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VISION GUARD USING MACHINE LEARNING

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Abstract: This Diabetic retinopathy is a disease caused by uncontrolled chronic diabetes that can lead to complete blindness if not treated in a timely manner. Therefore, early medical diagnosis of diabetic retinopathy and its medical treatment are essential to prevent serious side effects of diabetic retinopathy. Manual detection of diabetic retinopathy by ophthalmologists takes a lot of time and currently causes great suffering to patients. Automated systems help detect diabetic retinopathy quickly and make it easy to follow up on treatment to avoid further effects on the eyes. In this paper , we extracted three features such as effusion, hemorrhage, and microaneurysm and then after extracting these 3 features we classified them using a hybrid classifier that combines them with support vector machine, k-nearest neighbor, random forest, logistic regression, and multilayer perceptron network for machine learning method to classify. Hence, the proper analysis of retinal vessel is required to get the precise result, which can be done by Retinal Segmentation. Using the image classifier we can classify the infected eye from the normal eye just by uploading the image which saves time and money of the user, allowing him to check the symptoms at home rather than going to hospital. So we developed a system to reduce time.

***Index Terms*: Diabetic retinopathy, automated system, machine learning, dataset, processing, CNN, DenseNet**

I. INTRODUCTION

For Diabetic retinopathy is a debilitating eye disease that is one of the leading causes of blindness worldwide. It occurs as a result of high blood sugar levels damaging the blood vessels in the retina, leading to vision impairment or even complete loss of sight. Early detection is crucial for effective treatment and prevention of irreversible damage. Fortunately, advancements in machine learning techniques have opened up new possibilities for the early detection of diabetic retinopathy. Diabetes patients are one of the world's most populous disease categories today. diabetic fundus diseases, the leading cause of blindness, can cause visual loss. DR, Glaucoma, cataracts, and other fundus diseases now affect visual function. When fundus disease reaches a late stage, it greatly impairs the patient's vision and cannot be specifically treated.

II. EXISTING SYSTEM

2.1Litrature Review

In 2018 Lam's [1] summarize the existing literature on diabetic retinopathy and maculopathy automated detection and classification, emphasizing deep learning methods. It gives an overview of the existing researches in this field and it talks about the possibilities of various deep learning architectures, such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), and hybrid models

In 2017 by Ting's [2] paper in question intended to unveiling how transfer learning will be applied in the case of detection of diabetic retinopathy when pre-trained CNNs with large-scaleof datasets are exploited. It did a systematic review on transfers methods used to and analyze medical images like retinopathy, which came with tasks like diabetic retinopathy detection. It did a systematic review on transfers methods used to analyze medical images like retinopathy, which came with tasks like diabetic retinopathy detection. The article underlined the significance of transfer learning in which models acquire the new knowledge much quicker and demonstrate higher generalization capability than training the models from scratch.

In 2018 paper by Raju et al [3] aim of this work was to address a robust approach to diagnosis of diabetes retinopathy through a fusion of deep learning and traditional machine leaning methods. It did a systematic search of both the literature of deep learning-based methods and that of the generic feature-based approaches for diabetic retinopathy detection.

2.2 Limitation Existing system or research gap

1. Chances are that the data set might fail to account for the full diversity of retinal images that are often diagnosed in practice.
2. The possible lack of variety in the datasets that have been tested under limited validation on the multi-regional and diverse populations may limit the model's
3. The model may work too good or too bad, depending on whether the dataset isfrom different crowd or just with various imaging techniques.
4. There may be a situation when the model performance falls short when used to images taken from patients with other ocular problems

III. PROPOSED SYSTEM

3.1 Proposed System Architecture

This process starts by selecting a dataset of the retinal images that have the annotation information which indicates the intensity levels of diabetic retinopathy. This dataset is then divided into two subsets: a training set with a validation set. The training set on the one hand comprises the model training, while the validation set on the flip side is used to measure the model accuracy during training and prevent overfitting.

