A FIELD PROJECT REPORT

on

“DETECTION OF DIABETIC RETINOPATHY”

Submitted

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CERTIFICATE

This is to certify that the Field Project entitled **"DETECTION OF DIABETIC RETINOPATHY"** that is being submitted by P.Sanjay Kumar(221FA04061), G.Teja Sri (221FA04432), Ch.Vijaya Maruthi(221FA04550), B.Ankamma (221FA04619) for partial fulfilment of Field Project is a bonafide work carried out under the supervision of Ms. Sajida Sultana.Sk , Assistant Professor, Department of CSE.

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DECLARATION

We hereby declare that the Field Project entitled **"DETECTION OF DIABETIC RETINOPATHY"** is being submitted by P. Sanjay Kumar (221FA04061), G. Teja Sri (221FA04432), Ch. Vijaya Maruthi (221FA04550), B. Ankamma (221FA04619) in partial fulfilment of Field Project course work. This is our original work, and this project has not formed the basis for the award of any degree. We have worked under the supervision of Ms. Sajida Sultana.Sk ,, Assistant Professor, Department of CSE

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ABSTRACT

Diabetic Retinopathy or DR, is a great concern for long-term diabetic patients, and their vision will be lost unless they are diagnosed early. Thus, in the study mentioned below, it aims to propose a multimodel fusion that utilizes valuable information from retinal fundus images by merging two pre-trained models which are most frequently used VGG19, ResNet50, NASNetLarge, EfficientNet, DenseNet121, MobileNetV2, InceptiontionV2, Xception. These are fused using cross-pooling technique that capture considerable image details, which are crucial for precise diagnosis. Among the different models of fusion of pre-trained models, the fusion of VGG19 features with ResNet50 enhanced the model's capability to detect subtle variations in retinal images and predicted the correct severity level. A neural network architecture was applied for the classification with very high accuracy in the severity levels of DR.

Evaluation of model performance are done by using measures like Accuracy, Confusion matrix, and Receiver Operating Characteristic (ROC) curve. This proposed model was experimented on Kaggle APTOS 2019 dataset. Benchmark dataset was used in the experiment. The results for our suggested model were excellent. It achieved an accuracy of 83.33%. This superior accuracy reflects the efficacy of our method and depicts the promise of our fusion-based approach in diagnosing DR. It is a proposed model that promises an early intervention and preserving vision in diabetic patients besides showing outstanding performance with regard to normal, mild, and moderate classification stages of retinal fundus images.

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CHAPTER-1
INTRODUCTION

1. INTRODUCTION

This can result in diabetic retinopathy being suffered by the patient; this is a degenerative eye disease - it is brought about as direct exposure to high levels of blood sugar for a long period leads to the destruction of blood vessels in the retina. An early diagnosis and characterizing the severity levels with a high degree of accuracy is key to timely intervention and effective management of drug resistance. Deep learning techniques have been of great promise over recent years in improving automated DR diagnosis. Deep neural networks can now extract complex patterns and attributes from retinal pictures. More accurate and reliable classification of the DR severity will thus be possible.

This research work focuses on the model by integrating information from multiple imaging modalities and using sophisticated fusion techniques; it aims at improvement in the accuracy and consistency of DR diagnosis using our methodology. In this study, we introduced a multi-level fusion model designed to forecast the severity level stage by training the combination of VGG19 and ResNet50, and employing deep neural networks for classification. This high-level study will allow us to present the performance of each one of these models in various functional areas. Our research also underscores the need to address diabetic retinopathy in a general way since it may eventually lead to permanent loss of vision or even blindness unless treated. By pointing out the complex interplay that exists between hyperglycemia for a longer period and retinal vascular damage, we also hope to elucidate the mechanisms involved in the process of disease progression itself.

In addition, our study work focuses on an integrative approach for DR control, laying stress not only on early detection but also the initiation of personalized treatment regimens for the individual needs of the patient. In many ways, our study has contributed significantly to the science of predicting diabetic retinopathy disease; it has excellent distinguishing performance between normal, mild, and moderate states of retinal fundus images. Using a larger number of training images that belong to those specific classes achieves this model the ability to do better at intense and proliferative stages. In this paper, the components comprise structure. More information regarding the literature survey is given in Section II. The proposed method/methodology is briefly summarized in Section III. Results and a detailed presentation of the experiment are discussed in Section IV. Section V summary concludes in detail results. Reference List sources mentioned in Section VI have been consulted.

