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Acerbity of Diabetic Retina through Image Processing and Machine Learning Algorithm

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ABSTRACT

Untreated diabetic retinopathy, a complication of long-term high blood sugar levels, may lead to total blindness if it is not caught and treated quickly. Thus, in order to avoid its devastating consequences, diabetic retinopathy must be medically diagnosed and treated early. Diabetic retinopathy is difficult to diagnose manually, thus patients often have to wait a long period before receiving treatment from an ophthalmologist. With the use of an automated technology, we can discover diabetic retinopathy early and begin treatment immediately to prevent additional damage to the eye. The present study proposes a machine learning strategy for extracting three features—exudates, haemorrhages, and micro aneurysms and classifying them with the help of a hybrid classifier comprised of components from the support vector machine, k nearest neighbour, random forest, logistic regression, and multilayer perceptron network.

Keywords: *Skin disease, CNN, image processing, DNN*

INTRODUCTION

The eye disease known as diabetic retinopathy is a direct effect of the chronically elevated blood sugar levels that characterise diabetes. It might develop to blurred or no vision at all if left untreated. Blurred vision, darker regions of vision, eye floaters, and trouble distinguishing colour are all early indications of diabetic retinopathy. Diabetic retinopathy may cause permanent blindness if not caught and treated early. Diabetic retinopathy affects around a third of the world's 285 million individuals who have diabetes mellitus. The total human population today the number of people 126.6 million in 2010 and 191.0 million in 2030 afflicted by diabetic retinopathy. Little red dots, known as non-proliferative diabetic retinopathy (NPDR), are an early sign of retinal damage caused by diabetes. Bleeding may be represented by these small patches, and microaneurysms are aberrant pouching of blood vessels. Fluid and fatty substance termed exudates might seep out of the damaged lining of these blood vessels. Physical examinations such as pupil dilation, visual acuity testing, optical coherence tomography, etc., may help diagnose diabetic retinopathy. But they take a long time, and the patients have to go through a lot. In this research, a machine learning/hybrid model is used to automatically identify diabetic retinopathy in digital images using a feature extraction method to identify bleeding, microaneurysms, and exudates.

This suggested approach employs a classifier that combines support vector machines with kernel neural networks. [1]. Human eye health is affected by a wide range of factors. Type 2 diabetes, blood sugar levels, etc., fall within this category.

Retinopathy, edoemas, cataracts, and many more are all included. For starters, diabetic retinopathy, also known as diabetic eye disease, is a medical disorder in which damage to the retina of eye happens owing to the diabetes mellitus.

In the Western world, diabetic retinopathy is a leading cause of blindness. Diabetic retinopathy has an incidence rate of up to 80% in those who have had diabetes for 20 years or more. If people with diabetes are properly diagnosed, treated, and monitored, we can cut new cases by at least 90%. Someone's risk of having diabetic retinopathy increases in tandem with the length of time they've been diabetic. In the United States, 12% of all new instances of diabetic retinopathy result in blindness each year [2-4]. This condition is the most common cause of blindness among adults aged 20 to 64. In most cases, there are no warning signs for diabetic retinopathy.

Similarly, macular edoema, which may lead to sudden vision loss, often presents with no early signs. Blurred vision is a common symptom of macular edoema and may make everyday tasks like reading and driving dangerously difficult. However, in a few instances, daylight vision might improve or deteriorate.

Non-proliferative diabetic retinopathy (NPDR), the first stage of DR, presents no symptoms.

Patients with 20/20 vision and no awareness of their symptoms have been seen. Only with the use of fundus photography can NPDR be detected. This exhibits signs of microaneurysms. Vision loss is evident if a fluorescein angiograph reveals constricted or blocked blood vessels in the retina.

Macular edoema, when blood vessels leak their contents into the macula, may occur at any stage of NPDR, according to an observation. It manifests itself visually as a dimming or distortion of objects and colours. as a result of which the contents of each eye's visual field are different. Macular edoema is linked to visual loss in 10% of diabetes people. Optical Coherence Tomography can see regions of retinal thickness caused by the accumulation of fluid from macular edoema [3-5].

Proliferative diabetic retinopathy (PDR) progresses to its second stage when aberrant new blood vessels (neovascularisation) grow in the retina, obscuring the patient's vision with blood and other fluids. When this bleeding initially starts, it may not hurt too much. In most instances, just little patches of blood or what seem to be floating objects within the victim's range of vision remain after the attack. Yet these blemishes often disappear within a few hours. Blurred vision, floaters and flashes, and eventual loss of vision are the most prominent signs of DR. A healthy eye consists mostly of blood vessels, an optic disc, and macula. Any alterations to these parts are linked to eye illness. There are two phases of diabetic retinopathy, proliferative diabetic retinopathy (PDR) and non-proliferative diabetic retinopathy (NPDR) (PDR)[6].

