DETECTION OF DIABETIC RETINOPATHY USING SWISH ACTIVATION FUNCTION

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ABSTRACT

Diabetic retinopathy is a chronic condition inflicted as a result of uncontrolled diabetes. If not treated on time, it can lead to complete blindness. Therefore, it is important to diagnose and treat diabetic retinopathy early to prevent its dangerous side effects. Ophthalmologists currently spend a lot of time manually diagnosing diabetic retinopathy, which can be painful for patients. A system could be useful for automating this process, allowing diabetic retinopathy to be diagnosed quickly and easily, followed by treatment to prevent further damage to the eyes. A deep learning-based approach is presented in this paper to classify diabetic retinopathy using a binary classifier and decoding three properties: hemorrhages, exudates, and microaneurysms. The proposed approach has the potential to be a valuable tool for automating the diagnosis of diabetic retinopathy. It is fast, accurate, and can be used to detect the three most common signs of the disease. This will help to improve the early detection and treatment of diabetic retinopathy, which could prevent blindness in millions of people. The model has a 95% accuracy rate on test data, which is a significant improvement over previous method.

Keywords: Diabetes, Diabetic Retinopathy, Eye Disease, Detection of Disease, Swish Activation Function;

INTRODUCTION

Diabetic retinopathy is a condition which causes damage to the eyes of people with diabetes. It can cause blurry vision, dim vision, difficulty seeing colors, and even blindness in severe cases. One-third of the estimated 285 million people with diabetes worldwide have diabetic retinopathy. Diagnosing diabetic retinopathy manually now takes a lot of time from ophthalmologists and might be uncomfortable for patients. Required facilities are not available in most places for appropriate diagnosis which leads to deterioration of the medical condition. Figure 1 shows a retinal image that high- lights the many features of diabetic retinopathy. Small red patches are a feature of an early stage of diabetic retinopathy which is Non-Proliferative Diabetic Retinopathy (NPDR). These spots are signs of bleeding and indicate the presence of micro aneurysms, which are abnormal sacs in blood vessels.

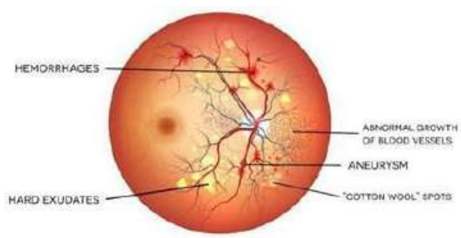

Fig. 1. Retina Image with Diabetic Retinopathy [1]

A machine-learning hybrid model can be used to per- form automated computer-aided detection of diabetic retinopathy by extracting features such as hemorrhages, microaneurysms, and exudates. A recent study found that deep neural networks struggle to identify features specific enough to recognize moderate diabetic retinopathy. In fact, 93% of all the classification errors made, are mild cases. This study demonstrates comprehensive learning assessment using an open-source retinal imaging database. This effort will help to develop accurate diagnostic tools for diabetic patients, individuals who are prone to early onset diabetic retinopathy.

The objectives of the paper are: a) to develop a machine learning diabetic retinopathy prediction model that can predict whether a user has diabetic retinopathy or not basedon their retinal images, b) to help people identify the risk ofdiabetic retinopathy at an early stage and specify the class.

The rest of the paper is organized as follows: The second part goes into further detail about the related work. The proposed system is thoroughly discussed in the third part. The paper's fourth portion examines system upgrades, and the last section wraps things up.

LITERATURE SURVEY

Various strategies have been employed for the detection of diabetic retinopathy. A few notable systems were examinedand taken into consideration for the development of the suggested system. Raju et al. [2] The authors analyze this deep learning model's performance in numerous experiments and give an overview of their fundamental ideas and architectural designs. Also, they draw attention to DR detection's difficulties, including the necessity for sizable datasets, the interpretability of deep learning models, and validation in actual clinical settings.

Jenuja et al. [3] The optical cup and disc components are used in conjunction with dual neural networks in the proposed method. This research aims to effectively divide the optic cup and disc in animage of the retinal fundus. Approach concentrates on separating the optic disc and cup in retinal fundus images. They probably use deep learning and/or image processing techniques to precisely identify and outline these structures. For later analysis, such as extracting features for classification or quantifying optic disc and cup properties, accurate segmentation is essential. There are no outcomes from the classification of glaucoma stages. Vallabha et al.[4] The use of Gabor filter bank outputs for the detection and categorization of retinal defects linked to various phases of retinopathy is described in the research. In image processing, gabor filters are frequently employed to record localized frequency data and textural properties. The strategy intends to automatically discover retinal anomalies and classify them according to the severity of retinopathy by using the Gabor filter bank outputs as input features for classification.

