Identification of Suitable Machine Learning or Deep Learning Algorithmfor Diabetic Retinopathy Detection

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***Abstract*— The frequency of Diabetic Retinopathy (DR) is increasing worldwide. Due to inadequate screening and treatment resources, particularly at the primary and secondary healthcare levels, a significant number of diabetic patients remain undiagnosed and untreated, leading to vision loss and blindness. To detect retinal damage, various Deep Learning and Machine Learning models have been used. Convolutional Neural Network (CNN), MobileNetV2 and Support Vector Machine (SVM), models were developed and evaluated using the APTOS dataset from Kaggle. The Training Set, Testing Set, and Validation Set combined to use 70%, 20%, and 10% of the images, respectively. The strategy contrasts CNN, SVM, and MobileNetV2 in order to ascertain which Deep Learning/Machine model performed the best in detecting diabetic retinopathy. As a result, the accuracy of CNN, SVM, and MobileNetV2 were determined to be 89%, 90%, and 97% respectively.**

Keywords*— *Diabetics, eye disorders, blindness, deep leaning, machine learning, CNN, SVM, MobileNetV2

I. Introduction

When an individual's blood sugar level is outside the normal range, they are diagnosed with diabetes. Blood sugar, obtained from the food we consume, provides the body with its primary source of energy. The pancreas produces insulin, a hormone that assists in the transport of glucose into cells, where it is converted into ATP to power various activities. Insufficient insulin production results in the accumulation of glucose in the bloodstream, resulting in diabetes.

Diabetic retinopathy (DR) is an eye condition that occurs as a result of diabetes. The retina, the light-sensitive tissue at the back of the eye, has blood vessels that can become damaged, which results in this condition. At first, it might not cause any symptoms or only have a minor impact on vision. It could, however, result in blindness if not caught in the early stages. This condition may affect anyone who has type I or type II diabetes. The likelihood of developing this eye disease increases as diabetes advances and blood glucose levels rise. High blood sugar levels have the potential to block the tiny blood capillaries in the retina, resulting in less blood reaching the retina. The result is an attempt by the eye to produce new blood vessels. These new blood vessels could rupture because they do not develop normally and are prone to leaking, which would make the vitreous humor opaque, resulting in permanent or temporary blindness.

According to global statistics gathered in 2015 as shown in Fig.1, 70 million people could have diabetic retinopathy that poses a threat to their vision by 2040. Additionally, 145 million people, or 35% of the population, experience diabetic retinopathy, and 415 million people worldwide experience diabetes, according to estimates (both Type I and Type II). It is evident that a diagnosis of diabetic retinopathy is urgently needed. Because DR cannot be treated, early discovery is the only way to halt its progression.

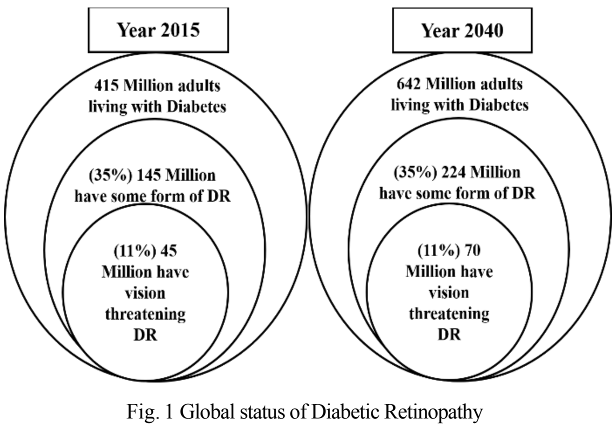


Fig. 1 Global status of Diabetic Retinopathy

In medical imaging analysis, the CNN is a widely used and highly effective deep learning method. Recent research works [1,2,3] used SVM learning classifier model to forecast the possible region of Hard Exudates and Hemorrhage. To tackle the issue of detecting diabetic retinopathy in fundus images, several transfer learning algorithms, such as CNN, are utilized to enhance the performance of image classification. The CNN architecture serves as the detection algorithm, allowing for the development of automated methods to recognize diabetic retinopathy in DR images. Mobeen-ur-Rehman et al shown that there are automated ways for identifying diabetes using DR images, with CNN architecture serving as the detection algorithm. For the purpose of categorizing DR images, this study uses both pre-trained CNN models and a customized CNN model. The recent research works on DR detection using deep learning approaches used CNN to extract features from unprocessed images, and conventional techniques are used to detect anomalies [4,5]. Mobeen-ur-Rehman et al shown that there are automated ways for identifying diabetes using DR images, with CNN architecture serving as the detection algorithm [6]. Extracting the feature using neural networks yields superior results to conventional feature extraction techniques. The screening tool is built on cutting-edge machine learning and computer vision techniques, including patch level projection. IR images of diseased and healthy eyes are classified using the Support Vector Machine (SVM) algorithm using a variety of statistical and texture characteristics in diabetic retinopathy. The retinal image, which can depict both healthy and diabetic retina, was captured using a fundus camera. The histogram-based feature is extracted using the Discrete Wavelet Transform after statistical features are found in the image through morphological and image pre-processing techniques. The SVM algorithm, which divides the input images into two types—images of diabetic retinopathy and images of normal retina—is used for the final classification. An accuracy of 85% is attained.

