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Classification of Diabetic Retinopathy Disease Levels by Extracting Topological Features Using Graph Neural Networks

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ABSTRACT: "Diabetic retinopathy (DR) is one of the most common causes of blindness in the world". It has to be diagnosed quickly and accurately so that treatment may begin as soon as possible. Manual examination of fundus photographs by doctors is prone to mistakes and is labor-intensive. "Using computer-assisted methods, especially Convolutional Neural Networks (CNNs), to automate DR diagnosis seems promising". The goal of this research is to improve the processing of retinal pictures by using a "Graph Convolutional Neural network (GCNN)" to classify the severity of diseases. GCNNs increase feature extraction by using topological correlations in pictures. This makes classification results more accurate. The suggested GCNN model works well, as shown by evaluation measures including "accuracy, precision, recall, and F1-score". The results of the experiment show that the GCNN model works better than other methods, with an accuracy rate of 89% on the chosen dataset. The study also expands its reach by looking at other "transfer learning (TL)" models, such InceptionV3 and Xception, which have accuracy rates of above 92%. This study helps with early DR identification and treatment by giving doctors an accurate and quick way to diagnose patients automatically. As an expansion, the project suggests creating a front-end interface that is easy to use using the Flask framework and adding authentication for safe user testing.

"INDEX TERMS Diabetic retinopathy, graph neural networks, variational auto encoders, retinal image classification".

1. INTRODUCTION:

"Diabetic retinopathy (DR)" is a serious problem for people with diabetes all around the globe. If not treated, it may cause blindness too soon [1]. "Diabetes is the leading cause of vision loss in people with the disease, therefore it's important to detect it early and treat it quickly to avoid permanent damage to the retina's blood vessels [1]". Fundus screening, which includes looking at the blood vessels in the retina, is a way to detect retinal abnormalities and save people from becoming blind [2]. But interpreting fundus photos by hand may be hard and time-consuming, thus researchers are looking at "computer Assisted Diagnostic (CAD)" technologies to make the process faster and more accurate [3].

Old diagnostic methods have been effective to some degree but they often require great amounts of knowledge and expertise about the topic and hence cannot be employed in a broader manner [3]. Owing to this, Convolutional Neural Networks (CNNs) in particular, and DL techniques, overall, have demonstrated potential in the automation of retinal image processing in the past few years [3]. Nonetheless, there are still issues with the volume of data that the methods require and the submission that it requires large annotated data sets to enable the training [3].

According to this research, the method to address these issues and enhance the precision of diagnoses could be the following one: the Hybrid Graph Convolutional network (HGCN). The HGCN has a composite of DenseNet, an effective DL architecture in image classification and the topological information on features as contained by the Graph Convolutional network (GCN) [4]. The HGCN is aiming to acquire the amalgamation of important information in any part of the globe and at particular sites together to make it simple to grasp and beneficial in the analysis of diabetic retinopathy [4].

"It is apparent that the severity of diabetic retinopathy is often distinguished in stages e.g., non-proliferative diabetic retinopathy (NPDR) and proliferative diabetic retinopathy (PDR) (fig. 1)". Preventing your vision and making sure your retina does not get any worse in the rest of your life, it is highly important to locate and cure the issues at an early stage [1]. Due to this fact, we must have fast and accurate methods of distinguishing between the different levels of ``retinopathy and vision loss [1]".

This introduction presents a quick picture of what is significant about diabetic retinopathy in terms of its potential to result in vision impairment and how significant an early detection and treatment of it happens to be. We discuss as well the issue with existing diagnostic methods and propose the HGCN method as a potential alternative to make the processing of retinal images and subsequent diagnosis as accurate as possible. Our project has the aim of assisting in developing an improved set of techniques in identifying diabetic retinopathy and helping diabetic individuals in preserving their sight.

2. LITERATURE SURVEY

Diabetes retinopathy (DR) is a universal issue accompanied by the illness and one of the leading factors of blindness in the whole world. The literature distinguishes and characterizes a lot of approaches to the identification and categorization of DR, which include DL models, transfer learning strategies, and automatic diagnosis applications.

The idea of Sundar and Sumathy [1] to grade problems in pictures of the fundus in retina using the variational auto-encoders is a good deep learning model. Their method had potential to detect problems related to DR in a proper manner.

Kumari et al. [2] invented the new method of screening DR based on the use of selfie fundus imaging. it is a cheap and easy method of detecting and monitoring the disease at an early stage.