Karegowda et al. [5] The eye with exudate and the normal eye were categorized in the study. Combining a genetic algorithm (GA) and CFS feature se- lection is known as GA-CFS. The decision tree and GA-CFS phases' chosen features are fed into a backpropagation neural network (BPNN), which uses them as input. Gupta and Chhikara [6] explored DR recognition strategies using Promotion support, Arbitrary Woodland, SVM and so on, utilized in the field of information science bit by bit displaying the hole that these old-style procedures present with respect to learning more illness related highlights. They probably concentrated on figuring out the drawbacks of these conventional methods for learning disease-related traits for DR recognition. Complex patterns and delicate elements in retinal pictures linked to DR may be difficult for traditional methods to accurately capture. The authors may have wanted to emphasize the necessity for more sophisticated and advanced methods in the field of DR recognition by pointing out the drawbacks of these traditional methodologies. These sophisticated strategies have demonstrated promise in a range of medical image processing tasks, including DR detection.

Lin et al. [7] improved the classification of lesions and presented the MCG-Net module, a Graph Convolutional Network (GCN)-based method for efficiently extracting features. The method seeks to enhance the precision and efficiency of lesion categorization in fundus images by utilizing GCN in the MCG-Net module. Contextual data and regional dependencies, which are essential for precise categorization of lesions, may be captured via the graph-based representation and feature extraction. Gupta et al. [8] has implemented a DR detection model usingthe Swish activation function on Google Cloud Services.A sizable collection of retinal pictures was used by the scientists to train their CNN model, which was then hosted on Google Compute Engine. The hosted model's accuracy and inference time performance was then assessed. The outcomes demonstrated the effectiveness of hosting on Google Cloud Services, with the hosted model achieving high accuracy and having a short inference time.

Sharma et al. [9] has explained the study focused on hosting the model on Google Cloud Services and evaluated the performance of Swish activation function with other activation functions in DR detection. A dataset of retinal pictures was used by the authors to train their CNN model, which was then hosted on Google Kubernetes Engine. The hosted model's accuracy, sensitivity, specificity, and inference time performance were assessed. Swish performed better than alternative activation functions in terms of accuracy and sensitivity, and hosting on Google Cloud Services allowed for quick deployment and scalability, according to the results. Usharani Bhimavarapu and Gopi Battineni et al. [10] The enhanced activation function employed in the modified CNN model reduces the process- ing duration of the model by around 7 ms by removing the indivisible classification of nonlinear input. Comparing the suggested activation function to existing methods, the classification of diabetic retinopathy was improved.

Muhammad Mateen et al. [11] The recommended technique first performs data preprocessing to standardize exudate patches. Furthermore, ROI localization is used to localize exudate properties, and then transferlearning is used to extract features using pretrained CNN models (Inception-v3, Visual Geometry Group Network-19, and Residual Network-50). Additionally, the SoftMax classifier uses fused features from fully connected (FC) layers to classify exudates. eOphtha and DIARETDB1, two well-known publicly accessible databases, were used to assess the performance of the proposed system. [12] It has been shown that utilizing a CNN-based system, the entropy picture of brightness of a fundus photograph may improve the detection performance for referable DR. This workproposes the use of the green component of the fundus picture to compute the entropy image. Before computing the entropy pictures, image enhancement by unsharp masking (UM) is used as a preprocessing step. A bichannel CNN that incorporates the characteristics of the green component pre-processed by UM and both the entropy pictures of the grey level is also suggested.

Praveen Modi et al. [13] used a deep forest approachand a bat-based feature selection algorithm to work on the smart identification and diagnosis of diabetic retinopathy. Using two datasets related to diabetic retinopathy, the effectiveness of the proposed BA-Deep Forest model is assessed. The outcomes of the simulation are contrasted against a number of current models, including KNN, InceptionV3, VGG16, SVM, ANN and Deep Forest. The findings shown that the suggested BA-Deep Forest model, when employing the 10-cross fold approach, obtains superior rates of accuracy, F1-score rates,sensitivity, and specificity. B. Revathi et al. [14] The introduction ofCNN with PSO helps to address the problems with DR. Theapproach for detecting diabetic retinopathy involves many phases. Pre-processing, optimization, and categorization are what they entail. The major goal of the suggested work is to categorize and report just that region from the input byusing the CNN algorithm to assess the sickness that appearsto be most affecting. The supplied categorized pictures are optimized using PSO, and then PSO combined with CNN will yield reliable results.

Ganeshsree Selvachandran et al. [15] The methods that have been created for the detection of DR are thoroughly evaluatedin this work, with a focus on machine learning models like CNN, ANN, and other hybrid models. Then, each AI will be classed according to its kind (such as CNN or ANN) andany specific tasks it has been given for DR detection. A fewessential traits of each model's unique CNN architecture will be further explored and used to classify the modelsthat employ CNN in particular. In order to give a thorough picture of the most current advancements in the detectionof DR, 150 research publications that were published in the last five years and were connected to the aforementioned topics were used in this evaluation. Pooja Bidwai et al.[16] The methods that have been created for the detection of DR are thoroughly evaluated in this work, witha focus on machine learning models like CNN, ANN, and other hybrid models. The models that use CNN in particular will be further examined and categorized in accordance with a few key characteristics of the individual CNN architectures of each model. In order to give a thorough picture of the most current advancements inthe detection of DR, 150 research publications that were published in the last five years and were connected to the aforementioned topics were used in this evaluation.