After preparing a model, we use data augmentation techniques on the training images. These operations called rotation, horizontal, and vertical reflection are used to obtain extra images from the first picture. Data expansion leads to introducing more different types of training data and improves model recognition of unseen data.

In terms of the model architecture, DenseNet is chosen because it is effective in resolving the problems of gradient vanishing in deep neural networks and reducing the effect of degradation. DenseNet blocks consist of diverse layers while dense convolutional layers are chained densely in each block. Transition layers are used to regulate the growing diameter of feature maps and decrease the number of network parameters by means of dimension reduction.

The training period DenseNet is done by adjusting the parameters of the model with the help of training dataset. The model is built with the relevant optimization algorithms (e.g., Adamax optimizer) and loss functions (e.g., categorical cross-entropy loss) to bring down the level of deviance of the outputs of the prediction and the true labels. Class weights are determined so as to take care of the class imbalance that might be observed within the dataset.

At training the model early stopping and model checkpoint after a specified delay are performed to control the model performance on the validation set. Via early stopping avoids overfitting, and it stops training when the validation performance no longer improves. While in the training and evaluating stage the model is trained on training and validation datasets; the testing phase, however, consists of the model making predictions on the unseen test data that were not used in the training and validation stage. The artificial vision system integrates text-to-speech processes, speech recognition systems and the essence of the human visual cortex

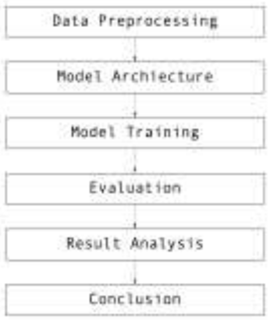

Figure 1 System Flow

This figure 1 shows us the flow of how the system works. This process starts by selecting a dataset of the retinal images that have the annotation information which indicates the intensity levels of diabetic retinopathy. This dataset is then divided into two subsets: a training set with a validation set. The training set on the one hand comprises the model training, while the validation set on the flip side is used to measure the model accuracy during training and prevent overfitting.

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At training the model early stopping and model checkpoint after a specified delay are performed to control the model performance on the validation set. Via early stopping avoids overfitting, and it stops training when the validation performance no longer improves. On the other hand, model checkpointing save the optimal model based on validation accuracy.

Lastly, after training the model, its performance is seen using metrics such as accuracy and loss measure. These metrics help us understand the accuracy of the prediction of the model and the percentage of errors, in terms of image classification, that may be found in the model's performance. While in the training and evaluating stage the model is trained on training and validation datasets; the testing phase, however, consists of the model making predictions on the unseen test data that were not used in the training and validation stage. The artificial vision system integrates text-to-speech processes, speech recognition systems and the essence of the human visual cortex.

3.2 Data and Sources of Data

The approach of this task was freely using readily available Kaggle Dataset for Diabetic Retinopathy Discovery. The dataset was built with pictures using the images from retinopathy discovery sets which are freely accessible. The Kaggle dataset comprises 1000 images of patients with diabetic retinopathy and 1000 images of patients without the disease. Therefore, we gather 122 photos of retinopathy patients with diabetic conditions and 122 typical photos. The selected focal images are characterized by exudates, haemorrhages, and microaneurysms, respectively. Number, distribution, and forecasting of diabetic retinopathy is depicted by appearance, spread, estimating, number of microaneurysms and hemorrhages. Exudates appear as the distinctive shiny zones with yellow colour that can change into the colour of optic plate in case of slight run. Exudates occur as the damaged blood vessel contains triglycerides of different types. Figure 2 shows us how the infected eye looks like after the scenning is and and filters are added to it. The rupture of small blood vessel of the arteries is caused by clumps of haemorrhages. Spackled spread of exudates and haemorrhages are revealed in serious diabetic retinopathy pictures.

