ISSN: 2454-9940

INTERNATIONAL JOURNAL OF APPLIED SCIENCE ENGINEERING AND MANAGEMENT

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INTERNATIONAL JOURNAL OF APPLIED SCIENCE ENGINEERING AND MANAGEMENT

ISSN2454-9940

www.ijasem.org

Vol 18, Issue 3, 2024

GRAPH NEURAL NETWORK BASED TOPOLOGICAL FEATURES TO CLASSIFY DIABETIC RETINOPATHY DISEASE LEVELS

G PRATHYUSHA[1], UDAYRANI[2], B AJITH KUMAR[3]
[1]Assistant Professor, Department of CSE, Sri Padmavathi Mahila Visvavidyalayam Tirupati, Email:prathyubmb@gmail.com
[2]P.G Scholar, Department of MCA, Sri Venkatesa Perumal College of Engineering & Technology, Puttur, Email: ssudayarani@gmail.com
[3]Assistant Professor, Department of MCA, Sri Venkatesa Perumal College of Engineering & Technology, Puttur, Email: ajithkumaryadav34@gmail.com

ABSTRACT:

Diabetic retinopathy (DR), the essential driver of visual deficiency universally, requires exact and speedy conclusion for treatment. Clinicians should physically analyze fundus pictures, which is difficult and blunder inclined. Mechanization of DR conclusion is conceivable with PC helped techniques, like CNNs. This review further develops retinal picture examination by grouping infection seriousness utilizing Graph Convolutional Neural Networks (GCNNs). By involving topological relationships in pictures, GCNNs increment highlight extraction and grouping exactness. The recommended GCNN model performs well in accuracy, precision, recall, and F1-score. Exploratory outcomes show that the GCNN model beats different techniques with 89% accuracy on the dataset. The review grows by inspecting Transfer Learning (TL) models like InceptionV3 and Xception, which accomplish accuracy paces of 92%. This disclosure gives experts an accurate and effective computerized finding strategy to early analyze and treat DR. A development of the undertaking gives a Flask based user-friendly front-end interact with confirmation for safe client testing.

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

1. INTRODUCTION:

Diabetic retinopathy (DR) can cause early visual impairment whenever left untreated [1]. Early analysis and treatment are fundamental to forestalling retinal vein annihilation, the primary driver of diabetic vision misfortune [1]. Fundus screening, which inspects retinal veins, is usually used to analyze retinal sicknesses and deflect visual deficiency [2]. Computer Assisted Diagnostic (CAD) arrangements are being researched for more effective and precise fundus picture translation [3]. Manual translation is relentless and blunder inclined.

Conventional indicative techniques are to some degree compelling, however they need subject information and experience, confining their utilization [3]. Late advances in deep learning, especially CNNs, have shown guarantee in mechanized retinal picture translation [27]. Nonetheless, information needs and the need for enormous commented on datasets for preparing remain issues [3].

The Hybrid Graph Convolutional Network (HGCN) is proposed to beat these issues and increment analytic exactness. The HGCN consolidates DenseNet, a deep learning design that characterizes pictures well, with GCN, which utilizes topological data to extricate highlights [4]. The HGCN

ISSN2454-9940
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consolidates worldwide and neighborhood information to improve diabetic retinopathy finding [4].

Figure 1 shows the seriousness of diabetic retinopathy, which is separated into non-proliferative and proliferative stages [1]. Avoidance of retinal degeneration and vision loss need early distinguishing proof and treatment [28]. In this manner, successful assessment strategies that can appropriately recognize retinopathy and visual impedance are required [1].

We talk about diabetic retinopathy's impact on vision loss and the need of early distinguishing proof and treatment in this presentation. We additionally investigate the constraints of current analysis draws near and recommend the HGCN strategy to increment retinal image processing and symptomatic accuracy. We trust this work will further develop diabetic retinopathy conclusion and avoidance strategies.

2. LITERATURE SURVEY

Diabetes intricacies including diabetic retinopathy (DR) are the essential driver of visual deficiency around the world. [30] DR location and classification writing incorporates deep learning models, move learning, and robotized symptomatic frameworks.

Sundar and Sumathy [1] fostered a deep learning model for retinal fundus irregularity evaluating utilizing variational auto-encoders. This model showed guarantee in recognizing DR-related oddities.

Kumari et al. [2] created "selfie" fundus imaging for early DR screening, simplifying it and available.

Transfer learning and deep learning were utilized to characterize DRs utilizing pre-prepared brain networks by Gangwar and Ravi [3].

A robotized technique for DR location using deep learning by Gargeya and Leng [4] showed great responsiveness and particularity in perceiving DR-related sores.

CANet, a cross-disease consideration organization, was presented by Li et al. [5] to grade diabetic retinopathy and macular edema together. They utilized consideration methods to gather infection explicit characteristics.

