DIABETIC RETINOPATHY DETECTION USING DEEP LEARNING

A Project Report

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In

ARTIFICIAL INTELLIGENCE & DATA SCIENCE

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CERTIFICATE

This is to certify that the project report entitled **"DIABETIC RETINOPATHY DETECTION USING DEEP LEARNING"** is a bonafide record of work carried out by **G. VAMSI KRISHNA (20481A5420), R. SAI NITHIN (20481A5448), V. KONDALA RAO (20481A5461), J. SUBASH (20481A5422)** under the guidance and super vision of **Mrs. K. BHANU** in the partial fulfillment of the requirements for the award of the degree of Bachelor of Technology in Artificial Intelligence and Data Science of Jawaharlal Nehru Technological University Kakinada, Kakinada during the academic year 2023-24.

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ABSTRACT

Recent advances in deep learning have shown promise in the field of medical imaging and disease diagnosis, especially when it comes to challenging problems like Diabetic Retinopathy, a dangerous condition marked by uncontrolled and abnormal cell division in the retina. The goal of this work is to distinguish between areas with and without diabetic retinopathy in retinal images from diabetic patients by using convolutional neural networks for image processing and data augmentation. Using the transfer learning approach, the study goes on to assess how well a new CNN model performs in comparison to well-known pre-trained models like VGG-16, ResNet-50, MobileNet, and EfficientB0. Even with the very limited dataset used, the outcomes demonstrate the effectiveness and computational efficiency of the suggested CNN model. This study shows how well our model performs, beating competing pre-trained models in accuracy and needing far less processing resources. The results point to the possibility of the suggested Deep Retina model as a useful instrument for the precise and effective classification of diabetic retinopathy in medical imaging applications. We developed a web application that supports the people in getting answers to their inquiries and understanding the gravity of their situation using the best model.

Keywords: Transfer Learning, VGG-16, ResNet-50, MobileNet, EfficientB0, CNN.

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ABBRIVATIONS

DR	-	Diabetic Retinopathy
DL	-	Deep Learning
CNN	-	Convolution Neural Network
NPDR	-	Non-Proliferative Diabetic Retinopathy
PDR	-	Proliferative Diabetic Retinopathy
ResNet	-	Residual Network
VGG	-	Visual Geometry Group
HTML	-	Hypertext Markup Language
CSS	-	Cascading Style Sheets

CHAPTER 1
INTRODUCTION

1.1 Introduction:

One of the main causes of blindness worldwide, diabetic retinopathy (DR), is extremely common; within 20 years of diagnosis, 80% of diabetic people will acquire DR. Timely and precise intervention is essential to reduce sight-threatening consequences; therapies may include intravitreal injections of anti-vascular endothelial growth factor, steroids, or laser therapy. The efficacy of these interventions depends on early detection of the disease's progression to a stage where action is required. However, the reliance on skilled ophthalmologists and the requirement for substantial training lead to an expensive and time-consuming diagnostic process, even with the rising incidence of diabetes and the seriousness of DR. Also, since classifications usually rely on professional clinical interpretation, the subjective character of DR severity categorization and early diagnosis typically introduces variability.

Diabetic retinopathy (DR) is a microvascular entanglement of type 1 and 2 diabetes. DR causes retinal irregularities and is one of the main causes of visual impairment around the world. Approximately 33% of individuals with diabetes have DR, and practically all diabetics will foster it after some time. By 2030, DR is predicted to afflict 191 million individuals [1,2]. Though the visual weakness and deficiency brought about by DR can be prevented [3], early discovery is critical [4].

To guarantee early discovery and brief treatment, current rules propose that individuals with inadequately controlled diabetes ought to be evaluated for DR once a year. Patients previously determined to have DR ought to be checked frequently. Evaluating for DR mainly includes catching a fundus picture of the retina, which is then assessed by expert ophthalmologists.

In this work, we present a thorough end-to-end deep convolutional neural network method intended for the automated diagnosis of diabetic retinopathy and the determination of referable status, with a focus on more severe cases such as severe non-proliferative DR. By adding ultra-widefield fluorescein angiography data, we improve the precision of ground truths. Furthermore, we explore the algorithm's adaptability to different image sizes and retinal slabs in order to determine the best way to acquire optical coherence tomography angiography images for DR classification.

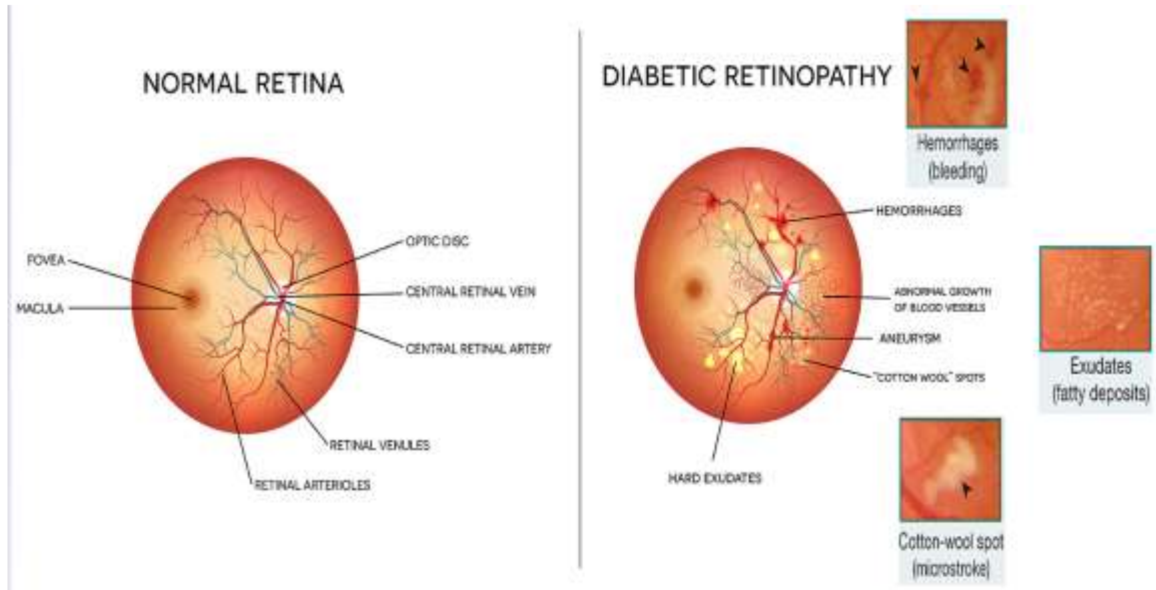


Fig: 1.1: Difference Between Normal retina and Diabetic Retina

The number of retina photographs generated via the screening program will rise with the number of diabetic patients, challenging the provision of specialized eye care for everyone, thereby imposing a huge labour-intensive burden on medical experts and costs for medical services; these issues and the growing waiting list for ophthalmic consultations are the main problems facing public health systems [5,6,7]. These problems can be alleviated by an automated system, which can be used as a support tool for medical experts or a complete diagnostic tool. Many studies have reported on the application of deep learning (DL) algorithms in the automatic detection of DR. These techniques demonstrate the great sensitivity and specificity of automatic detection systems based on deep learning artificial neural networks to the reference DR.

The automated system must be able to arrange retinal photographs in accordance with the severity of clinical practice, such as the suggested international clinical levels of diabetic macular edema and DR, which are also used in some countries, for it to be practically practicable. According to previous studies, the latest experimental results of the former DR scale can be obtained, but the latter is not used for the experimental classification of maculopathy. The enormous amount of annotated images needed for model learning is a significant barrier to the widespread and successful usage of deep learning systems

It quantitatively compares the performance of our proposed model with a machine learning-based classifier in order to verify its efficacy. Handcrafted characteristics taken from OCTA photos are used by this alternate classifier. Our results demonstrate not only the provided

model's viability but also its improved performance over conventional machine learning techniques. The present study provides significant contributions to the advancement of automated

DR detection and classification. It highlights the possible benefits of utilising UWF FA data and deep learning techniques in augmenting diagnostic precision.

Diabetic Retinopathy (DR):

Diabetic retinopathy, a complication arising from diabetes, poses a significant threat to vision if not effectively managed. This condition impacts the eyes and progresses through distinct stages. Initially, in the absence of diabetic retinopathy (No DR), there are no discernible signs. Mild non-proliferative retinopathy (mild NPDR) introduces microaneurysms in retinal blood vessels, followed by moderate NPDR where swelling or blockages may occur. Severe NPDR intensifies with more critical blockages, leading to decreased blood supply and an elevated risk of new vessel growth. Proliferative diabetic retinopathy (PDR) represents the advanced stage, characterized by the formation of fragile and abnormal blood vessels, posing a substantial risk of bleeding and retinal detachment. Proper management, including vigilant monitoring, blood sugar control, and timely medical interventions, is paramount to mitigate the risk of vision loss associated with diabetic retinopathy. Regular eye examinations are crucial for early detection and effective intervention in the varying stages of this diabetic complication.

No Diabetic Retinopathy (No_DR):

No Diabetic Retinopathy (No DR) marks the initial stage in the progression of diabetic retinopathy, a serious complication associated with diabetes that can lead to vision impairment if not adequately managed. At this early phase, individuals with diabetes exhibit no apparent signs of retinal damage during routine eye examinations. It underscores the importance of regular eye check-ups for those with diabetes to detect any potential development of retinopathy in its nascent stages. The absence of observable symptoms, however, does not diminish the significance of preventative measures and proactive diabetes management. Maintaining optimal blood sugar levels, adhering to a healthy lifestyle, and closely monitoring overall health become essential strategies to prevent the onset and progression of diabetic retinopathy. In this stage, healthcare professionals emphasize the crucial role of patient education and awareness to empower individuals with diabetes to take proactive measures in safeguarding their ocular health. By staying vigilant and addressing potential risk factors, individuals can work towards preserving their vision and avoiding the complications associated with diabetic retinopathy as they navigate through the various stages of this eye condition.

Mild Non-proliferative Retinopathy (Mild NPDR):

Mild Non-proliferative Retinopathy (Mild NPDR) constitutes an early stage in the progression of diabetic retinopathy, a condition affecting the eyes in individuals with diabetes. During this phase, small bulges known as microaneurysms manifest in the blood vessels of the retina. While these microaneurysms may not immediately impair vision, they serve as an indicator of potential vascular changes in the eye. The delicate nature of these early abnormalities underscores the importance of regular eye examinations for individuals with diabetes to facilitate the timely detection of retinopathy. Although Mild NPDR may not present with noticeable symptoms, it signals the need for proactive management of diabetes to mitigate the risk of further vascular complications. Maintaining optimal blood sugar levels, adopting a healthy lifestyle, and adhering to prescribed treatment plans are vital measures during this stage to prevent the progression of diabetic retinopathy. By addressing these factors and collaborating closely with healthcare professionals, individuals with Mild NPDR can actively contribute to the preservation of their ocular health and the prevention of more advanced stages of diabetic retinopathy, ultimately safeguarding their vision. Microaneurysms, small bulges in the blood vessels of the retina, may occur. There may be slight swelling or small amounts of fluid leakage in the retina.

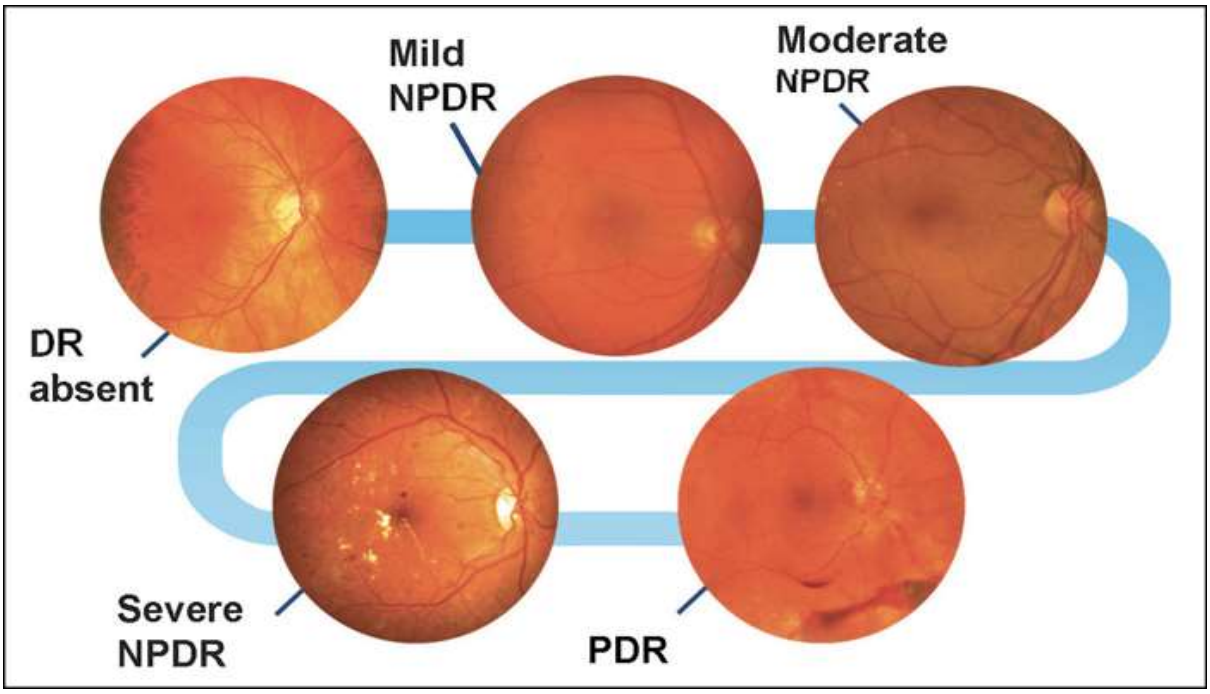


Fig: 1.2: Types of Diabetic Retinopathy

Moderate Non-proliferative Retinopathy (Moderate NPDR):

Moderate Non-proliferative Retinopathy (Moderate NPDR) signifies an intermediate stage in the development of diabetic retinopathy, a complication associated with diabetes that affects the eyes. During this phase, in addition to the presence of microaneurysms, blood vessels within the retina may exhibit signs of swelling, known as macular edema, or become obstructed. The occurrence of these vascular changes can lead to a more noticeable impact on vision compared to the earlier stage of Mild NPDR. Regular and thorough eye examinations are crucial at this point to monitor these alterations and implement timely interventions. While symptoms may still be subtle, the potential for vision impairment emphasizes the significance of proactive diabetes management. Optimal blood sugar control, adherence to prescribed medications, and lifestyle modifications become even more critical in mitigating the progression of diabetic retinopathy during Moderate NPDR. Collaborative efforts between individuals with diabetes and their healthcare providers are essential to develop effective strategies for maintaining ocular health and preventing the advancement of retinal complications. Timely interventions and continued vigilance are key components in preserving vision and mitigating the impact of diabetic retinopathy during the Moderate NPDR stage.

