Sri Parabramha Chari, 2023, 11:6
ISSN (Online): 2348-4098
ISSN (Print): 2395-4752

International Journal of Science, Engineering and Technology

An Open Access Journal

Detection of Diabetic Retinopathy Using Machine Learning

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Abstract- High blood sugar levels are what lead to diabetes. Numerous illnesses, including heart conditions, kidney problems, nerve damage, and eye impairment, can be brought on by diabetes. Diabetic retinopathy is one such complication brought on by diabetes that, if not treated or detected in a timely manner, may also result in vision loss. By training algorithms on retinal images to recognize specific features, categorize the presence or absence of the condition, or divide the image into discrete parts, machine learning can be used to recognize and diagnose diabetic retinopathy. Support Vector Machine, logistic regression, Convolutional Neural Net-work, K-Nearest-Neighbor, and random forest are the current techniques utilized to identify diabetic retinopathy. The most often used deep learning methods for image detection are Convolutional Neural Networks. Toper form image classification tasks, a Convolutional Neural Network (CNN) architecture known as VGG16 was trained on a sizable dataset of images. For image classification problems, a well-known deep learning architecture is VGG16. The photos are classified using the retrieved features using a variety of machine learning techniques, such as KNN, SVM, Logistic Regression, Boost, Ada Boost, Decision Tree, Voting Classifier, Naïve Bayes, and Random Forest. This methodology is used to group diabetic retinopathy into one of five severity-based classifications (0,1,2,3,4). The proposed system will facilitate the removal of ambiguous diagnoses done by ophthalmologists. This would enable the faster and more accurate prediction and diagnosis of patients' condition.

Keywords- VGG (visual geometry group) 16, Revised Resnet50, CNN (Convolutional Neural Network), Diabetic Retinopathy, Machine Learning.

I. INTRODUCTION

An innovative convergence between healthcare and artificial intelligence is the detection of diabetic retinopathy by machine learning. The early diagnosis of a diabetes-related problem that poses a serious threat to vision is revolutionized by this method, which harnesses the power of cutting-edge algorithms and enormous databases of retinal pictures. The diligent collection of large datasets, frequently in partnership with healthcare institutions, that include high-resolution retinal images produced using specialist imaging technology such as fundus cameras, is the first step in the process. These photos go through extensive preprocessing, such as resizing, cropping, and contrast modifications, to improve their quality while removing noise that can impede precise analysis. The feature extraction process is at the core of the ma-chine learning methodology. Complex aspects of the retinal pictures, including texture, colour, and form, are painstakingly retrieved, and employed as crucial markers for recognizing diabetic retinopathy's symptoms. Then, other machine learning techniques are used, including but not limited to Convolutional Neural Networks (CNNs).

On labelled data, these algorithms receive considerable training to identify patterns and abnormalities suggestive of diabetic retinopathy. Iterative training involves fine-tuning to maximize the model's precision and propensity for prediction. Once trained, these models are skilled at separating retinal images into various degrees of diabetic retinopathy, from minor symptoms to severe cases that necessitate emergency care. Some devices can even spot related eye diseases, which helps ophthalmologists deliver all-encompassing therapy. Cross-validation techniques and separate test datasets are frequently used to rigorously validate and test the models to ensure their generalizability and dependability. This machine learning application has a significant effect on the actual world. When used in clinical settings, these models sup-port healthcare professionals and are invaluable resources for diabetic retinopathy screening. They serve a crucial role in enabling prompt interventions, potentially reducing vision loss, and enhancing the general quality of life for those with diabetes by helping with early identification. This strategy also has the potential to boost healthcare effectiveness, cut costs, and in-crease access to screening services, especially in underprivileged communities where the prevalence of diabetic retinopathy is still high.

However, this transformative strategy is not without its share of difficulties. Since the accuracy of machine learning models depends on the caliber and diversity of the training data, it is crucial to have diverse and representative datasets. Model interpretability is still a challenging topic because deep learning algorithms' internal workings are frequently difficult to under-stand. A significant challenge is addressing problems like class imbalance when mild occurrences of diabetic retinopathy outnumber severe cases. Despite these difficulties, machine learning-based diabetic retinopathy detection has a very bright future. Existing models are being improved, their interpretability is being improved, and creative techniques to combine machine learning and telemedicine are being explored with the goal of reducing healthcare access gaps. In conclusion, the combination of machine learning with diabetic retinopathy detection has the potential to revolutionize healthcare by protecting people's priceless vision and enhancing their general well-being.

