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DIABETIC RETINOPATHY DETECTION USING MACHINE LEARNING TECHNIQUE

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Abstract - *A method for detecting diabetic retinal disease based on integrated shallow convolutional neural networks. Early diabetic retinal disease (DR) detection is crucial for diabetics to lower their risk of going blind. Numerous studies have demonstrated the effectiveness of Deep Convolutional Neural Network (CNN)-based techniques for automatically detecting DR through classification of patient retinal images. Such methods rely on a very big data set made up of retinal photographs with specified category labels to aid in their CNN training. It might occasionally be challenging to compile enough precisely labelled photos to use as model training examples. According t0 the trials on publicly accessible data sets show that, when compared to the most recent typical integrated CNN learning algorithms, the suggested technique can increase classification accuracy by 3% on small data sets. The test shows that although if the suggested approach's classification accuracy, its time cost drops to roughly 30% of the smallest dataset, which is approximately 10% of the original dataset and falls by 6%. A method for detecting diabetic retinal disease based on integrated shallow convolutional neural networks. Early diabetic retinal disease (DR)detection is crucial for diabetics to lower their risk of going blind. Numerous studies have demonstrated the effectiveness of Deep Convolutional Neural Network (CNN)-based techniques for automatically detecting DR through classification of patient retinal images. Such methods rely on a very big data set made up of retinal photographs with specified category labels to aid in their CNN training. It might occasionally be challenging to compile enough precisely labelled photos to use as model training examples. According t0 the trials on publicly accessible data sets show that, when compared to the most recent typical integrated CNN learning algorithms, the suggested technique can increase classification accuracy by 3% on small data sets. The test shows that although if the suggested approach's classification accuracy, its time cost drops to roughly 30% of the smallest dataset, which is approximately 10% of the original dataset and falls by 6%.*

Key Words: Convolutional neural network, diabetic retinopathy, image classification, integrated learning, performance integration.

1. INTRODUCTION

Blindness or vision loss may result from the eye disorder known as diabetic retinopathy. Early identification and treatment for DR patients are crucial to preventing blindness. All agree that early diagnosis and therapy can reduce DR patients' risk of blindness to 5%. Medical personnel have traditionally used 2D colour images of the eye fundus to manually distinguish DR. In these cases, a doctor's education and expertise are essential to a precise diagnosis. It makes logical to use automatic retinopathy picture classification for DR diagnosis given the size of the DR patient group. Many investigations on the categorization of retinal or other medical images have been carried out over the course of the last few decades. In traditional machine learning approaches, such as those using Support Vector Machine, K-Nearest Neighbor, Regression, and some other techniques, offline extraction of features is frequently required prior to training. Deep machine learning has been widely utilized in the categorization of photos in response to the most tremendous growth of image data on the Internet. In these cases, a doctor's education and expertise are essential to a precise diagnosis.

To attain high precision, these techniques frequently require massive datasets and incredibly deep networks. However in the actual world, it might be challenging to compile high-quality labelled datasets for model training. Another widely acknowledged fact is that manually labelling a dataset is extremely difficult and time-consuming. Another widely acknowledged fact is how difficult and error-prone manually labelling a dataset is. operation subject to mistakes. If mistakes are made while labelling, the accuracy of the model that is learning from the dataset will be significantly damaged. A highly deep neural network may demand specialised computing environments or take a long time to train. Additionally, it is believed that the likelihood of the model overfitting increases as a CNN gets deeper and fewer data samples are available. It is therefore intriguing to find out whether shallow neural networks can also accurately classify medical images, even on a small labelled sample. We want to investigate how retinal images can be classified using integrated multi-scale shallow CNNs in this paper,

focusing on the case where there aren't enough high-quality labelled training samples.

2. LITERATURE SURVEY

For diabetic people, diabetic retinopathy continues to be the predominant cause of legal blindness. More than 90% of visual loss can be avoided with proper medical and ophthalmologic care. There are therapies that can be extremely effective when used at the right time in the disease process. Routine management by an ophthalmologist is essential in advanced stages of diabetic retinopathy, such as NPDR, PDR, and diabetic macular edema [1]. Among adults aged 20 to 74, diabetic retinopathy is the most common factor in new instances of blindness. Nearly all type 1 diabetes patients and more than 60% of type 2 diabetic patients develop retinopathy throughout the first two decades of the disease. Legal blindness was present in 3.6% of type 1 diabetes patients with a younger onset and 1.6% of type 2 diabetes patients with an older start in the Wisconsin Epidemiologic Study of Diabetic Retinopathy (WESDR). 86% of blindness in the group with younger onset was caused by diabetic retinopathy. One-third of the instances of legal blindness in the older-onset group, when other eye disorders were prevalent, were brought on by diabetic retinopathy. Early identification, prompt enrolment into the health care system, patient education, regular lifelong evaluation, appropriate referral, and timely treatment are critical to avoiding vision loss. Frequent eye examinations are required for people with moderate-to-severe NPDR in order to decide whether to start treatment. The requirement for yearly dilated eye exams is less clear for individuals who don't have retinopathy or just have a few microaneurysms. Some have proposed a longer gap between examinations because for these patients, the annual rate of progression to either proliferative retinopathy or macular edema is modest. Factors which are considered in this are: *1)* Other visual function outcomes, such as visual acuity worse than 20/40, are clinically significant, occur significantly more frequently, and have economic effects. The analyses initially made the assumption that legal blindness was the sole level of visual loss having economic repercussions. *2)* The analyses made use of NPDR progression data from diabetic individuals who had just received their diagnosis.