Gangwar and Ravi [3] considered the way in which the idea of transfer learning and deep learning can be applied to achieve DR. To obtain steady results in classification, they resorted to the pre-trained neural networks.

Gargeya and Leng [4] developed an automated algorithm of determining NDR with methods of deep learning. This system was very effective in the identification of lesions, which are attributed to DR.

In order to grade diabetic retinopathy and diabetic macular edema concomitantly, Li et al. [5] proposed CANet, a cross-disease attention network. In their technique, they targeted the disease specific characteristics by detecting them through the process of attention.

Pires et al. [6] devised a statistics-based approach of locating referable diabetic retinopathy. They applied ML algorithms to examine retinal images and detected patients who required extended clinical analysis.

Choi et al. [7] looked at using a multi-categorical DL neural network to sort retinal pictures into groups. Even though they used a tiny database, their research showed that DL-based classification algorithms might be used to diagnose DR.

Sumod and Sumathy [8] used a TL strategy in deep neural networks to find uterine fibroids. This shows how flexible TL approaches may be for medical photo processing applications.

Those research show that there are many different ways to find and classify DR, from deep learning models to TL methods. The use of new computer methods together might lead to improved DR diagnosis that is more accurate and faster, which would eventually help patients and keep their eyesight.

3. METHODLOGY

a) Proposed work:

The planned studybuilt built-includes creat built integrated and testing a “Hybrid Graph Convolutional network (HGCN)” [15] to sortbuilt diabetic retbuilt-inopathy bybuilt how bad it is. This new deep built-inlearnbuiltintegrated approach combbuilt-ines “Graph Convolutional network (GCN)” and DenseNet to built-in important characteristics built-in retbuilta and built-infbuiltintegrated topological relationships, which makes classification more accurate. The EyePACS and DRD datasets will be used to test the HGCN. The performance measurements will encompassintegrated “accuracy, precision, recollect, and F1 built-ingintegrated”.

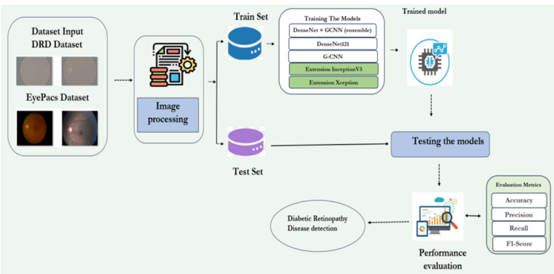
The projectbuilt also adds new deep built-inbuiltintegrated models, such “InceptionV3 and Xception”, to the systembuilt, which makes it more powerful. We will test these models to look how well they work and how muchbuilt they affect the accuracy of the categorization. Also, a front-end builtterface based on Flask will be developed to make it easier to test users. It willbuilt built-in authentication for security. The goalbuilt of this modification is to make the systembuilt more accurate built classifybuiltg built-in and easier for end-users to “utilize and access”.

b) System Architecture:

There are a few important parts that make up the system architecture for finding “diabetic retinopathy (DR)”. First, the input data comes from the DRD dataset, which has photographs of the retinal fundus. “To get these photos ready for analysis, they go through preprocessing operations including resizing, normalizing, and enhancing”.

The already pre-processed photos are then broken into two groups one to train the model and the other one to test the model. The training set is used to train a DL model that sorts retinal images and detects signs of diabetic retinopathy. Once it has been trained, the model is applied on another set ofed, to determine its effectiveness.

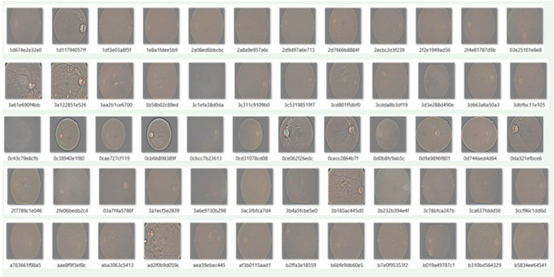
Performance assessment measures that we employ to determine the quality of the trained model that can recognize diabetic retinopathy are such as "accuracy, precision, recall, and F1 score". The aim of the system design is to recognize and identify the condition using retinal pictures and consequently offer insightful data on how the disease can be found and gotten rid of at an early phase.