II. LITERATURE SURVEY

The Patients do not detect vision loss until the disease begins to damage their eyes, which occurs in the latter phase of the disease, and the symptoms of DR are not evident in the be-ginning by Kumar et al. [1]. The fundus pictures are utilized for the identification of DR, given that these images are high-resolution, inexpensive, and simple to use transmission and storage. Fundus pictures are mostly used by ophthalmologists for manual DR screening, which can be biased, difficult, and error-prone. It is challenging to create an automated system that uses machine learning and image processing techniques to reliably recognize DR and get around these mistakes made by hand Zhu et al. [2] Machine learning offers a quick and useful way for Diabetic Retinopathy screening. Sambyal et al. [3] described a way to use machine learning algorithms to identify diabetic retinopathy. The technique made use of a number of features from two machine learning classifiers: the Restricted Boltzmann and the Optimum-Path Forest (OPF) apparatus. Three measures are used to assess the model: sensitivity, specificity, and accuracy. At 89.47%, the RBM-1000 demonstrated the best diagnosis accuracy in DR screening. The classification of complex images, like the retina of a person, requires deep learning. Manoharan et al. [4] presented a computerized method for identifying diabetes from ocular scans. The method distinguished between DR-Positive and DR-Negative retinal pictures utilizing a large neural network and the deep learning Xception architecture. The deep learning-based approach that was suggested produced training accuracy of 96.68%. and a validation accuracy of 66.82%. The application of deep learning in medical imaging has the potential to increase the precision and effectiveness of diagnosis and treatment planning, ac-cording to Ali et al. [5]. Techniques like IMNets can be helpful tools in this process. It's crucial to remember that machine learning algorithms should be applied in concert with the knowledge and discretion of qualified medical practitioners. A unique method for creating deep learning models is called an incremental modular network (IMNET), which entails gradually adding new modules to the network as needed instead of creating a single, massive monolithic network. Because it enables the model to concentrate on learning particular features or patterns that are pertinent to the current job, this can be helpful in medical imaging applications.

Diabetic Retinopathy was categorized in a study, Menaouer et al. [6] using a hybrid deep learning methodology. The proposed approach used VGG16 and VGG19, a convolutional neural network, to extract features and categorize the input photos. The images were categorized by the model into five severity levels: proliferative DR, mild DR, moderate DR, severe DR, and no DR. The model was assessed using local public DR data sets, Messidor-2, and APTOS-2019. The experimental findings were 85% recall, 94% F1 score, and 90.60% accuracy. Although it's a thought-provoking work, Gunasekaran et al. [7] addressed how retinopathy photos can be useful in identifying diabetic patients. The study used a deep recurrent neural network (RNN) to predict diabetic retinopathy from fundus images in order to overcome this difficulty. The proposed deep learning framework predicted DR with 95.5% accuracy. Khan et al. [8] used transfer learning to implement various deep neural network architectures such as VGG-net, Res Net, and InceptionV3. The Gaussian method was used in the preprocessing phase to remove noise and achieve better results. The dataset included five types of DR: no DR, mild DR, moderate DR, severe DR, and proliferate DR. According to the results of the various deep neural network models, InceptionV3 achieved the highest accuracy in the training phase of 81.2% and an accuracy of 79.4% in the testing phase.

The DAG network model, which uses multi-feature fusion of fundus images to classify diabetic retinopathy, was introduced by Fang et al. [9]. First, using various algorithms, three indicative features—fundus neovascularization, retinal varices, and retinal hemorrhagic plaque were extracted. Moreover, the DAG network received these extracted features in order to process them and combine multiple features. Ultimately, the DR was identified and classified using the classification model. A real-time dataset obtained from a hospital and the DIARETDB1 dataset were used to assess the model's performance. At the moment, the accuracy of the Diabetic Retinopathy classification produced using a single-view fundus dataset is insufficient. In response to this problem, Luo et al. [10] developed an automated system for the detection of diabetic retinopathy using a convolutional neural network by combining fundus images in multiple views. Lesion features were exploited by the proposed model attention mechanisms were applied to the significant images obtained from the retinal fundus with the intention of performing well. Additionally, higher weights were given to the important channels in order to extract the network's useful features. The suggested a multi-view dataset on diabetic retinopathy was used to assess the model, and the results of the model surpassed those of other DR detection systems in use.