M. Pamadi et al [7] shown that MobileNetV2 model was used to classify the DR disease. In order to classify, with theaid of deep learning, the five stages of contemporary DR— healthy, mild, proliferative, moderate, and severe was recognized and classified. The model's accuracy was 93.89%on average, with precision at 94.00%, recall at 92.00%, and f1- score at 90.00%. To aid experts in assessing the retina's influence at each stage, the corresponding image is also provided. Huynh et al [8] suggested that in addition toperforming better than recommended, a deep learning system could be used in clinical exams that call for finer grading, increasing the cost-effectiveness of screening and diagnosis.This project aims to identify a suitable ML or DL algorithm for detecting DR, based on the identification of the aforementioned issues. In this study, comparative analysis isdone between three ML or DL models. Convolutional NeuralNetwork, Support Vector Machine & MobileNetV2 were used. MobileNetV2 got the best accuracy of 97% among thethree models.

II. RELATED WORK

This discussion covers a wide range of topics, including the fundus camera's optical system, the design of an on-chip NIR bandpass filter, the creation of a reasonably priced, small-sized multispectral NIR camera, and the development of a selfie fundus camera prototype [9].

This challenge was ranked as the 54th out of 2943 different approaches. Also, taking detailed pictures with a high magnification and in low light frequently resulted in problems like lost details, uneven illumination, and noise, especially in the periphery. To allay these concerns, the ResCycleGAN architecture was employed to align the attributes of SC images with those captured by a standard fundus camera. To stop partial or total optical damage, diabetic retinopathy (DR) must be detected and treated early. Ophthalmologists must perform manual examinations, which takes time. So, in order to reduce workload and the chance of going completely blind, an automated screening system is required. Patients encountered difficulties in obtaining continuous images or videos due to the dazzling experience, resulting in pupils constricting [10, 11]. To recognize diabetic retinopathy, a variety of machine learning classification algorithms can be used, including logistic regression, random forests, artificial neural networks, support vector machines, decision trees, k- nearest neighbors, and convolutional neural networks [12,13,14,15,16]. The conventional methods for image classification consist of utilizing ML or DL techniques, where the study of algorithms that can automatically improve based on experience is known as machine learning (ML). A model for anomaly detection that is effective and that can be used for image classification is deep learning (DL) [17,18]. This process involves extracting image features to rebuild it, which is then compared to the targeted region to identify any anomalies. To address issues related to category imbalance and inadequate classification accuracy, some models combine traditional and deep learning techniques, often using CNN to extract features and traditional methods for anomaly detection [19,20]. Our proposed approach involves comparing three ML/DL models, including MobileNetV2, Convolutional Neural Network (CNN) and Support Vector Machine (SVM).

The proposed system involves capturing the image using condensing lens and NoIR Camera in the presence of IR & white light. Raspberry Pi is the main board used for capturing and storage of the image. Once the image is captured image processing is performed to extract the features of interest. Hard Exudates and Hemorrhages are used as features of interest. The images captured will be classified and displayed according to the 5 stages with the help of machine learning algorithms. The high accuracy algorithm identified in this work will be used for making a compact, portable and user-friendly device for DR detection. The graphical abstract for the proposed system is shown in Fig. 2