The many manifestations of NPDR include microaneurysms (Mas), bleeding (H), hard exudates (HE), and soft exudates. The severity of NPDR is once again determined by the number and location of these lesions. It is often agreed that the microaneurysm represents the first stage of DR. Tiny red specks are what you see. Hemorrhages are the next step in the DR process. Blot haemorrhages are bigger blood lesions, whereas dot haemorrhages are the smaller, brighter red dots. Vision impairment is caused by haemorrhages. The production of exudates is the third phase of the DR. Exudates refer to the lipid and protein fluids that seep out of blood vessels when they are injured. The hardness or softness of an exudate is determined by its boundary conditions, including its energy and threshold [7]. Soft exudates, which are the worst stage of exudates, presented as a grey-white colour. Hard exudates exhibited as a brilliant yellow colour. Cotton-wool spot is another name for it.

Diabetic retinopathy is a serious eye condition that requires prompt medical attention. Performing a human analysis of the fundus picture is a time-consuming and error-prone

process, which is why automatic detection is preferable.

LITERATURE REVIEW

Saranya et al. (2020) presented a convolutional neural network-based automated approach for the detection of non-proliferative diabetic retinopathy [1]. They employed two datasets, the MESSIDOR and the IDRiD. To begin, they up and down-sample equally to ensure that all data is representative. Removal of the optic disc is also performed to prevent false positives. The picture is preprocessed to improve the final output. Canny edge detection, resizing, interpolation, and normalising were the four stages of preprocessing. Different stages of diabetic retinopathy could be categorised with the help of a convolutional neural network (CNN). It was observed that in comparison to IDRiD's (90.29 percent accuracy), MESSIDOR showed better accuracy, that is 96.3 percent. Also, with Inception V3, diabetic retinopaths may better train the model VGG16.

Shankar et al. (2020a) conducted a study to identify and categorise diabetic retinopathy and presented a model called Hyperparameter Tuning Inception-v4 (HPTI-v4) [2]. Here, the contrast limited adaptive histogram equalisation (CLAE) model was used to boost the image's contrast in the preprocessing step. Segmentation of processed pictures was performed using histogram-based segmentation. Here, Bayesian optimization is used to fine-tune the hyperparameters. An epoch, a learning rate, and a momentum are the hyperparameters used. For this categorization, we use the multilayer perceptron (MLP). The results from this approach are more precise. The resulting 99.49% accuracy, 98.83% sensitivity, and 99.68% specificity are all quite impressive. The categorization model seems to be a useful addition to this procedure.

Ilyasova et al (2020) investigated the efficiency of employing decision trees for feature selection [3]. They were able to zero down on the selection traits technology's most relevant textural properties. In order to address the issue of identifying areas of interest, the method allowed for intelligent analysis of characteristics utilising colour subspaces. In this research, we build decision trees using texture characteristics for a previously suggested technique. More accurate decisions were made because to the use of decision trees, which identified additional indicators of interest. When the size of the window is more than 15, the optimal number of features is 3. Accuracy exceeding 98 percent was achieved using decision trees with more than six texture characteristics for 12-by-12-inch windows.

According to Prasad et al. (2015), in order to identify blood vessels, exudates, and microaneurysms, a thresholding technique and segmented procedure should be used [4]. They used Histogram equalisation to improve contrast in pre-processing, and cany edge detection is used to improve performance. Blood vessels, exudates, and microaneurysms were extracted using a threshold-based segmentation technique based on morphological operation. Both the Haar wavelet transform and principal component analysis (PCA) were used for feature selection. Diabetic retinopathy was classified using a One-Rule and Backpropagation neural network (BPNN) classifier. A 97.75% accuracy rate was achieved by the One Rule classifier, while a 93.8% success rate is achieved by the BPNN classifier. It was concluded that this approach has the potential for future integration of multistage classification for hazard identification.

Shankar et al. (2020b) created a cooperative deep learning model for automatically detecting and categorising photos of diabetic retinopathy in the fundus [6]. Here, preprocessing was employed to get rid of the fuzziness around the edges. Histogram equalisation is then used to do the segmentation. The technique aids in identifying and removing those parts of the picture that will be of value later on. For this categorization, they used the Synergic deep learning (SDL) model. Accuracy in the model was found to be 99.28, sensitivity was 98.54, and specificity was 99.38. Filters before processing, AlexNet, and the inception method for hyperparameter tweaking were found to be always useful to enhance the model.

Samanta et al. (2020) proposed use of convolutional neural networks for automated

diabetic retinopathy identification on a limited dataset [7]. In this case, contrast adaptive histogram equality (CLAHE) is employed in the preprocessing step to improve the picture. As a classifier, DenseNet121 was put to good use. The data were skewed, therefore precision was not useful. Here, Cohen's Kappa was the appropriate statistic to employ (k). It measures how accurately one class compares to another in close proximity. For validation data, the kappa is 0.8836, while for training data, it is 0.9809. With this model, the F1 score for mild DR is 0.64, whereas the score for moderate DR is 0.74. It was suggested that Semantic segmentation may be utilised to improve the performance of this model.

Harshitha et al. (2021) used deep learning to create a system that can identify the onset of diabetic retinopathy and its progression through its many phases [8]. Images in a new dimension are included in the dataset. It becomes a 256-by-256 representation. The prediction is made using a CNN model. The accuracy is 73% over the 15 epochs and 79% over the 50 epochs. When just a small set of neurons is employed, accuracy improves to 86%.