CHAPTER-2
LITERATURE SURVEY

2. LITERATURE SURVEY

2.1 Literature review

In recent years, approaches have ranged from the early detection of small vessels up to DR severity classification. With developments in artificial intelligence and medical imaging, it would be possible to counteract the effects of problems threatening vision and improve screening efficacy. Long-term diabetes mellitus patients suffering from DR represent a substantial threat to their vision. Gradually, enhanced glucose causes pathological growth of blood vessels in the retina; therefore, it progresses. Microaneurysms and hemorrhages are just one of the many retina abnormalities from this [2]. Greater loss in vision or blindness is more likely to occur as DR advances [3]. Development in medical imaging and artificial intelligence has made automation of screening technologies possible, hence emphasizing the necessity to detect DR as early as possible [4]. The principal technologies employed in routine screening encompass fundus photography and OCT, which have increased the accessibility of screening and may reduce the workload for healthcare providers [5].

Several approaches have been suggested to detect and classify DR. Some of the early approaches relied on microaneurysm detection, and others used data classification through random forests [6-7]. Among other deep learning approaches, CNNs have lately become very popular since they have proved useful in the detection of DR based on researches done [8][9]. Besides these methods, some new techniques were proposed, including Gaussian scale space method for fluid detection [10], and deep learning-based diagnostic systems [11]. These numbers of techniques depict the complexity involved in the management of emergency recovery using the state-of-the-art technology. Traditional machine learning techniques have also been extensively explored. Research has been performed on segmentation-based approaches. [13], ensemble models [12], and feature extraction based on evolutionary algorithms [14].

Some works have also been carried out in the domain of deep feature-based models, including CNN, fuzzy logic, and fuzzy C-means [16][17]. Such techniques depict how this novel and traditional approach can be merged to get over the challenges that are inherent in the DR diagnosis process. III. METHODOLOGY To analyze Diabetic Retinopathy, a proper data exploration, preprocessing strategy, besides the effective feature selection is required for the better classification models. Then, retinal image data have to closely be analyzed because the models will be more superior and robust, in particular with the balanced datasets. Any preprocessing techniques like VGG19 and ResNet50 must be used, and the deep neural networks need to be used. The technique strives to change the dataset to balanced mode to be utilized in exploring the distortion of diabetic retinal and training of models. Leverage the benefits of each architecture, and this may be enhanced as a research study on diabetic retinopathy by incorporating the models of ResNet50, VGG19, and a deep neural network. Both ResNet50 and VGG19 can do quite an excellent job in extracting high-level characteristics from the images of the retina, while DNN can provide hard classification tasks and really boost these features. The ensemble approach improves the model's diagnostic accuracy for diabetic retinopathy through incorporating various viewpoints and feature representations.

2.2 Motivation

DR often brings to fore severe questions because, for the majority of diabetes patients, it may eventually lead to complete irreversible vision impairment and cause eventual blindness. Therefore, it needs to be detected early because appropriate intervention and treatment can potentially prevent or delay the onset of impaired vision. Precise characterization of DR severity is important for the appropriateness of the approach to be taken in the treatment of each patient, as the management may vary with the stage and severity of the disease. This in fact drives home the critical need for early diagnosis and precise characterization of DR severity levels. Recently, new developments have taken place in deep learning techniques that have brought a large amount of promise for the improvement of automated DR diagnosis by obtaining complex patterns and attributes from retinal images, raising the correctness of DR classification based on its severity levels. Deep learning techniques have revolutionized the analysis of medical images by allowing intrinsic procedures of automatic extraction of intricate patterns and features from retinal images. This would allow for better classification of the level of DR severity and reduce dependency on a manual assessment, thus making the process faster and more uniform. The research into DR should also be conducted in its scope, such as early detection but also in applying treatment recommendations tailored according to specific patient needs. Such an approach is very fundamental to effective management of DR.
DR management is diagnosed and classified with various treatment plans and has entered the holistic approach where the plan suits each patient. This route opens a chance for far better results and patient satisfaction where it enters individual considerations of factors such as the general health and lifestyle status of the patients. So, this proposed model integrates information from multiple modalities and applies sophisticated techniques in fusion for the accuracy and consistency of diagnosis of DR. In particular, it aims at discriminating the normal, mild, and moderate stages from each other and achieving better accuracy during intense and proliferative stages. The contribution of the research to the scientific understanding and DR predictions is a very good contribution in terms of how excellent its performance is in classifying diseases, especially at challenging stages, and there are many detailed experimental results and conclusions.