Murugan A et al. [17] Glaucoma is easily identified using a CNN-based system. This study examines the effectiveness of color fundus images to discriminate glaucoma is with Deep Convolutional Neural Networks

(DCNNs), with the goal of improving CNN architectures through evolution to increase glaucoma diagnostic accuracy and sensitivity. The quality of the photographs affected the ability to discriminate, and adding low-quality images to the study reduces the area under the curve by 0.1 to 0.2. S Sudha et al. [18] The innovative background and foreground super pixel segmentation technique is pro- posed by the CNN-based automated detection of DR, and the primary Cascaded Rotation Forest classifiers, and Support Vector Machine. When the hybrid classifier'sperformance is compared to earlier works, parameters like specificity, sensitivity, and accuracy demonstrate that itperforms admirably and achieves an overall accuracy of 98%. The Cascaded Rotation Forest (CRF) classifier outperforms the others in terms of accuracy.

Hamid et al. [19] used the findings from optical coherence tomography angiography, patterns of retinal vessel oxygen saturation, and increased levels of circulating blood markers and cytokines are proposed as early indicators of diabetic retinopathy (DR). Researchers have created light-based molecular imaging techniques in rodents to illustrate alterations in protein expressions within retinal microvessels, serving as potential diagnostic biomarkers. This summary encompasses all studies concerning biomarkers for subclinical DR.

Imran Qureshi et al.[20] detailed the array of CAD systems created through diverse computational intelligence and image processing approaches, this comprehensive overview delves into the constraints and upcoming trajectories within contemporary CAD systems, offering valuable insights for researchers. The outcomes of this comparative analysis underscore an existing necessity for the precise advancement of CAD systems, particularly in supporting the clinical diagnosis of diabetic retinopathy.

Emma et al.[21] through observations conducted in eleven clinics in Thailand, we outline the existing processes for screening eyes, user anticipations regarding an AI-supported screening system, and the outcomes observed after implementation. They utilize these insights to emphasize the importance of incorporating human-centered evaluative research in conjunction with prospective assessments of model precision.

Thippa Reddy et al.[22] Initially, the raw dataset undergoes normalization through the Standard scalar technique, followed by the application of Principal Component Analysis (PCA) to identify and extract the most relevant features. Subsequently, a dimensionality reduction using the Firefly algorithm is executed. The outcomes produced by the model are assessed in comparison to established machine learning models, demonstrating the superior performance of the proposed model across metrics such as Accuracy, Precision, Recall, Sensitivity, and Specificity.

Alexandr Pak et al.[23] This research introduces a comparative analysis among three architectures: the commonly employed DenseNet and ResNet, and the newly optimized EfficientNet. The methods presented involve the classification of retinal images into five distinct classes, utilizing a dataset acquired from the 4th Asia Pacific Tele-Ophthalmology Society (APTOS) Symposium.

Andrzej et al.[24] article seeks to elucidate the latest advancements in AI technologies for diabetic retinopathy (DR) screening as documented in literature, with some already accessible in the market. Despite numerous groups reporting strong diagnostic capabilities of AI algorithms in DR screening, further investigation is needed to tackle various challenges such as medicolegal considerations, ethical concerns, and the establishment of clinical deployment models.

Gaurav et al.[25] Our models demonstrated significantly improved results compared to previous studies using the same datasets, establishing Convolutional Neural Networks as a leading option for automated detection of medical conditions in digital medical images. Additionally, the system offers quick model inference time (~1.5s) and the capability for batch processing of images, making it a practical choice for the preliminary screening of a large number of patients.

PROPOSED METHODOLOGY

In the proposed system the image dataset is taken and fed into the CNN model, where it is used for model training. The images are pre-processed using various methods before being used. The methods included are gray scaling, Gaussian filtering, and image resizing. The process of gray scaling involves changing an image from another color space, such as RGB, CMYK, HSV, etc., to a variety of grayscales.The intended area is blurred using the Gaussian filter, which also reduces noise at higher frequencies. It functions similarly to mean filters while uniformly displaying average weight.

The process of expanding or decreasing an image's size is known as image resizing. More specifically, itrefers to changing the width and height of a 2-dimensional image by calculating the pixel values for the updated (or resized) image. Images from the dataset that have been clipped are scaled to 224*224 pixels. The images are categorized according to the degree of parameters, which are hemorrhages, extrudates (soft and hard), and aneurysms. The image dataset is divided into training and testing samples. A binary classifier is used to classify the images and label them as either DR or No DR. Where DR stands for diabetic retinopathy and No DR denotes the absence of diabetic retinopathy.