Wang et al. (2020) could use deep learning to provide a simultaneous diagnosis of diabetic retinopathy severity and characteristics [8]. Here, a hierarchical multi-task deep learning architecture was used for identifying the degree of DR and DR-related features in the fundus picture. There was just one spine and a pair of heads. The SE network is the backbone of the system. To get features out of a picture, this tool is put to use. Two separate forward neural networks (one for feature identification and another for severity assessment) serve as the heads. Cohen's kappa and the receiver operating characteristic curve are used to evaluate this model. This model is restricted by the fact that it is only equipped to handle a modest NPDR training image (2%). As time goes on, the dataset may be enhanced by include additional photos with moderate NPDR.

Lam et al. (2018) proposed that diabetic retinopathy may be detected automatically using deep learning [9]. CLAHE is used to improve contrast during the preprocessing phase. Overfitting is mitigated by the data augmentation procedure. An image categorization system (pre-trained convolutional neural networks) from the deep learning GPU training system (DIGITS). Methods based on transfer learning were used, with the ImageNet-trained AlexNet and GoogLeNet architectures serving as the data source. Including the identification of mild illness in the model will help it perform better in the future.

Gabriel et al. diabetes eye disease detection via convolutional neural networks is proposed. Image resizing to 256x256 occurs during the preparation phase [10]. Application of CNN architecture to the diagnosis of exudates, microaneurysms, and haemorrhages. When it comes to speed and precision, VGG16noFC2 is superior. Future iterations of the model will benefit from a fully linked layer that facilitates the merger of two networks.

Classification

There are two basic types of diabetic retinopathy: proliferative and non-proliferative. "proliferative" refers to the presence or absence of neovascularization. Retinal angiogenesis abnormality (abnormal growth of blood vessels). Non-proliferative diabetic retinopathy (NPDR)describes an asymptomatic, early stage of the disease. Proliferative retinopathy (PDR) is the next stage of the illness and is characterised by the development of neovascularization, which may have devastating visual effects.

NPDR

Retinal capillaries are damaged by hyperglycemia. This causes microaneurysms, or weakening of the capillary walls that lead to pouching of the vessel lumens. Hemorrhages caused by the rupture of microaneurysms are contained by the inner limiting membrane deep into the retina (ILM) [8]. These haemorrhages are referred to as "dot-and-blot" haemorrhages because of their pinpoint appearance. The fluid seeps into the retina because the weaker arteries have become leaky. Macular edoema, the accumulation of fluid directly beneath the

macula, is thought to be a frequent cause of visual loss in people with DR.

Fluid lakes that dry out may leave silt behind, much like a river that drains after a flood. The lipid waste products that make up this silt are easily recognisable by its waxy, yellow coatings. The damaged vessels gradually get blocked as NPDR advances. Infarction of the nerve fibre layer may result in the characteristic cotton-like white patches known as "cotton spots" if blood flow to the area is impeded (CWS).

Microaneurysm Detection

Diabetic retinopathy is easily diagnosed using automated microaneurysm detection, which is crucial in the fight against blindness. Incorporating an automated system has made the task of Diabetic retinopathy screening costs may be lowered and the need for ophthalmologists can be decreased. Microaneurysm detection techniques typically consist of two phases: identifying potential microaneurysms and then classifying them. Preprocessing the picture to remove noise and improve the contrast is the first step. Since microaneurysms stand out more clearly against a green backdrop, this is the plane of the RGB picture that is processed first. Afterward, potential microaneurysm sites are identified. Due to the high likelihood that blood vessels would be misidentified as something else in the preprocessed picture, blood vessel segmentation algorithms are then employed to extract blood vessels from the candidates to reduce false positives [9]. The microaneurysms are then detected via feature analysis, which includes feature extraction and feature selection. The second step involves applying a classification algorithm to the characteristics to determine whether or not they meet the criteria for a microaneurysm candidate (abnormal) or a non-microaneurysm candidate (normal) classifier and a vast collection of microaneurysm-specific characteristics calculated for each potential patient. The ability to spot Microaneurysms (MAs) in an eye fundus picture is an essential part of DR. There are two main applications for MAs. Early identification is crucial since these are the first symptoms of DR. Analyzing the Academic Success of Detection of MA is crucial to computer-aided DR screening systems. For medical image processing, reliable microaneurysm identification in digital fundus pictures is essential. Ensemble-based Microaneurysm Detection (E-MD) which combines preprocessing approaches with candidate extractors [10]. The E-MD architecture improves MA detection performance for DR illness diagnosis. E-MD framework consists of two processes, preprocessing approaches and candidate extractors, for effective identification of MA in digital fundus pictures.

Choosing a preprocessing technique and potential extractor parts for an E-MD system is a laborious task. Before extracting MA candidates, preprocessing techniques are used. The digital fundus pictures used in an E-MD framework have had the noise reduced by preprocessing techniques, making them more suited for use in the diagnosis of illness.

In candidate extraction, any picture features that exhibit MA properties are flagged for further investigation. For many MA elimination strategies, individual MA detectors are used.