The Convolutional Neural Network (CNN), a model that focuses on classifying images based on object recognition, is used in this study and detection, is suggested for use. The primary goal is to categorize a collection of photos which includes each of the four classes in the development of Diabetic Retinopathy [2]. The Diabetic Retinopathy Detection dataset and the Indian Diabetic Retinopathy Image Dataset were both used. Based on accuracy, loss function, and AUC, statistical analysis is used to assess the suggested CNN's performance. The research results point to the potential for CNN to classify DR into its various degrees in people with diabetes mellitus, leading to the development of a prototype computer-aided diagnosis tool.

"ImageNet," a new image database and expansive ontology of images, is introduced [3]. Multispectral data is a viable source of data for autonomous nautical ship recognition since it combines information about both visible and infrared objects. In this paper, we convert multispectral ship recognition job into a convolution feature fusion issue and propose a feature fusion architecture called Hybrid Fusion in order to benefit from deep convolution neural network and multispectral data. Via three channels of single-spectral photos and four channels of multispectral images, we fine-tune the VGG-16 model that was previously trained on Image Net. To prevent over-fitting, we apply established regularization approaches. Investigated are the three other feature fusion architectures as well as hybrid fusion. Each fusion architecture has branches for extracting features from visible and infrared images, and the pre-trained and refined VGG-16 models are used in these branches as feature extractors. In every Image Net classifies the many image types into a semantic hierarchy that is densely populated. The first stage in the development of ImageNet is the collection of potential photos for each synset. To highlight the variations, the ImageNet database is contrasted with other datasets. Other datasets used for the comparison include Tiny Image, ESP dataset, LabelMe, and Lotus Hill datasets. The current condition of ImageNet, which consists of 12 subtrees, 5247 synsets, and 3.2 million images, is thoroughly examined in this work. Finally, we present three straightforward applications in automatic object clustering, image classification, and object identification to demonstrate the utility of ImageNet.

A support vector machine-based deep learning technique for feature extraction and categorization. The final fully connected layer's high-level properties, which act as the input features for classification using a Support Vector Machine, are created using convolutional neural network transfer learning [4]. The amount of calculation time needed for CNN-tuned classification can be decreased with this technique. Because to the ease of overfitting in deep models, such deep networks frequently exhibit poor performance on small datasets (CIFAR-10). Our findings show that, because to the enhancements we made, the deep CNN can successfully fit small datasets with results that are noticeably better than before. This study tries to boost multi-class DR classification performance. Retinal fundus pictures from four classes of unbalanced and small datasets are used in the proposed model. This study also assesses the accuracy value-based combination performance of CNN SVM and CNN Softmax in order to validate the conclusions.

This study also assesses the accuracy value-based combination performance of CNN SVM and CNN in order to validate the conclusions. So, a large portion of the imagenet datasets used to train deep convolutional neural networks. The network model is developed on top of such a vast dataset primarily ignores the incorporation of further network layers and the fact that the majority of application data sets are several times bigger than imagenet datasets. With the proper changes, small datasets can be accommodated by Deep Convolutional Neural Network, and the results are usually far more effective than those obtained earlier [5]. The weighted distance between the colour histograms of two images, expressed as a quadratic form, may be referred to as a match measure in image retrieval based on colour. This distance measurement uses high-dimensional characteristics and is computationally demanding (O(N)). We suggest using low-dimensional, straightforward distance measures to compare the colour distributions, and we demonstrate how these lower bounds on the histogram distance measure. According to results on colour histogram matching in big image databases, prefiltering using the more straightforward distance measures results in a significant reduction in processing time because the quadratic histogram distance is now performed on a smaller set of photos. Indexing into the database can also be done using the low-dimensional distance metric. Chronic diabetes is a condition that can result in diabetic retinopathy, which can lead to blindness. Consequently, to avoid the increased severity of diabetic retinopathy, early identification is crucial. In order to determine the appropriate follow-up treatment to prevent further retinal damage, an automated method can assist in the rapid detection of diabetic retinopathy. This paper suggests utilising a support vector machine to extract features and perform classification using deep learning. As input features for classification utilising the support vector machine, we employ the high-level features of the last fully connected layer based on transfer learning from Convolutional Neural Networks (CNN) (SVM). By employing this technique, the classification process using CNN with fine-tuning requires less calculation time. Using 77 and 70 retinal pictures from the Messidor database, the suggested approach is tested.By adopting Support Vector Machine technique, the calculation time needed for the CNN- tuned classification process can be decreased. Retinal images 77 and 70 from the Messidor database are used to test the suggested approach using bases 12 and 13, respectively.