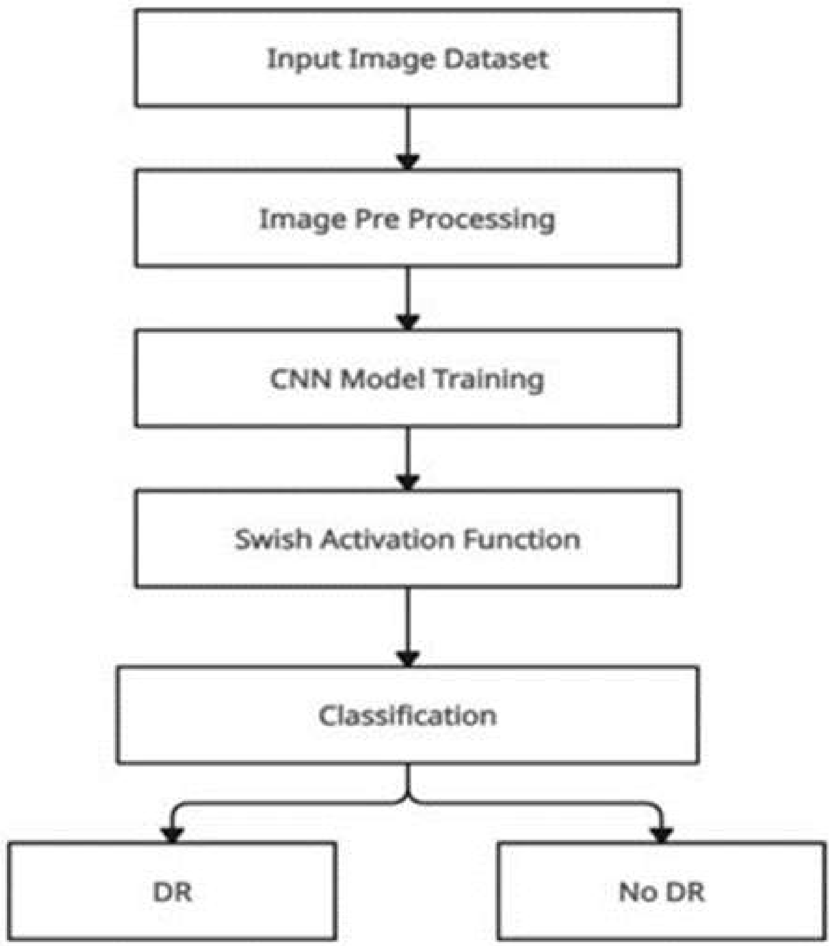

Fig. 2: Flow of the Proposed System

Convolutional Neural Network

CNN is an adept and adroit type of artificial neural network designed primarily for image recognition and computer vision tasks. The process of information flow in a CNN typically involves stacking multiple convolutional layers with activation functions and pooling layers. The last pooling layer's output is flattened into a one-dimensional vector, andthen one or more fully connected layers are used to make predictions based on the learned features. In a variety of computer vision tasks, including picture classification, object identification, segmentation, and style transfer, CNNs have displayed exceptional performance. They are ideal for a variety of visual identification applications due to their capacity to automatically learn hierarchical features from raw pixel data. General architecture of CNN is shown in Figure