Exudate-Based Diabetic Macular Edema Detection in Fundus Images

When it comes to DR complications, diabetic macular edoema (DME) is a major cause of concern. Large-scale screenings for DME rely on the ability to identify exudates in fundus images. To aid in the diagnosis of DME, the Feature based Macular Edema Detection (FMED) approach, which uses a collection of features based on colour, wavelet decomposition, and automated lesion segmentation. To obtain a DME diagnosis, the FMED approach uses a single feature vector from each picture and classes them accordingly. Exudate probability mapping, colour analysis, and Wavelet analysis are the three methods used to analyse the feature vector.

To determine the likelihood of exudate, the background subtraction method is used during the preprocessing phase. The exudate detection is carried out by assigning a score to each candidate on the exudate candidate map. To determine which exudates are most likely to be useful, we

use connected component analysis with 8 neighbor nodes. The FMED approach utilises the values at the exudates' periphery to gather potential lesion borders. The edge detector uses a kernel estimation in eight directions for each potential exudate. In order to merge the kernel outputs, we take the highest value from each individual pixel and use that. The FMED approach determines the significance of candidate boundaries in relation to the likelihood of genuine exudates.

Inter-patient colour variance is minimised with the use of colour analysis in the FMED procedure. Wavelet analysis is a method for analysing signals at several resolutions, and it has numerous practical uses including noise reduction and data compression. The mother wavelet is essential for picture analysis. In order to break the picture into manageable chunks, a series of scaling and wavelet functions are applied with the aid of the mother wavelet.

DME Feature Vector

It is a challenge to choose an appropriate feature vector for DME diagnosis. Training pictures for the FMED approach must include labels for outlining exudates and other lesions/pigmentation changes in each pixel of the image. Lesion sets are described by their intrinsic probability maps, colours, and wavelet features using the FMED approach. The analytical results are taken into account on a per-pixel basis by using the exudate probability map. Statistics such as mean, median, standard deviation, maximum, and minimum are computed for each extracted group of pixels. Color/wavelet analysis and the probability map of exudates may be linked using the FMED technique. It keeps the problematic photos that have a greater rate of false positives or extra erroneous detections that aren't essential.

By combining the weighted and unweighted statistical measures, the FMED technique is able to get a large set of characteristics for pictures. When it comes to the classification step, the total number of features is taken with the curse of dimensionality. There must be a method of automated feature selection. There is a wide variety of methods for choosing which features to use. Simple feature selection in FMED is accomplished by the use of Information Gain, which is related to conditional entropy to estimate the importance of all characteristics. The HEI-MED dataset is partitioned into three subsets, each of which is used in the feature selection procedure. Using the mean of the three folds that allow for choosing features, a final score is calculated for each feature. The feature subsets are chosen with the help of DME Feature Vector.

METHODOLOGY

To begin selecting the characteristics of the optic cup in digital fundus pictures for DR disease detection, the Diabetic Fundus Image Recuperation (DFIR) approach is presented. The digital fundus pictures are segmented using the DFIR technique. With the Sliding Window method, you may choose a window size that works best for you. DFIR's overall sliding window block determines two histograms performances. By using Group Sparsity, we may combine these two sets into a single working one.

Histogram Intensity Range Function With No Overlap: Histograms are used to depict the characteristics of the optic cup in digital fundus imaging. The Group Sparsity Non-overlapping Function in the DFIR technique gets rid of the overlapping pixel values that pick the optic cup feature in Fundus pictures in a speedy manner. The DFIR technique efficiently reduces the amount of effort spent on feature selection while diagnosing DR diseases. An improved ranking efficiency in disease diagnosis is achieved by using a support vector model to rate the severity of DR based on the specified properties of the optic cup.

In order to extract the characteristics of the optic cup in digital fundus pictures for DR illness detection, we next present the Top-hat Mathematical Transform Fuzzy based Feature Clustering (TMTF-FC) approach. Reduced noise in digital fundus images is one of the main benefits of the TMTF-FC approach.

Using grey mathematical morphology, the TMTF-FC technique enhances digital fundus images of diabetic retinal blood vessels. In order to retrieve optic cup characteristics from digital

fundus images in shorter increments of time, the TMTF-FC approach employs a fuzzy based feature clustering algorithm. In DR illness diagnosis, it shortens the amount of time spent on feature extraction. The pixel values of colour characteristics are extracted from the mean, standard deviation of the initial picture using Top-hat mathematical transform in the TMTF-FC approach, which allows for more effective clustering during illness detection.

Last but not least, the performance of DR illness diagnosis in early detection is enhanced by the development of a Spectral Classifier with Predictive Rules (SC-PR) framework. Using a simple sliding window, the SC-PR framework can quickly and accurately identify the most relevant optic cup characteristics from digital fundus pictures, allowing for more efficient disease detection. In order to speed up the process of diagnosing diseases, the SC-PR framework employs feature clustering to expeditiously extract characteristics from the optic cup. In order to effectively classify data, the SC-PR system used a spectral classifier.