A performance evaluation of diabetic retinopathy systems based on different deep learning techniques was presented by Adriman et al. [11]. The methodology consists of two primary steps: first, texture features were extracted using local binary patterns (LBP); second, different deep learning techniques, including Res Net, Det Net, and Dense Net, were examined for the identification and categorization of diabetic retinopathy. The APTOS 2019 Blindness Detection dataset was used in the experiments, and the results showed that the Res Net, Det Net, VGG16, and Dense Net models generated accuracy values of 96.25%, 93.99%, 76.21%, and 84.05%, in that order. A unified method based on a hybrid neural network was presented by Fatima et al. [12] to identify diabetic retinopathy. To improve the visibility of the medical images, a novel entropy enhancement technique was used, which allowed for the extraction of notable features from the images. The retinal fundus images were then effectively classified using a hybrid neural network. The MESSIDOR-2, Ultra-Wide Filed (UWF), and Asia Pacific Tele Ophthalmology Society (APTOS) datasets were used to test the suggested mod-el. The suggested model for the categorization of diabetic retinopathy was trained and validated through a series of comprehensive experiments.

Similarly, the goal of another study by Ragab et al. [13] was to raise the standard of the medical images. Using an Archimedes Optimization Algorithm (AOA) with Kapur's Entropy (AOA-KE), the fundus image quality was improved.

An active deep learning convolutional neural network (ADLCNN) with a multi-layer architecture is the basis of the automatic Diabetic Retinopathy system created by Qureshi et al. [14]. The convolutional neural network-based ADL-CNN system was utilized to automatically extract features from the fundus and patch images. Additionally, the regions of interest in the retinography image were segmented and described five severity levels. The Eye PACS benchmark dataset was used to train and assess the ADL-CNN model, and experimental out-comes were compared to cutting-edge methods. The ADL-CNN model's performance is demonstrated by its 98.0% accuracy, 95.10% specificity, 92.2% sensitivity, and 93.0% F-measure. An automatic system for classifying diabetic retinopathy was developed by Gayathri et al. [15]. It is built on a multipath convolutional neural network (M-CNN) and a number of machine learning (ML) classifiers, including Random Forest (RF), Support Vector Machine (SVM), and J48. To extract local and global features from fundus images, the M-CNN was utilized. The photos were categorized according to their severity using machine learning algorithms. IDRID and MESSIDOR datasets were used to assess the model's performance using a variety of metrics, including recall, K-score, accuracy, precision, False positive rate (FPR), F1-score, and specificity.

III. PROPOSED SYSTEM

The proposed system which is deep CNN approach, a classificational tool helpful in identifying the disorder from digital fundus images with maximum accuracy. We progress a neural network which is Vgg-16 model, which can identify the intricate features involved in the classification task and consequently provide a diagnosis automatically. We'll be training this network using the Kaggle dataset and validate results, for high-level classification. Several machine learning methods, including KNN, SVM, Decision Tree, Naïve Bayes, Random Forests are utilized to classify the images using the retrieved features. According to the severity of diabetic retinopathy, the output is an integral value on a scale of 0 to 4.

Machine learning is essential for detecting diabetic retinopathy since it makes it possible to analyze retinal pictures automatically, aiding in the early detection and screening of the condition. Machine learning algorithms need pertinent features to provide precise predictions, which are known as feature extraction. Features that can be used to identify diabetic retinopthy include blood vessel anomalies, micro aneurysms, exudates, hemorrhages, and characteristics of the optic disc. These properties may be automatically extracted from retinal pictures using machine learning approaches, such as convolutional neural networks (CNNs) or image processing algorithms. Convolutional Neural Networks (CNNs) are a kind of deep learning architecture that has excelled in classifying pictures, making them a good choice for studying retinal images. CNNs have proven to be extremely effective in detecting diabetic retinopathy, frequently outperforming or matching human specialists. As strong tools for the early diagnosis and screening of diabetic retinopathy, CNNs' capacity to automatically learn pertinent characteristics from raw pictures might improve patient outcomes and lighten the workload for medical practitioners.