The various phases of DR are recognized and categorized in color fundus pictures using a Convolutional Neural Network ensemble-based framework. The method is trained and tested using the largest publicly accessible dataset of fundus pictures (the Kaggle dataset). A meta-algorithm that combines different machine learning methods is called the ensemble method, is used to generate the prediction model [6]. Data from different prediction models are combined using a stacking model to build a new model. A match measure for colour could be defined as the weighted separation between the colour histograms of two photographs, which is represented by a quadratic form. These are the lowest limitations of the histogram distance measure, as demonstrated by a comparison of the colour distributions using low-dimensional, easily calculable distance measurements. With stacking, all of the outputs from the many models are combined to create a single output. This method combines the Resnet50, Inceptionv3, Xception, Dense - 121, and Dense169, which are five deep CNN models.

The retrieval of content-based images and videos in this paper makes extensive use of colors. The issues of colour spaces, illumination invariance, colour quantization, and colour similarity functions have all been the subject of projects [7]. An eye condition known as diabetic retinopathy (DR) harms the retinal blood vessels. If DR is not identified in its early stages, it can cause vision impairment and ultimately result in blindness. Normal, mild, moderate, severe, and PDR are the five phases or grades of DR (Proliferative Diabetic Retinopathy. For the purpose of identifying this fatal ailment, the coloured fundus photographs are frequently examined by highly qualified doctors. Manually diagnosing this ailment by professionals is time-consuming and error-prone. Thus, several computer vision-based methods have been developed to automatically identify DR and its various stages from retinal pictures. However, because they are unable to encapsulate the underlying complex features, these approaches can only accurately detect DR's numerous stages, especially for the early stages. In this study, we made use of the widelyA few of the suggested algorithms (distance measure) have been created to implement machine colour constancy, although their use in actual environments is currently being researched. Since images with "similar" feature distributions are frequently seen as having similar appearances without requiring any semantic interpretation of this, the concept of feature similarity also plays a crucial role in content-based retrieval. This method aids in calculating the similarity between two photos' features after a critical analysis.

The study demonstrates that current glaucoma screening methods based on intraocular pressure (IOP) measurements are insufficiently sensitive [8]. A persistent eye condition called glaucoma causes vision loss. Early disease detection is crucial because there is no treatment for it. For population-based glaucoma screening, the intraocular pressure (IOP) assays now in use are not sensitive enough. Assessment of the optic nerve head in retinal fundus pictures is superior and more promising. This study suggests utilizing superpixel classification to segment the optic disc and optic cup for glaucoma screening. Histograms and centre surround statistics are employed in optic disc segmentation to categories each

super pixel as a disc or a non-disc. In order to analyse the effectiveness of the automated optic disc segmentation, a self-assessment reliability score is calculated. Together with histograms and centre surround statistics, the feature space for optic cup segmentation also contains position data.An eye condition known as diabetic retinopathy (DR) harms the retinal blood vessels. If DR is not identified in its early stages, it can cause vision impairment and ultimately result in blindness. Normal, mild, moderate, severe, and PDR are the five phases or grades of DR (Proliferative Diabetic Retinopathy). The coloured fundus photos are often examined by highly qualified professionals to identify this catastrophic condition. It takes time and is prone to error for clinicians to manually diagnose this illness. Determining DR and its various stages automatically from retinal images has so been proposed using a variety of computer vision-based techniques. Nevertheless, these techniques can only identify DR's many stages with a relatively poor level of accuracy, especially for the early stages, because they are unable to encode the underlying intricate properties. In this study, we made use of the widely. According to the study, super pixel classification can be used to distinguish between the optic disc and optic cup when performing glaucoma screenings. To quantify the efficiency of the automated optic disc segmentation, a self-assessment reliability score is developed. The histograms and centre surround statistics for the optic cup segmentation are also included to the feature space in order to enhance performance. The suggested segmentation techniques have been tested using a database of 650 photographs on which the boundaries of the optic disc and the optic cup have been meticulously delineated by knowledgeable specialists. The average overlapping errors for segmenting the optic disc and cup were 9.5% and 24.1%, respectively. The method proves the efficiency of the self-evaluation by showing that overlapping error increases as the reliability score decreases. Segmentation and glaucoma screening are also possible applications of the technology.