Preprocessing, segmentation, and feature ranking are the procedures used to find diabetic retinopathy. To guarantee that the dataset is continuous and only shows features that are pertinent, preprocessing is necessary. To reduce the workload of the processes that follow, this step is important. The photos are then divided into segments to distinguish between normal and pathological chemicals. Green The contrast between both the blood arteries, exudates, and haemorrhages is best apparent in the green channel of the image's three colour channels (Red, Green, and Blue), which is neither under-illuminated nor excessively like the other two.

Dataset Description

To conduct our experiments, we utilised the Kaggle1 dataset, which was collected and labelled by EyePacs and is, to the best of our knowledge, the biggest collection of fundus pictures for diabetic retinopathy. There are a total of 88,702 photos in the EyePACS collection, 35126 of which have been labelled and 53,576 of which have not. Detecting and categorising diabetic retinopathy phases is a supervised learning issue, hence we relied only on the labelled pictures provided by this dataset. In the future, we may use a semi-supervised learning approach that makes use of the whole dataset. The dataset is split up into five categories, each representing a different level of DR severity.

Image Pre-Processing and Augmentation

For a deep learning application, the data set is the most important and fundamental component. Since most of the fundus images in our data set are collected with various equipment in different environments, there is a great deal of variance in the fundus photographs themselves, such as discrepancies in brightness or resolution. Thus, the fundus pictures undergo a number of pre-processing techniques in order to normalise them, remove duplicate information, and eliminate environmental artefacts.:

1) Reduce the width of the photos such that the height remains 299 pixels while maintaining the original aspect ratio. The photos should be cropped along their long axis, leaving just the central 299 pixels. To facilitate comparison with the monocular mthod suggested in [9], we will standardise picture size to 299299 pixels.

2) Images may be processed by subtracting each pixel's value from the average of its neighbours and then adding 50% grayscale to the result. This method, which is analogous to the "high pass" filter in Adobe Photoshop, enhances the clarity of fundus pictures by highlighting the capillaries and lesions. Next, a mask with a transparent circle in the middle is used to clip the fundus region in photos to 95% of the original size, so eliminating the boundary effects introduced by the previous step. In this stage of processing, we make use of Graham's suggested algorithm. [11].

3) Before feeding photos into the network, change the pixel values from [0, 255] to [1, 1]. The goal of this process is to normalise the input data in order to reduce the impact of poorly conditioned values on the network and improve its ability to disseminate the data. Furthermore, the picture data set is too tiny for a deep learning model to effectively address the issue of medical image identification. This is why, in addition to the pre-processing stages, several image

augmentation techniques are imposed on the data set to boost the proposed model's generalisation performance. It's important to remember, however, that the initial fundus photos already include a wealth of information about patients' physiological states before any enhancements are made. For instance, despite the fact that some fundus images are inverted due to the varying imaging modes of fundus cameras, one can still determine whether or not the image was obtained from the left or right eye by observing the slope of the connection line between the macula and the optic nerve, which is always negative for the left eye and positive for the right. Our binocular model has to keep physiological details and relative location relations like these intact. Furthermore, the augmentation is carried out between steps 1) and 2) of pre-processing, and both the left and right eyes of the patient's binocular fundus pictures undergo the same processing at the same time. Listed below are the explicit procedures for the enhancement.:

1) Mix up the horizontal orientation of the left and right eye pictures at random. Binocular pictures may be flipped horizontally and swapped before being sent into the network since the human eye is fundamentally symmetrical.

2) Applying geometric transformations at random to images includes inverting them, randomly cropping them by 0%-5% of their height or width, scaling them to 90%-110% of their original size, randomly translating them by -5 to +5 pixels, randomly rotating them by -30 to 10 degrees, and randomly shearing them by -10 to 10 degrees.

3) Modify the brightness and contrast of photographs in a random fashion by performing operations such as multiplying or dividing the image value by 10, setting the brightness to 85%-115%, and adjusting the contrast downwards from -100 to +100. During the training process, there is a 50% chance that each of the augmentation phases and their respective sub steps will be carried out.