CHAPTER-3
PROPOSED SYSTEM

3. PROPOSED SYSTEM

Patients who are suffering from diabetes can suffer from diabetic retinopathy, which is a degenerative eye disease. For this reason, it happens due to the destruction of the blood vessels in the retina because of continuous exposure to high levels of blood sugar. Early diagnosis and accurate characterization of the severity levels play an important role in timely intervention and effective drug resistance management. Recent deep learning techniques have indicated a promising future for improving the automated diagnosis of DR. Based on retinal images, deep neural networks can extract complex patterns and features to allow more accurate classification with low errors concerning DR severity levels. This paper is centered around the model by integrating the information from several imaging modalities and making use of sophisticated fusion techniques our methodology has the aim of augmenting accuracy and consistency in DR diagnosis. We have designed a multi-level fusion model that aims to predict the stage of severity during the training of a combination of VGG19 and ResNet50 for the introduction of deep neural networks-based classification. This refined approach allows us to explore how each model performs in diverse functional zones. Moreover, our study puts forth a holistic approach to DR, as this condition carries a danger of permanent loss of vision up to total blindness, and therefore, needs to be brought to notice soon. Elucidating the intricate interplay between prolonged hyperglycemia and retinal vascular damage aims at throwing light on the most plausible mechanisms of disease progression. But otherwise, our study supports a holistic management approach of DR since it addresses, not only the early detection but also implements treatment regimens tailored to individual patient needs. This research makes an enormous contribution to science in predicting diabetic retinopathy disease in multiple manners : It shows excellent performance in distinguishing between normal, mild, and moderate stages of retinal fundus images. This model can achieve higher accuracy during intense and proliferative stages by using a larger number of training images that belong to those particular classes. These components comprise the structure of this paper. More information regarding the literature survey is given in Section II. The proposed method/methodology is briefly summarized in Section III. In Section IV, the results and detailed presentation of the experiment are discussed. Section V Conclusion The findings are summarized in detail. Section VI Sources Consulted.

3.1 Input dataset:

The APTOS 2019 dataset has 3,662 eye retinal fundus images segmented into 5 severity levels corresponding to a different stage of DR progression: Normal class (0), Mild class (1), Moderate class (2), Intense class (3) and ProliferativeDR class (4).
We have downloaded this APTOS from Kaggle.

3.1.1 Dataset Detailed Features

Severity level	Number of samples
Normal - 0	**1805**
Mild - 1	**370**
Moderate - 2	**999**
Intense - 3	**193**
Proliferative - 4	**295**
Total	**3662**

Content: The dataset contains thousands of retinal images and their respective grades. These grades correspond to the severity level based on the International Clinical Diabetic Retinopathy scale. It ranges from grade 0 (no diabetic retinopathy) to grade 4 (proliferative diabetic retinopathy). The dataset also includes labels that denote the presence or absence of diabetic macular edema. This is another common complication with diabetes, affecting the macula.

Image Characteristics: The images contained in the database are generally of high resolution and offer a good view of the interior of the eye, namely, the retina. They are likely to vary in quality, lighting conditions, presence of artifacts, etc., and other realism variability settings that can be encountered in the clinic.

Annotations: All images in the database have been manually annotated with ground truth by subject matter experts to use for training and testing the machine-learning algorithms. Annotation is considered an important task in developing reliable computer algorithms for automated disease detection and grading.

Usage: The Aptos dataset has been used very widely by researchers and data scientists in the areas of medical image analysis, machine learning and ophthalmology. The dataset may also be termed as an evaluation dataset, for it is indeed used for evaluating the performance of algorithms designed for automatic detection and grading of diabetic retinopathy.

3.2 Data Pre-processing

The objective of pre-processing is an improvement of image data which suppresses unwanted distortions or enhances some image features important for further processing, although geometric transformations of images like rotation, scaling, translation, reshape are classified among pre-processing methods here since similar techniques are used.

1. **Balanced Dataset Creation:**

   Converting the raw images into the format of balanced datasets for the study of diabetic retinal distortion and model training.

2. **Reshaping the images:**

   An image is represented by pixels, height and width for size, and number of channels for color or black/white. Reshaping helps to prepare an image in a way that would help feed data into the model's algorithm.