Image analysis in the context of medical imaging with computer assistance. Deep learning, one of the most recent developments in machine learning aids in finding, categorizing, and quantify patterns in medical images. They explained the principles of deep learning techniques and reviewed their achievements in image registration, tissue segmentation, identification of anatomical and cellular features, computer-aided disease diagnosis and prognosis, and addressed research challenges and future possibilities for advancement [9]. Both clinical applications and academic research have been significantly impacted by computational modelling for medical image processing. Deep learning's recent advancements have opened up new perspectives on medical image analysis by making it possible to identify morphological and/or textural patterns in images entirely based on data. Although deep learning techniques have attained cutting-edge performance in a variety of medical applications, there is still potential for development.

The identification and classification of leukocytes, or white blood cells, which are crucial for the diagnosis of diseases, are covered in this article. Skilled workers manually operate the blood cells, which has several limitations including poor analysisspeed. This study suggests a system for automatically identifying and categorizing WBCs in peripheral blood pictures. [10] Due to its crucial uses in the diagnosis of diseases, the detection and classification of white blood cells (WBCs, also known as leukocytes) is a hot topic. The morphological study of blood cells is now performed manually by qualified workers, which has some disadvantages like sluggish analysis, non-standard accuracy, and reliance on the operator's abilities. Few articles take both into account, despite the fact that numerous papers have looked at the detection of WBCs or the classification of WBCs separately. This study suggests a system for automatically identifying and categorising WBCs in peripheral blood pictures. It first suggests an algorithm based on a straightforward relationship between the colours R, B, and morphological operation to identify WBCs in microscope images. Then a pairwise rotation granularity featureThe neutrophil, monocyte, and lymphocyte subtypes of WBCs are identified by random forest using the high-level properties that are automatically extracted from WBCs by convolution neural networks. Pairwise rotation invariant co-occurrence local binary pattern, or PRICoLBP, is used in conjunction with SVM as a granularity feature to discriminate between eosinophil and basophil, is employed as a granularity feature along with SVM. A detection method is more accurate, less expensive, and virtually as effective as an iterative threshold method.

3. PROPOSED SYSTEM

We suggest a machine learning-based strategy. In order to further increase the classification accuracy, a more effective method of combining shallow CNNs will be investigated. The performance of the integrated shallow CNN model will be enhanced by the transformation of picture samples and the repetitive sampling of the dataset. Backend of the system is created using VGG 16 image classification algorithm which is a multilayered convolutional neural network. For the front end, a User Interface is created using the tkinter python library, this allows the users to input the images to the algorithm and see the predicted output. Prediction with prediction accuracy and confidence score is shown as result. Multi-scale shallow CNNs with performance integration are introduced to the early identification of diabetic retinopathy through the classification of retinal images. When there aren't enough high-quality labelled examples, it can nevertheless perform well at picture classification because multiple base learners are capable of sensing

features under diverse vision-related receptive fields and sampling repeating datasets. The trials indicate that the performance integration model is more accurate than other integration models, such as those based on mean and voting. In addition, the suggested approach outperforms previous approaches when comparing classification effect and efficiency on small datasets.

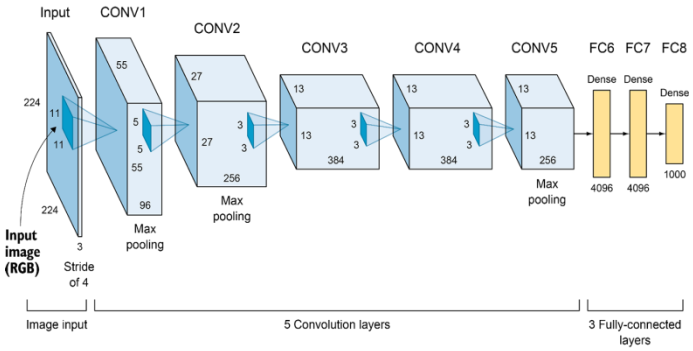

Fig3.1 Proposed Model

4. CONCLUSIONS

We conclude that the CNN-based image classification method, there are categories for Proliferative DR, Mild DR, Moderate DR, Severe DR, and No DR. This is significantly more helpful than the two- class classification techniques that are currently in use, which classify images into yes-or-no groups according onwhether the patient has DR or not. This does not supply us with any information on the severity and extent of the patient's condition, but our algorithm gives us deeper insights into the severity and extent of the sickness, enabling the doctors to offer appropriate care. Future research will refine our suggested strategy in the manner described below. To further increase the classification accuracy, a more efficient method of combining shallow CNNs will be investigated. By integrating the modification of picture samples with repetitive dataset sampling, the integrated shallow CNN model would operate more effectively.

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