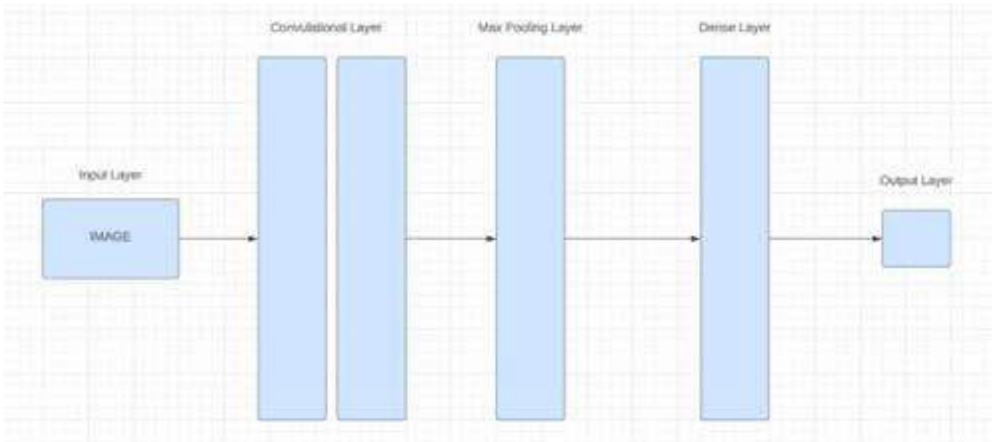

Fig. 3: Architecture of CNN

Feature extraction in CNNs is performed by the convolution layers. The convolution layers apply a series of filters to the input image, which extracts different features from the im- age. During the training process, the filters are learned and they are designed to identify specific features that are relevant to the task at hand such as edges, shapes, and textures that are common to dogs and cats. When the filters are used on the input image, a collection of feature maps is created. The feature maps are subsequently passed on to the CNN's typically pooling-based next layer. The pooling layer reduces the size of the feature maps, which helps to reduce the computational complexity of the CNN. The pooling layer also helps to preserve the most important features in the feature maps, which helps to improve the accuracy of the CNN. After the pooling layer, the feature maps are passed to the fully connected layers. For the implementation of the proposed system, the CNN model with four convolutional layers having 16 filters each is followed by two dense layers. For the activation function, 'swish' is used with a dropout rate equal to 0.2. For the output layer, the 'sigmoid' activation function is used as it is a binary classification application. The initial learning rate of 0.0001 is used, which eventually halved as the number of epochs increased. 'Adam' optimizer is used along with binary cross entropy as a loss function and accuracy metric to keep track of the improving accuracy as epochs increase.

Swish Activation Function

The training dynamics and task performance of Deep Neural Networks are significantly influenced by the choice of activation functions. The Rectified Linear Unit (ReLU), which has been the most effective and popular activation function to date, is defined as f(x) = max (0, x). Despite the many alternatives to ReLU that have been put forth, none have been able to fully replace it because of variable rewards. Swish is a smooth, non-monotonic function that, when used with deep networks and applied to a number of difficult domains including image classification and machine translation, regularly equals or surpasses ReLU performance. It is bounded below and unbounded above, and the distinction is really made by the non-monotonic feature. In a self-gating scenario, only one scalar input is needed, but numerous two- scalar inputs are needed in a multi-gating scenario. Swish networks can be trained deeper than ReLU networks when using Batch Norm despite having gradient squishing property. The advantages of Swish and its similarity to ReLU make it easy for practitioners to replace ReLUs with Swish units in any neural network. Swish function is defined as shown in Equation 1,

$$f(x) = x * sigmoid(x) \quad (1)$$

where x is the input image

The results demonstrate that Swish frequently outperforms ReLU on deeper models across a variety of difficult data sets. However, when optimization becomes challenging, Swish surpasses ReLU by a significant margin in the region around approximately 40 layers and above. Swish outperforms ReLU in very deep networks for test accuracy. Both activation functions perform worse as batch size grows, possibly because of severe minima, in terms of batch size. Swish performs better than ReLU in every batch size, indicating that the two activation functions' performance gap persists despite batch size variations.

The Swish activation function has several advantages over other activation functions in CNNs, including

- **Smoothness:** The Swish function is a smooth function, which means that it does not have any sharp discontinuities. This makes it easier for the gradient to flow through the network, which can improve the training process.
- **Non-linearity:** The Swish function is a non-linear function, which means that it can learn more complex relationships between the input and output of the net-work. This can improve the accuracy of the network.
- **Efficiency:** The Swish function can be implemented efficiently in hardware, which can make it faster to train and deploy CNNs.

In a study comparing the Swish activation function to other activation functions, the Swish function was shown to achieve better accuracy on a variety of tasks, including image classification, NLP, and machine translation. Comparison between swish and ReLU is performed and shown in Table 1.

Table 1: Comparison Between Relu And Swish Activation Function

Feature	ReLU	Swish
Equation	f(x) = max (0, x)	f(x) = x * sigmoid(x)
Where is	A constant, typically 1	A learnable parameter
Output range	0 to +	0 to +
Derivative range	0 to 1	0 to 1
Monotonicity	Monotonic increasing	Non-monotonic
Vanishing gradients	Can occur for large negative inputs	Less likely to occur than ReLU
Computational complexity	O (1)	O (1)
Popularity	More popular	Less popular

With the comparison it is clear that while ReLU thresholds all negative weights to zero, Swish lets a limited number of negative weights to pass through. This can help to prevent the vanishing gradients problem, which can occur in deep neural networks.

RESULT ANALYSIS

Input Dataset

The data containing retinal images is collected via Kaggle datasets. This dataset contains 3500+ retinal images of different severity. These sources provide images of different classes which are Healthy, Mild, Moderate, Proliferate, Severe. The images are then pre-processed and normalized sothat they can be used to train the CNN model. Image data generators are used to create three different sets of data: - Training set, Test set, and Validation set. 25% of the data isused to create the Test set, 15% is used for the validation set,and the remaining 60% of data is used for the training set. Sample of dataset is shown in Figure 4.