3.3 Model Building :

VGG19 :

The VGG19 model, or VGGNet-19, is the same general concept as the VGG16 model but accommodates 19 layers instead of 16. The terms "16" and "19" are always referring to the number of weight layers of the model, which denote convolutional layers. Compared to VGG16, VGG19 includes three more convolutional layers. In the last part of this paper, we will illustrate the characteristics of VGG16 and VGG19 models.

ResNet50:

The original ResNet architecture was ResNet-34 and had 34 weighted layers. It provided a straightforward way to add more convolutional layers to a CNN without the problem of the vanishing gradient by introducing shortcut connections. Shortcut connection "skips over" some layers and converts a regular network to a residual network.
The underpinning of the regular network is based on VGG neural networks, (VGG-16 and VGG-19). Each convolutional network is equipped with a 3×3 filter. A ResNet, however, has fewer filters and is less complicated than a VGGNet. A 34-layer ResNet could attain a performance of 3.6 billion FLOPs, and a much smaller 18-layer ResNet could attain 1.8 billion FLOPs, much faster than the VGG-19 Network's 19.6 billion FLOPs.

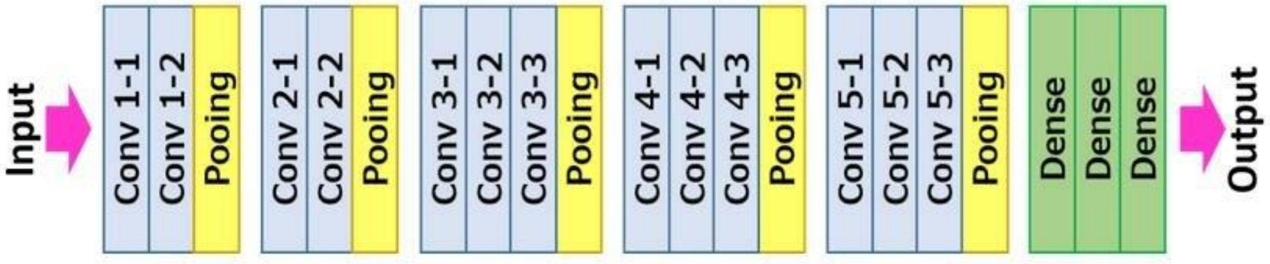
3.4 System methodology

While studying Diabetic Retinopathy, there must be appropriate data exploration, preprocessing, and feature selection strategies that would enhance the quality of the classification models. Where the datasets are balanced, further improvement of quality and strength of the models must be established. This is through the adequate scrutiny of the retinal image data. In preprocessing, methods applied include VGG19 and ResNet50, and deep neural networks must also be applied.

This approach intends to convert the dataset into a balanced format of carrying out the study on diabetic retinal distortion as well as training the model. By comparing the merits and demerits of both architectures, research on diabetic retinopathy can be improved by combining ResNet50, VGG19, and a deep neural network. In this ensemble method, the proposed model for diabetes retinopathy diagnosis can be found more precise with a higher precision rate by incorporating many possible representations as well as viewpoints.

Feature Extraction using VGG19

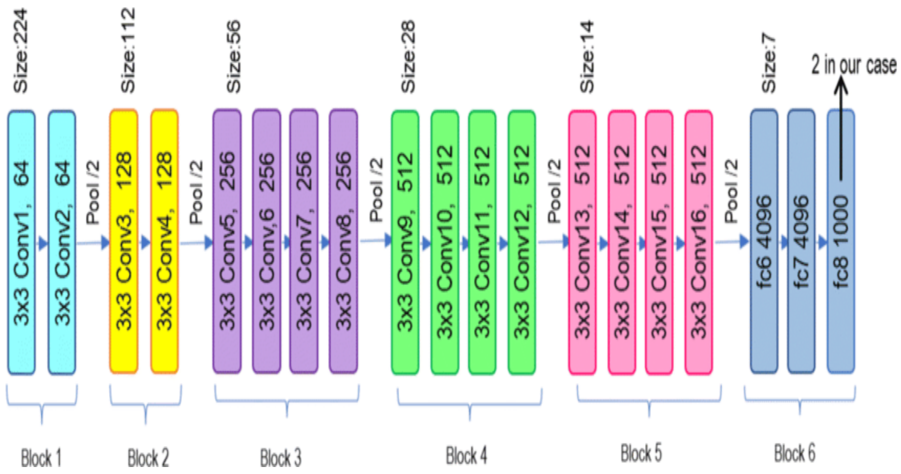
The network for the Visual Geometry Group comprises 19 layers, referred to as VGG-19. In this design, sixteen convolutional layers are there, then three fully linked layers, and the SoftMax classifier for the robust classification in the last layer.
This network can classify pictures into more than 1,000 distinct item categories, making the freedom in classification options about a picture dataset very high. While it simplifies integration and experimentation, VGG19 is used in most deep-learning frameworks these days. To help