Severe Non-proliferative Retinopathy (Severe NPDR):

Severe Non-proliferative Retinopathy (Severe NPDR) marks an advanced stage in the progression of diabetic retinopathy, a complication stemming from diabetes that affects the eyes. At this stage, individuals experience more critical blockages in the blood vessels of the retina, leading to a decreased blood supply to specific areas of the retina. This diminished blood flow increases the risk of developing new and abnormal blood vessels, signalling a heightened threat to vision. The severity of vascular changes underscores the importance of regular and vigilant eye examinations to detect and address these advanced complications. While symptoms may not yet be overtly noticeable, the potential for further vision impairment becomes more significant. Managing diabetes becomes even more crucial during Severe NPDR, requiring meticulous control of blood sugar levels and adherence to prescribed treatments. Collaborative efforts between individuals with diabetes and healthcare professionals are imperative to develop personalized strategies for managing the condition and preventing further retinal damage. Severe NPDR serves as a critical juncture in the progression of diabetic retinopathy, highlighting the need for proactive intervention to mitigate the risk of vision loss and promote ocular health in individuals with diabetes.

Proliferative Diabetic Retinopathy (PDR):

Proliferative Diabetic Retinopathy (PDR) represents the advanced and potentially sight-threatening stage of diabetic retinopathy, a complication associated with diabetes affecting the eyes. During PDR, fragile and abnormal blood vessels develop on the surface of the retina or extend into the vitreous gel, the clear gel filling the eye. These new vessels are prone to bleeding, leading to vitreous haemorrhage, and can result in the formation of scar tissue. The growth of this scar tissue increases the risk of retinal detachment, a serious condition that can lead to permanent vision loss. PDR poses a significant threat to vision, and individuals at this stage often experience symptoms such as floaters, blurred vision, or even sudden and severe vision loss. Timely and comprehensive management is crucial, involving interventions such as laser therapy or injections to reduce the risk of complications. Tight control of blood sugar levels, along with ongoing collaboration between individuals with diabetes and healthcare providers, is essential in navigating the challenges posed by PDR. Regular eye examinations and proactive measures are pivotal in preserving vision and mitigating the severe consequences associated with proliferative diabetic retinopathy. This is the advanced and potentially sight-threatening stage of diabetic retinopathy. New blood vessels, which are fragile and abnormal, grow on the surface of the retina or into the vitreous gel (the clear gel that fills the inside of the eye). These new vessels can bleed into the eye, leading to vitreous haemorrhage. Scar tissue may form, pulling on the retina and increasing the risk of retinal detachment.

1.2 Objectives:

The following are the objectives of this project:

- Assess the model's efficacy in identifying diabetic retinopathy quantitatively by comparing it to existing techniques and measuring accuracy, sensitivity, and specificity.
- Examine the model's flexibility and stability in relation to different retinal slabs and picture sizes in order to maximise the diagnostic procedure.
- Assess the clinical viability of the suggested model by contrasting its results with those of other diagnostic modalities, like human grading and conventional clinical evaluations.
- Explore how adding OCTA data to the deep learning model can improve its specificity and accuracy while offering more information about the retinal microvasculature and better diagnostic tools

1.3 Problem Statement:

To deploy Deep Learning (DL) interface on DR in multi-class classification by building a progressive web application that classifies the images of eye based on the level of diabetes.

Automated Detection: Develop a deep learning model capable of automatically detecting diabetic retinopathy from fundus images, eliminating the need for manual screening and reducing the time and cost associated with diagnosis.

Severity Classification: Implement a classification system within the model to categorize detected cases of diabetic retinopathy into different severity stages (mild, moderate, severe, proliferative), enabling tailored treatment plans and interventions based on the severity of the condition.

Address Data Imbalance: Employ techniques to mitigate data imbalance issues within annotated datasets, ensuring that the model is trained effectively across all severity stages of diabetic retinopathy and yielding more accurate predictions, particularly for minority classes.

Validation and Compliance: Conduct rigorous validation studies to assess the model's performance, including cross-validation on diverse datasets and comparison with manual grading systems. Ensure compliance with medical regulations and standards, such as FDA approval and data privacy regulations, to ensure the legality, safety, and ethical use of the developed solution in clinical settings.

CHAPTER 2
LITERATURE REVIEW

A prospective randomised trial comparing the effectiveness of intravitreal bevacizumab with laser therapy is used in the study by Michaelides et al. to address the management of diabetic macular edoema [1]. If diabetes-related macular edoema is not adequately managed, it may result in visual impairment. The major outcome measure was the change in visual acuity over a 12-month period, and the approach involved randomly assigning patients to groups receiving either bevacizumab or laser therapy. Variations in illness severity and the particular patient demographics may have an impact on how generalizable the findings are. The limitations point out the importance of interpreting results carefully and offer directions for further study to overcome these limitations.

In their research, Ozieh et al. look into the patterns in healthcare spending among American individuals with diabetes[3].The financial consequences of managing diabetes are a major public health concern, and healthcare policy and resource allocation depend heavily on this knowledge. Technical specifics would include the utilisation of datasets like the Medical Expenditure Panel Survey and the inclusion standards for choosing the research subjects. Determining healthcare utilisation trends, direct medical expenditures, and variables impacting changes in spending during the years under study are probably all part of the analysis. The use of self-reported data, the omission of certain cost components, or differences in the research population's healthcare coverage are some potential drawbacks.

The development and validation of a deep learning algorithm intended for the identification of diabetic retinopathy in retinal fundus pictures is the main subject of the JAMA article by Gulshan et al[6].The procedures used to train and validate the deep learning algorithm are described in the methodology section. The researchers most likely employed a convolutional neural network architecture for feature extraction and classification, working with a sizable collection of retinal fundus photos. To improve the algorithm's capacity to generalise across different diabetic retinopathy presentations, it was trained on a wide range of pictures. The interpretability of deep learning models, potential biases in the training data, and the requirement for ongoing updates to account for changing patterns of diabetic retinopathy are a few examples of these constraints.

Gargeya and Leng's study uses deep learning techniques to automate the diagnosis of diabetic retinopathy [8]. The authors most likely describe the deep learning model's architecture in the technique section, maybe using a convolutional neural network. A sizable collection of retinal images with manual annotations for the severity of diabetic retinopathy most likely played a role in the training process. To make sure the model is accurate and reliable in real-world situations, its robustness is probably put to the test through stringent validation methods.The limits section may address issues with model interpretability, potential biases in training data, and the requirement for ongoing upgrades to stay up to speed with changing patterns of diabetic retinopathy, all while acknowledging the intricacies of deep learning models.

The study conducted by Eladawi and colleagues centres on the timely identification of indicators of diabetic retinopathy by employing Optical Coherence Tomography Angiography images[11]. The methods section perhaps sheds light on the 3D multi-path CNN's architecture and the preprocessing techniques used on the scans. It is likely that a large dataset containing annotations for early indicators of diabetic retinopathy was used in the training procedure. The multi-path technique, which allows for a more thorough comprehension of the complicated aspects in data, may be the study's unique contribution. It is possible to highlight potential limitations, such as the need for additional validation in a variety of patient populations, potential artefacts, and difficulties in obtaining standardised OCTA scans.

CHAPTER 3
PROPOSED METHOD

3.1 Convolution Neural Network:

Convolutional Neural Networks (CNNs) are a class of deep neural networks designed primarily for processing structured grid data, such as images and videos. One of the key features that sets CNNs apart from traditional neural networks is their use of convolutional layers. These layers employ convolutional operations, which involve small filters or kernels that move across the input data to extract local patterns. This spatial hierarchy allows CNNs to capture hierarchical representations of features, learning low-level features like edges and textures in early layers and progressively combining them to recognize more complex patterns and objects in deeper layers.

The convolutional layers in CNNs are pivotal for their success in computer vision tasks. These layers consist of filters that convolve over the input data, performing element-wise multiplications and aggregations to create feature maps. The filters' weights are learned during the training process, enabling the network to automatically adapt and identify relevant patterns in the data. This localized connectivity ensures that CNNs are robust to translations and can effectively capture spatial dependencies, making them highly suitable for image recognition.

CNNs are uniquely adept at capturing intricate patterns and hierarchical representations within visual data, mimicking the way the human visual system operates. The architecture of a CNN is designed to mimic the biological processes of the human visual system, making it exceptionally proficient in discerning features and recognizing objects within images. Convolutional layers, pooling layers, and fully connected layers work in tandem to create a network capable of learning and extracting hierarchical features from raw pixel data.

In a regular Neural Network there are three types of layers:

3.1.1 Input Layers:

It's the layer in which we give input to our model. The number of neurons in this layer is equal to the total number of features in our data (number of pixels in the case of an image). The input layers takes the input data and pre process the data according the input required for the hidden layers to process the data to train the model and give the desired output or classification.

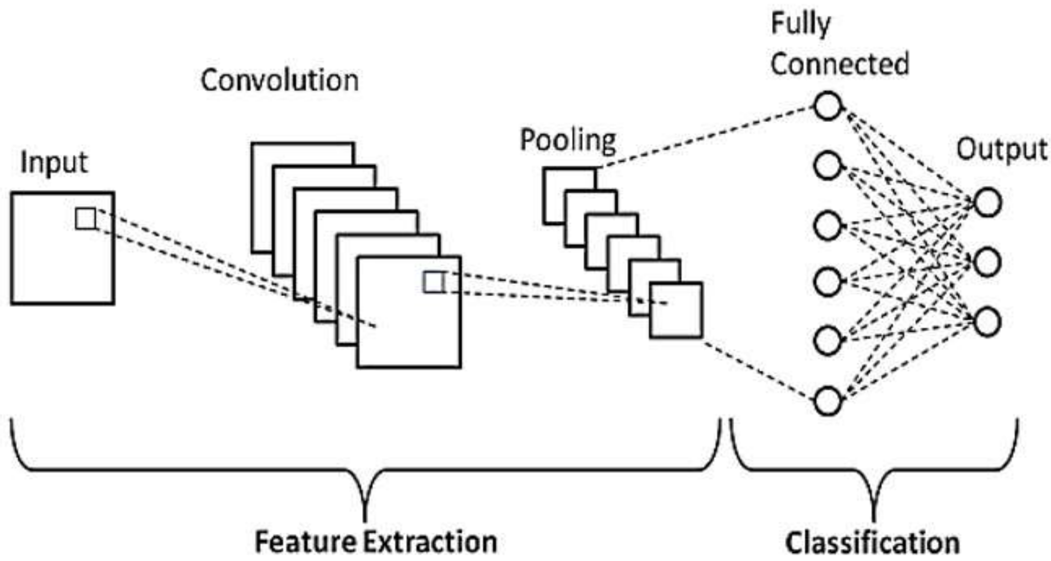


Fig: 3.1: Simple Convolution Neural Network Model

3.1.2 Hidden Layer:

The input from the Input layer is then fed into the hidden layer. There can be many hidden layers depending on our model and data size. Each hidden layer can have different numbers of neurons which are generally greater than the number of features. The output from each layer is computed by matrix multiplication of the output of the previous layer with learnable weights of that layer and then by the addition of learnable biases followed by activation function which makes the network nonlinear.

3.1.3 Output Layer:

The output from the hidden layer is then fed into a logistic function like sigmoid or softmax which converts the output of each class into the probability score of each class.

Additionally, pooling layers are often interspersed between convolutional layers to down sample the spatial dimensions of the feature maps. Common pooling operations include max pooling, which retains the maximum value in a local region, and average pooling, which computes the average. This down sampling reduces the computational load and makes the network more resilient to variations in input scale and orientation. The combination of convolutional and pooling layers allows CNNs to efficiently learn hierarchical representations, starting with simple features and progressing to complex, high-level abstractions.

Furthermore, CNN architectures often conclude with fully connected layers that integrate the learned features for final classification or regression. The hierarchical nature of CNNs, coupled with their ability to automatically extract relevant features, has made them indispensable in tasks like image classification, object detection, and facial recognition. As technology advances, CNNs continue to evolve with improvements in architecture, regularization techniques, and training strategies, solidifying their role in various applications beyond traditional computer vision domains.

The architecture of a typical CNN consists of multiple layers, including convolutional layers, pooling layers, and fully connected layers. Convolutional layers play a crucial role in feature extraction, while pooling layers help reduce the spatial dimensions of the data, preserving important information and reducing computational complexity. The fully connected layers at the end of the network consolidate the extracted features and map them to the final output classes. CNNs have achieved remarkable success in computer vision tasks, such as image classification, object detection, and image segmentation, due to their ability to automatically learn hierarchical representations and capture spatial dependencies in data.

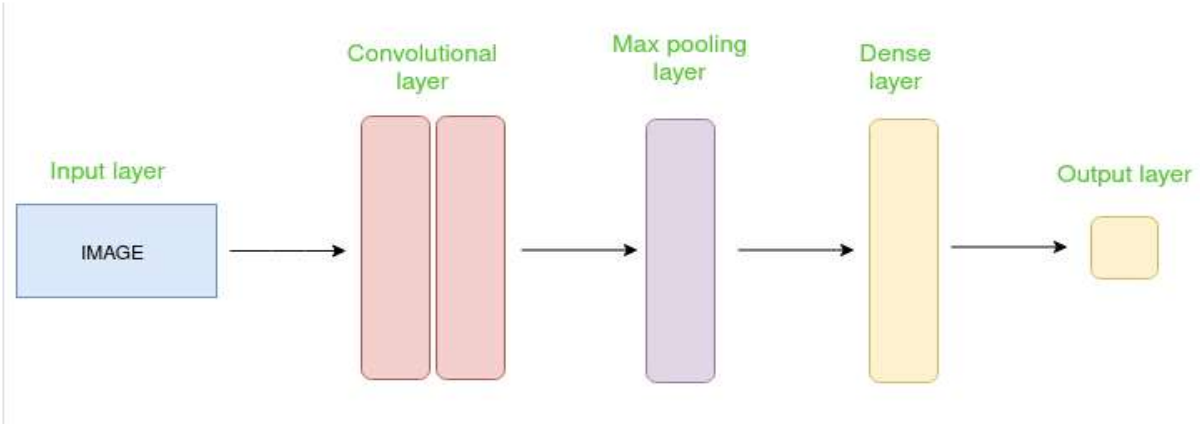


Fig: 3.2: Simple Architecture of Pre-trained Models

The training process of a CNN involves optimization through backpropagation and gradient descent, where the network learns to minimize the difference between its predicted output and the true labels. Transfer learning, where a pre-trained CNN is fine-tuned on a specific task, has become a common practice, leveraging the knowledge gained from large datasets like ImageNet. CNNs have found applications beyond computer vision, including natural language processing and speech recognition, showcasing their versatility and effectiveness in various domains. As computational resources continue to advance, CNNs are likely to play an increasingly vital role in addressing complex problems across different fields.

3.2 Methodology:

An emphasis on speed, precision, and real-time processing characterises the suggested method for identifying and managing diabetic retinopathy in retinal pictures. First, it makes use of the EfficientNetB0 model, which is well known for its remarkable accuracy and economical use of memory. In situations where processing resources are scarce, such embedded systems and mobile devices, this option is especially beneficial because it meets the demand for quick and resource-efficient medical picture analysis.

In order to improve the model's resilience and make the most of the available training data, the method makes use of ImageDataGenerator for data augmentation. By applying random modifications to training images, this method enhances the generalisation capabilities of the model. The method also incorporates additional pre-trained models, such as ResNet50, VGG16, MobileNetV2, and EfficientB0, to further expand its capabilities. Using pre-trained weights from the ImageNet dataset speeds up training and improves model performance.