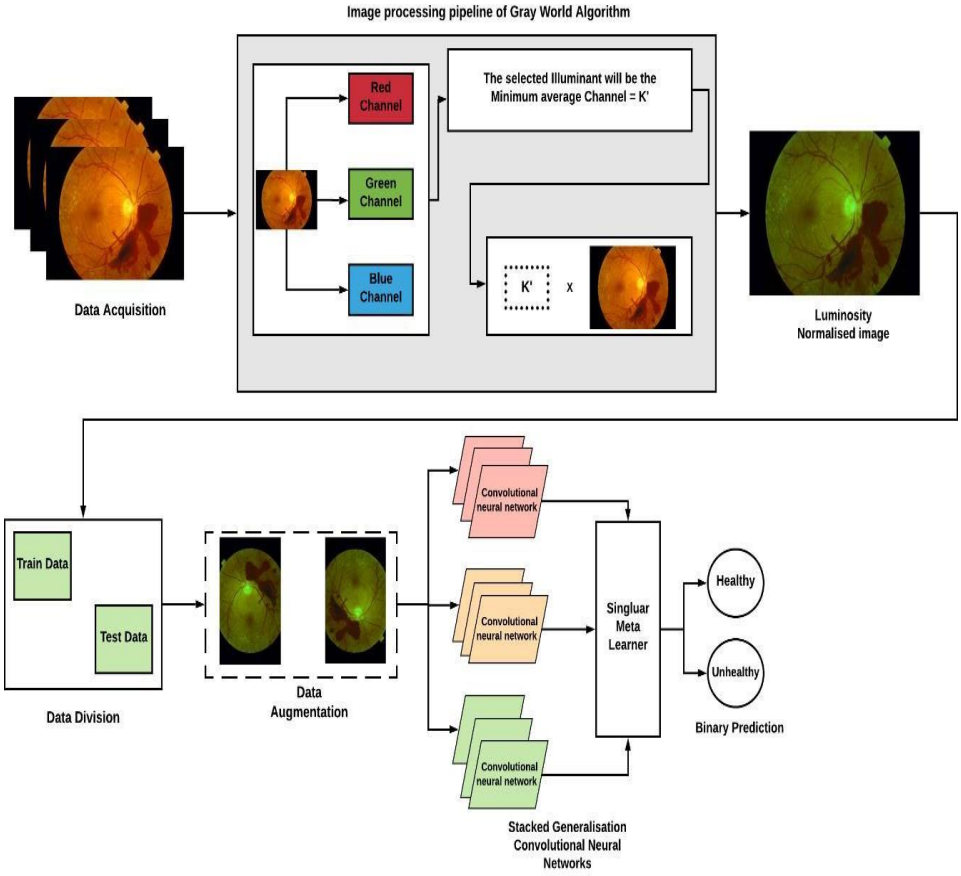

FIGURE 1: A diagrammatic flow of the proposed methodology and the training process

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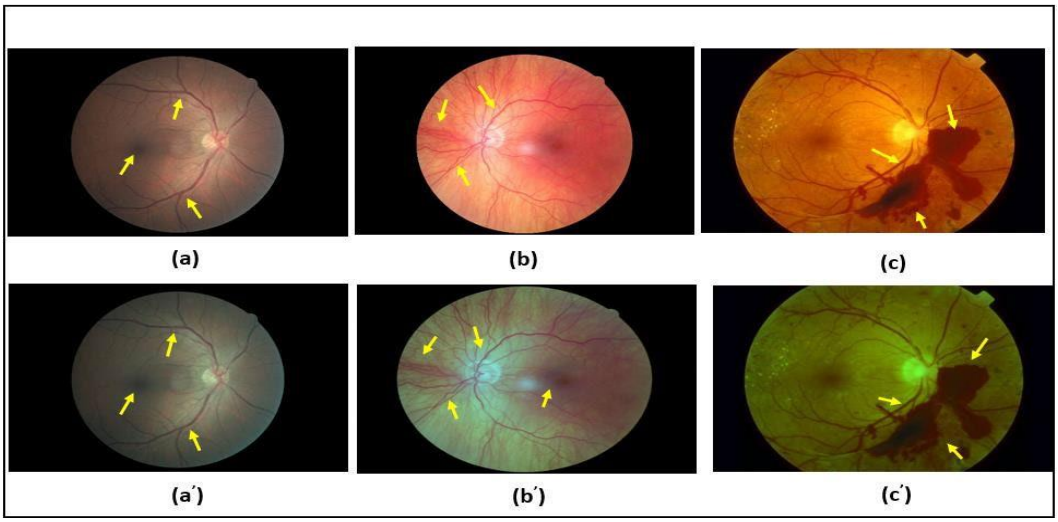

FIGURE 2: Color constancy algorithm image normalisation outcomes. Three photos, one in its original form and two with their colours adjusted using the grey world technique, are shown in the top row. Blood vessels, the macula, and haemorrhages are still discernible after luminosity normalisation, as shown by the yellow arrow.