VGG-19 Architecture[1.1]

extract key features from input images and manage any computing resource on a large scale. The

VGG-19 shrinks the feature maps through maxpooling layers. The VGG-19 is pre-trained but robust architecture enables users to adapt it to many applications. It can even be fine-tuned on specific datasets to add new image classification tasks. It is mostly the natural choice for high-precision object recognition and image classification due to its pre-trained weights and deep structure makes transfer learning effective. Flexibility and effectiveness of VGG19 as a tool. Cautionary arrangement of layers and flexibility of network, which adapts to different data and applications, make it really strong in this big expanse of profound learning and computer vision.



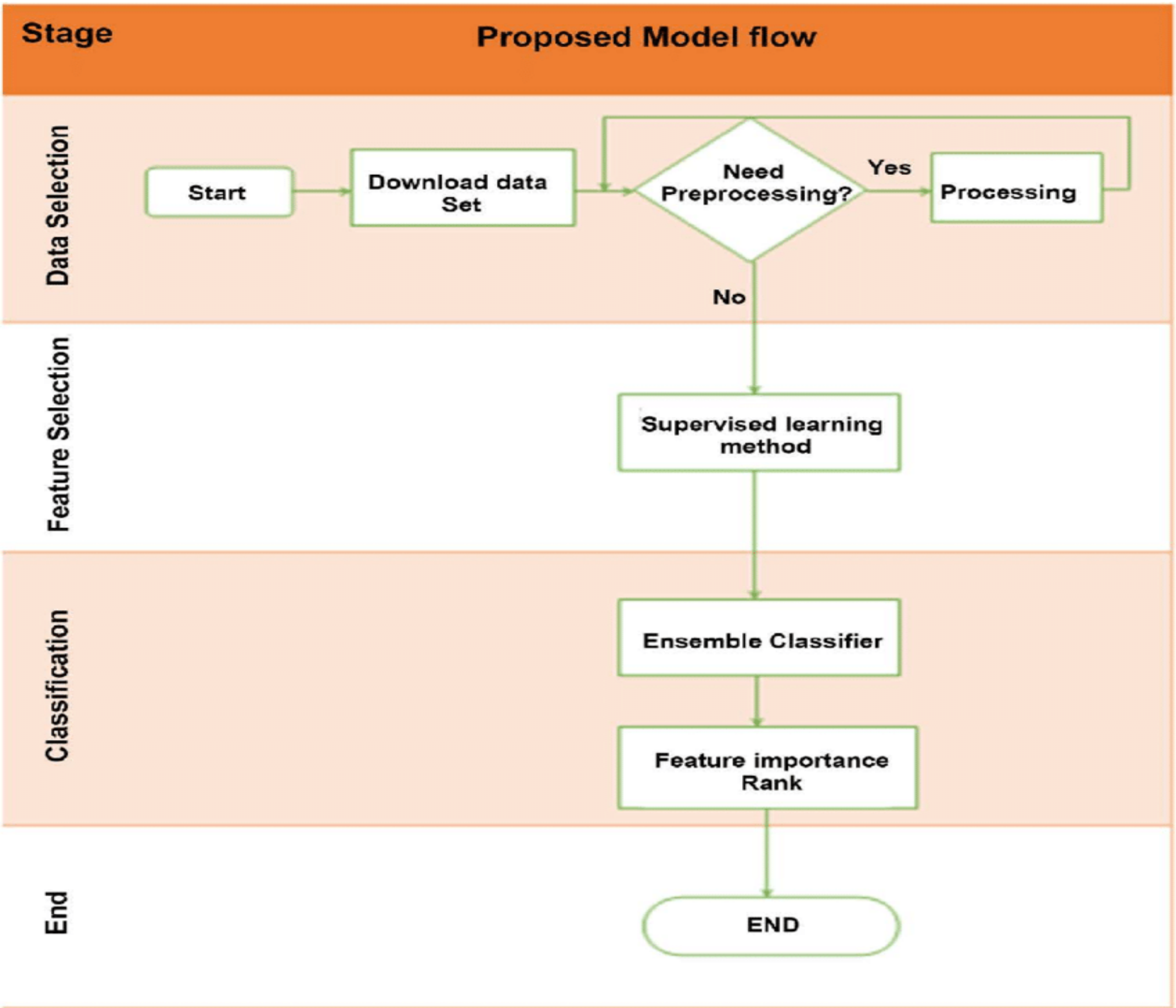
[1.2]