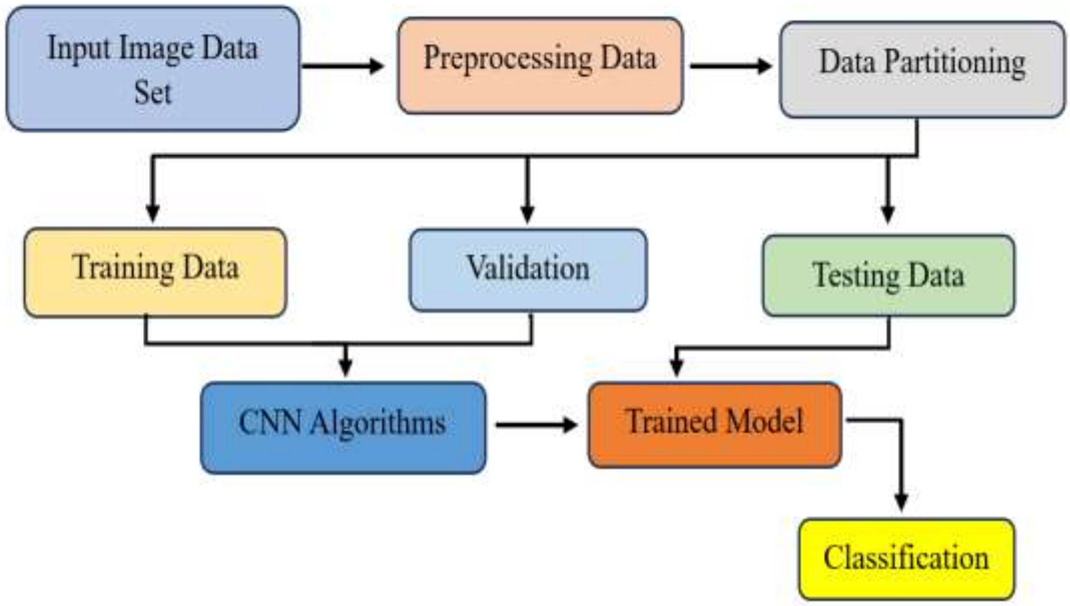


Fig: 3.3: Proposed Model of Diabetic Retinopathy Detection

Important layers in the model architecture, such as Dropout and GlobalAveragePooling2D, are included to help with efficient feature extraction and guard against overfitting. The last Dense layer divides photos into four groups, each of which represents a distinct diabetic retinopathy condition. By using a number of callbacks, such as LambdaCallback for reporting confusion matrices, Model Checkpoint for storing model weights, Early Stopping to avoid overfitting, and ReduceLROnPlateau to maximise the learning rate during training, the method significantly improves the training process. This all-inclusive method is especially made to deal with the special difficulties involved in identifying diabetic retinopathy in retinal pictures. The suggested technique has the potential to have a big impact on the healthcare sector by offering a rapid and accurate solution as well as an effective diagnostic tool.

3.2.1ResNet50 (Residual Network):

A well-known deep convolutional neural network architecture known for its depth and creative use of residual connections is called ResNet50, or Residual Network with 50 layers. ResNet50 stands out for its capacity to effectively train deep networks, even in the face of obstacles like the vanishing gradient problem. With 50 layers, the network has an outstanding depth, denoted by the number "50".

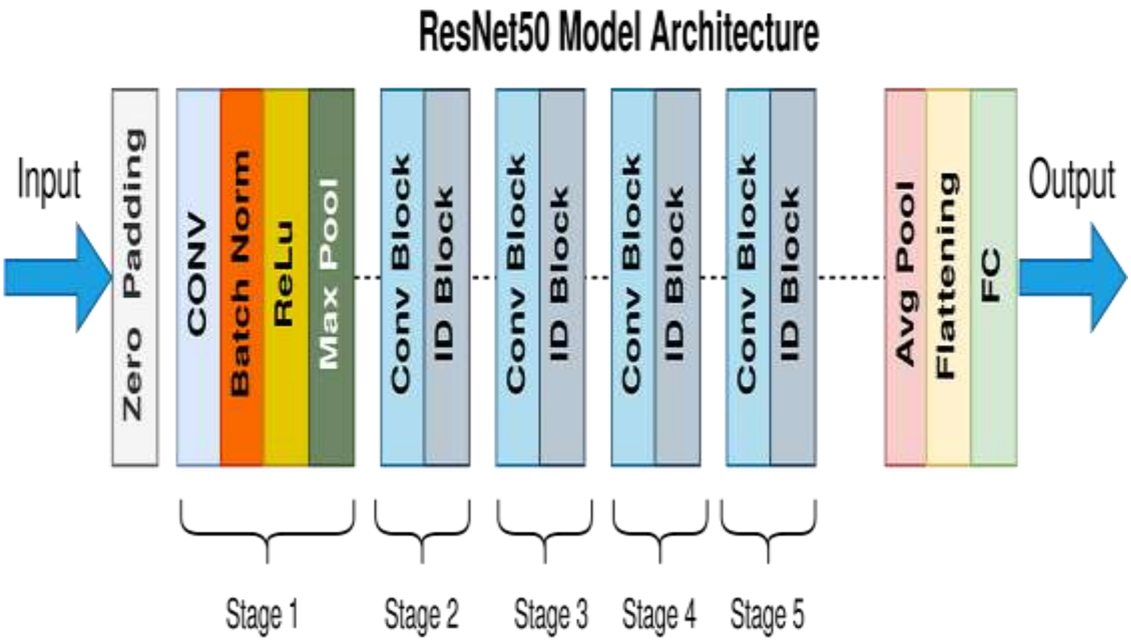


Fig: 3.4: Resnet-50 Model Architecture

Renowned for its extraordinary precision, ResNet50 finds wide use in picture classification applications and performs exceptionally well across a range of computer vision areas. ResNet50 is a medical image processing tool that has been used to classify diabetic retinopathy and other conditions by taking use of its ability to recognise complex patterns and characteristics in images.

3.2.1 VGG16:

One of the most effective and straightforward deep learning models is the VGG16 (Visual Geometry Group 16) architecture. VGG16, which consists of 16 layers, uses 3x3 convolutional filters with small strides and max-pooling layers. Especially, VGG models like VGG16 are praised for their strong feature extraction powers. Because of its repeating and layered layer architecture, VGG16 is a popular choice for a variety of computer vision tasks, especially in medical picture analysis. VGG16 is utilised in the particular context of the previously mentioned project for classification tasks pertaining to diabetic retinopathy. It is a useful tool in deep learning applications due to its shown effectiveness in feature learning and picture categorization.

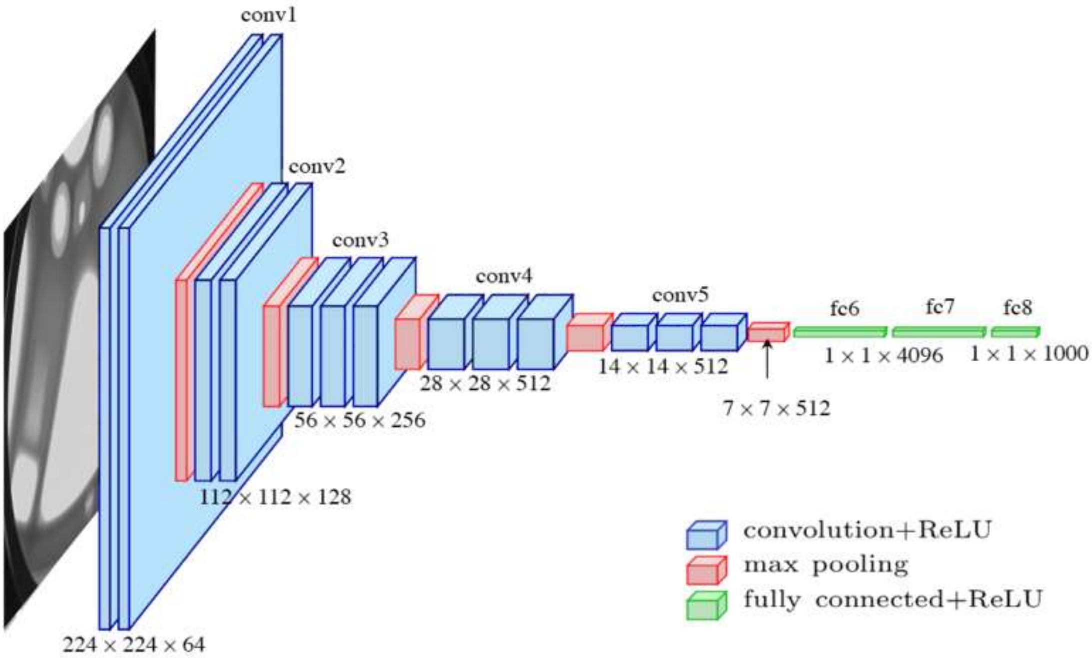


Fig: 3.5: VGG16 Model Architecture

Often used as a pretrained model, VGG16 is first trained on large-scale datasets such as ImageNet and then adjusted for particular tasks. Transfer learning using VGG16 has proven to be highly useful in the field of medical image analysis, particularly for tasks like the recognition and classification of characteristics associated with diabetic retinopathy in retinal pictures. Because of its adaptability and dependability, VGG16 is a crucial part of the project's deep learning framework and helps classify diabetic retinopathy accurately and effectively.

3.2.3 MobileNetV2:

An important tool in the context of the endeavour in concern is MobileNetV2, an extension of the MobileNet architecture created especially for embedded and mobile vision applications. Because of its efficient and lightweight architecture, MobileNetV2 is especially useful for mobile devices that operate in contexts with limited resources.

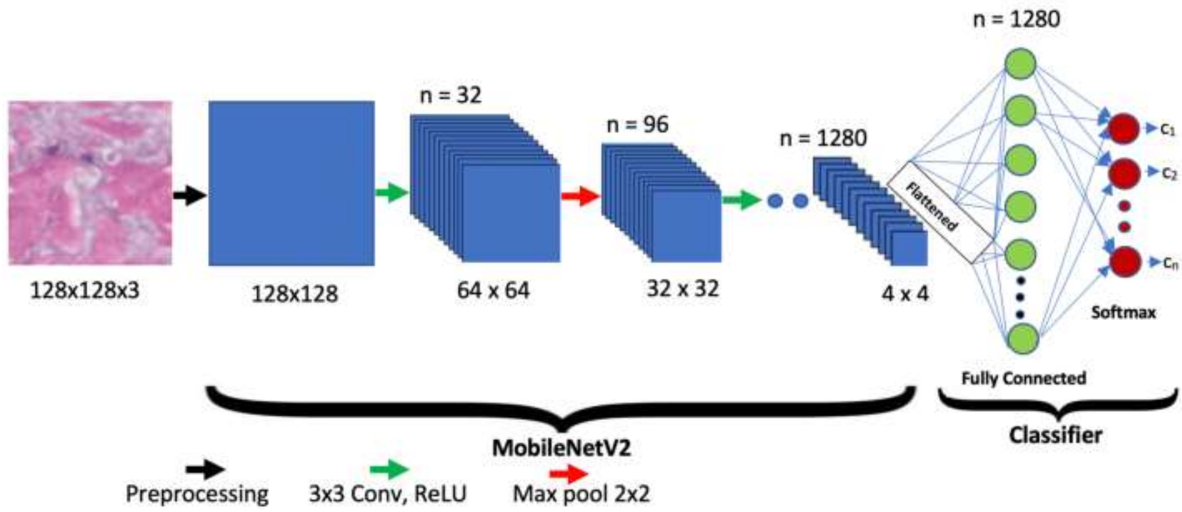


Fig: 3.6: MobileNetV2 Model Architecture

Especially in healthcare applications, its efficiency is critical for real-time photo analysis. Battery life preservation and reduced computational load are made possible by MobileNetV2's lightweight design, which is a crucial component for embedded and mobile systems. MobileNetV2 is a logical candidate for implementing AI-driven diagnostic tools in the medical area because of its versatility and resource-friendly nature, particularly in the project's focus on diabetic retinopathy classification.

3.2.4 EfficientNetB0:

Within the family of EfficientNet models is the convolutional neural network architecture known as EfficientNetB0. EfficientNetB0 was created with the goal of achieving higher accuracy while utilising less CPU power. It has become well-known for its abilities in picture classification and feature extraction, among other computer vision applications. The architecture is made to maximise computational resources by balancing the model's width, depth, and resolution. The EfficientNet-B0 is a mobile architecture that only has 11 million trainable parameters. This model uses 7 inverted residual blocks and Swish activation function (it is a multiplication of Linear and Sigmoid activation). The reason why these models perform so well is because it does not solely focus on scaling for depth like the Res Net models. Here width, resolution and depth are all scaled in a compound manner leading to better results. This model servers as a base for the family of Efficient Net models that range from EfficientNet-B0 to EfficientNet-B7. The Efficient Net family of models is probably the most advance CNN architecture because it achieves high accuracy while using a considerably smaller number of parameters.

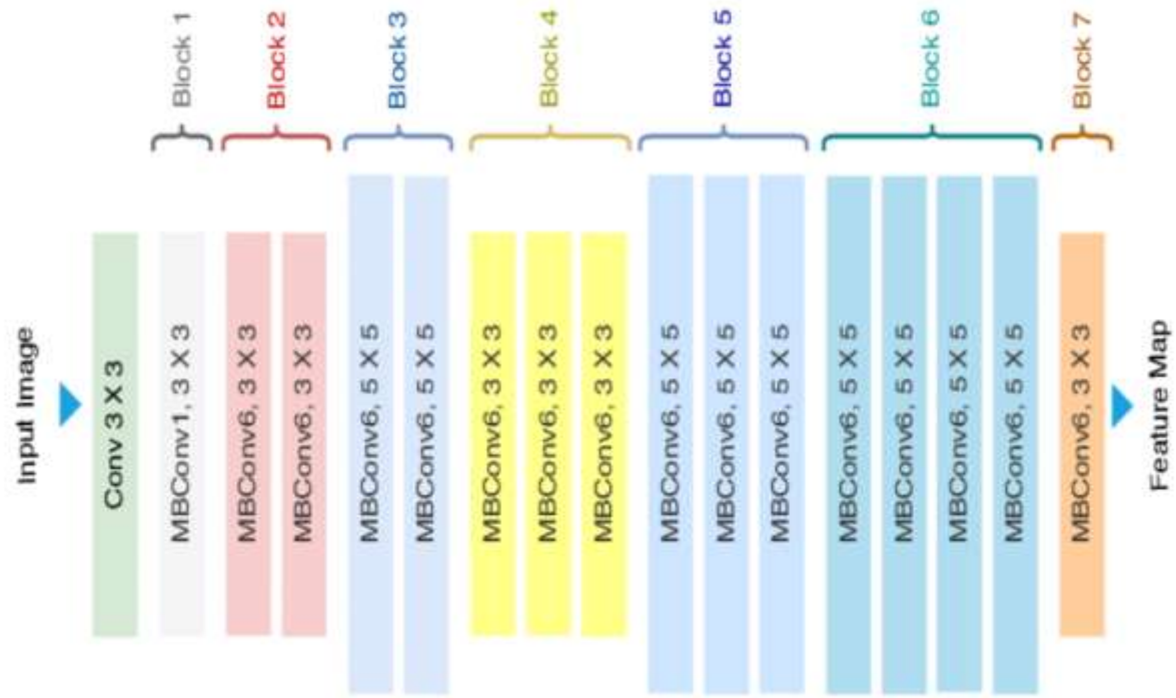


Fig: 3.7: EfficientB0 Model Architecture

For deployment in situations where resources are few, like embedded systems or mobile devices, EfficientNetB0 is especially well-suited. Because of its precision and efficiency, EfficientNetB0 is a useful tool when it comes to medical imaging duties. It could help with activities where real-time processing and resource optimisation are essential, such as brain tumour diagnosis or diabetic retinopathy categorization.