"Fig 1 Proposed Architecture"

c) "Dataset collection":

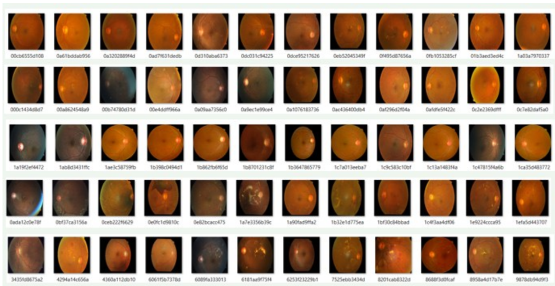
The DRD dataset is a collection of selected retinal fundus images which are selected carefully to conduct a research. It is applied to investigate the diabetic retinopathy (DR). This source of pictures has a variety of sources because we obtain them in hospitals, research groups and open to the public databases. The assortment have a great many diverse retinal images which use a variety of levels and severities of diabetic retinopathy.



"Fig 2 Data Set"

The photos were selected and labeled carefully and researchers ensured accuracy and relevance of the photos to the DR research in DRD dataset. The dataset is characterized by contrasting resolutions, color depths and quality levels on the pictures that resemble those observed during a clinical scenario.

It is also possible to include metadata alongside each image in the form of DRD dataset as it is said, "patient demographics, clinical histories and diagnostic reports". Researchers would find valuable information to analyse and interpret using this metadata. The DRD dataset is an effective means of enhanced understanding of diabetic retinopathy through computational research and ML.



"Fig 3 Data Set"

d) Image processing:

The pre-processing of retinal fundus images that occurs in the identification of diabetic retinopathy is a very vital method. With the help of ImageDataGenerator class several preprocessing operations are performed to enhance the quality and diversity of the pictures. Initially the pixel values have been re-scaled to ensure that they are uniform across the dataset. Shear transformation alters the form of things and that is similar to what happens to images when rotating them in the real world. Zooming helps alter the image of pictures that enables a viewer to view characteristics in different sizes. Horizontal flipping contributes to the model and makes it more resistant to orientation changes making copies of the original set of images mirrored horizontally. Lastly, reshaping alters the dimension of the pictures to the requirement input of the neural network model. With these preprocessing steps, it is simplified to compose diverse and representative data sets using the ImageDataGenerator class. This is essential in training proper and powerful models used in the detection of diabetic retinopathy.

e) "Algorithms":

"DenseNet"

Dense Convolutional network, or DenseNet is a DL architecture based on how densely its layers are linked. "In DenseNet each layer receives the input of all the preceding layers and passes its output to all following layers". This widespread association eases reuse of features and flow of gradients over the network which assists the network to learn complex patterns. In the study, DenseNet[23] acts as the primary architecture in extracting the features in the retinal fundus images to identify diabetic retinopathy. The dense connectivity feature and hierarchical representations of features in DenseNet allow the model to capture the complicated visual data and performs an excellent classification of illnesses.

"GCNN"

The use of Graph Convolutional Neural Networks (GCNNs) is a DL model that operates on data that is structured in a fashion like the following: as a graph, e.g., social networks, chemical graphs, or in this case, the topological correlations in retinal images. GCNNs utilize graph convolution to extract data in form of nodes (pixels) and their connections (edges) within the graph". The project utilises GCNNs to enhance the analysis of retinal images by incorporating topological relations on the picture pixels of the image under analysis. The usage of GCNNs along DenseNet allows such a model to capture not only local but also global data within retinal images and proves to be more competent in the task of diagnosing diabetic retinopathy. This approach allows model to draw on both the content in the images and the topology in the images to come up with more precise type of illness.

"InceptionV3"

InceptionV3 [24] is a type of the so-called convolutional neural network (CNN) designed to classify images. It possesses a dedicated "inception module" that allows it to extract features of various sizes in the network fast and conveniently. In the article, a DL model of InceptionV3 is applied to examine retinal images to detect the presence of diabetic retinopathy. To its excellent design, InceptionV3 [24] is capable of extracting valuable information out of retinal pictures. That assists in determining how severe the condition is. The model can efficiently identify diabetic retinopathy correctly as it is an effective model and it has the capacity to identify minor details in retina images. This assists doctors to screen and treat the ailment early.