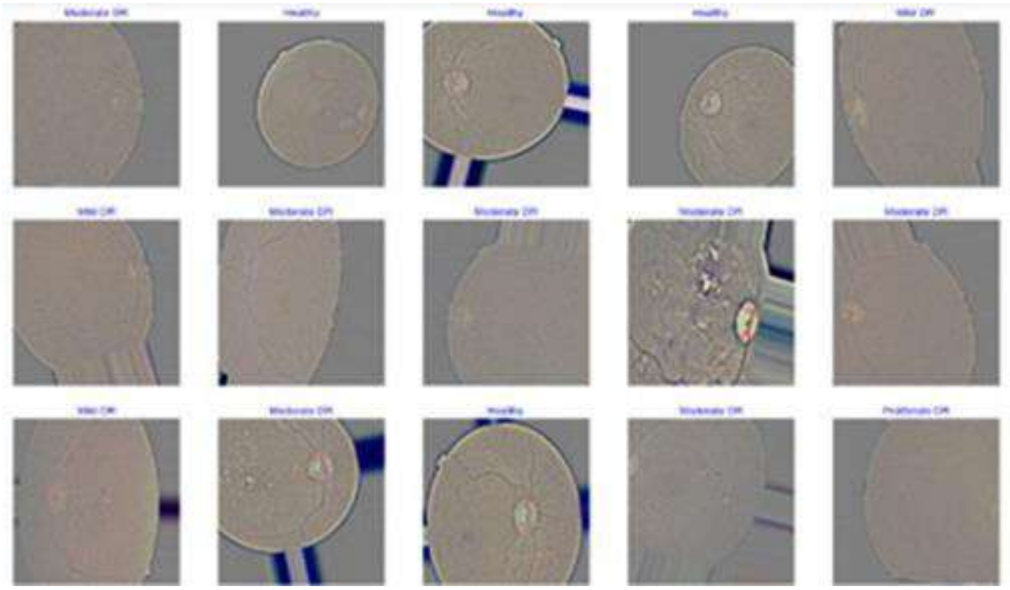

Fig. 4: Sample Dataset

Evaluation Parameters

The proposed system's performance is evaluated using various parameters like precision, recall, accuracy and more.

Precision: Precision enables us to see the machine learning model's dependability in classifying the model as successful. It is described as the proportion of correctly categorized positive samples (True Positive) to the total number of correctly or mistakenly classified positive samples. The precision equation is specified in Equation 2.

$$Precision = \frac{TruePostive\ (TP)}{TruePositive\ (TP) + FalsePositive\ (FP)} \quad (2)$$

Recall: The recall is determined as the proportion of Positive samples that were correctly identified as Positive to all Positive samples. The recall gauges how well the model can identify positive samples. The more positive samples that are identified, the larger the recall. Equation 3 defines recall.

$$Recall = \frac{TruePostive\ (TP)}{TruePositive\ (TP) + FalseNegative\ (FN)} \quad (3)$$

Accuracy: It is utilized to gauge the extent of accurately arranged cases from the all-out number of articles in the dataset. To figure the metric, partition the quantity of right expectations by the absolute number of forecasts made by the model. Equation 4 is used to calculate accuracy.

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \quad (4)$$

Implementation Details

This website is designed to provide important details and spread awareness about the disease. It provides easy and hassle-free detection of the presence of the diabetic retinopathy condition. It encompasses efficient and effective navigation, accessibility, and interactive interface. This web- site can help users recognize potential warning signs and seek prompt medical attention. The graphic of Figure 5 depicts the home page of the designed website named" Diabetic Retinopathy Project", from which the user may gain an overview of the website and, using the sidebar, pick the desired page for reference. This page helps the user to understand the website's numerous sections and assists them in understanding the core concept of the Diabetic Retinopathy website produced with Streamlit.

Fig 5. Homepage of designed website

The Predictor tab on the sidebar assists the user in deter- mining if the input image contains diabetic retinopathy or not after uploading an image. Another website is the Q&A page, which contains answers to commonly asked questions about diabetic retinopathy and related symptoms from diverse users. The last page is the Infographics page, which displays various statistics based on data from global sites. Figure 6 represents all the sections.

The figure displays the predictor page of the online dynamic website constructed to provide an accurate prediction of the condition when any retinal input is entered. The predictor page of the website looks like Figure 7, where the user has to submit a retinal picture using the browse file option. The image being uploaded should have one of the following extensions: .png, .jpeg and .jpg. The maximum file size is set at 200MB. The image may be easily dragged and dropped from the device's user folder.

Fig. 6. Various Sections of the Website

Fig. 7. Predictor Page

The Figure 8 depicts the predictor page, where the website will indicate whether or not the image was successfully uploaded; if not, the user can retry uploading the image. It also displays the prediction for the user's successfully submitted image. The predictor will provide an accurate prediction of up to 95% for retinal images with and without diabetic retinopathy.