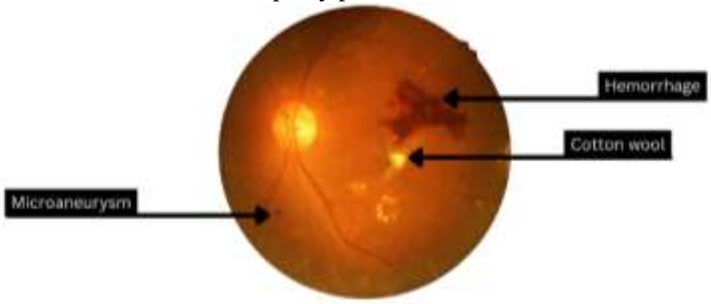

Figure 2. Diabetic Retinopathy Infected eye

IV. RESEARCH METHODOLOGY

Convolutional Neural Network (CNN) is the type of deep learning model that specializes in dealing with image and video data, which are mainly visual data. The inspiration behind this flowchart can be conveniently explained as the stepwise process that is employed for building a machine learning model intended for the diagnosis of diabetic retinopathy starting with retinal images. Here's a detailed narrative explanation of each component shown in the flowchart: Here's a detailed narrative explanation of each component shown in the flowchart

4.1 Data and Sources of Data

For this study secondary data has been collected. From the website of KSE the monthly stock prices for the sample firms are obtained from Jan 2010 to Dec 2014. And from the website of SBP the data for the macroeconomic variables are collected for the period of five years. The time series monthly data is collected on stock prices for sample firmsand relative macroeconomic variables for the period of 5 years. The data collection period is ranging from January 2010 to Dec 2014. Monthly prices of KSE -100 Index is taken from yahoo finance.

4.2 Theoretical framework

The dimension is changing and the number of channels of the CNN is also depended on this point of view. Each architecture of CNNs engineering is allocated to a separate layer. The CONV layers are where unique channels doing the image's convolving to extract the background. In every second convolutional layer the Pooling layer is also implemented to collapse the dimensions of the feature maps. undefined

Convolutional Layers: This procedure uses filtering of learnable kernels which drives extraction of features such as edges, textures and patterns from the image input.

Pooling Layers: Pooling layers filter the features map which are generated from convolutions layers, hence the spatial dimensions are reduced while preserving the important details.

Activation Functions: Thinking in dissimilar way like ReLU (Rectified Linear Unit) with using non-linear activation functions introduces non-linearity to the network that enables it to learn complex patterns and relationships in the data.

Fully Connected Layers: Feedforward layers, which also goes by the name of dense layers, interconnect each neuron in one layer to every neuron in a next level so that the network can learn complex representations and make accurate forecasts.

4.2.1 Convolutional Neural Network (CNN)

CNNs are among the most successful architectures in the field of computer vision applied to the different tasks starting from image classification, object detection, segmentation and many others. The block encompasses the information fed in by all layers from the current layer it is placed in as well as distributes the results to all forthcoming layers in the block.

Some factors and elements help in detecting the infected images of the eye, especially for identifying cases of diabetic retinopathy Thus, data preprocessing procedures turn out to be vital first. The parameters such as data augmentation strategies (e.g., rotation, horizontal and vertical flip images) are used to increase the variation in the training dataset. Through its extrapolation, the model acquires more knowledge about the various differences between seen and unseen images and thus, is able to accurately distinguish infected images. Furthermore, the dataset is divided into training, validation, and testing sets that allow for model training on a wide spectrum of images and evaluating the model using a set of unseen data, which give a measure of its performance in generalization.

4.2.2 Dense-Net

The DenseNet121 based model that comprises a number of parameters of the very construction itself determines its possibility to faculty with identification feature sensitive images. They include the count of bulky blocks, growth speed, filter number, reduction factor, dropout rate and weight decoration. DenseNet architectures (or, so-called deep cores of them) are rich in the fine network structure leading to efficient feature reuse and better gradient flow during training. The ability of the architecture to handle robustness and retain doing it to more detailed patterns in the data is what make this model effective in identifying infected pictures. Although computation of parameters should be optimized during model training, learning rate planning is also a key component.