3.3 Implementation:

Fine-tuning a pre-trained model involves taking a model that has been trained on a large dataset and then adapting it to a new, smaller dataset. In the context of diabetic retinopathy detection, you would typically take a pre-trained model (like ResNet50) and adjust its weights to better suit the task of classifying retinal images for signs of diabetic retinopathy.

Here's a step-by-step implementation of how you might fine-tune a pre-trained model for diabetic retinopathy detection:

Step 1: Choose a Pre-trained Model

Step 2: Load the Pre-trained Model

Step 3: Modify the Model Architecture

Step 5: Compile the Model

Step 6: Prepare the Data

Step 7: Train the Model

Step 8: Evaluate the Model using Evaluation Metrics

Step 9: Save the Model in .h5 file.

Below is a step-by-step implementation guide for building a web application for Diabetic Retinopathy detection using Flask and a pre-trained deep learning model.

Step 1: Setup Flask Environment by importing required Libraries

Step 2: Create Flask Application

Step 3: Define Constants and Load Model

Step 4: Implement Utility Functions

Step 5: Define Flask Routes

Step 6: Handle Image Uploads and Prediction

Step 7: Create HTML Templates by using CSS and Bootstrap

Step 8: Run the Flask Application

3.3.1 Pre-Trained Model:

Among computer vision techniques, using pre-trained deep convolutional neural network models is a common and successful approach, especially when it comes to classifying diabetic retinopathy (DR). Usually, a wide variety of images and object categories are provided to these models during their pre-training phase using extensive benchmark datasets such as ImageNet. Using pre-trained models has the benefit of saving a great deal of time and computational power compared to training a new model from scratch. This approach, which is also known as "transfer learning," uses well-known models like ResNet50, VGG16, EfficientNetB0, or MobileNetV2 as a basis for a fresh computer vision job.

Custom layers are usually added to a pre-trained model to customise it for a particular use case. The task-specific features are learned by these custom layers. To preserve the important characteristics and representations discovered from ImageNet data, the pre-trained layers' weights are frequently frozen during the early phases of training. The model as a whole or individual layers can then be adjusted to better match the target dataset. Pre-trained models have a number of benefits, such as improved model performance, faster convergence, and the capacity to function with smaller datasets. The pre-trained model's generalization abilities make it a good fit for a number of computer vision tasks, such as the categorization of diabetic retinopathy.

3.4 Software Requirements:

3.4.1. PYTHON (version 8.0 and above):

Python is a general-purpose interpreted, interactive, object-oriented, and highlevel programming language. Python is designed to be highly readable. It uses english keywords frequently where as other languages use punctuation, and it has fewer syntactical constructions than other languages.

Applications of Python As mentioned before, Python is one of the most widely used languages over the web.

Here are a few applications of Python:

- Easy-to-maintain − Python's source code is fairly easy-to-maintain.
- A broad standard library − Python's bulk of the library is very portable and cross-platform compatible on UNIX, Windows, and Macintosh.
- Interactive Mode − Python has support for an interactive mode which allows interactive testing and debugging of snippets of code.
- Portable − Python can run on a wide variety of hardware platforms and has the same interface on all platforms.
- Extendable − You can add low-level modules to the Python interpreter. These modules enable programmers to add to or customize their tools to be more efficient.
- Databases − Python provides interfaces to all major commercial databases.
- GUI Programming − Python supports GUI applications that can be created and ported to many system calls, libraries and windows systems, such as Windows MFC, Macintosh, and the X Window system of Unix.

3.4.2 NumPy:

NumPy is a general-purpose array-processing package. It provides a highperformance multidimensional array object, and tools for working with these arrays.

It is the fundamental package for scientific computing with Python. It contains various features including these important ones:

- A powerful N-dimensional array object
- Sophisticated (broadcasting) functions
- Tools for integrating C/C++ and Fortran code

- Useful linear algebra
- Fourier transform, and random number capabilities

3.4.3 Pandas:

Pandas is the most popular python library that is used for data analysis. It provides highly optimized performance with back-end source code is purely written in C or Python. We can analyse data in pandas with

1. Series
2. Data frames

3.4.4 Matplotlib:

Matplotlib is a Python library widely used for creating static, interactive, and animated visualizations. It offers a range of plotting functions for various types of plots such as line plots, scatter plots, bar plots, histograms, pie charts, and more. Matplotlib provides both a state-based interface (via pyplot module) and an object-oriented interface, giving users flexibility in creating and customizing plots. With Matplotlib, you can customize almost every aspect of your plots, including colors, styles, labels, and annotations. It supports multi-plotting within the same figure, saving plots as image or vector files, and seamless integration with Jupyter Notebooks. Overall, Matplotlib is a powerful tool for data visualization in Python, widely used in fields like data science, machine learning, and scientific computing.

3.4.5 TensorFlow:

TensorFlow, an open-source software library developed by the Google Brain team, is a versatile and powerful tool in the realm of dataflow and differentiable programming. It functions as a symbolic math library, allowing users to define and execute mathematical operations symbolically, especially in the context of machine learning tasks such as building and training neural networks.

The library's name, "TensorFlow," reflects its fundamental data structure — tensors. Tensors are multi-dimensional arrays, and TensorFlow's computational graph efficiently represents and executes operations on these tensors. This graph-based approach enables automatic differentiation, a crucial feature for optimizing and training machine learning models.

One of TensorFlow's strengths lies in its broad applicability. Researchers and practitioners leverage TensorFlow across a spectrum of tasks, from developing novel machine learning algorithms to deploying production-grade models. Its flexibility and scalability make it an ideal choice for projects ranging from academic research to large-scale industrial applications.

The library has played a pivotal role in advancing the field of deep learning. TensorFlow provides a comprehensive ecosystem that includes high-level APIs for quick model development (such as Keras) and lower-level APIs for fine-grained control over model architecture and training processes.

TensorFlow's impact extends beyond the research and development phases. It has become an integral part of Google's infrastructure, utilized in various production systems and services. This real-world deployment at Google underscores the reliability and efficiency of TensorFlow in handling complex tasks at scale.

In summary, TensorFlow stands as a powerhouse in the world of machine learning, offering a flexible and scalable platform for dataflow and differentiable programming. Its adoption in both research and production settings, coupled with its rich ecosystem, positions TensorFlow as a cornerstone in the ever-evolving landscape of artificial intelligence and machine learning.

3.4.6 Keras:

Keras is an open-source neural-network library written in Python. It is capable of running on top of TensorFlow, Microsoft Cognitive Toolkit, R, Theano, or Plaid ML. Designed to enable fast experimentation with deep neural networks, it focuses on being user-friendly, modular, and extensible. Keras contains numerous implementations of commonly used neural-network building blocks such as layers, objectives, activation functions, optimizers, and a host of tools to make working with image and text data easier to simplify the coding necessary for writing deep neural network code.

3.4.7 Flask:

Flask is a lightweight web application framework for Python, known for its minimalist design and flexibility. It follows the WSGI standard, making it compatible with various web servers. Flask uses simple routing with decorators to map URLs to Python functions and includes the Jinja2 template engine for dynamic HTML generation. While Flask's core is small, it's highly extensible through a wide range of extensions for tasks like database integration and authentication. It's suitable for building RESTful APIs and supports both small projects and large-scale applications. Overall, Flask is valued for its simplicity, versatility, and active community support.

3.4.8 HTML, CSS and Boot strap:

HTML (Hypertext Markup Language):

HTML is the standard markup language used to create the structure and content of web pages. It consists of a series of elements, which are represented by tags enclosed in angle brackets (< >).

Each HTML tag describes different content or structure on the page. For example, <html>, <head>, <title>, <body>, <div>, <p>, <a>, <img>, etc. HTML provides the basic building blocks for web pages.

CSS (Cascading Style Sheets):

CSS is a stylesheet language used for describing the presentation of a document written in HTML. It allows you to control the layout, design, and appearance of HTML elements on a web page. With CSS, you can specify styles such as colours, fonts, margins, padding, borders, and more. CSS styles can be applied inline within HTML elements, embedded within the <style> tag in the document's <head>, or defined externally in separate CSS files.

Bootstrap:

Bootstrap is a popular front-end framework for building responsive and mobile-first websites and web applications. It provides a set of pre-designed HTML and CSS templates, components, and utilities that help developers create consistent and visually appealing user interfaces quickly. Bootstrap includes styles for typography, forms, buttons, navigation bars, grid layout system, modal dialogs, and more. By using Bootstrap, developers can save time and effort in designing and styling their web projects, as it offers a standardized and customizable set of components.

3.5 Hardware Requirements:

- Processor: Intel Core i5 or above.
- 64-bit, quad-core, 2.5 GHz minimum per core
- Ram: 4 GB or more
- Hard disk: 10 GB of available space or more.
- Display: Dual XGA (1024 x 768) or higher resolution monitors
- Operating system: Windows

3.6 Data Preparation:

Compile an image dataset of DR scans and the labels that correspond to the presence or absence of DR. The endeavor's dataset is a sizable collection of high-resolution retinal photographs taken under various imaging settings. Both the left and right eye fields are used to represent each subject, and the photos are labelled with the subject ID and the eye side (e.g., 1_left.jpeg corresponds to the left eye of patient ID 1). The clinicians' assessments, which evaluate each image for the presence of diabetic retinopathy (DR) on a scale from 0 to 4, are the most important component of this collection. 0 represents no DR, 1 indicates mild DR, 2 indicates moderate DR, 3 indicates severe DR, and 4 indicates proliferative DR.

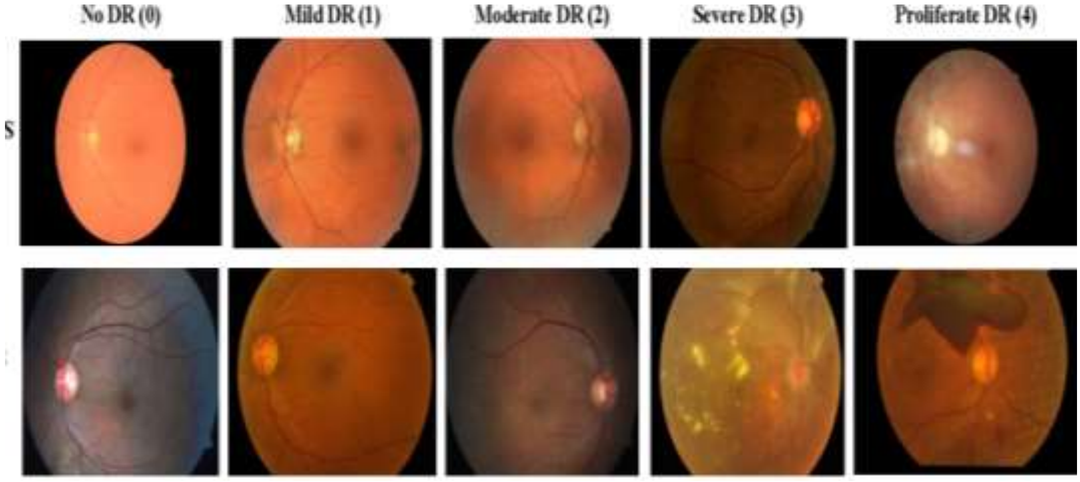


Fig: 3.8: Types of Sample DR in Dataset

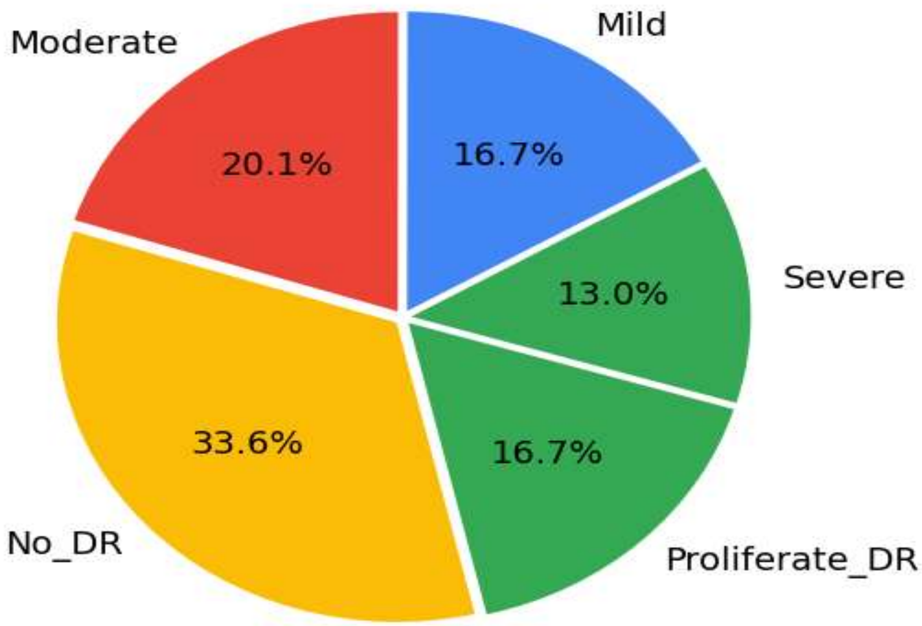


Fig: 3.9: Percentage of images of each type in DR-Dataset

3.6.1 Load and split the Data:

Obtaining medical pictures of the retina is critical for the classification of diabetic retinopathy (DR). Fundus photography is frequently used to get retinal images, which offer a thorough view of the retina's internal structures and make it possible to identify anomalies linked to diabetic retinopathy. Retinal scans serve as the main source of data for this study; each image has a caption indicating the severity of diabetic retinopathy. Digital file formats like JPEG and PNG might be used to store these pictures. The data is splited in to train and validation or test data for the validation of the model.

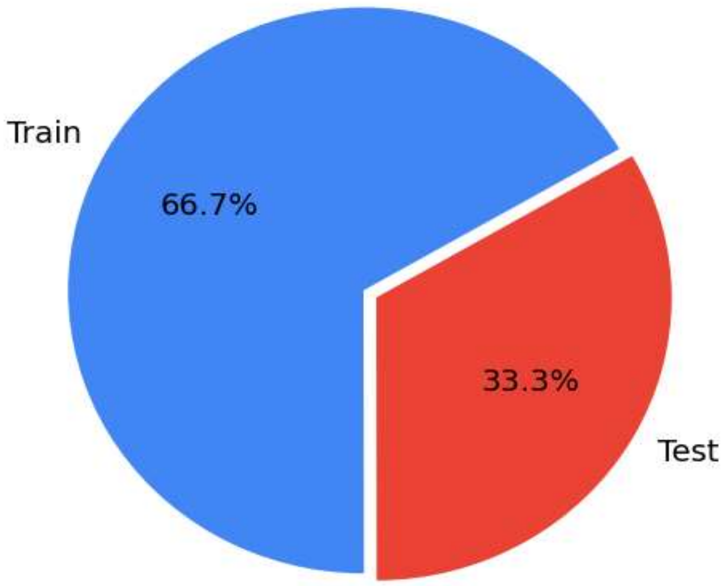


Fig: 3.10: Percentage of Train and Test Dataset

3.6.2 Pre-processing:

Before using medical pictures in a machine learning framework for the categorization of diabetic retinopathy (DR), preprocessing is essential to improving their quality and relevance. To guarantee the best possible data quality, a number of common preprocessing methods are used on the retinal images.