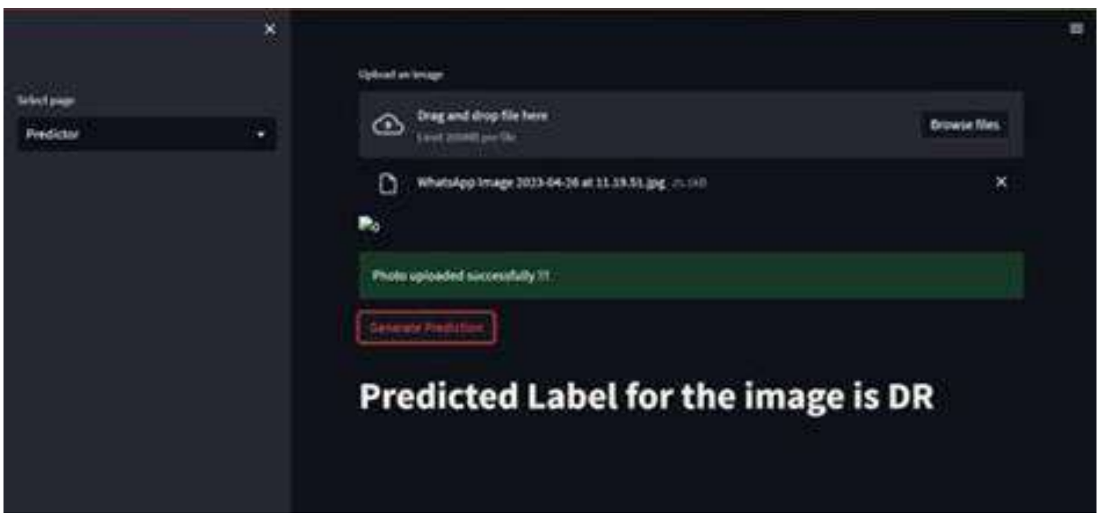

Fig. 8. Predictor Page

Figure 9 illustrates the Q&A section page of the online dynamic website developed to contain all relevant illness information. This section contains answers to frequently asked questions submitted by users. It also connects visitors to videos via links, allowing them to better comprehend the severity of diabetic retinopathy and what precautions may be taken to avoid such condition.

Figure 10 illustrates the infographics section page of the online dynamic website developed to contain all of the disease's data and graphs. This page displays statistics data based on worldwide numbers about diabetic retinopathy. Also, what opportunities exist for medical research in the field of diabetic retinopathy.

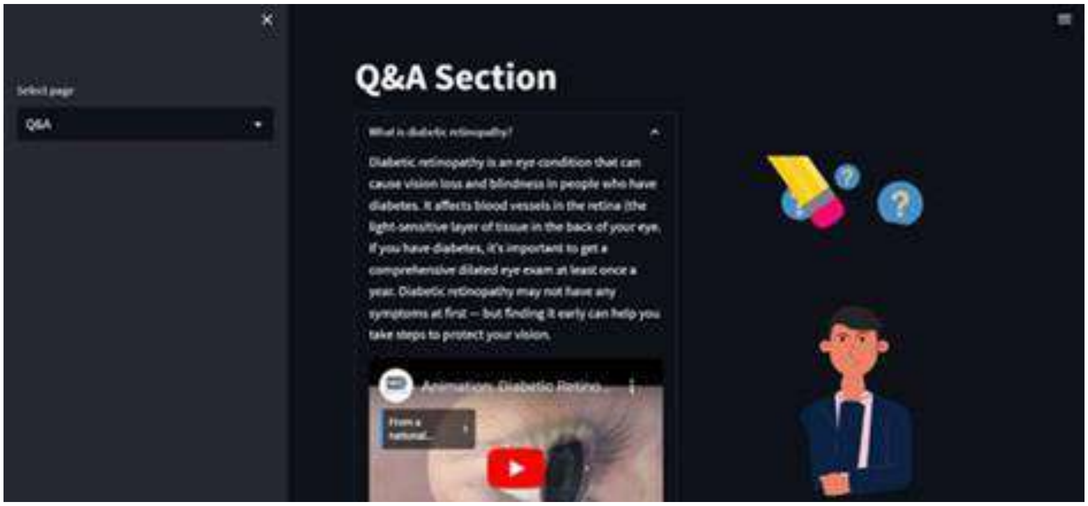

Fig. 9. Q&A Section Page

Fig. 10. Infographics Section

The proposed system is implemented with two activation functions, ReLU and Swish, and the CNN model is trained on the mentioned dataset. The system is evaluated using various metrics like precision, accuracy, and recall as described above. The training and validation accuracy of the system is calculated with the ReLU and Swish activation function. Using the ReLU activation function system has achieved an accuracy of 77.09 %, and when the swish activation function is used, the accuracy rises to 95.74 %. System gives precision rate of 95.31%, and a recall rate of 95.41% when implemented with swish function. Figure 11 shows the accuracy plot of ReLU and Figure 12 shows the accuracy plot of Swish function. With the plots it is clear that ReLU thresholds all negative weights to zero whereas Swish let a few negative weights to pass through. This aids in preventing the disappearing gradients issue, which improves the accuracy of Swish.