Information driven referable diabetic retinopathy recognizable proof by Pires et al. [6] utilized ML calculations to assess retinal pictures and distinguish cases requiring clinical evaluation.

Choi et al. [7] ordered retinal pictures utilizing a multi-straight out profound learning brain organization. Their examination showed that profound learning-based DR characterization calculations work with a restricted data set.

Sumod and Sumathy [8] utilized transfer learning in deep neural networks to recognize uterine fibroids, exhibiting its relevance in clinical picture handling.

These papers exhibit the range of DR detection and classification techniques, from deep learning to transfer learning. High level computational strategies might further develop DR analytic accuracy and speed, expanding patient results and visual conservation.

3. METHODLOGY

a) Proposed work:

A Hybrid Graph Convolutional Network (HGCN) [15] will be created and tried to order diabetic retinopathy retinal seriousness. The interesting

ISSN2454-9940
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profound learning method utilizes Graph Convolutional Network (GCN) and DenseNet to remove retinal qualities and track down topological connections, further developing arrangement precision. The HGCN will be evaluated utilizing EyePACS and DRD datasets for accuracy, precision, recall, and F1 score.

The undertaking additionally incorporates InceptionV3 and Xception deep learning[32] models to upgrade the framework. These models will be surveyed for order precision. For client testing, a Flask-based front-end connect with worked in verification will be made. This improvement further develops order precision and end-client usability and accessibility.

b) System Architecture:

The framework design for identifying diabetic retinopathy (DR) includes a few key parts. First and foremost, the DRD dataset[33], containing retinal fundus pictures, fills in as information. These pictures go through preprocessing steps, for example, image processing, including resizing, standardization, and upgrade, to set them up for examination.

The preprocessed pictures are then parted into preparing and testing sets for model turn of events and assessment, separately. Utilizing the preparation set, a profound learning model is prepared to order retinal pictures and identify indications of diabetic retinopathy. When prepared, the model is tried on the different test set to evaluate its exhibition.

Execution assessment measurements like accuracy, precision, recall, and F1 score are determined to gauge the viability of the prepared model in recognizing diabetic retinopathy. The framework engineering intends to precisely analyze the sickness utilizing retinal images and give important experiences to early detection and intervention.

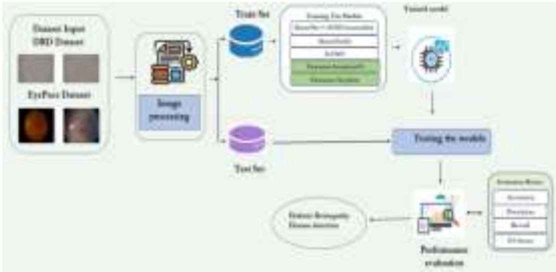

Fig 1 Proposed Architecture

c) Dataset collection:

The DRD dataset contains retinal fundus pictures coordinated for concentrate on diabetic retinopathy (DR). These photographs come from clinical foundations, research gatherings, and public assets. The assortment incorporates retinal pictures of different diabetic retinopathy stages and seriousness.

Fig 2 Data Set

Analysts painstakingly chose and commented on photographs for the DRD assortment to guarantee precision and significance to DR research. Pictures of different goals, variety profundities, and quality portray clinical conditions.

The DRD dataset may furthermore incorporate patient socioeconomics, clinical accounts, and demonstrative reports for each image, giving setting for investigation and understanding. The DRD dataset is valuable for computational exploration and Ml of diabetic retinopathy.

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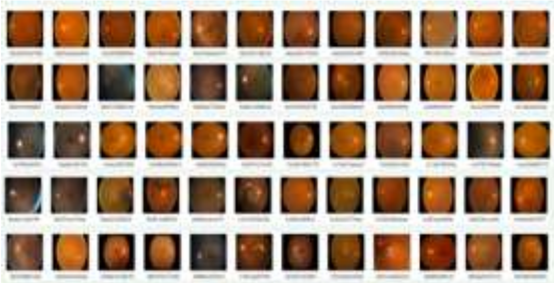

Fig 3 Data Set

d) Image processing:

Image processing is fundamental for diabetic retinopathy ID from retinal fundus pictures. Utilizing the ImageDataGenerator class, numerous arrangement processes further develop picture quality and fluctuation. To normalize the dataset, pixel values are rescaled first. Shear change gives pictures mathematical mutilations that match certifiable picture direction. Zooming photos allows you to see qualities at various amplifications. Even flipping adds reflected pictures to the dataset, making models more direction safe. At long last, reshaping modifies picture size to fit neural network model information sources. The ImageDataGenerator class makes an expansive and delegate dataset for preparing exact and tough diabetic retinopathy location models through preprocessing.

e) Algorithms:

DenseNet

The Dense Convolutional Network (DenseNet) is a deep learning design known for its thick layer association. Each DenseNet layer gets input from past levels and results to succeeding layers. Highlight reuse and angle development all through the organization empower confounded design learning because of thick association. The exploration utilizes DenseNet[23] to separate elements from retinal fundus pictures to recognize diabetic retinopathy. The model can catch complex visual attributes and perform well in disease characterization errands utilizing DenseNet's thick association and progressive element portrayals.

