy detection," *Artificial intelligence in medicine*, vol. 96, pp. 93–106, 2019.

[16] Y.-T. Hsieh, L.-M. Chuang, Y.-D. Jiang, T.-J. Chang, C.-M. Yang, C.-H. Yang, L.-W. Chan, T.-Y. Kao, T.-C. Chen, H.-C. Lin *et al.*, "Application of deep learning image assessment software verisee™ for diabetic retinopathy screening," *Journal of the Formosan Medical Association*, vol. 120, no. 1, pp. 165–171, 2021.

[17] Y.-P. Liu, Z. Li, C. Xu, J. Li, and R. Liang, "Referable diabetic retinopathy identification from eye fundus images with weighted path for convolutional neural network," *Artificial intelligence in medicine*, vol. 99, p. 101694, 2019.

[18] S. Das, K. Kharbanda, M. Suchetha, R. Raman, and E. Dhas, "Deep learning architecture based on segmented fundus image features for classification of diabetic retinopathy," *Biomedical Signal Processing and Control*, vol. 68, p. 102600, 2021.

[19] P. Cao, F. Ren, C. Wan, J. Yang, and O. Zaiane, "Efficient multi-kernel multi-instance learning using weakly supervised and imbalanced data for diabetic retinopathy diagnosis," *Computerized Medical Imaging and Graphics*, vol. 69, pp. 112–124, 2018.

[20] G. Molodij, E. Ribak, M. Glanc, and G. Chenegros, "Enhancing retinal images by extracting structural information," *Optics Communications*, vol. 313, pp. 321–328, 2014.

[21] S. D. Babacan, R. Ansorge, M. Luessi, P. R. Matarán, R. Molina, and A. K. Katsaggelos, "Compressive light field sensing," *IEEE Transactions on image processing*, vol. 21, no. 12, pp. 4746–4757, 2012.

[22] M. Zhou, K. Jin, S. Wang, J. Ye, and D. Qian, "Color retinal image enhancement based on luminosity and contrast adjustment," *IEEE Transactions on Biomedical engineering*, vol. 65, no. 3, pp. 521–527, 2017.

[23] A. Mitra, S. Roy, S. Roy, and S. K. Setua, "Enhancement and restoration of non-uniform illuminated fundus image of retina obtained through thin layer of cataract," *Computer methods and programs in biomedicine*, vol. 156, pp. 169–178, 2018.

[24] L. Xiong, H. Li, and L. Xu, "An enhancement method for color retinal images based on image formation model," *Computer methods and programs in biomedicine*, vol. 143, pp. 137–150, 2017.

[25] B. M. Williams, B. Al-Bander, H. Pratt, S. Lawman, Y. Zhao, Y. Zheng, and Y. Shen, "Fast blur detection and parametric deconvolution of retinal fundus images," in *Fetal, Infant and Ophthalmic Medical Image Analysis: International Workshop, FIFI 2017, and 4th International Workshop, OMIA 2017, Held in Conjunction with MICCAI 2017, Québec City, QC, Canada, September 14, Proceedings 4*. Springer, 2017, pp. 194–201.

[26] A. Bourouis, M. Feham, M. A. Hossain, and L. Zhang, "An intelligent mobile based decision support system for retinal disease diagnosis," *Decision Support Systems*, vol. 59, pp. 341–350, 2014.

[27] D. Mahapatra, B. Bozorgtabar, S. Hewavitharanage, and R. Garnavi, "Image super resolution using generative adversarial networks and local saliency maps for retinal image analysis," in *Medical Image Computing and Computer Assisted Intervention- MICCAI 2017: 20th International Conference, Quebec City, QC, Canada, September 11-13, 2017, Proceedings, Part III 20*. Springer, 2017, pp. 382–390.

[28] D. Mahapatra, B. Bozorgtabar, and R. Garnavi, "Image super-resolution using progressive generative adversarial networks for medical image analysis," *Computerized Medical Imaging and Graphics*, vol. 71, pp. 30–39, 2019.

[29] M. Singla, S. Soni, P. Saini, A. Chaudhary, and K. Shukla, "Diabetic retinopathy detection using twin support vector machines," in *Advances in Bioinformatics, Multimedia, and Electronics Circuits*

and Signals: Proceedings of GUCON 2019. Springer, 2020, pp. 91–104.

[30] Y. Kang, Y. Fang, and X. Lai, "Automatic detection of diabetic retinopathy with statistical method and bayesian classifier," *Journal of Medical Imaging and Health Informatics*, vol. 10, no. 5, pp. 1225–1233, 2020.

[31] G. G. Gardner, D. Keating, T. H. Williamson, and A. T. Elliott, "Automatic detection of diabetic retinopathy using an artificial neural network: a screening tool." *British journal of Ophthalmology*, vol. 80, no. 11, pp. 940–944, 1996.