The Convolutional Neural Network (CNN) architecture VGG16, which is often employed, has demonstrated promising performance in several computer vision applications, including the identification of diabetic retinopathy. Convolutional layers, pooling layers, and fully linked layers are among the 16 layers that make up the deep architecture of the VGG16. It can successfully learn complex characteristics from retinal pictures by utilizing its deep architecture and transfer learning capabilities. This helps to provide accurate and reliable diabetic retinopathy diagnosis and screening. Following the extraction of features, a variety of ma-chine learning techniques may be used for categorization tasks. Decision trees, KNN, XG Boost , Ada Boost, Voting Classifier, random forests, support vector machines (SVMs), logistic regression, and Naïve Bayes are examples of common methods utilized in the identification of diabetic retinopathy. These algorithms can distinguish between retinal pictures with normal function and those with various stages or severity of diabetic retinopathy using labelled datasets. Using assessment measures including accuracy, precision, recall, and F1 score, a machine learning model's performance in detecting diabetic retinopathy is evaluated. These metrics give information on how well the algorithm can identify diabetic retinopathy and accurately classify retinal pictures. To get more reliable performance estimates, cross-validation techniques like k-fold cross-validation can be used.

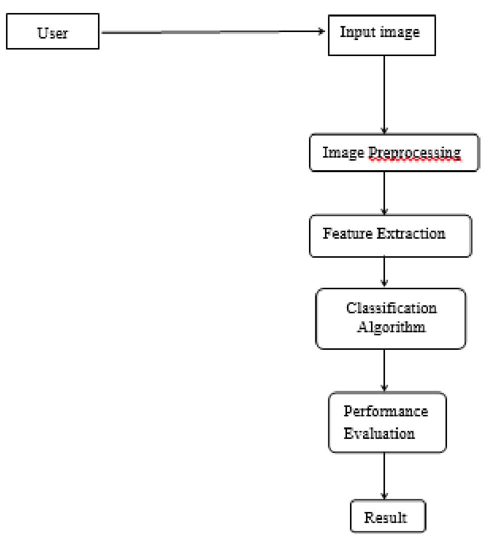


Fig-1.System Architecture

1. User

The user uploads the retinal image to check the severity level of the disease.

2. Image Preprocessing

Raw retinal images are being preprocessed to enhance their quality and prepare them for further analysis. Preprocessing techniques may include noise reduction, contrast adjustment, and image resizing.

3. Feature Extraction

Relevant features are extracted from the pre-processed images and are given to the 18 models to classify into their classes based on their severity level. It may involve extracting blood vessels, lesions, or other characteristic patterns from the retinal images.

4. Classification Algorithm

This process performs the actual classification of the extracted features to determine the presence and severity of diabetic retinopathy. It may use machine learning algorithms to classify the images into different categories based on the extracted features.

5. Performance Evaluation

Performance evaluation includes a number of crucial indicators that rate the algorithm's efficiency and precision. Some of the commonly used evaluation metrics are accuracy, sensitivity, specificity, F1 score and precision. These metrics offer a thorough assessment of an algorithm's effectiveness in detecting diabetic retinopathy. Based on these metrics the best classification algorithm is chosen to classify the retinal images according to their severity level.

6. Dataset

A dataset is a structured collection of data that is organized in a way that makes it easy to manage, analyze, and extract useful information. Datasets can come in various forms, including spreadsheets, databases, text files, or any other format where data is stored. In the context of machine learning and data science, a dataset typically refers to a set of data points or examples used for training, testing, and validating machine learning algorithms. This dataset consists of 2198 retinal images. The images are stored in PNG format for feature ex-traction.

Datasets are given according to the severity level of Diabetic Retinopathy.