For hemorrhages and microaneurysms instance parameters of median filter, thresholding, image erosion and image dilation are applied. Image conversion and scaling called morphological operations are the basic operations done on image. Thresholding

divides an image into two sections, background and the foreground. Here, one of the types of image processing mechanism is called image segmentation, through which the image objects are separated out, converting the gray scale images as binary images. As a result, distances which separate each TV will increase thereby leading to an exaggeration of the differences between each sets.
DenseNet is a deep learning structure which introduces the essence of densely distributed communication between the layers. Originally, deep neural networks were considered a straightforward network since all the layers after each other were connected in a vertical fashion and classification or predictions were represented as the output parameter down the line. DenseNet is, different from residual where each layer is connected to each previous layer and outputs a feature map. This elaborately patterned connectedness has proved to be advantageous in respect to for example feature reuse; solving the vanishing-gradient problem and achieving more compressing.

DenseNet has demonstrated superior performance in terms of parameter efficiency, gradient flow, and feature propagation, making it an attractive architecture for various computer vision tasks.
In summary, while CNNs have revolutionized the field of computer vision, DenseNet represents a significant advancement in deep learning architectures by introducing dense connectivity, which has shown to improve feature reuse and gradient flow within the network.
Key Features of DenseNet:
• Dense Connectivity: The role of each layer is to take the feature maps from the preceding layers and to provide its own as the inputs of the layers which follow it.
• Bottleneck Layers: DenseNet is based in the implementation of bottleneck layers. These layers dramatically reduce the number of feature maps for each layer which makes the model shorter and, consequently, less expensive to compute.
• Transition Layers: These resolutions define the number of filters and spatial length provided at every successive step.
Besides that, patch-based methods and deep learning networks which were pre-trained with DenseNET have demonstrated their usefulness in a precise identification of DR in digital eye fundus images. In the end, the aggregated conclusions demonstrate a high level of progress by way of employing the deep learning approach in deep royal diagnosis and classification. These developments open up possibilities for making healthcare in the ophthalmology sphere more effective and this also opens the gateway for further research and innovations in the future in this field.
DenseNet has shown superiority in the aspect of the parameter count, the gradient flow, and the feature propagation among all of computer vision jobs, and it can be a nice architecture which will be used. In a nutshell, by increasing the amount of information flow and sharing existing knowledge within the network, the integration of dense connections has significantly enhanced the architectures of deep learning to improve feature reuse and gradient flow at the same time. DenseNet121.