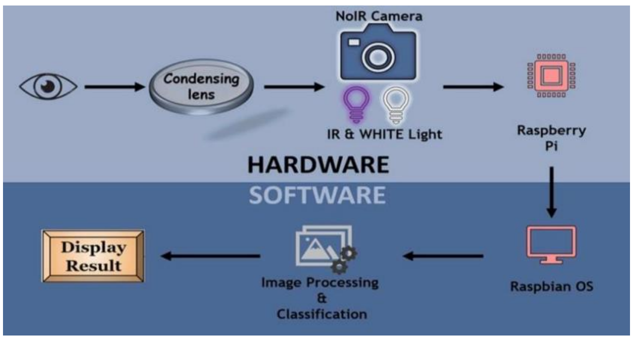


Fig.2 Block diagram of the proposed system

III. METHODOLOGY

The aim of this project is to create an inexpensive, easily transportable, non-mydriatic fundus camera that can be used to identify instances of diabetic retinopathy. The aim is to automate the process of detecting DR in captured images by recognising Hard Exudates and Haemorrhages. To improve analysis and more to obtain more accurate results DL/ML will be employed to enable faster primitive screening. The majority of fundus photography methods need pharmacologic pupil dilation, which is a common and significant ophthalmic standard practice. A mydriatic agent is used in commercially available conventional ocular photography tools for screening to generate fundus images. It has a number of important drawbacks, such as the fact that novice practitioners are unsure of how to administer mydriatic agent dilating drops, which causes issues for both the doctor and the patient. Non-mydriatic fundus camera systems do not use a mydriatic agent to dilate the pupil. Other devices that use this concept are made portable by including other functionalities like as zooming in and out, changing direction, and so forth. These devices take fundus photographs, which are subsequently sent to a professional for diagnosis. These non-mydriatic fundus camera systems are expensive and difficult to use since they require some training. The purpose of this study is to examine the various Deep Learning and Machine Learning approaches used to detect DR. By examining the captured image, the deep learning model determines whether DR is present or not. The models that are used for comparative analysis were CNN, SVM and MobileNetV2 as shown in Fig. 3. The proposed methods classify the retinal image based on the dataset obtained from APTOS. It is possible to classify the presence or absence of DR using an image dataset (APTOS) that has been trained and tested using Deep Learning and Machine Learning models. MobileNetV2, Convolutional Neural Networks (CNN), and Support Vector Machines (SVM) were the ML/DL techniques used. By comparative analysis, MobileNetV2 outperformed the other two models in terms of accuracy.

IV. Results & Discussion

A. Software Implementation

Google Colab. is used for Deep learning algorithm verification using the deep learning data obtained from Kaggle.

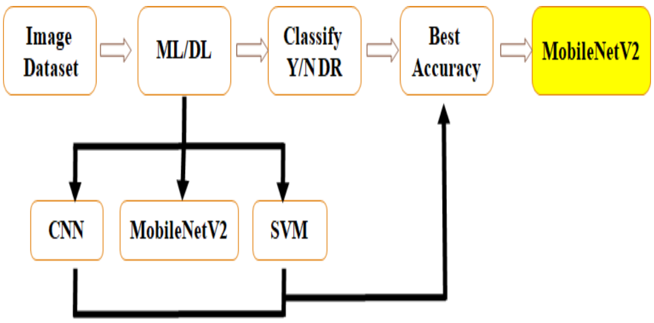


Fig. 3 Process flow diagram

B. Evaluation Criteria:

When testing a classification model or classifier on a test dataset with known actual values, a table called confusion matrix is frequently used.

Important terms:

- **Precision:** The ratio of the total number of positive instances that a model correctly classifies to the total number of instances that fall into the positive class is provided.

$$\text{Precision} = \frac{TP}{TP + FP} \qquad (1)$$

- **Recall:** This can be described as the proportion of patterns or instances that are accurately classified by a model, regardless of their class label.

$$\text{Recall} = \frac{TP}{TP + FN} \qquad (2)$$

- **F1 Score**: This gives the Harmonic mean between Recall and Precision values

$$\text{F1 Score} = 2 * \frac{\text{Recall} * \text{Precision}}{\text{Recall} + \text{Precision}} \qquad (3)$$

- **Accuracy Score:** Accuracy is a metric that measures the proportion of accurate or correct predictions made by a model, relative to the total predictions made.