[32] R. Rajalakshmi, R. Subashini, R. M. Anjana, and V. Mohan, "Automated diabetic retinopathy detection in smartphone-based fundus photography using artificial intelligence," *Eye*, vol. 32, no. 6, pp. 1138–1144, 2018.

[33] P. Ruamviboonsuk, J. Krause, P. Chotcomwongse, R. Sayres, R. Raman, K. Widner, B. J. Campana, S. Phene, K. Hemarat, M. Tadarati *et al.*, "Deep learning versus human graders for classifying diabetic retinopathy severity in a nationwide screening program," *NPJ digital medicine*, vol. 2, no. 1, p. 25, 2019.

[34] V. Bellemo, Z. W. Lim, G. Lim, Q. D. Nguyen, Y. Xie, M. Y. Yip, H. Hamzah, J. Ho, X. Q. Lee, W. Hsu *et al.*, "Artificial intelligence using deep learning to screen for referable and vision-threatening diabetic retinopathy in africa: a clinical validation study," *The Lancet Digital Health*, vol. 1, no. 1, pp. e35–e44, 2019.

[35] M. B. Hansen, M. D. Abràmoff, J. C. Folk, W. Mathenge, A. Bastawrous, and T. Peto, "Results of automated retinal image analysis for detection of diabetic retinopathy from the nakuru study, kenya," *PloS one*, vol. 10, no. 10, p. e0139148, 2015.

[36] M. T. Hagos and S. Kant, "Transfer learning based detection of diabetic retinopathy from small dataset," *arXiv preprint arXiv:1905.07203*, 2019.

[37] R. Sarki, S. Michalska, K. Ahmed, H. Wang, and Y. Zhang, "Convolutional neural networks for mild diabetic retinopathy detection: an experimental study," *BioRxiv*, p. 763136, 2019.

[38] D. Selvathi, N. Prakash, V. Gomathi, and G. Hemalakshmi, "Fundus image classification using wavelet based features in detection of glaucoma," *Biomedical and Pharmacology Journal*, vol. 11, no. 2, pp. 795–805, 2018.

[39] S. Maheshwari, R. B. Pachori, and U. R. Acharya, "Automated diagnosis of glaucoma using empirical wavelet transform and correntropy features extracted from fundus images," *IEEE journal of biomedical and health informatics*, vol. 21, no. 3, pp. 803–813, 2016.

[40] F. Guo, Y. Mai, X. Zhao, X. Duan, Z. Fan, B. Zou, and B. Xie, "Yanbao: a mobile app using the measurement of clinical parameters for glaucoma screening," *IEEE Access*, vol. 6, pp. 77 414–77 428, 2018.

[41] A. Chakravarty and J. Sivaswamy, "Glaucoma classification with a fusion of segmentation and image-based features," in *2016 IEEE 13th international symposium on biomedical imaging (ISBI)*. IEEE, 2016, pp. 689–692.

[42] R. Priya and P. Aruna, "Svm and neural network based diagnosis of diabetic retinopathy," *International Journal of Computer Applications*, vol. 41, no. 1, 2012.

[43] M. N. Bajwa, M. I. Malik, S. A. Siddiqui, A. Dengel, F. Shafait, W. Neumeier, and S. Ahmed, "Two-stage framework for optic disc localization and glaucoma classification in retinal fundus images using deep learning," *BMC medical informatics and decision making*, vol. 19, pp. 1–16, 2019.

[44] M. Juneja *et al.*, "Automated detection of glaucoma using deep learning convolution network (g-net)," *Multimedia Tools and Applications*, vol. 79, no. 21, pp. 15 531–15 553, 2020.

[45] S. Karkuzhali and D. Manimegalai, "Computational intelligence-based decision support system for glaucoma detection," *BIOMEDICAL RESEARCH-INDIA*, vol. 28, no. 11, pp. 4737–4748, 2017.

[46] N. A. Mohamed, M. A. Zulkifley, W. M. D. W. Zaki, and A. Hussain, "An automated glaucoma screening system using cup-to-disc ratio via simple linear iterative clustering superpixel approach," *Biomedical Signal Processing and Control*, vol. 53, p. 101454, 2019.

[47] J. J. Gómez-Valverde *et al.*, "Automatic glaucoma classification using color fundus images based on convolutional neural networks and transfer learning," *Biomedical Optics Express*, vol. 10, no. 2, p. 892, Feb 2019.

[48] V. Bellemo, P. Burlina, L. Yong, T. Y. Wong, and D. S. W. Ting, "Generative adversarial networks (gans) for retinal fundus image synthesis," in *Computer Vision – ACCV 2018 Workshops*, G. Carneiro and S. You, Eds., vol. 11367. Springer International Publishing, 2019, pp. 289–302.

[49] R. Asaoka *et al.*, "Validation of a deep learning model to screen for glaucoma using images from different fundus cameras and data augmentation," *Ophthalmology Glaucoma*, vol. 2, no. 4, pp. 224–231, Jul 2019.

[50] J. T. Guibas, T. S. Virdi, and P. S. Li, "Synthetic medical images from dual generative adversarial networks," *arXiv preprint arXiv:1709.01872*, 2017.