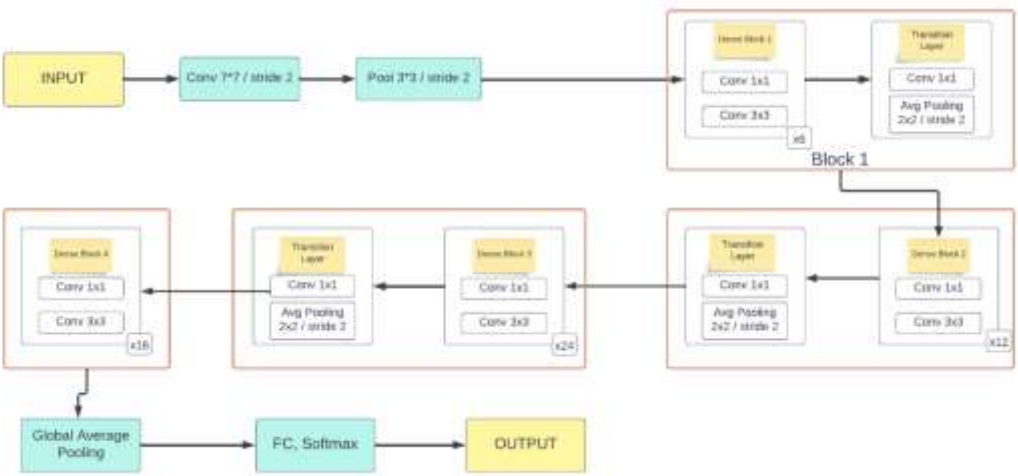

Figure 3. System Architecture

Therefore as at the beginning dense layer, there is a transition layer here at the end. After the second and also the third dense block, you will have a transition layer that will help you get into the final result. Therefore, we have a collection of six convolutional blocks. Each of the layers is closely associated with, irrespective of which layer we talk about. As for the backbone, there is the center stack of neurons in a highly compact den block where every layer is connected to all other layers. The process of feature extraction starts with the initial layer, which receives the feature maps provided by the previous layer. You can see here. All right, this is our tricky block of gray pen with blue lines which I call special feature maps. I've named it "X0" for now, which is a gray feature map to me. This is the input which we are feeding to the densely connected block.

4.3Statistical tools and econometric models

They are the methods to solve PDEs using non-linear partial differential equations and with computation potential to solve large mathematical models. So, there we have it: six convolutional layers. Each layer of our dense block build is connected to every other layer blurring their separation. A larger framework consists of rather small layers that interconnect with each other.
With this input features we supplied to first the convolutional layer, the first convolutional level shall start to make a few features. Indeed, beside this, the old features are finally blended with the new ones, and you may also have a look at the feature map like this. Furthermore, the fact that the deeper the neural network is, the higher the level of learning is. So you see, this. Consequently this will be the connections that we are making here, we are aggregating these green features that we have obtained through the layer two convolutions, and we will merge them with the other two feature maps that we have extracted before. Therefore as the same, you can recognize each element has a feature map from the former layer, so the density block input for one layer is the idea of the feature maps from the pasts layer of the concatenation. This forms the gateway to that lateral. The output of this layer is to

be the input to this regression step. And we are respectively and partially, concatenating these features to the feature maps of that particular layer. Well, from the technical point of view - that's how it goes.

V. RESULTS AND DISCUSSION

5.1 Results of Descriptive Statics of Study Variables

Specificity is the sensitivity of the test that determines whether a sick person can be accurately identified.

$$Sensitivity = \frac{TP}{TP + FN} \times 100$$

The specificity, which is the state of the assess, is described as the power to exclude from the patients with the disease state all individuals without a real one.

$$Specificity = \frac{TN}{TN + FP}$$

TP – is when the test result is positive, and the patient suffers from the disease.
TN – a negative result and no infection has been confirmed.
FP – is the case when the result test is positive, but the patient is healthy.
FN – a negative result despite the fact that the patient is may be a carrier of the disease.
The accuracy when the classifiers were tuned was 82% on the test Of 48 trials, 36 showed the same results as the actual ones.

5.2 GRAPHS

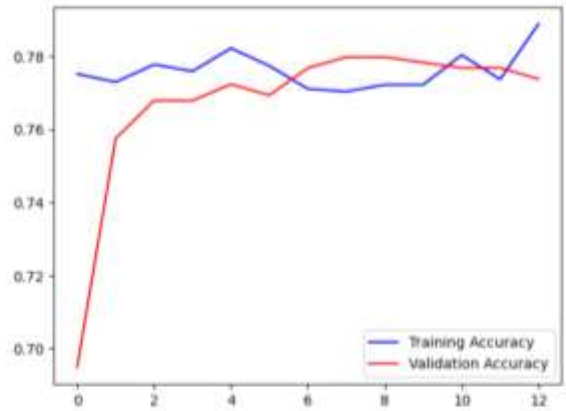

Figure 4 Accuracy Graph

Based on the description of accuracy graph, here are some analytics:

Initial Increase: The red line represents the accuracy of the training which curves over sharply, thus demonstrating an improvement in the learning speed at the early epochs.

Stabilization: The graph shows that the accuracy of the training is increasing before it finally stabilizes, which means a good sign that the model is converging and learning well.

Validation Accuracy: The legitimacy (blue line) of the validation accuracy also grows up but with waves. This could potentially mean that the model had been perfecting to the training set unrealism or the validation set may not be adequate to represent the general population.