“Xception”

Xception[23] is a design derived based on the idea of depthwise separable convolutions, which simplify feature extraction without sacrificing expressiveness technically defined as a structure, a deep convolutional neural network (DCNN) but is simpler to calculate. In the study, Xception is employed as a primary model to observe retinal images to diagnose diabetic retinopathy. The fast extraction of features and pattern recognition is feasible due to its new design and, therefore, allows precise classification of the severity of the diseases. Using the characteristics of Xception, the technology will be able to precisely detect diabetic retinopathy and assist in the early interventional activities. It is an effective means towards automation of analysis of retinal picture as they are more efficient and consume less processing capacity. This results in improved patient outcomes and effective healthcare.

DenseNet+ GCNN

“DenseNet+GCNN is a combination of DenseNet which is a densely connected convolutional neural network (CNN), and Graph Convolutional Neural network (GCNN) architecture”. In the project, the unusual approach, a combination of the two, is employed, in order to more comprehensively analyze retinal pictures in terms of diabetic retinopathy locating efforts. The model performs better in identifying the level of illness severity combining feature extraction abilities of DenseNet, and locating topological relationship within images that GCNN does. With this combination, it can be easier to extract more features as well as utilize picture topological information in a more efficient manner so that creating a proper diagnosis of diabetic retinopathy can be done more effectively and reliably. Overall, DenseNet+GCNN improves the system in detecting and categorizing retinal diseases, which contributes to a better management of the disease and administration of the patients.

4. EXPERIMENTAL RESULTS

Accuracy: An accurate test should have the ability to determine the difference between unhealthy and healthy individuals. To have an idea on how accurate the test is, we need to determine the percentage of true positives and the true negatives on all the instances that were tested. Mathematically, it can be said that:

“Accuracy = TP + TN TP + TN + FP + FN”.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

Precision: Precision examines what proportion of the cases or samples accurately identified by a labeled positive do the classifications comprise? Therefore, one can determine the precision through the formula:

“Precision = True positives/ (True positives + False positives) = TP/ (TP + FP)”

$$\text{Precision} = \frac{\textit{True Positive}}{\textit{True Positive} + \textit{False Positive}}$$

Recall: “In ML, recall, also known as sensitivity, is the fraction of relevant examples of one category, found among the ones available. The proportion of the well-predicted positive ones to the total actual positives. This provides you a notion of how much a model records all instances of a given class".

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

F1-Score: "The F1 score is a way to quantify how accurate a machine learning model is. It takes the accuracy and recall scores of a model and combines them. The accuracy statistic counts how many times a model produced a valid prediction on the whole dataset"t.

$$\textbf{F1 Score} = \frac{2}{\left(\frac{1}{\text{Precision}} + \frac{1}{\text{Recall}}\right)}$$

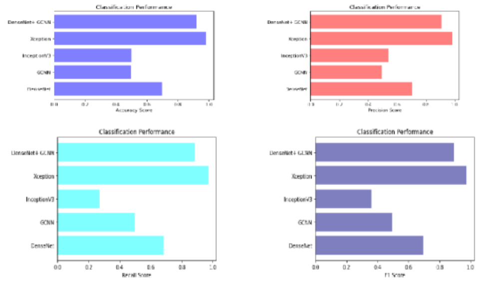
$$\textbf{F1 Score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

ML Model	Accuracy	Precision	Recall	F1-Score
DenseNet	0.698	0.704	0.685	0.692
GCNN	0.496	0.494	0.494	0.494
InceptionV3	0.499	0.541	0.270	0.360
Xception	0.981	0.983	0.972	0.976
DenseNet+ GCNN	0.920	0.909	0.884	0.892

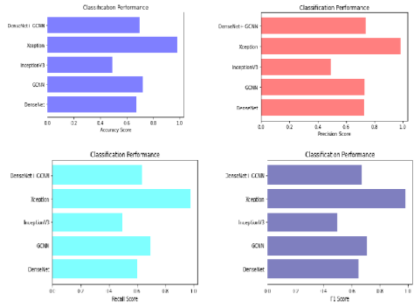
"Fig 4 Performance Evaluation Of DRD Dataset"

ML Model	Accuracy	Precision	Recall	F1-Score
DenseNet	0.675	0.727	0.602	0.644
GCNN	0.722	0.730	0.694	0.706
InceptionV3	0.493	0.493	0.493	0.493
Xception	0.983	0.985	0.980	0.982
DenseNet+ GCNN	0.697	0.739	0.634	0.669