[51] D. J. Hemanth, O. Deperlioglu, and U. Kose, "An enhanced diabetic retinopathy detection and classification approach using deep convolutional neural network," *Neural Computing and Applications*, vol. 32, no. 3, pp. 707–721, 2020.

[52] N. Lunscher, M. L. Chen, N. Jiang, and J. Zelek, "Automated screening for diabetic retinopathy using compact deep networks," *Journal of Computational Vision and Imaging Systems*, vol. 3, no. 1, 2017.

[53] K. Zhu, Y. Chen, P. Ghamisi, X. Jia, and J. A. Benediktsson, "Deep convolutional capsule network for hyperspectral image spectral and spectral-spatial classification," *Remote Sensing*, vol. 11, no. 3, p. 223, 2019.

[54] A. A. Bosale, "Detection and classification of diabetic retinopathy using deep learning algorithms for segmentation to facilitate referral recommendation for test and treatment prediction," *arXiv preprint arXiv:2401.02759*, 2024.

[55] S. Sundar and S. Sumathy, "Classification of diabetic retinopathy disease levels by extracting topological features using graph neural networks," *IEEE Access*, 2023.

[56] A. R. Chłopowiec, K. Karanowski, T. Skrzypczak, M. Grzesiuk, A. B. Chłopowiec, and M. Tabakov, "Counteracting data bias and class imbalance—towards a useful and reliable retinal disease recognition system," *Diagnostics*, vol. 13, no. 11, p. 1904, 2023.

[57] A. Choudhary *et al.*, "A deep learning-based framework for retinal disease classification," *Healthcare*, vol. 11, no. 2, 2023.

[58] H. Pratt, F. Coenen, D. M. Broadbent, S. P. Harding, and Y. Zheng, "Convolutional neural networks for diabetic retinopathy," *Procedia Computer Science*, vol. 90, pp. 200–205, 2016.

[59] E. V. Carrera, A. Gonzalez, and R. Carrera, "Automated detection of diabetic retinopathy using svm," in *2017 IEEE XXIV International Conference on Electronics, Electrical Engineering and Computing (INTERCON)*, 2017, pp. 1–4.

[60] C. Lam, D. Yi, M. Guo, and T. Lindsey, "Automated detection of diabetic retinopathy using deep learning," *AMIA summits on translational science proceedings*, vol. 2018, p. 147, 2018.

[61] V. Bellemo *et al.*, "Artificial intelligence screening for diabetic retinopathy: the real-world emerging application," *Curr Diab Rep*, vol. 19, no. 9, p. 72, 2019.

[62] S. Wang *et al.*, "Diabetic retinopathy diagnosis using multichannel generative adversarial network with semisupervision," *IEEE Trans. Automat. Sci. Eng.*, vol. 18, no. 2, pp. 574–585, 2021.

[63] S. Sreng, N. Maneerat, K. Hamamoto, and K. Y. Win, "Deep learning for optic disc segmentation and glaucoma diagnosis on retinal images," *Applied Sciences*, vol. 10, no. 14, p. 4916, 2020.

[64] W. L. Alyoubi, M. F. Abulkhair, and W. M. Shalash, "Diabetic retinopathy fundus image classification and lesions localization system using deep learning," *Sensors*, vol. 21, no. 11, p. 3704, 2021.

[65] A. Singh, S. Sengupta, M. A. Rasheed, V. Jayakumar, and V. Lakshminarayanan, "Uncertainty aware and explainable diagnosis of retinal disease," *arXiv:2101.12041 [cs, eess]*, Jan 2021, accessed: Nov. 20, 2021. [Online]. Available: http://arxiv.org/abs/2101.12041

[66] J. B. Odili, M. N. M. Kahar, and S. Anwar, "African buffalo optimization: a swarm-intelligence technique," *Procedia Computer Science*, vol. 76, pp. 443–448, 2015.

[67] S. Wan, Y. Liang, and Y. Zhang, "Deep convolutional neural networks for diabetic retinopathy detection by image classification," *Computers & Electrical Engineering*, vol. 72, pp. 274–282, 2018.

[68] H. Jiang, K. Yang, M. Gao, D. Zhang, H. Ma, and W. Qian, "An interpretable ensemble deep learning model for diabetic retinopathy disease classification," in *2019 41st annual international conference of the IEEE engineering in medicine and biology society (EMBC)*. IEEE, 2019, pp. 2045–2048.

[69] J. Wang, J. Luo, B. Liu, R. Feng, L. Lu, and H. Zou, "Automated diabetic retinopathy grading and lesion detection based on the modified r-fcn object-detection algorithm," *IET Computer Vision*, vol. 14, no. 1, pp. 1–8, 2020.

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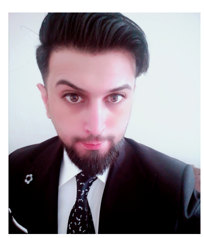

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