Feature Extraction by ResNet50

ResNet50 is a residual version of the network architecture, introduced by Microsoft Research in the year 2015 that specializes in visual recognition. ResNet-34 had 34 weighted layers as the first design for ResNet. For ResNet50, its layers comprise an average pool layer, a max pool layer, and forty-eight convolutional layers. ResNet50 is highly effective and deep in the case of image classification applications.
We apply the same formulas as in VGG19 to ResNet50 as well.

Cross pooling technique

Cross-pooling is used to integrate the output of several models that have been trained on different subsets of the same data. In this technique, overfitting reduces, and generalization accuracy increases for the model. Cross-pooling is calculated by averaging the predictions of every model in order to achieve the result. "Ensembling" is a term coined for the method of integrating various models for better accuracy of the forecast. Given two feature vectors, P and Q, as inputs, cross-polling to create a new feature vector R in the d-dimensional real number space, where all three reside. One of three methods is applied to compute each component ri of the produced vector R.



[1.3]

3.5 Model Evaluation

Model evaluation is the most important part of Diabetic retinopathy classification. Model evaluation can be called information regarding the performance and accuracy of models towards new, unseen data.

Model evaluation that has been used in our system :

1. Accuracy

Accuracy is probably the most intuitive measure of performance and is simply a ratio of correctly predicted observations to total observations. It gives a sense of how often a model is correct across all classes in general.

Accuracy = Number of correct predictions/Total number of predictions * 100%

Accuracy = (TP+TN)/(TP+TN+FP+FN)

2. Precision (Positive Predictive Value)

Precision is the ratio of correctly predicted positive observations to the total predicted positive observations. It emphasizes that the model is able to return relevant instances.

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

(TP = True positive, FP = False positive)

3. Recall (Sensitivity, True Positive Rate)

Recall is the ratio of correctly predicted positive observations to the all observations in actual class - yes. It measures the model's capacity to capture real positives.

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

(TP = True Positives, FN = False Negatives).

4. F1 Score

The F1 score is the weighted average of Precision and Recall. Therefore, this score incorporates false positives into account as well as false negatives. It is thus helpful specially in the case when one class has an imbalance with others.

F1 score = 2* precision x Recall / precision + Recall

$$\text{F1 score} = 2^* \frac{\text{TP/TP+FP * TP/TP+FN}}{\text{TP/TP+FP + TP/TP+FN}}$$

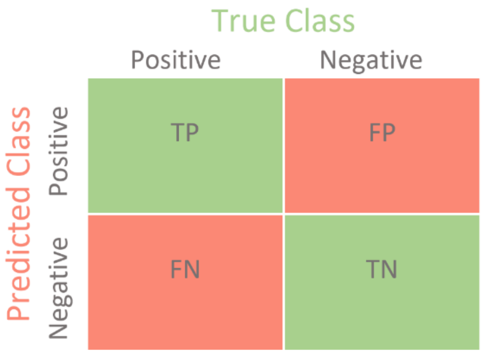
5. ROC curve:

An ROC curve represents the graphical image of the ability of a binary classifier system in their discrimination as threshold varies. It has become largely applied in medicine and radiology, biometrics, and other applications of machine learning to judge the comparative strength of their models. It is designed as a graphical plot of the true positive rate against the false positive rate for different settings of threshold levels.

- **Area Under the Curve (AUC)**: This one of the more important absolute performance measures for a two-class classifier plotted by an ROC curve. An AUC of 1.0 means a perfect classifier, while an AUC of
  0.5 Nonsense classifier-no better than random guess.
- **An Curve Shape of ROC Curve**: The shape of the ideal curve should be such that it bends up from the left corner of the plot and such that the highest value of TPR with its lowest value of FPR.. If the curve just touches and goes along with both the left and the top border of the ROC space, then the test is as accurate as possible.

6. Confusion Matrix

A confusion matrix is a table that often describes the performance of a classification model on a set of test data for which true values are known. It enables visualising the performance of an algorithm.
True Positive(TP): Correctly predicted positives
False Positive (FP): Number of false predictions that are positive
TN: True Negative, Correct Negative Predictions
False Negative (FN): No True Negatives; wrong predictions of negatives..