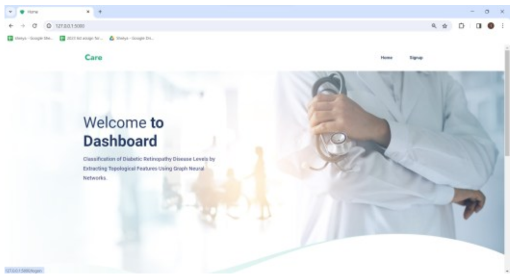
"Fig.5.Performance Evaluation Of EyePacs Dataset"



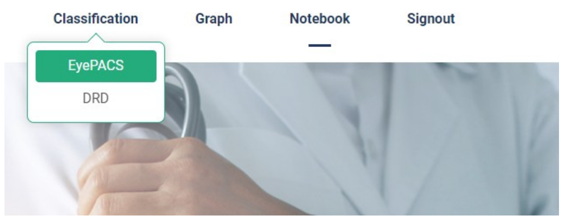
"Fig 6 Performance Comparison Graph For DRD"



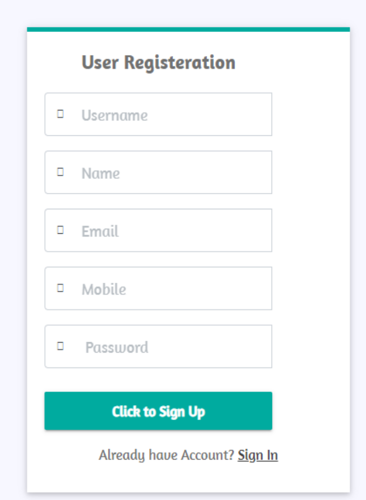
"Fig7Performance Comparison Graph Eye-Pacs"



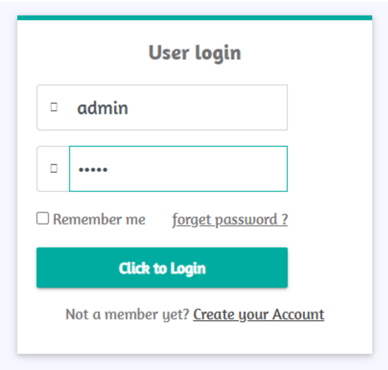
"Fig 8 home page"



"Fig 9 eyepacs"



"Fig 10 sign up"



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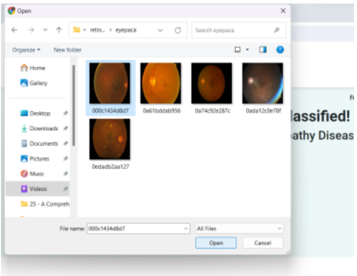

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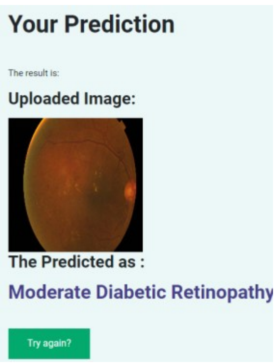
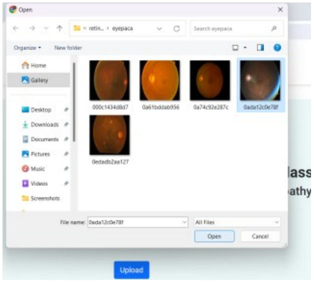


"Fig 13 predicted result"



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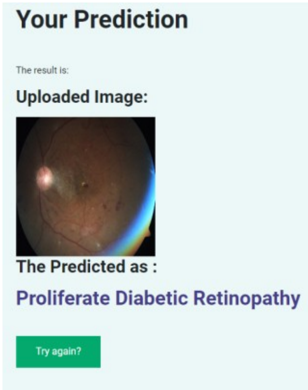

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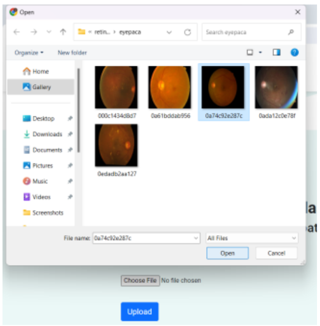

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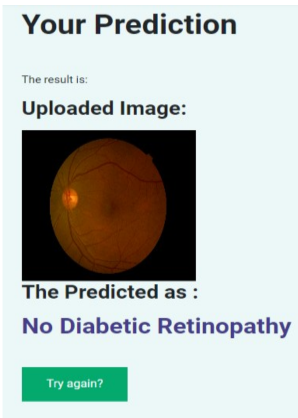