Table 3.1: Scaled Values of Each DR.

Type of DR	Scaled Value
NO_DR	0
Mild_DR	1
Moderate_DR	2
Severe_DR	3
Proliferative_DR	4

3.6.3 Data Normalization:

Because unscaled input variables could produce a lethargic or inaccurate learning process. The pixel values images must be scaled prior to providing the images as input to a deep learning neural network model during the training or evaluation of the model

Traditionally, the image would have to be scaled prior to the development of the model and stored in memory or on disk in the scaled format

An alternative approach is to scale the images using a preferred scaling technique past-in-time during the training or model evaluation process. Keras supports this type of data preparation for image data via the ImageDataGenerator class and API

We are going to use Standard Scaler from the sklearn library to scale the data. The scaler is fit on the training set and it is used to transform the unseen data on validation and test set. If we would fit the scalar on all data, the model would overfit and it would achieve good results on this data, but performance would suffer on the real-world data

3.6.4 Data Augmentation:

Data augmentation is a potent machine learning technique that shows promise in the classification of diabetic retinopathy (DR). Enhancing the model's capacity for generalization, resolving data shortages, and maximizing overall performance are its main goals. Essentially supplementing the dataset, this strategy entails modifying the current data in a variety of ways to produce new training instances. Data augmentation plays a crucial role in allowing the model to learn from a wider variety of examples in situations where there is a shortage of training data. Rotation, flipping, and scaling are common transformations used in this context.

The particulars of the situation at hand and the properties of the DR dataset determine how effective a certain augmentation strategy will be. Finding a balance during augmentation is essential to adding diversity while maintaining the data's semantic significance. The performance of predictive models can be greatly enhanced by carefully choosing and configuring augmentation procedures, particularly when there is an imbalance or lack of data.

3.6.5 Bilateral Filtering:

In order to reduce noise in the retinal pictures while maintaining important details and edges, bilateral filtering is used. In medical imaging, noise reduction is particularly important for precise diabetic retinopathy diagnosis and analysis. Bilateral filtering helps to improve overall image quality and reduce artifacts in fundus photos. Better separation between the diabetic retinopathy's symptoms and the surrounding retinal tissues is made possible by this procedure.

3.6.6 Resize:

Consistency in data dimensions is necessary for efficient input into a deep learning model for the classification of diabetic retinopathy. In order to enable efficient processing within deep learning frameworks, the resizing stage resizes the retinal images to a standard size, such as 128x128 pixels. Figures 11 illustrate how important this uniformity in image dimensions is for training and optimizing the model's performance.

Fig: 3.11: Before and After Image Preprocessing

CHAPTER 4

RESULTS AND DISCUSSIONS

4.1 Evaluation and Metrics:

A classifier's standard evaluation is based on a number of predefined performance indicators. Our models are assessed using the following metrics: Accuracy, Specificity, F-score, Precision, and Recall. First, we used a confusion matrix and made inferences from it for the classification algorithms. A confusion matrix is a table that, given a set of test data for which the real values are known, provides details on the quality or performance of a model for two or more types of classes. The simplest confusion matrix for the classifier 2 class, as seen in Fig: 4.1, is a two-dimensional confusion matrix.

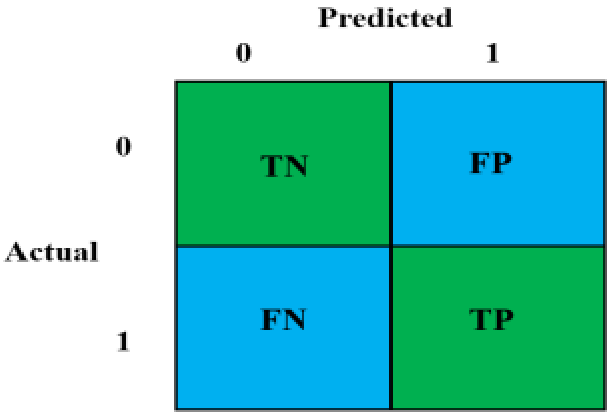


Fig: 4.1: Confusion Matrix

- ***True Positives (TP):*** When the model correctly predicts the positive class, the result is a true positive.
- ***True Negatives (TN):*** Similarly, a true negative outcome occurs when the model predicts the negative class with accuracy.
- ***False Positives (FP):*** This is the outcome when the model predicts the positive class with an error.
- ***False Negatives (FN):*** This is an equivalent result when the model forecasts the negative class wrongly.

We can forecast accuracy, precision, recall, and F1-score based on the confusion matrix.

4.1.1 Accuracy:

Accuracy is a measure that's used to characterise the model's overall performance across all classes. It is calculated by taking the total number of guesses and dividing it by the number of right forecasts.

$$\text{Accuracy} = \frac{\text{True Positive} + \text{True Negative}}{\text{Total Population}}$$

4.1.2 Precision:

Precision can be defined as the ratio of the total number of positive predictions to the number of real positives. What percentage of favourable forecasts were true is the question it addresses.

$$\text{Precision} = \frac{\text{True Positive}}{\text{Predicted Positive (TP+FP)}}$$

4.1.3 Recall:

It's the ratio of real positives to the total number of false negatives and true positives. "What portion of actual positives were identified correctly?" is the question it addresses.

$$\text{Sensitivity / Recall} = \frac{\text{True Positive}}{\text{Actual Positive (TP+FN)}}$$

4.1.4 F1 Score:

The F1 score is the harmonic mean of precision and recall, a weighted average.

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

4.2 Results:

Of the four architectures used it is clear that EfficientNetB0 had the best accuracy (95.39%) in the context of classifying diabetic retinopathy. It was expected to perform better because it was the newest and most advanced architecture. Additionally, ResNet50, VGG16, and MobileNetV2 demonstrated exceptional accuracy, consistently averaging 90%. Notably, MobileNetV2 demonstrated its effectiveness with a noteworthy accuracy of 91.88% using the fewest parameters. Nonetheless, VGG16 encountered difficulties in correctly detecting diabetic retinopathy, which may have been related to the small dataset consisting of MRI images from three different perspectives (sagittal, coronal, and axial). The comparatively small number of photos for each view and class limited the model's ability to learn, as Fig:4.2 and Table: 4.1. illustrates.

Table: 4.1: Comparison Table

Model Name	Precision	Recall	F1 Score	Accuracy
ResNet 50	0.926320	0.924320	0.933200	0.933440
VGG 16	0.894000	0.883330	0.890040	0.897730
MobileNet	0.945450	0.919900	0.915320	0.918870
EfficientNet B0	0.946543	0.944578	0.954454	0.953900

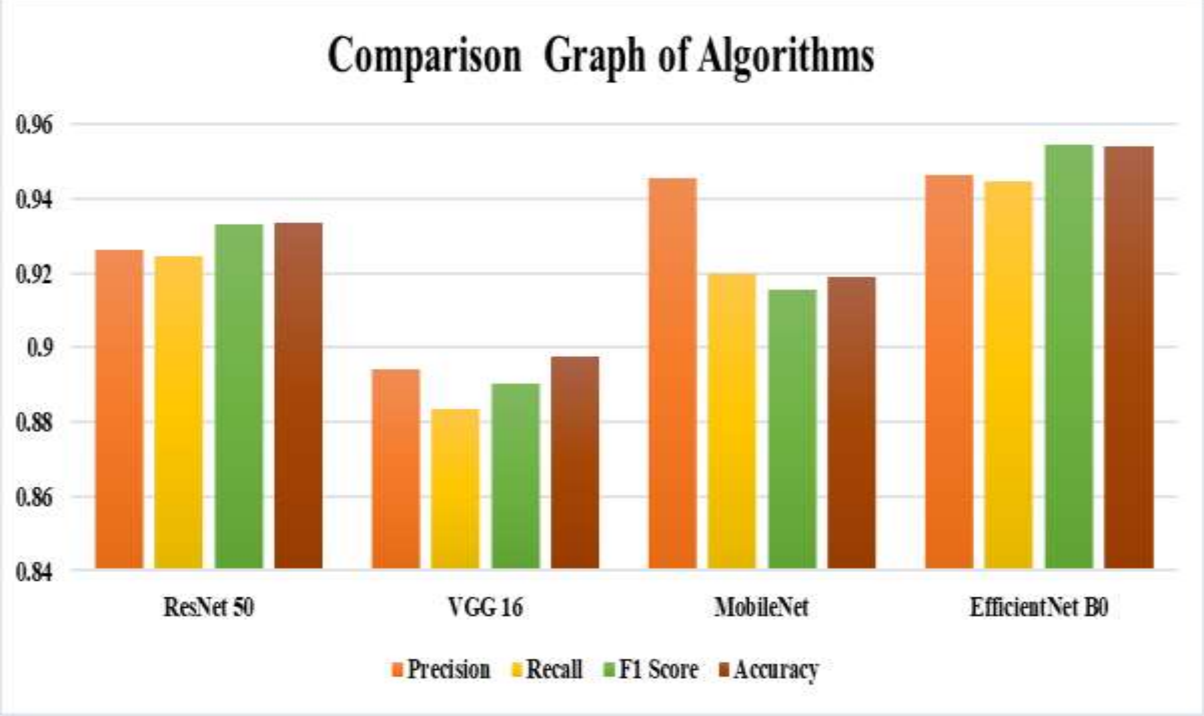
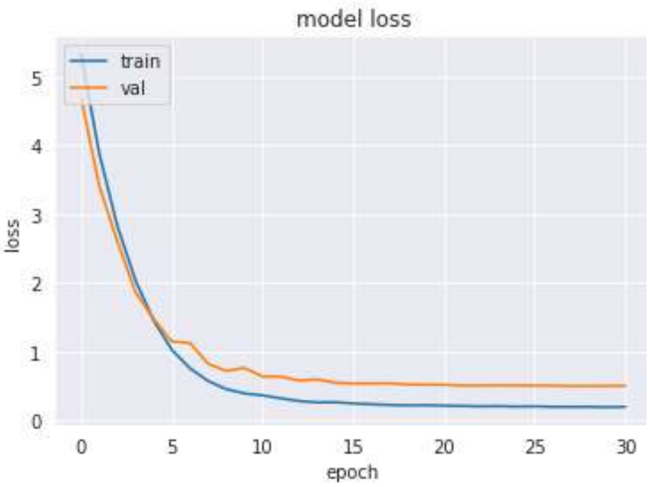


Fig: 4.2: Comparison Graph

When more training cases are gradually added, the acquisition and confirmation losses of a sample are plotted on instructional curves. When determining whether increasing the number of training examples could improve the confirmation score, these curves are useful tools. Increasing the amount of training instances may help overfit models perform better when dealing with unknown data. On the other hand, more training instances might not always result in an improvement for underfit models. Precision and reduction curves are the two types of curves that are most frequently used. Fig:4.3 shows the loss curve, which illustrates the system's performance throughout several epochs. This experiment used five epochs, and the accuracy curve, which computes the loss, and the loss curve had the same function.



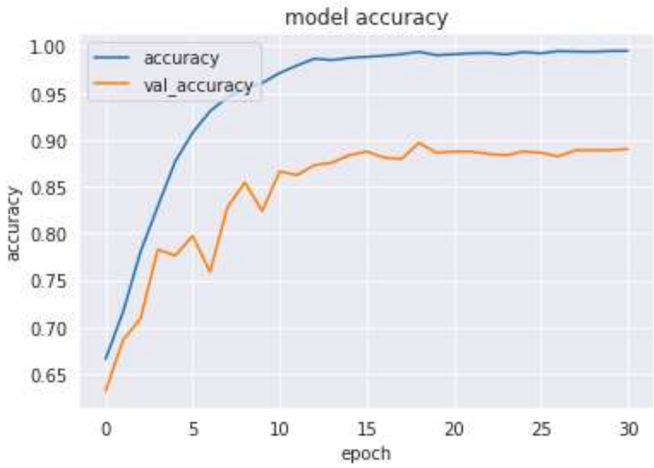


Fig: 4.3: Loss Curves ***Fig: 4.4 Model Accuracy***

Acquisition curves show how a sample of learning examples performs and becomes more reliable when more and more examples are added. These curves play a crucial role in determining if increasing the number of training examples will improve the verification value, which stands for the score on unknown data. A visual depiction of how adding more training instances can increase the accuracy of an overfit model with unknown data can found Fig:4.4.

4.3 Wed Application:

The Diabetic Retinopathy Detection Web Application is a Flask-based web application developed to assist in the early detection of diabetic retinopathy, a complication of diabetes that can lead to blindness if left untreated. This application utilizes Deep learning algorithms to analyse retinal images and provide predictions regarding the presence and severity of DR.

Features:

- ***User-friendly Interface:*** The web application provides a simple and intuitive interface for users to interact with.
- ***Image Upload:*** Users can upload retinal images for analysis.
- ***Prediction Display:*** Upon image upload, the application provides predictions regarding the presence and severity of diabetic retinopathy.
- ***Two HTML Pages:***
  - ***Index Page:*** The landing page of the application, where users can learn about the purpose of the application and initiate the analysis process.
  - ***Prediction Page:*** This page displays the prediction results based on the uploaded retinal image.

Technologies Used:

- ***Flask:*** Flask is a lightweight WSGI web application framework in Python used for building web applications.

- ***HTML/CSS:*** Used for designing and styling the user interface.
- ***Deep Learning:*** Deep learning algorithms are employed for analyzing retinal images and making predictions.
- ***Libraries:*** Libraries such as TensorFlow, Kereas, and scikit-learn are utilized for image processing and machine learning tasks.