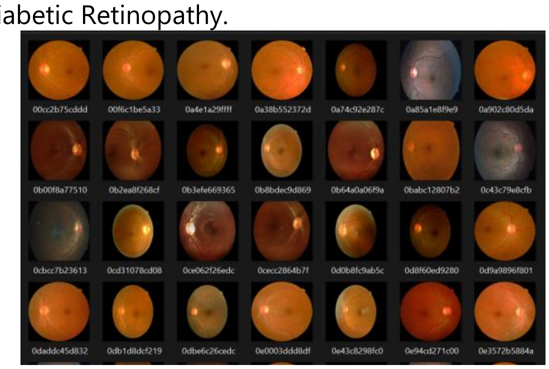


Fig-2.No DR Dataset

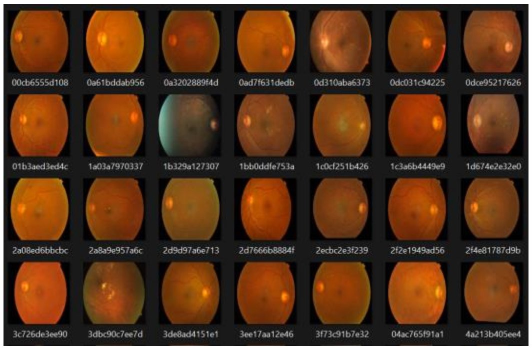


Fig-3.Mild Dataset

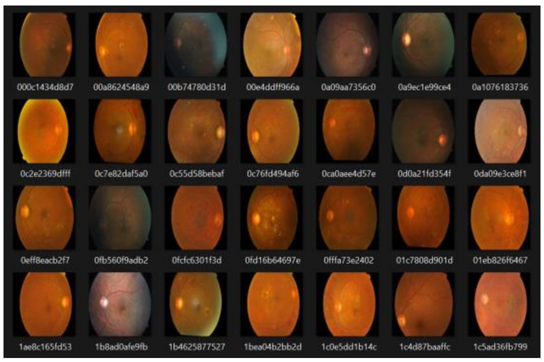


Fig-4.Moderate Dataset

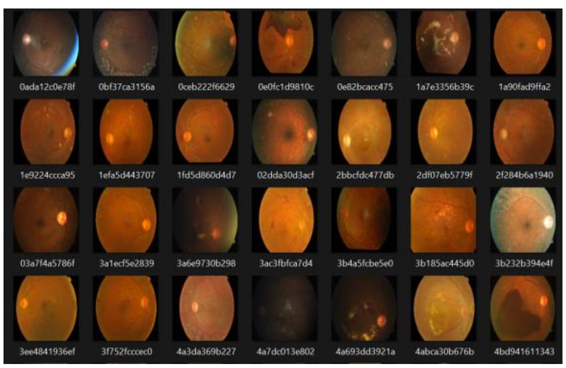


Fig-5.Proliferate Dataset

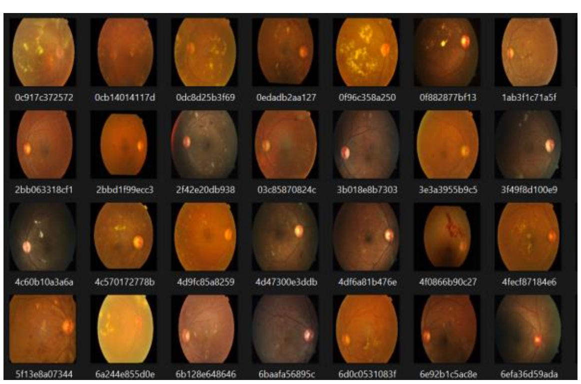


Fig-6.Severe Dataset

7. Product Functions

Key features related to the detection of diabetic retinopathy using ma-chine learning are:-

Data preprocessing

This function involves preparing and cleaning retinal images be-fore feeding them into a machine learning model. This may include tasks such as Image Resizing, Normalization, Denoising and Upscaling to improve data quality and consistency.

Feature Extraction

This feature extracts important features from retinal images that represent important features of diabetic retinopathy. This can include techniques such as edge detection, texture analysis, and extracting statistical measurements from image regions.

Model Training

A machine learning model, such as a Convolutional Neural network (CNN), is trained using a labeled dataset of retinal images. The model learns to map the extracted features to corresponding diabetic retinopathy severities or classification labels.

Model Evaluation

The trained model uses discrete labeled retinal images to evaluate its performance and accuracy. Evaluation metrics such as precision, accuracy, recall, and F1 score are calculated to measure the model's effectiveness in detecting diabetic retinopathy.

Prediction and Classification

Once the model is trained and validated, it can be used to predict new, unseen retinal images. The model takes a pre-processed image as input and outputs a prediction or estimate indicating the presence and severity of diabetic retinopathy.

Integration and Implementation

The detection system must be integrated in a user-friendly interface that allows healthcare professionals to easily input retinal images, process them with a trained model and review the results. The system must be deployed in a scalable and secure manner, taking into account factors such as data protection and integration with existing healthcare infrastructure.