GCNN

Graph Convolutional Neural Networks (GCNNs) are deep learning models explicitly for diagram organized information, like interpersonal organizations, atomic charts, or topological connections in retinal pictures. GCNNs use chart convolutions to extricate highlights from diagram hubs (pixels) and edges. The review utilizes topological relationships between's pixels to further develop retinal picture handling with GCNNs. GCNNs and DenseNet help the model gather nearby and worldwide retinal qualities, further developing diabetic retinopathy conclusion. The model might involve picture content and topological data for more precise sickness arrangement.

InceptionV3

InceptionV3 [24] is a picture classification CNN. Its inventive "initiation module" proficiently extricates highlights at assorted network sizes. The review involves InceptionV3 as a DL model to identify diabetic retinopathy in retinal pictures. InceptionV3[34] can order sickness seriousness by removing huge data from retinal pictures utilizing its complex plan. Because of its powerful presentation and ability to record retinal elements, the model dependably analyze diabetic retinopathy, helping specialists recognize and treat it early.

Xception

DCNN design Xception[23,36] utilizes depthwise distinct convolutions to further develop highlight extraction and decrease computational expense. The review utilizes Xception to investigate retinal

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pictures for diabetic retinopathy recognizable proof. Its original plan further develops include extraction and example acknowledgment, permitting precise ailment seriousness arrangement. The innovation can distinguish diabetic retinopathy and work with early administration through Xception. Its remarkable presentation and computational effectiveness make it helpful for mechanizing retinal picture handling, working on tolerant results and medical services productivity.

DenseNet+GCNN

DenseNet+GCNN is a mixture model that consolidates thickly connected convolutional brain network with GCNN engineering. In the undertaking, this crossover strategy further develops retinal picture handling for diabetic retinopathy ID. Coordinating DenseNet's strong element extraction By catching topological connections in pictures, GCNN further develops ailment seriousness arrangement. This mix further develops highlight extraction and picture topological data, making diabetic retinopathy conclusion more precise and trustworthy. DenseNet+GCNN further develops retinal anomaly identification and characterization, further developing sickness the board and patient consideration.

4. EXPERIMENTAL RESULTS

Accuracy: The model's accuracy is the percentage of true predictions at a grouping position. Mathematically, this can be stated as:

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

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

Precision: Precision quantifies the percentage of certain events or tests that are well characterized. To attain accuracy, use the formula:

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

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

Recall: ML recall measures a model's ability to catch all class occurrences. The model's ability to recognize a certain type of event is measured by the percentage of precisely anticipated positive prospects that turn into real earnings.

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

F1-Score: The F1 score captures both false positives and false negatives, making it a harmonized precision and validation technique for unbalanced data sets.

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ISSN2454-9940
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$$\textbf{F1 Score} = \frac{2}{\left(\frac{1}{\text{Precision}} + \frac{1}{\text{Recall}}\right)}$$

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

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	0.841	0.270	0.360
Xception	0.983	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	0.738	0.634	0.669