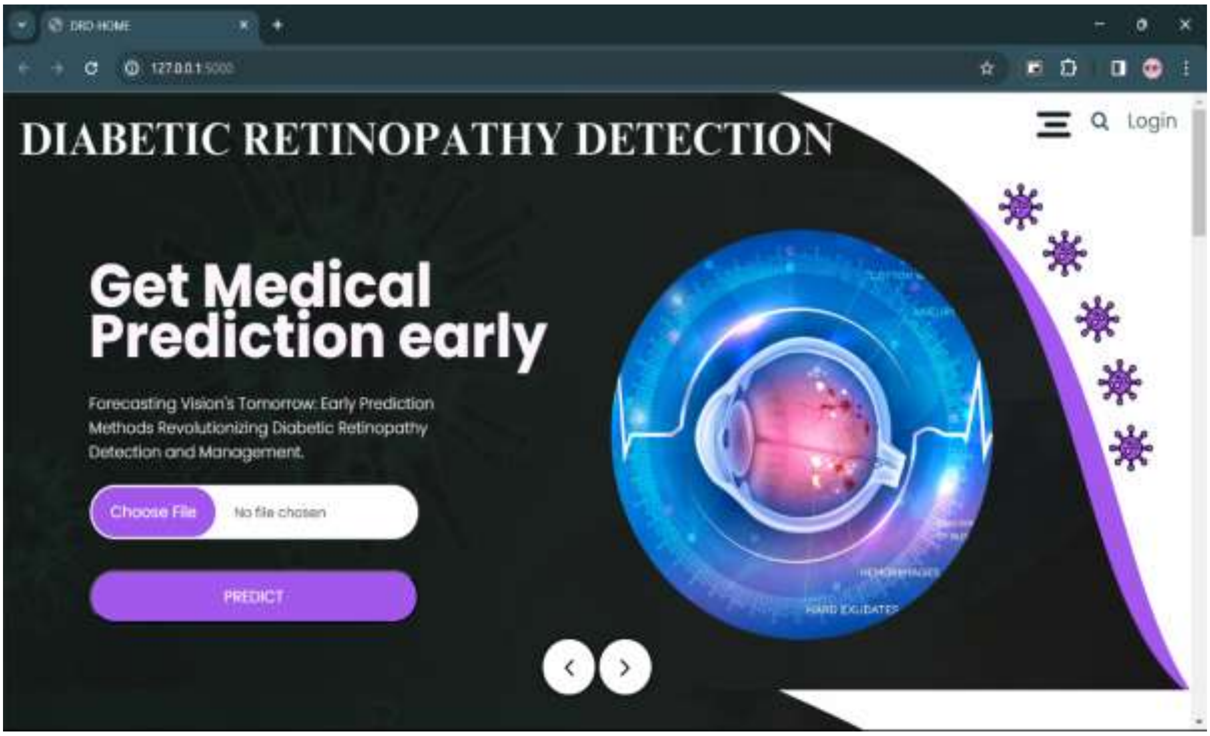


Fig: 4.5: User-friendly Interface

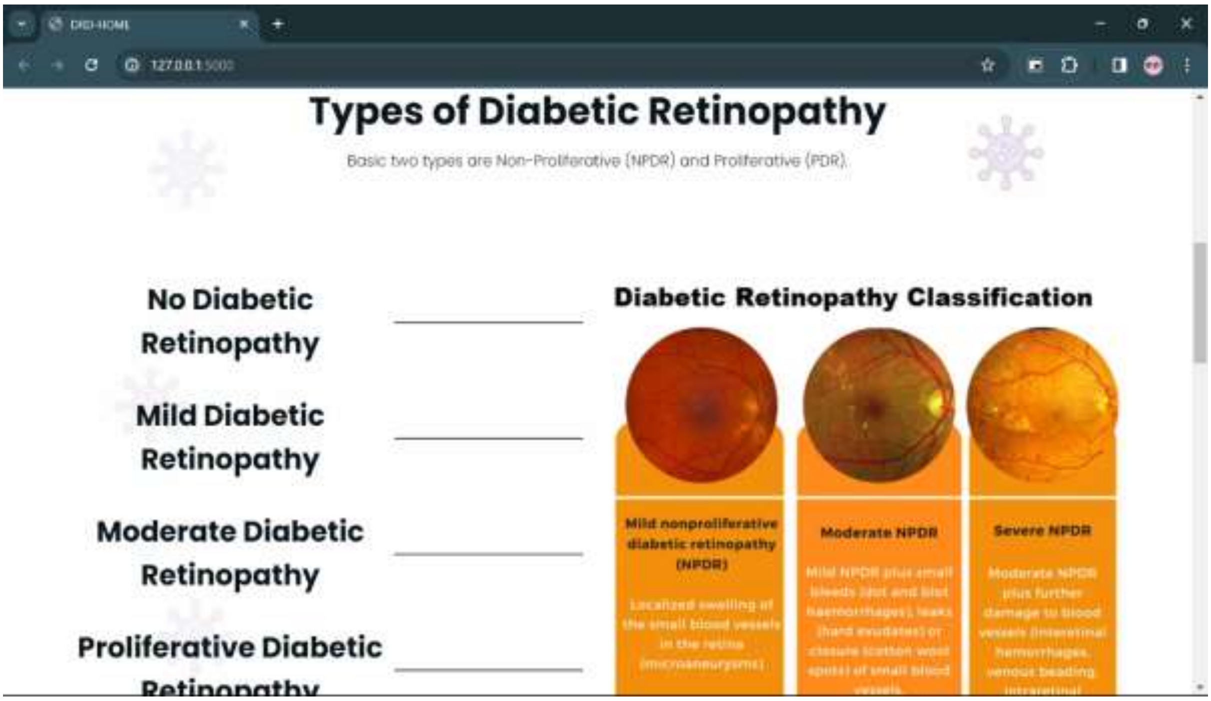


Fig: 4.6: Interface showing Types of DR

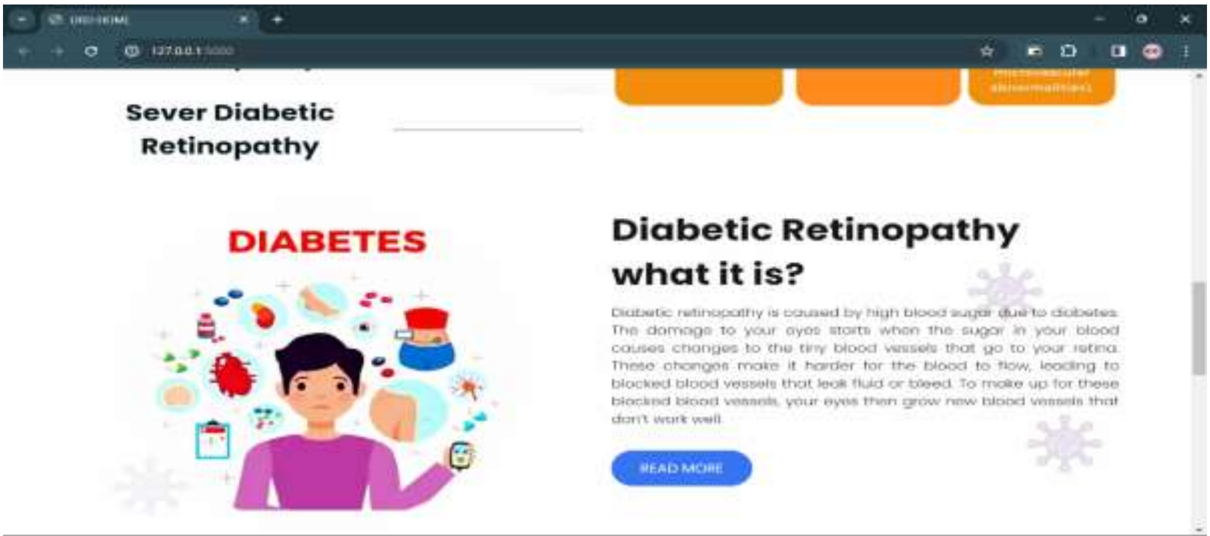


Fig: 4.6: About DR

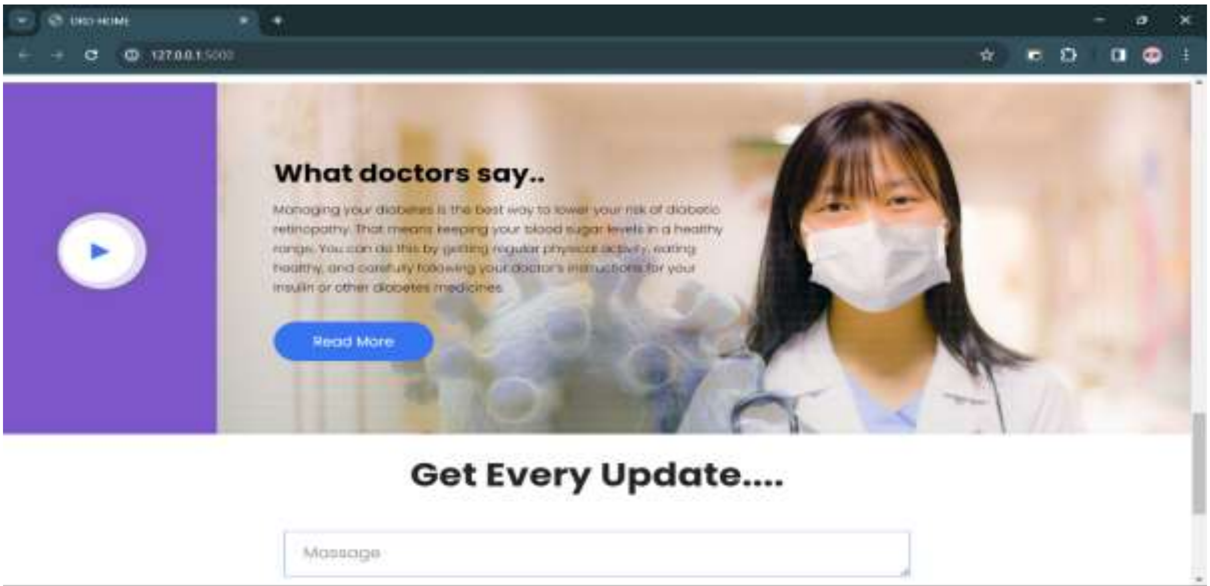


Fig: 4.7: Doctors about DR

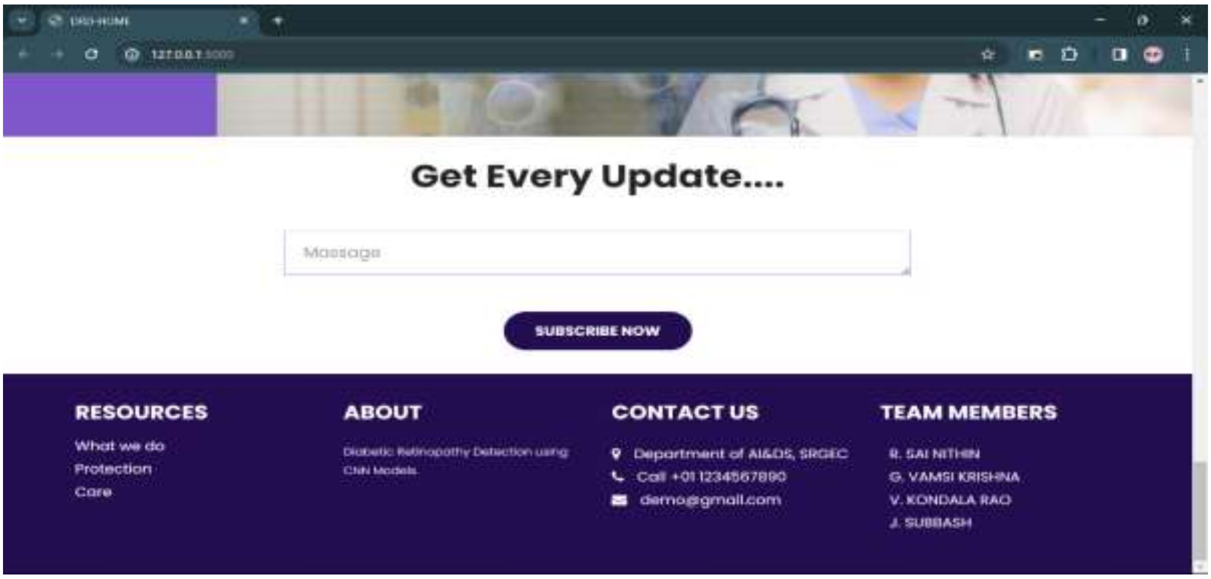


Fig: 4.8: Web Application details

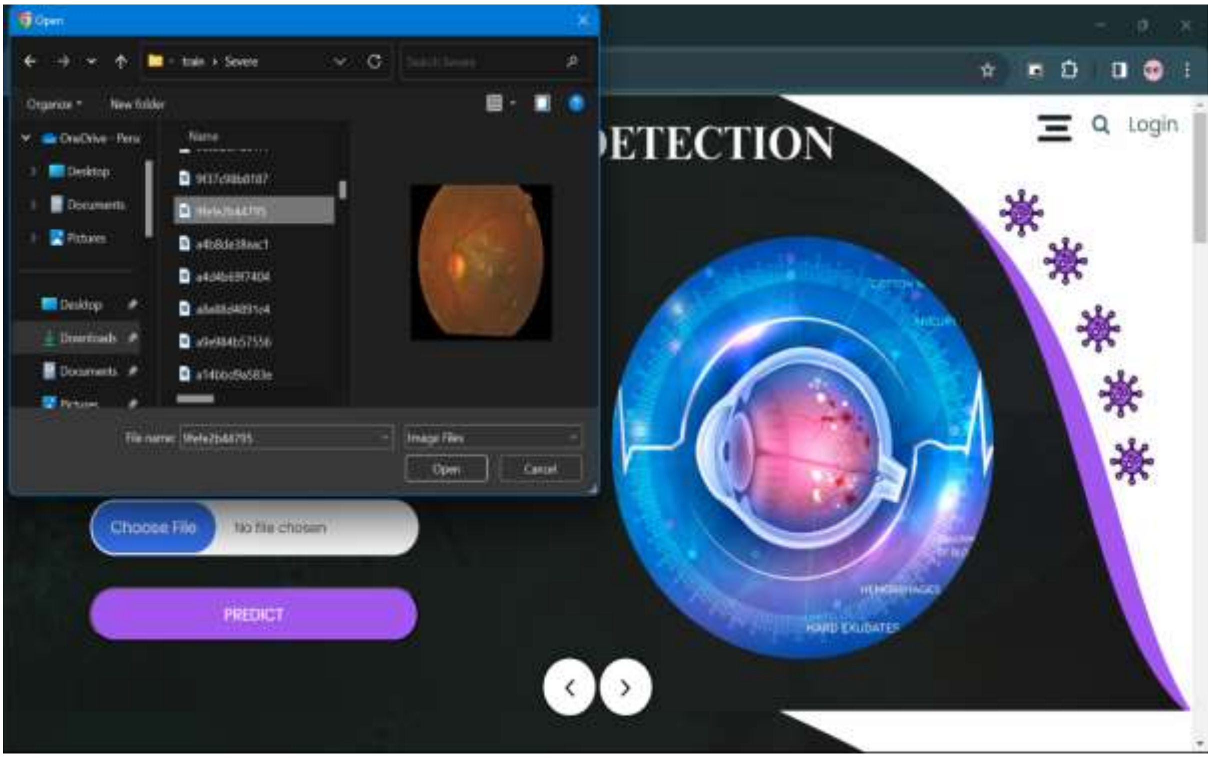


Fig: 4.9: Image Upload

Fig: 4.10: Prediction Display

CHAPTER 5
CONCLUSION AND FUTURE SCOPE

5.1 Conclusion:

In conclusion, the experiment that was shown shows how well deep learning models more especially, EfficientNetB0, ResNet50, VGG16, and MobileNetV2 work when it comes to classifying diabetic retinopathy in images of the retinal fundus. The models display excellent accuracy percentages; EfficientNetB0 leads the pack with an astounding 95.39%. The models' strong performance is a result of the use of pre-trained models, transfer learning, and careful consideration of data augmentation. The use of EfficientNetB0, which is renowned for its accuracy and efficiency, makes it stand out as a potent instrument for the real-time identification of diabetic retinopathy, in line with the rising demand for precise and efficient medical solutions. Furthermore, analyzing various architectures offers insightful information about their performance attributes. Although EfficientNetB0 is the best performer, the comparison analysis shows that ResNet50, VGG16, and MobileNetV2 have advantages and disadvantages. In the field of diabetic retinopathy diagnosis, the study emphasizes the significance of utilizing cutting-edge deep learning architectures. This will lay the groundwork for future developments in medical image analysis and support continuous efforts to improve healthcare diagnostics.