Model Tuning: To prevent problems of overfitting, you could also utilize techniques such as dropout, early stopping, or employ a more complex model if the current model isn't intricate enough. However besides that, you must check the data if it was preprocessed correctly and use data augmentation for a big variety of the training dataset.

Such revelations will assist you in making paradigm shifts for early and accurate adaption of the model in diagnosing diabetic retinopathy. However, be aware that the right balance between high performance on the training and validation subsets is a key objective for developing a stable model

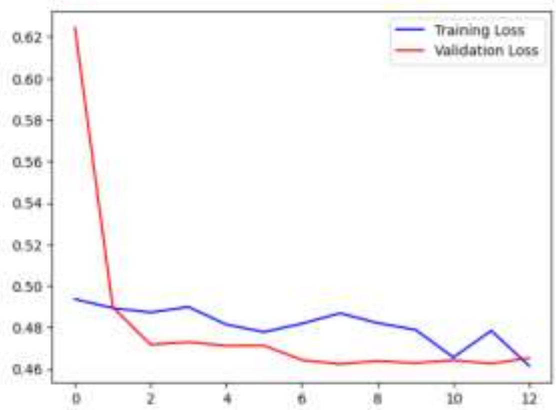

Figure 5. Loss Graph

Initial Decrease: This training loss exhibits a rapid downhill pattern of decrease at first, and this is a clear indication that the model is rapidly gathering useful information from its training dataset.

Validation Fluctuations: However, learning rate by the validation loss is more stable but in some cases fluctuating. This could suggest that the model is not capable of generalizing to the unknown data; these are the general issues of machine learning.

Overfitting Check: In case the training loss is still lowering when the validation loss does not decrease either it might be an overfitting case. It is crucial to be on the lookout for this behavior.

Model Performance: To improve the model, dive into new architectures, regularization approaches or use a more diverse training dataset. Furthermore, the data should be balanced and preprocessed sometimes for the task of detecting diabetic retinopathy.

Commence your analysis by interpreting the findings of the model. Subsequently, use the information to improve your model in order to obtain better results. In fact, the aim is to eliminate as many errors as possible through a model which is not over fit to the training data.

VI. CONCLUSION

Throughout this paper, we have maneuvered through the intricate landscape of diabetic retinopathy (DR) detection, highlighting the paramount role of machine learning in revolutionizing early diagnosis and management. The discussion traversed the evolution of machine learning applications, the stages of diabetic retinopathy, and the significant advancements in algorithmic detection methods. These technological strides not only underscore the importance of early and accurate DR detection but also illuminate the path towards enhanced patient-specific care, through the use of deep learning and AI-enhanced imaging technologies. As we peer into the future of healthcare, the integration of AI and machine learning in diabetic retinopathy detection emerges as a beacon of hope for mitigating vision loss among diabetic patients. The promise of telehealth innovations and the refinement of diagnostic algorithms hold the potential to expand access to essential screening services and elevate the precision of DR detection. By embracing these technological advancements and addressing the accompanying challenges, the medical community can look forward to improved patient outcomes and a new era in the proactive management of diabetic retinopathy.

VII. FUTURE DEVELOPMENTS

Exploring the future developments and research directions in diabetic retinopathy detection using machine learning reveals two promising avenues: the expansion of telehealth and remote screening capabilities, and the exploration of advanced image detection and classification methods through deep learning (DL) approaches. Both areas hold significant potential for improving access to screening services and enhancing the accuracy of DR detection.

1.Telehealth and Remote Screening Innovations:
- Handheld Devices and Smartphone Attachments
- Impact on Access to Care

2.Advancements in Deep Learning for DR Detection:
- Advanced Image Detection and Classification
- Improving Diagnostic Accuracy

These future developments and research directions underscore the dynamic nature of diabetic retinopathy detection using machine learning. As technology continues to evolve, the integration of telehealth solutions and the refinement of deep learning models offer promising pathways for enhancing the effectiveness of DR screening and diagnosis, paving the way for improved patient care and management in the field of ophthalmology

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