[1.4]

- High Precision, Low Recall: This result shows that the model is highly confident to be correct when it predicts positive but misses an excellent number of actual positives.
- Low Precision, High Recall: The model identifies most of the actual positives but also misclassifies many negatives as positives.
- Balanced Precision and Recall (High F1 Score): It shows a balance between precision and recall within the model, hence performing accurately on both the metrics.

3.6 Constraints

1. The early diagnosis at the time of the severity level description of diabetic retinopathy.
2. The urgency for timely intervention and managerial efficacy of drug resistance by overcoming the difficulties of dealing with emergency recovery using innovative technology.
3. The absence of training images leading to misclassification of the high and growing classes.

These shortcomings therefore give rise to more motivations for further researches and development, to tune up model training to address these shortcomings.

3.7 Cost and sustainability Impact

Cost Impact:

Cost impact refers to the cost of executing a transaction in any share, for a particular pre-defined order size, at any point of time in history.

1. It is cost effective since it exploits free T4 GPU services offered in the Google colabortory.

Sustainability Impact:

Applying deep learning techniques and medical imaging advances may improve the effectiveness of screening for potentially vision-threatening conditions in patients with diabetes, ultimately generating higher longer-term sustainability of healthcare resources and improving quality of life for patients.

3.8 Use of Standards

1.Standardized Evaluation Metrics:

Remember that recall,accuracy,F1-score, and precision should be used along with the confusion matrix and ROC curve for full assessment of the developed model.

2. Model Fusion Standards:

VGG19 and ResNet50 fusion model can also be utilized in the project to ensure the upswing in DR severity classification accuracy.

3. Dataset Standardization:

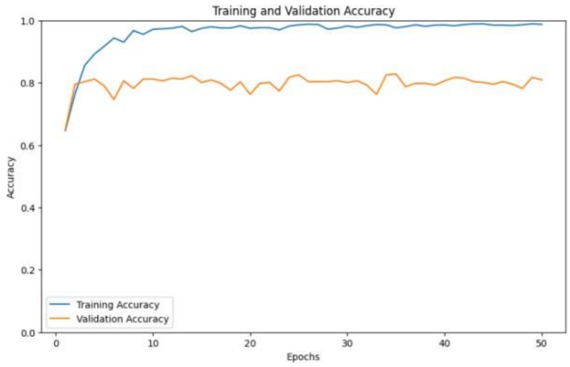
KaggleAPTOS 2019 dataset normalized with standardized levels of severity for stable training and testing of the model.

4. Experiment / Product Results :

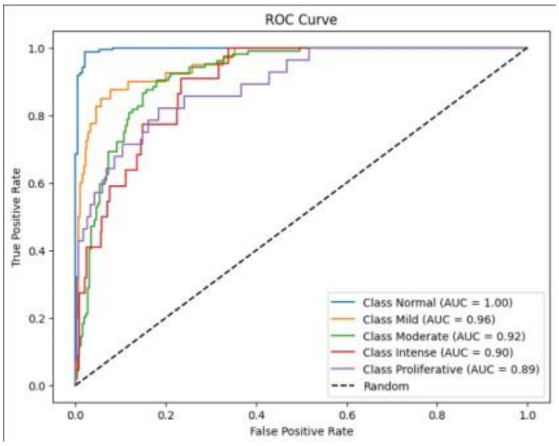
The proposed fusion model has been tested using a variety of pre-trained models. The outcomes of our experimental models are shown here. The combination of VGG19 and ResNet50 produced the best accuracy out of all the models.

Models	Accuracy
VGG19 + ResNet50 + DNN	**83.33%**
NASNetLarge + EfficientNetV2S + DNN	**77.32%**
DenseNet121 + MobileNetV2 + DNN	**72.13%**
InceptionResNetV2 + Xception + DNN	**70.21%**

The training and testing accuracy graphs that we obtained from our model's experiments on neural networks for classification are as follows:



ROC curve and AUC score of the proposed model in details :
Class Normal has the highest AUC score =1.00. This indicates that the categorization model is working at a high level.