5.2 Future Scope:

The initiative's future scope encompasses multiple promising directions in the realm of diagnosing diabetic retinopathy and medical image analysis. Accuracy and efficiency can be improved by further optimizing and refining the deep learning models, for example, by investigating new or modified EfficientNet designs. Integrating the model with cutting-edge image processing methods and cutting-edge technologies like explainable AI can help improve comprehension and interpretation of the model's judgements, promoting confidence in clinical applications. The deployment of these models in standard medical practice can also be facilitated by working with healthcare organizations and experts to conduct extensive clinical validation and practical application. This will ultimately increase the diagnostic efficacy and accessibility of diabetic retinopathy on a larger scale.

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Program Outcomes (POs):

Engineering Graduates will be able to:

1. **Engineering knowledge**: Apply the knowledge of mathematics, science, engineering fundamentals, and an engineering specialization to the solution of complex engineering problems.
2. **Problem analysis**: Identify, formulate, review research literature, and analyze complex engineering problems reaching substantiated conclusions using first principles of mathematics, natural sciences, and engineering sciences.
3. **Design/development of solutions**: Design solutions for complex engineering problems and design system components or processes that meet the specified needs with appropriate consideration for the public health and safety, and the cultural, societal, and environmental considerations.
4. **Conduct investigations of complex problems**: Use research-based knowledge and research methods including design of experiments, analysis and interpretation of data, and synthesis of the information to provide valid conclusions., component, or software to meet the desired needs.
5. **Modern tool usage**: Create, select, and apply appropriate techniques, resources, and modern engineering and IT tools including prediction and modeling to complex engineering activities with an understanding of the limitations.
6. **The engineer and society**: Apply reasoning informed by the contextual knowledge to assess societal, health, safety, legal and cultural issues and the consequent responsibilities relevant to the professional engineering practice.
7. **Environment and sustainability**: Understand the impact of the professional engineering solutions in societal and environmental contexts, and demonstrate the knowledge of, and need for sustainable development.
8. **Ethics**: Apply ethical principles and commit to professional ethics and responsibilities and norms of the engineering practice.
9. **Individual and team work**: Function effectively as an individual, and as a member or leader in diverse teams, and in multidisciplinary settings.
10. **Communication**: Communicate effectively on complex engineering activities with the engineering community and with society at large, such as, being able to comprehend and write effective reports and design documentation, make effective presentations, and give and receive clear instructions.

11. **Project management and finance**: Demonstrate knowledge and understanding of the engineering and management principles and apply these to one's own work, as a member and leader in a team, to manage projects and in multidisciplinary environments.
12. **Life-long learning**: Recognize the need for, and have the preparation and ability to engage in independent and life-long learning in the broadest context of technological change.

Program Specific Outcomes (PSOs):

PSO1: Process, interpret the real-world data to formulate the model for predicting and forecasting.

PSO2: Apply machine learning techniques to design and develop automated systems to solve real world problems.

PROJECT PROFORMA

Classification of Project	Application	Product	Research	Review
	√			

Note: Tick Appropriate category

Project Outcomes	
Course Outcome (CO1)	Identify and analyse the problem statement using prior technical knowledge in the domain of interest.
Course Outcome (CO2)	Design and develop engineering solutions to complex problems by employing systematic approach.
Course Outcome (CO3)	Examine ethical, environmental, legal and security issues during project implementation.
Course Outcome (CO4)	Prepare and present technical reports by utilizing different visualization tools and evaluation metrics.

Mapping Table

AD3512: MAIN PROJECT															
Course Outcomes	Program Outcomes and Program Specific Outcome														
	PO 1	PO 2	PO 3	PO 4	PO 5	PO 6	PO 7	PO 8	PO 9	PO 10	PO 11	PO 12		PSO 1	PSO 2
CO1	3	3	1					2	2	2				1	1
CO2	3	3	3	3	3			2	2	2		1		3	3
CO3	2	2	3	2	2	3	3	3	2	2	2			3	
CO4	2		1		3				3	3	2	2		2	2

Note: Map each project outcomes with POs and PSOs with either 1 or 2 or 3 based on level of mapping as follows:

1-Slightly (Low) mapped 2-Moderately (Medium) mapped 3-Substantially (High) mapped

PAPER PUBLISHED

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Sai Nithin Rayapalli <nithinrsn1515@gmail.com>

Acceptance of Paper ID #455 for ICONIC 2K24 Presentation

1 message

PECTEAM <pecteamiconic2k24@gmail.com> Fri, Feb 23, 2024 at 1:43 PM

To: nithinrsn1515@gmail.com, kodamala1983@gmail.com, vamsikrishnagudipudi45@gmail.com, sjajjara0505@gmail.com, naniveerabhathina@gmail.com

Dear Authors,

Congratulations on the acceptance of your paper ID #**455** titled **"Diabetic Retinopathy Detection Using CNN Models"** for oral presentation at **ICONIC 2K24**. We appreciate your contribution to the conference. To proceed with the publication process, please carefully go through the attached reviewer comments and make necessary modifications to address the identified deficiencies in your paper. Ensure that the corrected version follows the CRP (Camera-Ready Paper) format provided in the websites.

Submission Guidelines:

- ➢ Upload the CAMERA-READY version of your paper along with a "Response to Reviewer Comments" addressing all the comments received by the reviewers.
- ➢ Strictly adhere to the template provided on the website; no other styles are allowed.
- ➢ The plagiarism report is attached below. Maintain a similarity index of less than 15% and ensure there is no AI-generated content in the paper.
- ➢ Register for the conference before 28th Feb 2024, using the provided registration link below: https://docs.google.com/forms/d/e/1FAIpQLScMCbClrtyzSuIzkuAA2V4Xu8HKw53rR_zREbWGiP5mttO34Q/viewform?usp=sf_link
- ➢ For Camera Ready Paper (CRP) format, please visit https://pecteam.co.in/.

Please note that your registration becomes valid after your payment. View registration details and process at 7th INTERNATIONAL CONFERENCE on INTELLIGENT COMPUTING(https://pecteam.co.in/)

Details of the bank for registration:

Bank Name: UCO Bank
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Bank Account Number: 01570110103951
Branch Name: Chetput, Chennai.
IFSC code: UCBA0000157

Thank you for your cooperation, and we look forward to your final submission by the deadline.

Reviewer Comment 1

Questions

1. The paper is related to the scope of the conference
Yes

2. Does the title clearly reflect the content and outcomes in the manuscript?
Yes

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Sai Nithin Rayapalli <nithinrsn1515@gmail.com>

Registration and Payment Acknowledgment for ICONIC 2K24

1 message

PECTEAM <pecteamiconic2k24@gmail.com> Fri, Mar 15, 2024 at 5:50 PM

Bcc: nithinrsn1515@gmail.com

Dear Authors,

Thank you for completing your registration for ICONIC 2K24. We appreciate your participation and are delighted to confirm that we have received your payment and all documents.We will share the Paper Presentation schedule details before the date of conference.

Registration details are as follows:

Event: ICONIC 2K24

Payment Status: Received

If you have any additional questions or require further assistance,please don't hesitate to reach out to our dedicated support team at pecteamiconic2k24@gmail.com

We look forward to welcoming you to ICONIC 2K24 and hope you have a memorable experience.

Best regards,

Prof.S.Vimala
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PECTEAM ICONIC 2K24
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Diabetic Retinopathy Detection Using CNN Models

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Abstract. Recent breakthroughs in deep learning have showed promise in the field of medical imaging and disease detection, particularly for difficult challenges such as diabetic retinopathy, a severe condition characterized by uncontrolled and aberrant cell division in the retina. The purpose of this study is to use convolutional neural networks for image processing and data augmentation to identify between regions with and without diabetic retinopathy in diabetic patient's retinal pictures. Using the transfer learning approach, the study goes on to assess how well a new CNN model performs in comparison to well-known pre-trained models like VGG-16, ResNet-50, MobileNet, and EfficientB0. Even with the very limited dataset used, the outcomes demonstrate the effectiveness and computational efficiency of the suggested CNN model. Interestingly, our model obtained 89.7% accuracy for VGG-16, 93.3% for ResNet-50, 91.8% for MobileNet, and a remarkable 95.3% for EfficientB0. This study shows how well our model performs, beating competing pre-trained models in accuracy and needing far less processing resources. The results point to the possibility of the suggested Deep Retina model as a useful instrument for the precise and effective classification of diabetic retinopathy in medical imaging applications.

INTRODUCTION

Diabetic retinopathy (DR), one of the most frequent causes of blindness globally, affects 80% of diabetics within 20 years after diagnosis. To prevent sight-threatening outcomes, timely and precise intervention is required; treatments may include intravitreal injections of anti-vascular endothelial growth factor, steroids, or laser therapy. The efficacy of these interventions depends on early detection of the disease's progression to a stage where action is required. However, the reliance on skilled ophthalmologists and the requirement for substantial training led to an expensive and time-consuming diagnostic process, even with the rising incidence of diabetes and the seriousness of DR. Also, since classifications usually rely on professional clinical interpretation, the subjective character of DR severity categorization and early diagnosis typically introduces variability.

In the present work, we describe a comprehensive end-to-end deep convolutional neural network technique for the automated diagnosis of diabetic retinopathy and determining referable status, with an emphasis on more severe instances such as severe non-proliferative DR. By including ultra-widefield fluorescein angiography data, we increase ground truth accuracy. Furthermore, we investigate the algorithm's adaptability to various picture sizes and retinal slabs in order to discover the optimal method for acquiring optical coherence tomography angiography images for DR classification using CNN architecture shown in Fig. 1.

It compares the performance of our suggested model against a machine learning based classifier to ensure its usefulness. This alternative classifier uses handcrafted properties extracted from OCTA pictures. Our findings demonstrate not only the model's feasibility, but also its superior performance over traditional machine learning approaches. The current work contributes significantly to the improvement of automated DR detection and categorization. It emphasizes the potential benefits of combining UWF FA data and deep learning approaches to improve diagnostic accuracy.

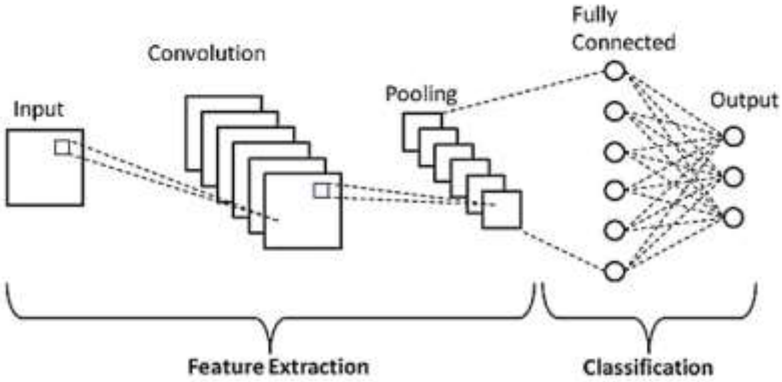

FIGURE. 1. Convolutional neural networks

Contributions of Proposed System

Diabetic retinopathy may now be accurately and efficiently detected in retinal scans thanks to the creation of an automated deep learning algorithm. Provides a consistent and dependable method for differentiating between the phases of diabetic retinopathy, hence reducing the need for manual screening. Investigates how OCTA data can be integrated, giving the model more information on the retinal microvasculature and improving its diagnostic potential. Potentially increases the accuracy of severity classification by advancing a more thorough and sophisticated understanding of diabetic retinopathy. Evaluates the accuracy, sensitivity, and specificity of the model using comprehensive quantitative analyses. determines the proposed deep learning model's effectiveness in detecting diabetic retinopathy by comparing it to other models and conventional machine learning classifiers.

LITERATURE REVIEW

A prospective randomized trial comparing the effectiveness of intravitreal bevacizumab with laser therapy is used in the study by Michaelides et al. to address the management of diabetic macular edoema [1]. If diabetes-related macular edoema is not adequately managed, it may result in visual impairment. The major outcome measure was the change in visual acuity over a 12-month period, and the approach involved randomly assigning patients to groups receiving either bevacizumab or laser therapy. Variations in illness severity and the patient demographics may have an impact on how generalizable the findings are. The limitations point out the importance of interpreting results carefully and offer directions for further study to overcome these limitations.

In their research, Ozieh et al. investigate the patterns in healthcare spending among American individuals with diabetes [2]. The financial consequences of managing diabetes are a major public health concern, and healthcare policy and resource allocation depend heavily on this knowledge. Technical specifics would include the utilization of datasets like the Medical Expenditure Panel Survey and the inclusion standards for choosing the research subjects. Determining healthcare utilization trends, direct medical expenditures, and variables impacting changes in spending during the years under study are probably all part of the analysis. The use of self-reported data, the omission of certain cost components, or differences in the research population's healthcare coverage are some potential drawbacks.

The JAMA paper by Gulshan et al [3] focuses on the construction and validation of a deep learning system for detecting diabetic retinopathy in retinal fundus images. The methods section describes the techniques for training and validating the deep learning algorithm. The researchers most likely used a convolutional neural network architecture for feature extraction and classification, working with many retinal fundus pictures. To increase the algorithm's ability to generalize across varied diabetic retinopathy presentations, it was trained on a diverse set of images. Some examples of these limits are the interpretability of deep learning models, possible biases in training data, and the need for continuing updates to account for changing diabetic retinopathy patterns.

Gargeya and Leng's study use deep learning techniques to automate the diagnosis of diabetic retinopathy [4]. The authors most likely describe the deep learning model's architecture in the technique section, maybe using a convolutional neural network. A sizable collection of retinal images with manual annotations for the severity of diabetic retinopathy most likely played a role in the training process. To make sure the model is accurate and reliable in real-world situations, its robustness is probably put to the test through stringent validation methods. The limits section may address issues with model interpretability, potential biases in training data, and the requirement for ongoing upgrades to stay up to speed with changing patterns of diabetic retinopathy, all while acknowledging the intricacies of deep learning models.

The study conducted by Eladawi and colleague's centers on the timely identification of indicators of diabetic retinopathy by employing Optical Coherence Tomography Angiography images [5]. The methods section perhaps sheds light on the 3D multi-path CNN's architecture and the preprocessing techniques used on the scans. It is likely that a large dataset containing annotations for early indicators of diabetic retinopathy was used in the training procedure. It is possible to highlight potential limitations, such as the need for additional validation in a variety of patient populations, potential artefacts, and difficulties in obtaining standardized OCTA scans.

CNN MODELS

Here are the CNN models that are used for diabetic retinopathy detection.

ResNet50 (Residual Network)

A well-known deep convolutional neural network architecture known for its depth and creative use of residual connections is called ResNet50, or Residual Network with 50 layers [6]. ResNet50 stands out for its capacity to effectively train deep networks, even in the face of obstacles like the vanishing gradient problem. With 50 layers, the network has an outstanding depth, denoted by the number "50". Figure 2 shows Renowned for its extraordinary precision, ResNet50 finds wide use in picture classification applications and performs exceptionally well across a range of computer vision areas. In medical image processing it is tool that has been used to classify diabetic retinopathy [7] and other conditions by taking use of its ability to recognize complex patterns and characteristics in images.