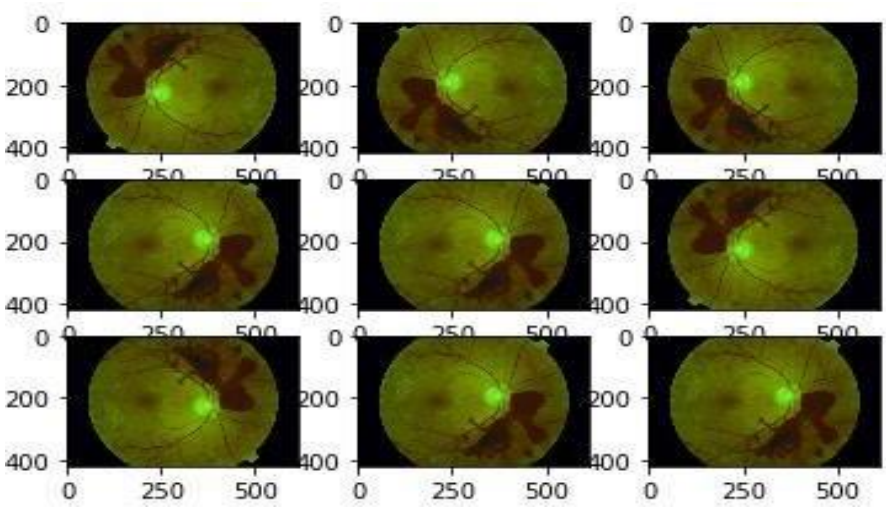

FIGURE 3: An Illustration of data augmentation in retinal images

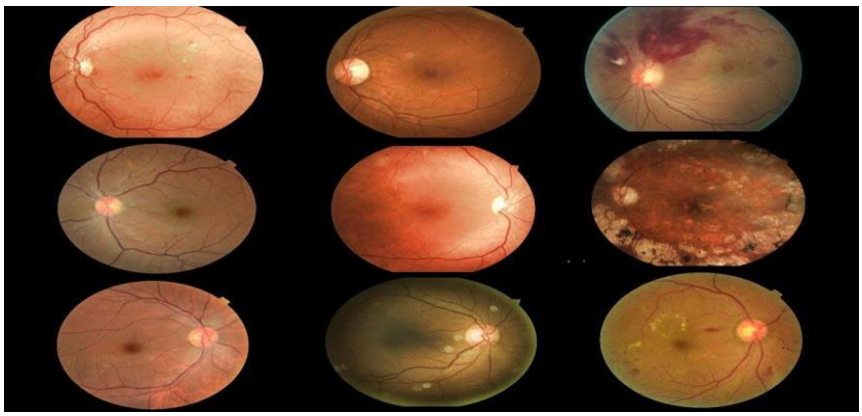

FIGURE 4: Sample fundus images from the Kaggle dataset

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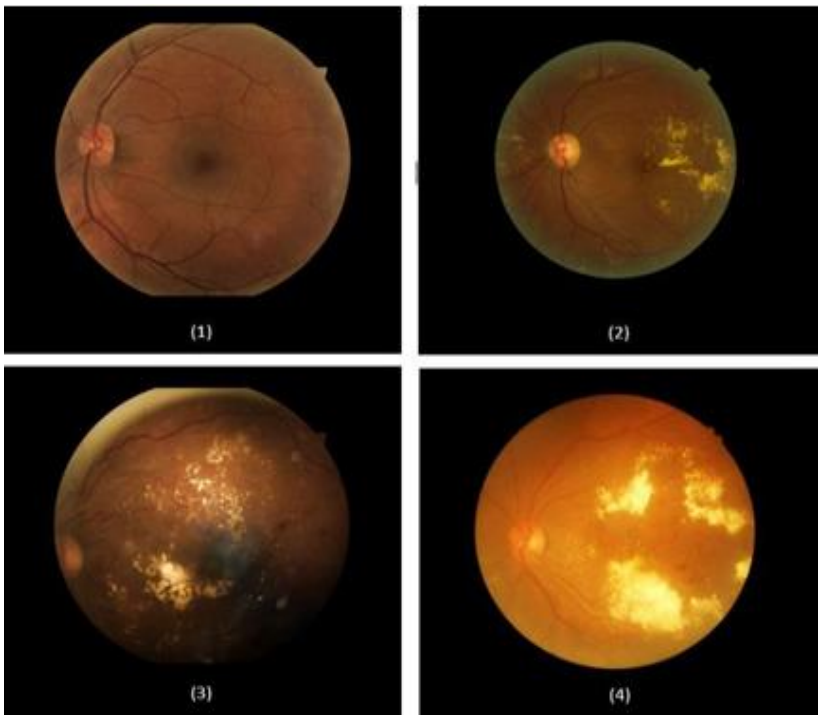

FIGURE 5: Diagnosis using DR images of the fundus. In Figure 5 (1), we see a normal retina without any lesions or bleeding. Due to the presence of a few lesions, the unhealthy retinal picture in Figure 5 (2) is classified as having mild stage DR. In the picture of an unhealthy retina, as shown in Figure 5 (3), yellowish uneven margins may be seen. These are the hard exudates.. Cotton-wool patches, indicative of axoplasmic material accumulations in the retina, characterise the unhealthy retinal picture with advanced DR seen in Figure 5(4).