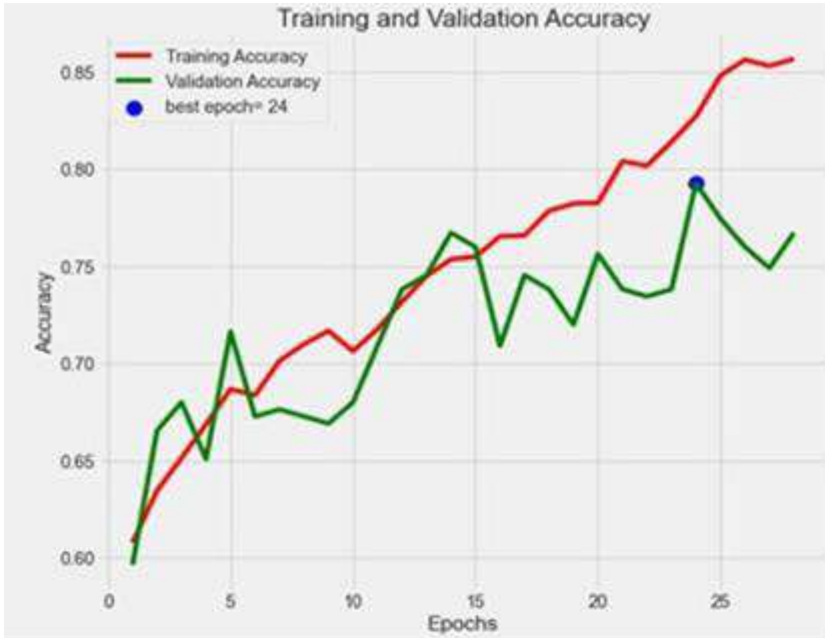

Fig. 11. Accuracy Plot for ReLU Activation Function

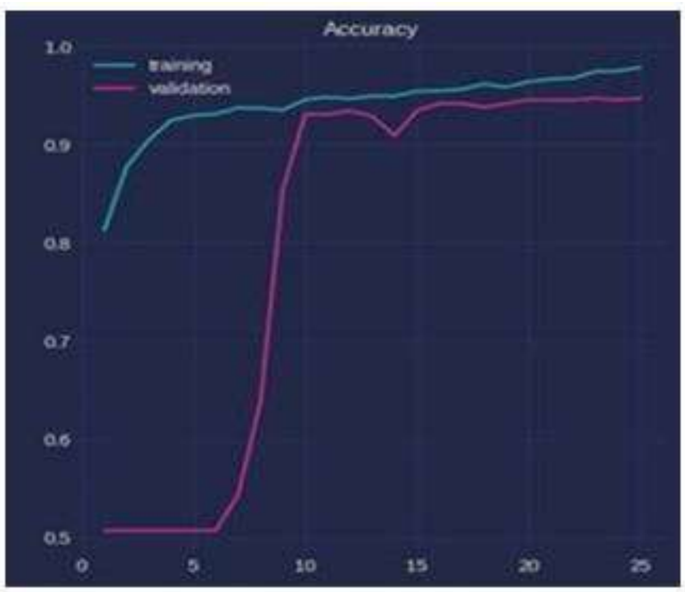

Fig. 12. Accuracy Plot for Swish Activation Function

CONCLUSION AND FUTURE WORK

Early detection and diagnosis of diabetic retinopathy helps patients avoid blindness and also reduces the serious consequences of the disease. This information can be useful for healthcare professionals in identifying risk factors for diabetic retinopathy and recommending preventive measures topatients. For example, if a patient has high DR level, they may be advised to take professional advice, or even start medication and prevent the onset of diabetic retinopathy. Hence a system is proposed for detecting diabetic retinopathy using deep learning algorithms such as CNN model and Swish activation was implemented. The system collects information from the dataset, pre-processes and selects relevant features using advanced techniques. Trained models are stored in a database and their accuracy is maintained through testing. The system offers healthcare professionals the ability to identify risk factors for diabetic retinopathy and recommend preventive measures to patients. The proposed strategy helps to quickly detect diabetic retinopathy and facilitate follow-up to prevent further effects on the eye. After training the CNN model on the Diabetic retinopathy gaussian filtered dataset, an accuracy of 95% is obtained. This means that the model is able to correctly predict the diabetic retinopathy status of a patient in 95% of cases, basedon their retinal images. The Swish activation function has increased the accuracy of the training model as compared tothe Relu activation function. This model has the potential tobe employed in clinical practice as a tool for the early identification and prevention of diabetic retinopathy with additional enhancements and optimizations.

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