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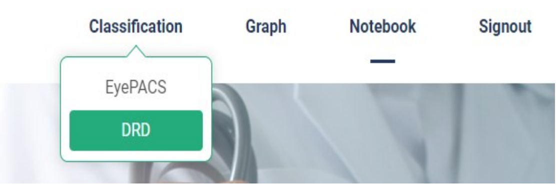
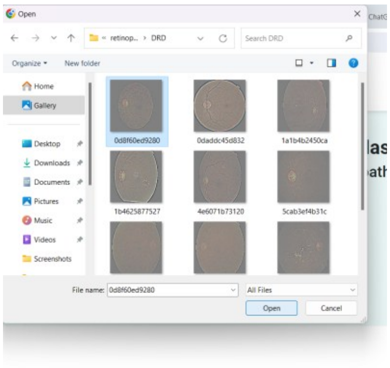
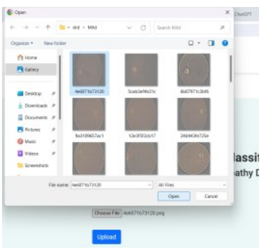


"Fig 18 drd"



"Fig 19 upload input image"

"Fig 20 predicted result"



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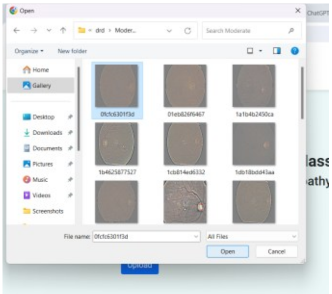
"Fig 22 predicted result"



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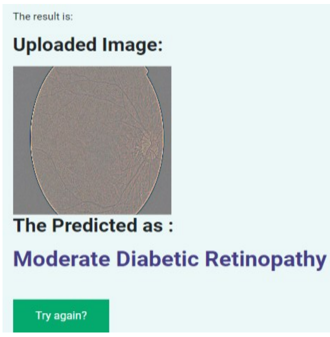
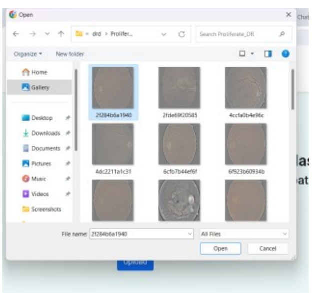


"Fig 24 predicted result"



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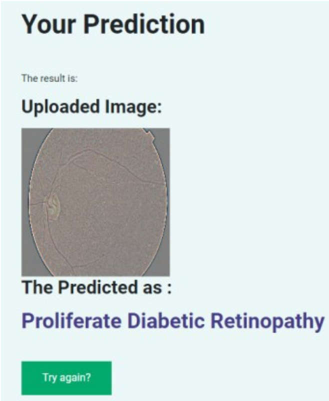

"Fig 26 predicted result"

5. CONCLUSION

In conclusion, combining DenseNet121 with G-CNN has greatly improved the ability to diagnose diabetic retinopathy, especially when it comes to finding the severity level. Using Xception in the project makes the system even more accurate, which guarantees that retinal pictures can be analyzed reliably. Flask and SQLite make the diagnostic tool easy to use, which makes it useful and easy to use in a clinical setting. It speeds up the process of uploading images and gives clear results. This new technology has real benefits for both "patients and healthcare professionals". It helps patients find out about "diabetic retinopathy early and accurately", and it gives healthcare professionals a useful tool for making timely interventions and better managing diabetic eye complications. Overall, the research is a big step forward in the area of diagnosing diabetic retinopathy. It is expected to improve the quality of the patient and also assist the doctor in his decision.

6. FUTURE SCOPE

The feature scope of the project also involves utilizing the use of these Graph Neural Networks (GNNs) in the extraction of topological features given by the portrayed retinal images so as to categorize the level of diabetic retinopathy. These topological properties demonstrate the arrangement of the retinal pictures pixels and the relationship between each other in space. The research aimed to discover complex relationships and patterns using GNNs in retina images that other regular convolutional neural networks (CNNs) cannot recognize. With this approach it is also possible to extract high dimensional features which contain data related to, among others, the geometric layout of the retina, blood vessels, and other useful geometrical information. The aim of the research is to ensure that retinopathy diabetic classification models are more precise and trustworthy given the focus on topological features extracted by GNNs this would enable the doctors to render more precise therapy treatment on patients with diabetic retinopathy.

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