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

Feature Extraction for DR Image

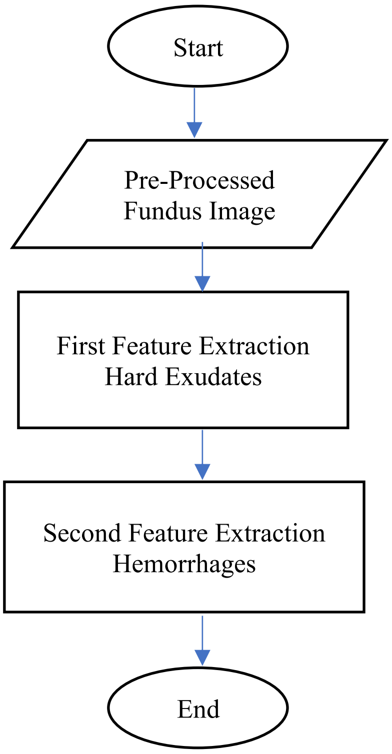


Fig. 4 Process flow of DR Detection

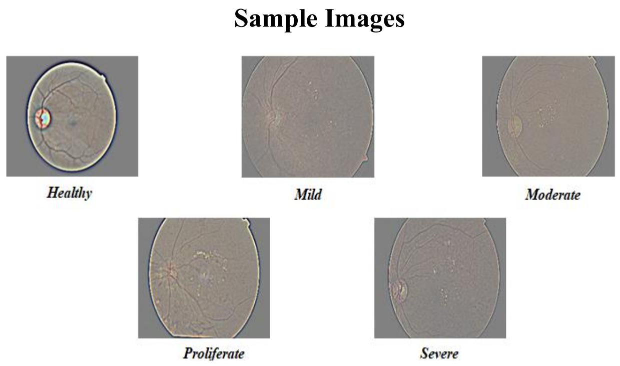


Fig. 5 Sample Images used in the present work

Fig.4 explains about the feature extraction techniques where hard exudates and hemorrhages are extracted to detect DR for primitive screening. Fig.5 shows the sample images used in this study. In this study, comparative analysis is done between three ML/DL models. Convolutional Neural Network, Support Vector Machine & MobileNetV2 were used. MobileNetV2 got the best accuracy of 97% among the three models.

Convolutional Neural Networks (CNN)

CNN is a type of artificial neural network that utilizes the convolution operation, rather than typical matrix multiplication, in one or more of its layers. These networks are specifically designed for working with image data, allowing for improved image recognition and processing capabilities by operating on pixel-level features. CNN is usually employed for image and speech recognition tasks. It incorporates convolutional layers that effectively reduce the dimensionality of images while preserving vital information. This characteristic makes CNNs particularly well-suited for this application. CNN involves the use of a convolution layer, a pooling layer, and a fully connected layer. Convolution Layer reduces the dimensions of the image. The pooling layer, specifically the max pooling layer, receives the output of the convolutional layer as input. Its primary function is to further decrease the dimensionality of the data while also capturing and retaining the essential features present in the image. In addition, the pooling layer effectively eliminates noise from the image by disregarding elements that have little impact on the classification process. It filters out irrelevant information that does not contribute significantly to the overall analysis. The fully-connected layers contribute to reducing the dimensionality of the data and demanding fewer resources during the training phase. This reduction in dimensions allows for more efficient resource utilization, requiring less memory and computational power. Convolutional neural networks employ a technique where images are divided into smaller regions to be processed individually. This allows the network to analyze different parts of the image separately and extract relevant features from each region. CNNs work well for classifying images because the idea of dimensionality reduction fits the vast array of parameters in an image. CNNs are great at reducing the number of parameters while keeping the models' quality high. High dimensions are present in images. Fig. 6 displays the accuracy of the CNN model, with a final accuracy of 89%.

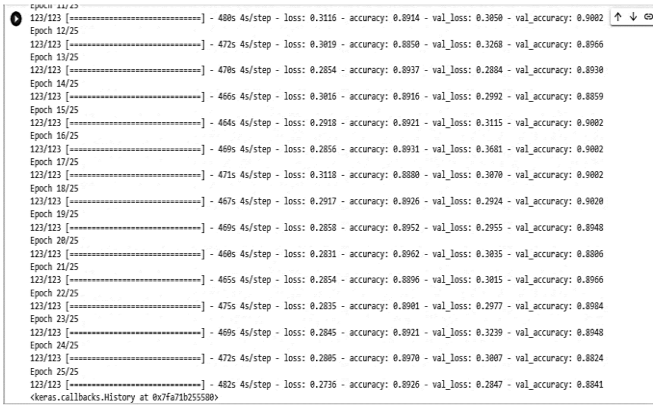


Fig. 6 Accuracy obtained for CNN Model

Support Vector Machine (SVM)

In the SVM technique, each data item is represented as a point in an n-dimensional space, where the number of dimensions (n) corresponds to the number of features. The value of each feature is assigned to a specific coordinate in this space. To categorize the data, the SVM algorithm selects the hyperplane that effectively separates the two classes. With the aid of supervised learning, SVM uses deep learning to categorize or forecast groups of data. AI and machine learning supervised learning systems provide labelled data for categorization that includes both input and intended output. The SVM algorithm aims to construct the best decision boundary or line that can divide n-dimensional space into classes so that we can quickly classify new data points in the future. Fig. 7 shows the accuracy of SVM model where the final accuracy obtained is 90%.