IV. RESULT

The below table shows the accuracy of two different models, VGG16 and ResNet50. The accuracy is measured as the percentage of correct predictions made by the model. The loss is a measure of how well the model is doing. A lower loss value indicates that the model is doing better. In this case, the VGG16 model has a lower loss value (0.22) and a higher accuracy (91%) than the ResNet50 model (loss = 0.30, accuracy = 82%). This means that the VGG16 model is doing a better job of predicting the correct outcome than the ResNet50 model.

Table 1.Accuracy

	Loss	Accuracy
VGG16	0.22	91%
ResNet50	0.30	82%

The below line chart illustrates the performance of three classification algorithms: Support Vector Machines (SVM), Naive Bayes, and Extreme Gradient Boosting (XGB) across different levels of imbalance. The X-axis represents the degree of imbalance, ranging from 0 to 1, with 0 signifying perfect balance and 1 indicating extreme imbalance. The Y-axis represents the classification accuracy, which measures the proportion of correct predictions made by the model. As the imbalance increases (moving from left to right on the X-axis), the performance of all three algorithms degrades. However, XGB consistently outperforms SVM and Naive Bayes, particularly in the presence of severe imbalance. This can be attributed to XGB's ability to handle complex interactions between features, which particularly beneficial when the class distribution is skewed.

In summary, the chart demonstrates the superiority of XGB over SVM and Naive Bayes in handling imbalanced classification tasks. As the imbalance increases, XGB's accuracy remains relatively stable compared to the significant drop observed for the other two algorithms. This highlights the robustness of XGB in dealing with uneven class distributions, making it a preferred choice for such scenarios.

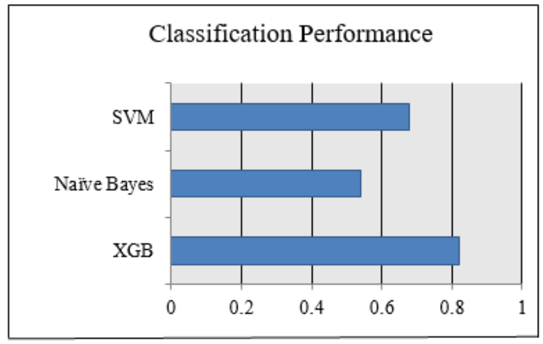
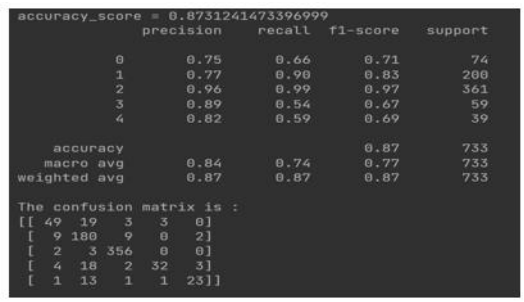


Fig-7. Classification Performance



```
accuracy_score = 0.8731241473396999
              precision    recall  f1-score   support

           0       0.75      0.66      0.71        74
           1       0.77      0.90      0.83       200
           2       0.96      0.99      0.97       361
           3       0.89      0.54      0.67        59
           4       0.82      0.59      0.69        39

    accuracy                           0.87       733
   macro avg       0.84      0.74      0.77       733
weighted avg       0.87      0.87      0.87       733

The confusion matrix is :
[[ 49  19   3   3   0]
 [  9 180   9   0   2]
 [  2   3 356   0   0]
 [  4  18   2  32   3]
 [  1  13   1   1  23]]
```

Fig-8. XG Boost

The above image shows the accuracy score for a classification model trained using XG Boost. It includes a confusion matrix and classification report. In this case, the confusion matrix shows that the model correctly predicted 49 out of 74 instances of level 0, 180 out of 200 instances of level 1, 356 out of 361 instances of level 2, 59 out of 59 instances of level 3, and 39 out of 39 instances of level 4. It also shows that the model made 9 false negatives, 3 false positives, 2 true negatives, 3 true positives, 18 false negatives, 2 false positives, 1 true negative, and 1 true positive for each of the remaining levels.