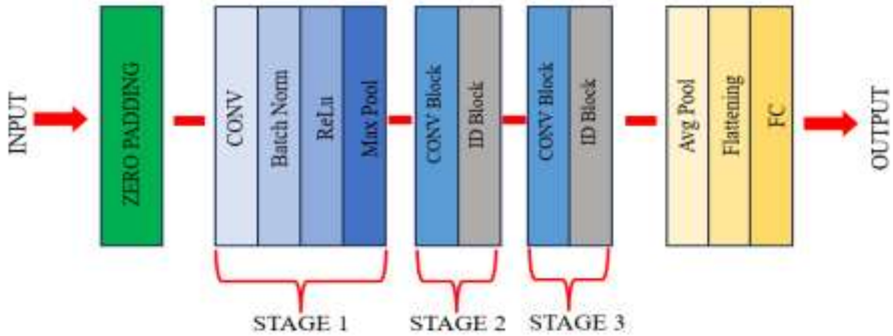

FIGURE. 2. ResNet50

VGG16

One of the most effective and straightforward deep learning models is the VGG16 (Visual Geometry Group 16) architecture. VGG16, which consists of 16 layers, uses 3x3 convolutional filters with small strides and max-pooling layers. Especially, VGG models like VGG16 are praised for their strong feature extraction powers [8]. Because of its repeating and layered layer architecture, VGG16 is a popular choice for a variety of computer vision tasks, especially in medical picture analysis. VGG 16 is utilized in the context of the previously mentioned project for classification tasks pertaining to diabetic retinopathy. It is a useful tool in deep learning applications due to its shown effectiveness in feature learning and picture categorization.

MobileNetV2

An important tool in the context of the endeavor in concern is MobileNetV2, an extension of the MobileNet architecture created especially for embedded and mobile vision applications. Because of its efficient and lightweight architecture, MobileNetV2 is especially useful for mobile devices that operate in contexts with limited resources. Especially in healthcare applications, its efficiency is critical for real-time photo analysis. Battery life preservation and reduced computational load are made possible by MobileNetV2's lightweight design, which is a crucial component for embedded and mobile systems. MobileNetV2 is a logical candidate for implementing AI-driven diagnostic tools in the medical area because of its versatility and resource-friendly nature, particularly in the project's focus on diabetic retinopathy classification [9].

EfficientNetB0

Within the family of EfficientNet models is the convolutional neural network architecture known as EfficientNetB0. EfficientNetB0 was created with the goal of achieving higher accuracy while utilizing less CPU power. It has become well-known for its abilities in picture classification and feature extraction, among other computer vision applications. The architecture is made to maximize computational resources by balancing the model's width, depth, and resolution. For deployment in situations where resources are few, like embedded systems or mobile devices, EfficientNetB0 is especially well-suited. Because of its precision and efficiency, EfficientNetB0 [10] is a useful tool when it comes to medical imaging duties. It could help with activities where real-time processing and resource optimization are essential, such as brain tumor diagnosis or diabetic retinopathy categorization.

FIGURE. 3. EfficientNetB0

PROPOSED METHODOLOGY

An emphasis on speed, precision, and real-time processing characterizes the suggested method shown in Fig. 4 for identifying and managing diabetic retinopathy in retinal pictures. First, it makes use of the EfficientNetB0 model, which is well known for its remarkable accuracy and economical use of memory. In situations where processing resources are scarce, such embedded systems and mobile devices, this option is especially beneficial because it meets the demand for quick and resource-efficient medical picture analysis.

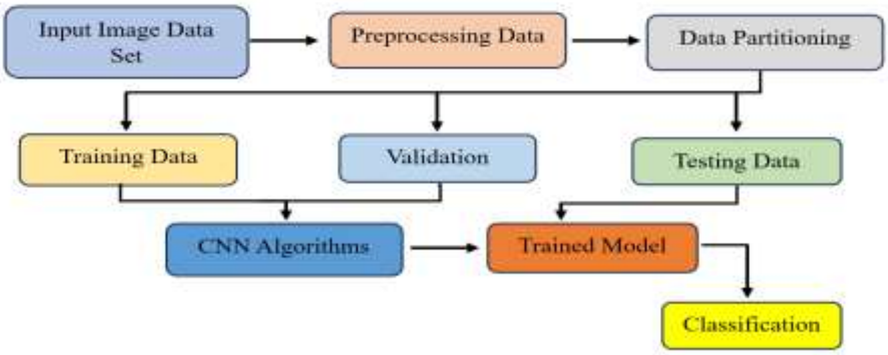

FIGURE. 4. Proposed Model

To increase the model's robustness and make the most use of available training data, the technique employs Image Data Generator for data augmentation. By introducing random alterations to training pictures, this strategy improves the model's generalization capabilities. To improve its capabilities, the technique combines other pre-trained models such as ResNet50, VGG16, MobileNetV2, and EfficientB0. Using pre-trained weights from the ImageNet dataset accelerates training while improving model performance.

Important layers in the model architecture, such as Dropout and GlobalAveragePooling2D, are added to aid in efficient feature extraction and prevent overfitting. The final Dense layer splits pictures into four groups, each representing a certain diabetic retinopathy state. The approach substantially enhances the training process by utilizing a variety of callbacks, including Lambda Callback for reporting confusion matrices, Model Checkpoint for saving model weights, Early Stopping to minimize overfitting, and ReduceLROnPlateau to maximize the learning rate during training. This all-inclusive strategy is specifically designed to cope with the unique problems associated with diagnosing diabetic retinopathy in retinal images.

Dataset Collection

The project's dataset includes many high-resolution retinal images taken under various imaging settings. The term NPDR refers to Non-Proliferative Diabetic Retinopathy. They are classified into five types: no DR, mild NPDR, moderate NPDR, severe NPDR, and proliferative diabetic retinopathy shown in the Fig 5.

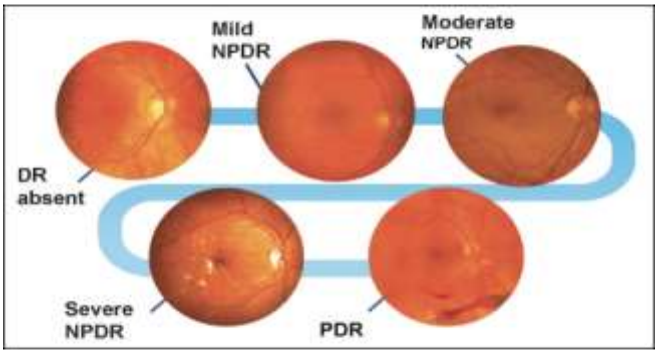

FIGURE. 5. Types of DR

Data Preparation

Compile an image dataset of DR scans and the labels that correspond to the presence or absence of DR. Make that the data covers a range of DR kinds, patient demographics, and imaging conditions and that it is representative of the target population. The count of images of each type is shown in the Fig 6.

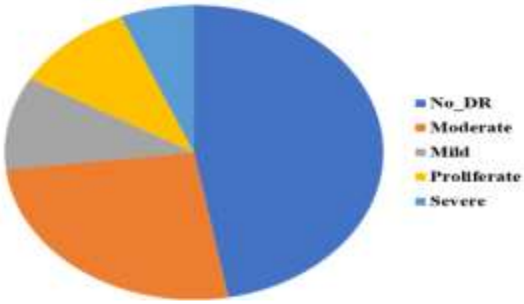

FIGURE. 6. Data set

Data Preprocessing

Before using medical pictures in a machine learning framework for the categorization of diabetic retinopathy (DR), preprocessing is essential to improving their quality and relevance. To guarantee the best possible data quality, several common preprocessing methods are used on the retinal images. The clinicians' assessments, which evaluate each image for the presence of diabetic retinopathy (DR) on a scale from 0 to 4 shown in Table 1.

TABLE 1. Scaled Values of Each DR.

Type of DR	Scaled Value
NO_DR	0
Mild_DR	1
Moderate_DR	2
Severe_DR	3
Proliferative_DR	4

Pre-Trained Model

Pre-trained deep convolutional neural network models are a popular and effective strategy in computer vision, particularly for diagnosing diabetic retinopathy. During the pre-training phase, these models are often exposed to a wide range of pictures and object categories via extensive benchmark datasets such as ImageNet. Using pre-trained models saves a significant amount of time and processing power over training a new model from scratch. This technique, sometimes known as "transfer learning," builds on well-known models such as ResNet50, VGG16, EfficientNetB0, and MobileNetV2 to tackle a new computer vision task.

Custom layers are usually added to a pre-trained model to customize it for a particular use case. The task-specific features are learned by these custom layers. To preserve the important characteristics and representations discovered from ImageNet data, the pre-trained layers' weights are frequently frozen during the early phases of training. The model as a whole or individual layers can then be adjusted to better match the target dataset. Pre-trained models have a number of benefits, such as improved model performance, faster convergence, and the capacity to function with smaller datasets. The pre-trained model's generalization abilities make it a good fit for a number of computer vision tasks, such as the categorization of diabetic retinopathy.

RESULTS

Evaluation and Metrics

A classifier's standard evaluation is based on a number of predefined performance indicators. Our models are assessed using the following metrics: Accuracy, Specificity, F-score, Precision, and Recall. First, we employed a confusion matrix to draw conclusions for the classification algorithms. A confusion matrix is a table that, given a set of test data with known real values, offers information about a model's quality or performance for two or more classes. Fig. 7 shows the simplest confusion matrix for the classifier 2 class: it is two-dimensional.

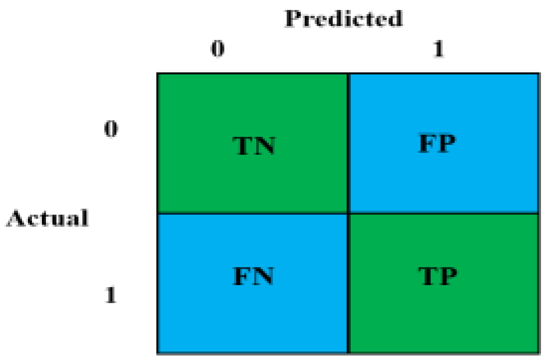

FIGURE. 7. Confusion Matrix

True Positives (TP): A true positive occurs when the model correctly predicts the positive class.
True Negatives (TN): A true negative outcome occurs when the model accurately predicts the negative class.
False Positives (FP): A false positive occur when the model incorrectly predicts the positive class. It is a Type I error.
False Negatives (FN): A false negatives are the counterpart of the model's wrong negative class forecast. It is a Type II error.
We forecast accuracy (1), precision (2), recall (3) and F1-score (4) based on the confusion matrix.

$$\text{Accuracy} = \frac{\text{True Positive} + \text{True Negative}}{\text{Total Population}} \quad (1)$$

$$\text{Precision} = \frac{\text{True Positive}}{\text{Predicted Positive (TP+FP)}} \quad (2)$$

$$\text{Sensitivity / Recall} = \frac{\text{True Positive}}{\text{Actual Positive (TP+FN)}} \quad (3)$$

$$\text{F1 Score} = \frac{2*(\text{Recall}*\text{Precision})}{\text{Recall} + \text{Precision}} \quad (4)$$

Of the four architectures used it is clear that shown in Table 2 and Fig. 8, EfficientNetB0 had the best accuracy (95.39%) in the context of classifying diabetic retinopathy. It was expected to perform better because it was the newest and most advanced architecture. Additionally, ResNet50, VGG16, and MobileNetV2 demonstrated exceptional accuracy, consistently averaging 91%. Notably, MobileNetV2 demonstrated its effectiveness with a noteworthy accuracy of 91.88% using the fewest parameters. Nonetheless, VGG16 encountered difficulties in correctly detecting diabetic retinopathy, which may have been related to the small dataset consisting of MRI images from three different perspectives (sagittal, coronal, and axial). The comparatively small number of photos for each view and class limited the model's ability to learn.

TABLE 2. Results Table

Model Name	Precision	Recall	F1 Score	Accuracy
ResNet 50	0.926320	0.924320	0.933200	0.933440
VGG 16	0.894000	0.883330	0.890040	0.897730
MobileNet	0.945450	0.919900	0.915320	0.918870
EfficientNet B0	0.946543	0.944578	0.954454	0.953900

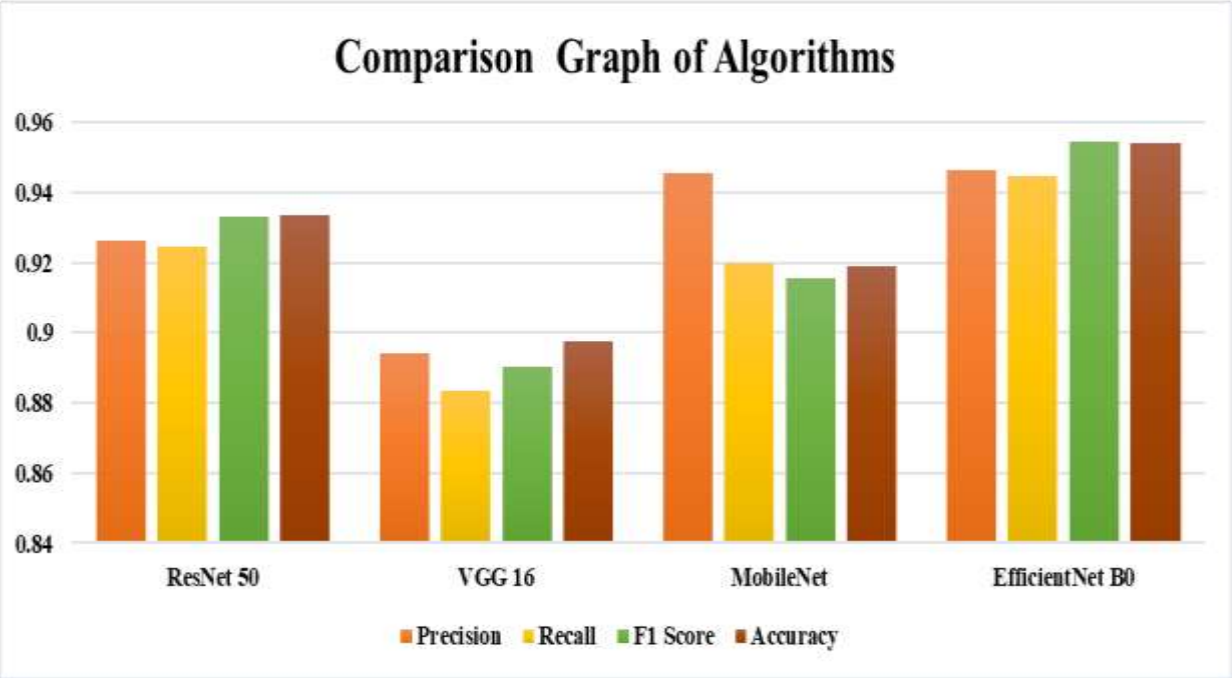

FIGURE. 8. Comparison Graph

CONCLUSION

In conclusion, the experiment that was shown shows how well deep learning models more especially, EfficientNetB0, ResNet50, VGG16, and MobileNetV2 work when it comes to classifying diabetic retinopathy in images of the retinal fundus. The models display excellent accuracy percentages; EfficientNetB0 leads the pack with an astounding 95.39%. The models' strong performance is a result of the use of pre-trained models, transfer learning, and careful consideration of data augmentation. The use of EfficientNetB0, which is renowned for its accuracy and efficiency, makes it stand out as a potent instrument for the real-time identification of diabetic retinopathy, in line with the rising demand for precise and efficient medical solutions. Furthermore, analyzing various architectures offers insightful information about their performance attributes. Although EfficientNetB0 is the best performer, the comparison analysis shows that ResNet50, VGG16, and MobileNetV2 have advantages and disadvantages. In the field of diabetic retinopathy diagnosis, the study emphasizes the significance of utilizing cutting-edge deep learning architectures. This will lay the groundwork for future developments in medical image analysis and support continuous efforts to improve healthcare diagnostics.

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