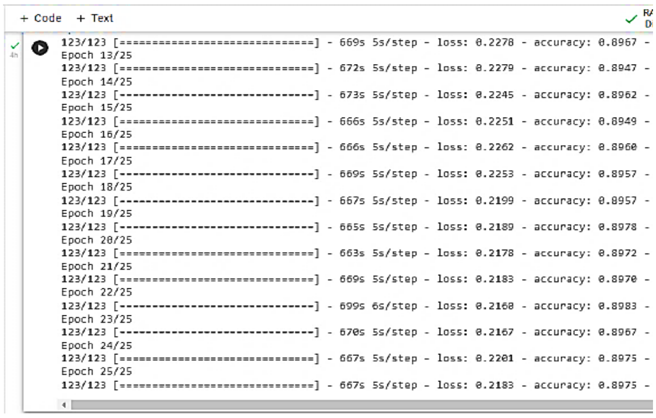
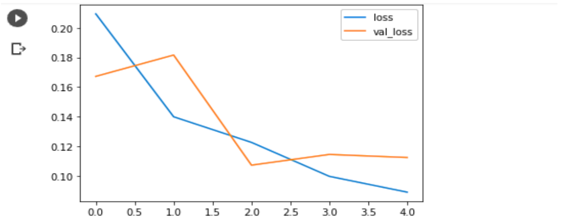


Fig. 7 Accuracy obtained for SVM Model

MobileNetV2

A convolutional neural network with 53 layers is called MobileNet-v2. It is a classification model created by Google that is different from MobileNetSSDv2. It offers real-time classification capabilities. MobileNetV2 uses depth wise separable convolutions. It significantly lowers the number of parameters when compared to a network with regular convolutions of the same depth in the nets. This leads to lightweight deep neural networks. Fig. 8 shows the accuracy of CNN model where the final accuracy obtained is 97%.



Accuracy on the test set: 96.73%

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12/12 [==============================] - 13s 974ms/step
The first 5 predictions: ['DR', 'DR', 'No_DR', 'No_DR', 'No_DR']
              precision    recall  f1-score   support

          DR       0.96      0.97      0.97       178
       No_DR       0.97      0.96      0.97       189

    accuracy                           0.97       367
   macro avg       0.97      0.97      0.97       367
weighted avg       0.97      0.97      0.97       367
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Fig. 8 Accuracy obtained for MobileNetV2 Model

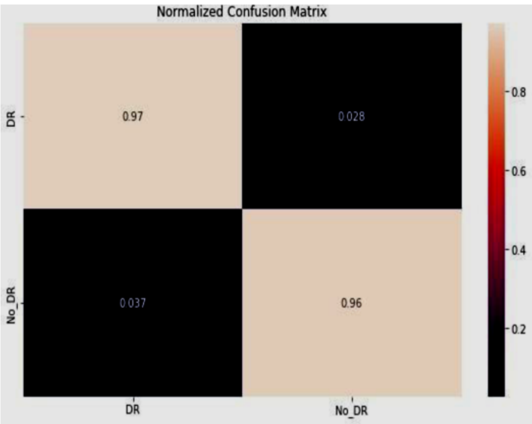

Fig. 9 Confusion Matrix of MobileNetV2 model

Table.1 gives the information about the accuracies obtained for different types of algorithms used in the study.

Table1. Accuracies obtained for different algorithms

	Training Set (%)	Testing Set (%)	Validation (%)	Accuracy (%)
CNN	70	20	10	89
SVM	70	20	10	90
MobileNetV2	70	20	10	97

V. Conclusion

In machine learning, SVM is a classification model that performs incredibly well. Convolutional computations are performed by CNN, a feed-forward neural network with a complex architecture. The most well-known deep learning algorithm for classifying images is this one. This study discovered that SVM has a 90% accuracy rate and CNN has an 89% accuracy rate with the dataset used. The most frequently used convolutional layer in CNN is 2D convolution. In MobileNetV2, a vastly faster and more compact CNN architecture, depth wise separable convolution, a novel type of convolutional layer, is utilised. Due to its small size, there is a very slight trade-off in accuracy when compared to larger fully convolutional architectures, but it is very small. The advantages of Proposed System have no complexities, it is user-friendly and it is compact and portable. The constraints of using the mentioned technique are that the obtained image quality is inferior to the conventional fundus cameras, thus limiting its use to basic screening purposes only. Nevertheless, it is possible to identify various other diseases like Glaucoma, Hypersensitive Retinopathy, Retinoblastoma, and Toxoplasmosis using the fundus images. To accomplish this, specific DL/ML models can be created for each disease type. Additionally, an app for Android or IOS could be designed to produce reports and maintain patient data, which would be accessible to ophthalmologists. Based on the comparison, we can conclude that MobileNetV2 detects diabetic retinopathy more accurately than CNN and SVM.

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