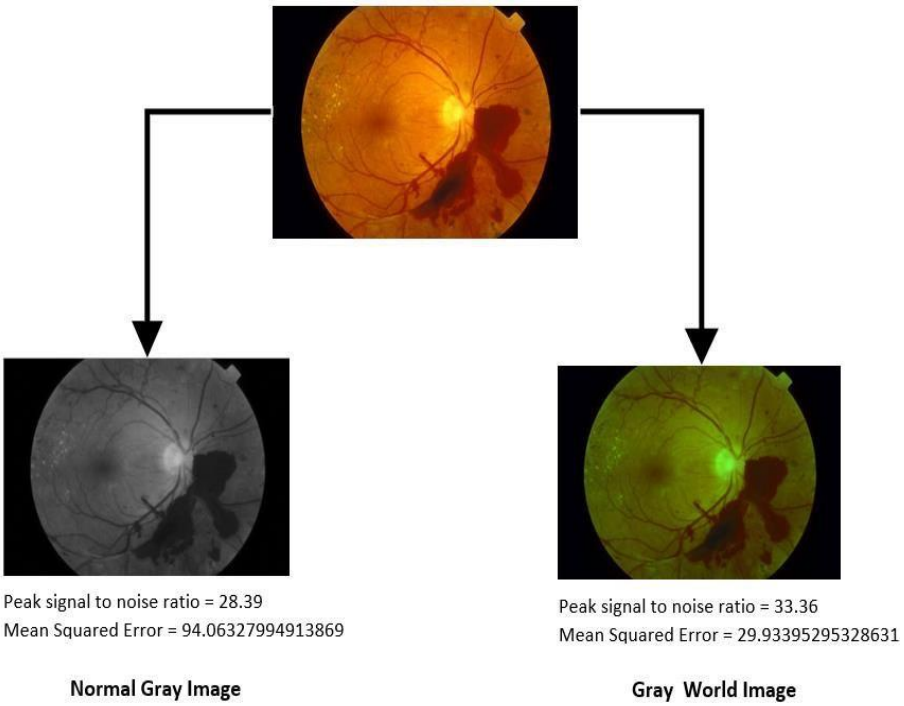

FIGURE 6: Statistical comparative analysis between normal gray image and gray world normalized image based on PSNR and MSE values

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Quantitative Analysis

We've successfully passed three important milestones in our experiments. First, desaturating photos using statistical information like mean pixel values and an optimal scaling factor to normalise non-uniform brightness across several sources. Second, using the notion of weighted majority sub-models, an advanced artificial intelligence approach called stacking generalization of CNNs was developed to provide an automatic detection system for the normalised fundus pictures. Third, to provide evidence for our experimental outcomes, we compare them against state-of-the-art deep transfer learning models in a variety of ways.

DISCUSSION

Our investigations contribute by making use of a Kaggle EyePACS dataset that is open to the public. Images come from a wide variety of sources, and there are sometimes disparities between them, such as because of differences in cameras or lighting. Therefore, normalisation of images is crucial. To improve the candidate areas, the photos are pre-processed for luminosity normalisation using the grey world colour constancy technique. In order to back up and verify the normalising findings, we performed an analysis of the improved pictures using PSNR and MSE metrics. Since can be seen in Figure 6, our colour correcting scheme is both effective and efficient, as the PSNR value was increased after being applied.

According to the literature study, several researchers have reported comparable work on colour constancy and retinal image enhancement using other techniques. Unfortunately, an automated tool that makes use of these methods has not yet been introduced. Most of the algorithms did not address luminosity normalisation as a pre-processing step, instead focusing on extracting characteristics including cotton-wool spots, exudates, lesion presence, and haemorrhage detection to aid in disease diagnosis. Stacked generalisation of CNNs handled the diagnostic decision-making step, outperforming VGG-16, ResNet50, and CNNs. Accuracy, sensitivity, specificity, precision, recall, and F-measure comparisons are also made between the proposed model and other models.

There are two key hypotheses that underpin efforts to create a deep learning-based automated validation tool for removing suboptimal lighting from retinal fundus pictures. The first was to use the capabilities of AI and image processing methods to automatically extract and improve information for Diagnosis, hence reducing the amount of manual labour required. The second was the availability of optimization strategies such different regularisation techniques to improve the performance of deep learning models, allowing them to tackle a wider range of issues. It was also a priority of ours to drastically cut down on false negatives, and the fact that we were able to do so in our experimental findings on unseen test data is proof of the robustness of our model. Since our technique does not need high-end hardware or devices with powerful graphics processing units (GPUs), it is also cost-effective to execute. DR detection sensitivity ratings over 60% are shown to be economically viable. Moreover, the fact that our model can properly analyse fundus pictures despite their less-than-ideal illuminations is another evidence of our model's great adaptability and resilience, given that it was trained on a dataset with a lot of variations.

CONCLUSION

We suggested utilising the grey world algorithm to correct for less-than-ideal lighting in retinal fundus pictures and create a fully automated DR prediction system. The three CNNs are used to create an ensemble model that relies on generalisation. The PSNR and MSE of the base and improved pictures are used as statistical measures to evaluate the success of the image normalisation process. The stacked ensemble model is a cutting-edge method for combining the best features of many neural networks into a single model by using a fusion approach that takes into account the strengths of each individual network. Fundus photos may be classified and DR detected using machine learning algorithms. However, when using photos from a variety of sources, the results may be greatly enhanced by using proper pre-processing and feature extraction techniques. Due to the fact that DR photos are often captured using many cameras in a variety of lighting

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circumstances, we found it necessary to implement an effective colour constancy solution to help smooth out the inevitable colour shifts. The suggested model's efficacy in binary and multi-class DR classification tasks is tested by extensive tests. We verify our model, which achieves better results than state-of-the-art models in binary and multi-class classification tasks, by taking the acquired results into account using a number of evaluation measures.

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Data Availability Statement

The database generated and /or analysed during the current study are not publicly available due to privacy, but are available from the corresponding author on reasonable request.

Declarations

Author(s) declare that all works are original and this manuscript has not been published in any other journal.

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