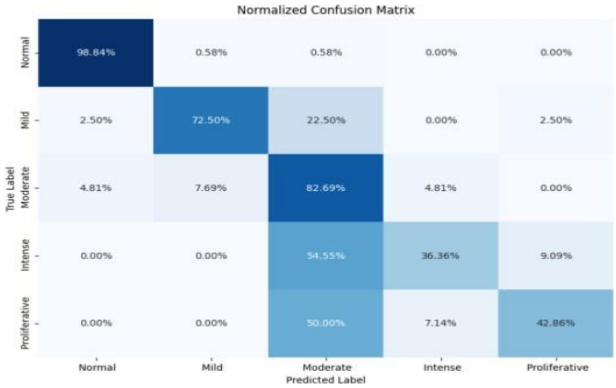


AUC scores of the class Mild, Moderate, Intense and proliferative are 0.96, 0.92, 0.90, 0.89 respectively, which show the high performance level of the classification model of each.

The above table shows performance metrics Precision, Recall, F1-Score, and AUC values corresponding to individual levels of severity in Table below:

Severity Level	Precision	Recall	F1-score	AUC
Normal (0)	**99**	**97**	**98**	**100**
Mild (1)	**72**	**76**	**74**	**96**
Moderate (2)	**83**	**70**	**76**	**92**
Intense (3)	**36**	**53**	**43**	**90**
Proliferative (4)	**43**	**80**	**56**	**89**
Macro avg	**67**	**75**	**69**	**93.4**
Weighted avg	**86**	**83**	**84**	**95.5**

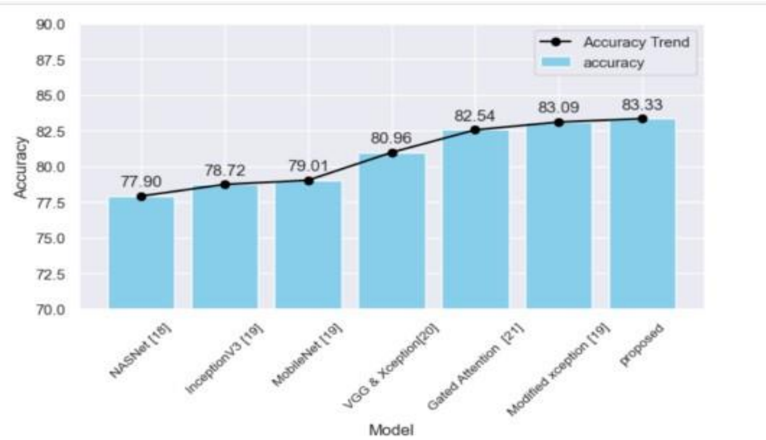
Confusion matrix description of the proposed model: Class Normal got the highest classification accuracy .Class Intense got the lowest accuracy, and most of the Intense class images are misclassified as Moderate class.Most of the Profilerative class images are also misclassified as Moderate class.



PERFORMANCE COMPARISION OF PROPOSED MODEL WITH EXISTING MODELS:

Model	Accuracy (%)
NASNet + t-SNE + SVM	77.90
InceptionV3 + MLP	**78.72**
MobileNet	**79.01**
Blended VGG & Xception + DNN	**80.96**
Composite Gated Attention DNN	**82.54**
Modified xception	**83.09**
Multi-Model fusion (proposed)	**83.33**

This is a comparison of the accuracy of the proposed model and the models in existence. With an accuracy of 83.33%, the proposed model could outperform the existing models by accuracy.



We are using fusion of pre-trained convolutional models for diabetic retinopathy classification. We did pre-processing of the images, reshaped, feature selection through pre-trained models, and classified using a neural network. We have trained through the training data set, tested the model with the validation data set, and achieved an accuracy of 83.33%.

Now we are provided with a new retinal fundus image, for which the model correctly predicts the stage of diabetic retinopathy.

5. Conclusion:

In summary, this work presents a unique method for the multi-model fusion diagnosis of diabetic retinopathy (DR). Using a neural network architecture, this was able to classify DR severity levels with an impressive 83.33% accuracy on the Kaggle APTOS 2019 dataset. This performance underscores the effectiveness of our fusion-based method in DR diagnosis, offering a promising avenue for early intervention and vision preservation in diabetic patients. We have observed that we gain high accuracy in normal, mild, and moderate stages as they have a high number of training images belonging to these classes, when compared to intense and proliferative their classification accuracy is because of less number of training images of intense and proliferative stage. Due to a lack of training images, the model can't classify intense and proliferative classes accurately. We intend to improve the model training in future by incorporating additional training images of intense and proliferative stages to improve the model performance

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