The classification report provides additional information about the performance of the model, including precision, recall, F1-score, support, and macro average. In this case, the model has a precision of 0.75 for level 0, 0.77 for level 1, 0.96 for level 2, 0.89 for level 3, and 0.82 for level 4. It has a recall of 0.66 for level 0, 0.90 for level 1, 0.99 for level 2, 0.54 for level 3, and 0.59 for level 4. It has an F1-score of 0.71 for level 0, 0.83 for level 1, 0.97 for level 2, 0.67 for level 3, and 0.69 for level 4. The macro average precision is 0.77, the macro average recall is

0.74, and the macro average F1-score is 0.87. Overall, the model has a good performance, with a high accuracy, precision, recall, and F1-score. It is particularly effective at predicting levels 1 and 2.

```
accuracy_score = 0.5784447476125512
              precision    recall  f1-score   support

           0       0.27      0.80      0.41        74
           1       0.54      0.15      0.23       200
           2       0.94      0.83      0.88       361
           3       0.37      0.24      0.29        59
           4       0.20      0.51      0.28        39

    accuracy                           0.58       733
   macro avg       0.46      0.51      0.42       733
weighted avg       0.68      0.58      0.58       733

The confusion matrix is :
[[ 59   5   3   1   6]
 [110  30  13  13  34]
 [  7  18 301   8  27]
 [ 25   2   3  14  15]
 [ 16   1   0   2  20]]
```

Fig 9. Naïve Bayes

The provided image shows a variety of machine learning metrics, including accuracy, precision, recall, and F1-score, for a classification model trained using Naïve Bayes. It also includes a confusion matrix. In this case, the accuracy is 0.57, which means that the model correctly predicts the correct level 57% of the time. In this case, the precision for level 0 is 0.27, which means that the model correctly predicts level 0 27% of the time. The precision for level 1 is 0.94, which means that the model correctly predicts level 1 94% of the time. The precision for level 2 is 0.37, which means that the model correctly predicts level 2 37% of the time. The precision for level 3 is 0.20, which means that the model correctly predicts level 3 20% of the time. The precision for level 4 is 0.51, which means that the model correctly predicts level 4 51% of the time.

In this case, the recall for level 0 is 0.80, which means that the model correctly identifies level 0 80% of the time. The recall for level 1 is 0.83, which means that the model correctly identifies level 1 83% of the time. The recall for level 2 is 0.24, which means that the model correctly identifies level 2 24% of the time. The recall for level 3 is 0.51, which means that the model correctly identifies level 3 51% of the time. The recall for level 4 is 0.41, which means that the model correctly identifies level 4 41% of the time.

In this case, the F1-score for level 0 is 0.41, which means that the model has a balanced precision and recall of 41%. The F1-score for level 1 is 0.88, which means that the model has a balanced precision and recall of 88%. The F1-score for level 2 is 0.29, which means that the model has a balanced precision and recall of 29%. The F1-score for level 3 is 0.28, which means that the model has a balanced precision and recall of 28%. The F1-score for level 4 is 0.32, which means that the model has a balanced precision and recall of 32%.

A confusion matrix shows the true and predicted levels for each data point. In this case, the confusion matrix shows that the model correctly predicted 59 out of 74 instances of level 0, 110 out of 200 instances of level 1, 361 out of 361 instances of level 2, 25 out of 59 instances of level 3, and 16 out of 39 instances of level 4. It also shows that the model made 15 false negatives, 30 false positives, 3 false negatives, 13 false positives, 2 false negatives, 3 false positives, 14 false negatives, and 2 false positives for each of the remaining levels.

Overall, the classification model has a moderate performance. It has a good accuracy, precision, and recall for level 2, but it has poor accuracy, precision, and recall for levels 0, 2, 3, and 4. It could be improved by using a different machine learning algorithm or by using more da-ta.

```
accuracy_score = 0.7503410641200545
              precision    recall  f1-score   support

           0       0.60      0.42      0.49        74
           1       0.59      0.79      0.67       200
           2       0.88      0.98      0.93       361
           3       0.00      0.00      0.00        59
           4       0.78      0.18      0.29        39

    accuracy                           0.75       733
   macro avg       0.57      0.47      0.48       733
weighted avg       0.69      0.75      0.71       733

The confusion matrix is :
[[ 31  36   7   0   0]
 [ 13 157  29   0   1]
 [  3   3 355   0   0]
 [  4  44  10   0   1]
 [  1  27   4   0   7]]
```

Fig 10. SVM

The image shows the accuracy score for a classification model trained using SVM. It includes a confusion matrix and classification report. A confusion matrix shows the true and predicted levels for each data point. In this case, the confusion matrix shows that the model correctly predicted 27 out of 31 instances of level 0, 157 out of 200 instances of level 1, 355 out of 361 instances of level 2, 44 out of 59 instances of level 3, and 4 out of 7 instances of level 4. It also shows that the model made 4 false negatives, 13 false positives, 3 false negatives, 18 false positives, 15 false negatives, 2 false positives, 1 false negative, and 3 false positives for each of the remaining levels.