Fig 5 Performance Evaluation Of EyePacs Dataset

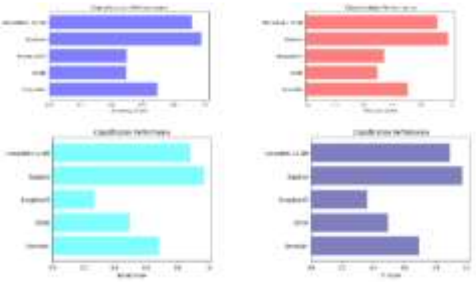

Fig 6 Performance Comparison Graph For DRD

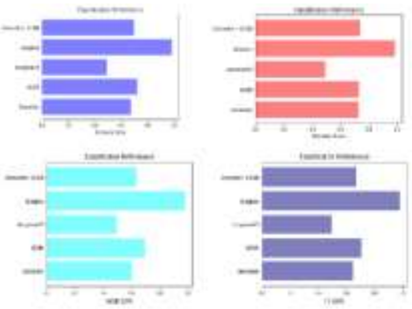

Fig7Performance Comparison Graph Eye-Pacs

Fig 8 home page

Fig 9 eyepacs

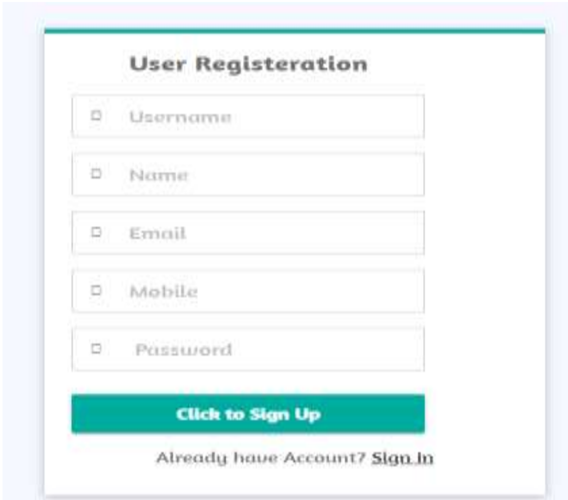

Fig 10 sign up

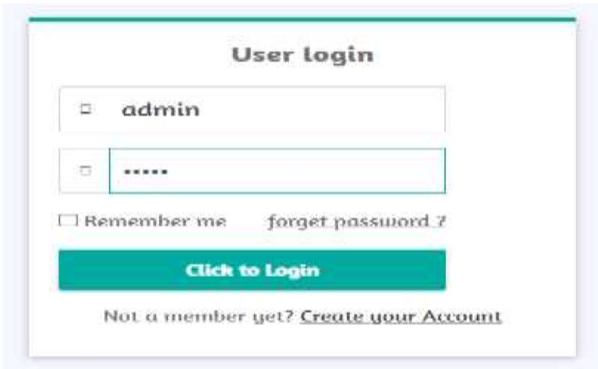

Fig 11 sign in

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Fig 12 upload input image

Fig 13 predicted result

Fig 14 upload input image

Fig 15 predicted result

Fig 16 upload input image

Fig 17 predicted result

Fig 18 drd

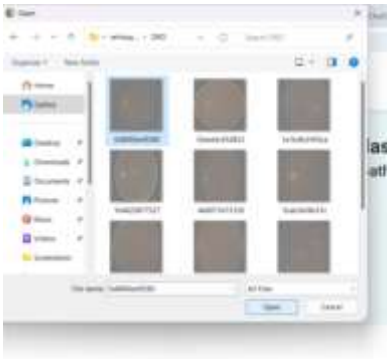

Fig 19 upload input image

Fig 20 predicted result

Fig 21upload input image

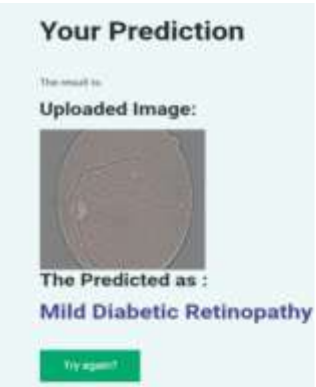

Fig 22 predicted result

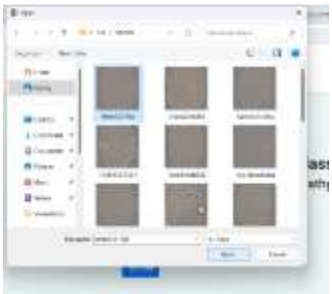

Fig 23 upload input image

Fig 24 predicted result

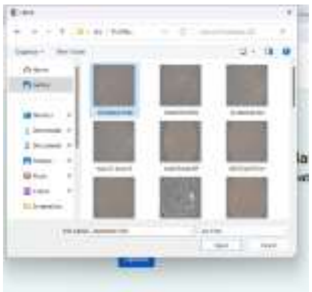

Fig 25 upload input image

Fig 26 predicted result

5. CONCLUSION

The integration of DenseNet121[35] with G-CNN has further developed diabetic retinopathy analysis, especially seriousness level location. The examination utilizes Xception to further develop retinal picture investigation accuracy. Flask with SQLite's easy to understand interface works on

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picture transfers and gives clear outcomes, making the demonstrative instrument practical for clinical use. The early and exact location of diabetic retinopathy for patients and a productive instrument for opportune mediations and further developed administration of diabetic eye intricacies are substantial advantages of this advancement. The drive progresses diabetic retinopathy analysis, working on quiet results and clinical direction.

6. FUTURE SCOPE

The review utilizes Graph Neural Networks (GNNs) to extricate topological data from retinal pictures to arrange diabetic retinopathy illness seriousness. Topological properties in retinal pictures incorporate underlying and spatial collaborations between pixels. GNNs are utilized to catch confounded visual examples and relationships that normal convolutional brain organizations might miss. This strategy removes high-layered attributes that address retinal calculation, vein designs, and other spatial data. The review centers around topological qualities recovered by GNNs to upgrade diabetic retinopathy grouping models' accuracy and versatility, empowering more accurate analysis and treatment arranging.

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