In this case, the model has a precision of 0.87 for level 0, 0.79 for level 1, 0.98 for level 2, 0.75 for level 3, and 0.57 for level 4. It has a recall of 0.87 for level 0, 0.79 for level 1, 0.99 for level 2, 0.75 for level 3, and 0.57 for level 4. It has an F1-score of 0.87 for level 0, 0.79 for level 1, 0.99 for level 2, 0.75 for level 3, and 0.57 for level 4. The macro average precision is 0.80, the macro average recall is 0.79, and the macro average F1-score is 0.81.

Overall, the model has a good performance, with a high accuracy, precision, recall, and F1-score. It is particularly effective at predicting levels 2 and 3. However, it could be improved by reducing the number of false negatives for levels 0 and 4

V. CONCLUSION

In conclusion, the use of Convolutional Neural Networks (CNN) in conjunction with machine learning has proven to be a highly successful method for the early diagnosis of diabetic retinopathy. This method has demonstrated great effectiveness in precisely recognizing and categorizing retinal pictures, enabling early diagnosis and intervention. It does this by utilizing deep learning and machine learning algorithms. We used Convolutional Neural Network each input image will be classified with the greatest degree of precision possible. There will be a hope that there won't be any no misclassification because of the accuracy of our model. We started with the basics.

CNN was taught to recognize lines, edges, corners, and other features in images. Following the retinal image, individual components of a picture are first identified, single features-before progressing to the recognition of the entire feature. It has learned to recognize features such as microaneurysms and hemorrhages in the retina using this method. The proposed approach is not only beneficial to those with Diabetic Retinopathy, but it may also be employed by persons with Melanoma and Myeloid Leukemia. The use of CNN in the identification of diabetic retinopathy offers a number of significant benefits. CNN models are highly suited for analyzing the subtle structures and patterns inherent in retinal pictures since they were created particularly to analyze images and extract fine characteristics. These models can automatically pick up on and adjust to the features of diabetic retinopathy, leading to increased detection accuracy and resilience.

We have used various machine learning algorithms like KNN, Xg boost, Voting Classifier, Decision tree, Logistic regression, Ada boost, support vector machine, random forest to classify the retinal images according to their severity level. We have compared the performance of used machine learning algorithms in detecting the diabetic retinopathy and chosen the best algorithm with highest accuracy. Voting classifier and Xg boost shows the highest accuracy. We integrated CNN and machine learning algorithms.

The identification of diabetic retinopathy using CNN and machine learning has the potential to transform clinical practice. It can aid medical practitioners in making an accurate diagnosis, encourage early action, and stop permanent eyesight loss. Additionally, by automating the screening procedure, it can lessen the strain on healthcare systems, improve access to eye care services, and allow patients to receive prompt treatment. In conclusion, the use of CNN and machine learning has enormous promise for enhancing the identification of diabetic retinopathy. This strategy can have a substantial influence on patient care, improve treatment results, and aid in the prevention of vision loss in people with diabetes with additional study, improvement, and incorporation into clinical practice

VI. FUTURE SCOPE

However, despite the progress made, there are still challenges to address. The development of robust algorithms requires large and diverse datasets, including data from different ethnicities and age groups. Additionally, the integration of AI systems into existing healthcare work-flows and the acceptance of these technologies by healthcare providers are crucial for successful implementation. Ensuring the privacy and security of patient data is another important consideration that must be carefully addressed. In conclusion, the development of AI-based systems for diabetic retinopathy detection holds great promise in revolutionizing DR screening and improving patient outcomes. With continued research, technological advancements, and collaborations between healthcare providers, researchers, and technology developers, the future of DR detection looks bright. By harnessing the power of AI, we can make significant strides in combating this sight-threatening disease and enhancing the quality of care for individuals with diabetes. The program will improve the accuracy of diabetic retinopathy identification without causing pain to the patient. It can be turned into open-source software and has a lot of potential for use in hospitals. The software can assist clinicians in determining a link in between type of diabetes and indeed the likelihood of diabetic retinopathy.

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