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Diabetic Retinopathy Disease Level Classification via Topological Feature Extraction using Graph Structure

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Abstract: An innovative approach to improving DRD level classification is taken up in this study by using Graph Neural Networks (GNNs).
The goal of this study is to improve the DRD classification accuracy by building networks using topological properties extracted from retinal pictures.
This program aspires to provide a more accurate and comprehensive assessment of DRD levels by using GNNs, which are very adept at identifying intricate relationships in graph-structured data. Early intervention and tailored treatment programs will be better understood in light of the findings.

I. INTRODUCTION

Diabetic retinopathy causes serious damage to the eyes of people with diabetes. The complex web of links seen in retinal pictures may be too much for traditional DRD classification algorithms to manage. In this paper, GNNs are used to classify retinal images as graphs and to derive topological properties.

This is an innovative strategy. Potentially transforming DRD classification, GNNs excel at simulating complicated graph connections. By offering a more complex picture of DRD levels via an exhaustive investigation of topological features, the research aspires to pave the way for tailored medicinal therapies.

II. LITERATURE SURVEY

1) Sundar, S., & Sumathy, S. (2022). An effective deep learning model for grading abnormalities in retinal fundus images using variational auto-encoders. In International Journal of Imaging Systems and Technology (Vol. 33, Issue 1, pp. 92– 107). Wiley. https://doi.org/10.1002/ima.22785, The complexity of carrying out early analysis of DR and DME through efficient methods increased the need to develop a computer-aided diagnosis technique. In this work, a novel technique is proposed and implemented to grade the retinal images with different severity classes based on their abnormalities.

2) Kumari, S., Venkatesh, P., Tandon, N., Chawla, R., Takkar, B., & Kumar, A. (2021). Selfie fundus imaging for diabetic retinopathy screening. In Eye (Vol. 36, Issue 10, pp. 1988–1993). Springer Science and Business Media LLC. https://doi.org/10.1038/s41433-021-01804-7, Fundus images were captured by patients using SFI without major difficulty and were comparable to images taken by trained specialist. With greater penetrance, advances, and availability of mobile photographic technology, we believe that SFI would positively impact the success of diabetic retinopathy screening programs by breaking the barriers of availability, accessibility, and affordability. SFI could ensure continuation of screening schedules for diabetic retinopathy, even in the face a highly contagious pandemic.

3) Li, X., Hu, X., Yu, L., Zhu, L., Fu, C.-W., & Heng, P.-A. (2020). CANet: Cross-Disease Attention Network for Joint Diabetic Retinopathy and Diabetic Macular Edema Grading. In IEEE Transactions on Medical Imaging (Vol. 39, Issue 5, pp. 1483–1493). Institute of Electrical and Electronics Engineers (IEEE). https://doi.org/10.1109/tmi.2019.2951844, In this work, we present a cross-disease attention network (CANet) to jointly grade DR and DME, and explore the individual diseases and also the internal relationship between two diseases by formulating two attention modules: one to learn disease-specific features and another to learn disease dependent features. After that, the network leverages these two features simultaneously for DR and DME grading to maximize the overall grading performance.

III. PROPOSED SYSTEM

To facilitate the extraction of topological characteristics using Graph Neural Networks, this research represents retinal imagery as graphs. By seeing the spatial connections between pixels as graph edges, GNNs provide a more thorough approach to feature extraction. Because of this, the system is able to identify subtle patterns that represent different levels of DRD. A better understanding of the spatial links necessary for DRD classification, more accuracy, and improved generalizability to other cases are some of the advantages.

A. Implementation

1) *Upload EyePacs Dataset:* In this module, all the photographs and labels will be scanned when we upload the dataset folder to the program. After that, it will match the sizes of all the images.
2) *Pre-process Dataset:* This module's application will shuffle, normalize, and extract features from all of the pictures.
3) *Split Dataset Train & Test:* With this module applied, the dataset will be divided into two sections: the train set and the test set. The train set will include 80% of the pictures, while the test set will have 20%.
4) *Train Propose GraphCNN Algorithm:* The GraphCNN algorithm will be fed 80% of the training features in order to train a model, and then 20% of the test pictures will be fed into the trained model in order to determine the accuracy of the predictions.
5) *Train DenseNet121 Algorithm:* Eighty percent of the training characteristics will be used to train the DenseNet121 algorithm. Twenty percent of the test images will be used to evaluate the prediction accuracy.
6) *Comparison Graph:* by use of this module, a comparison graph may be generated depicting all methods
7) Training Accuracy Graph: By using this module, you may see the training accuracy of DenseNdet121 and GraphCNN simultaneously.
8) *Retinopathy Grade Detection:* GraphCNN may be used to extract features map images as output after uploading test images to the program using this module. Then, the application can forecast severity grades.

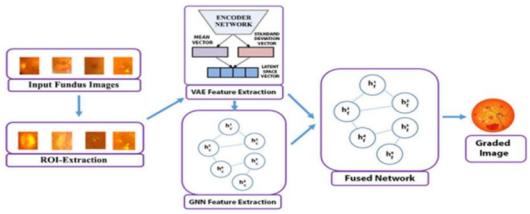
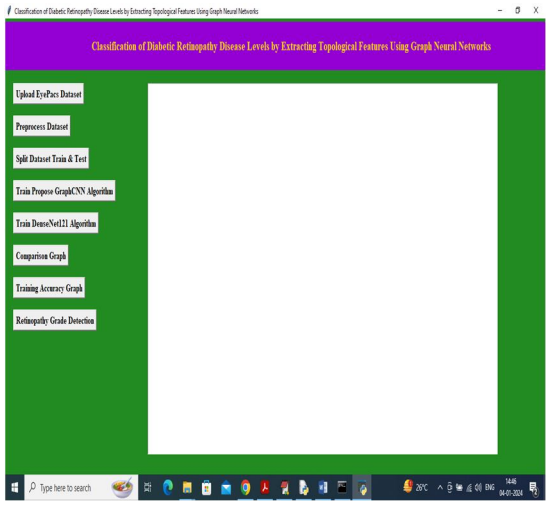
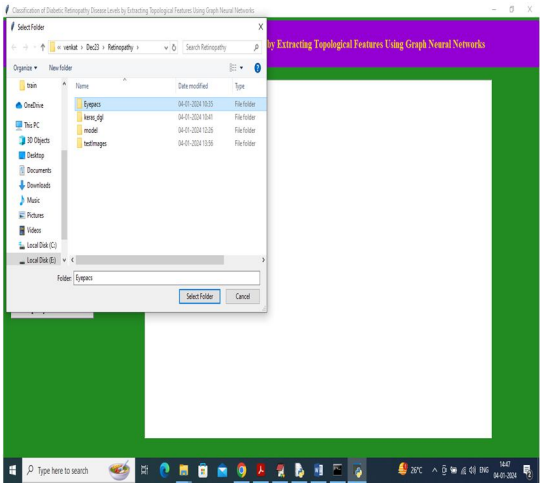


Fig 1:Architecture

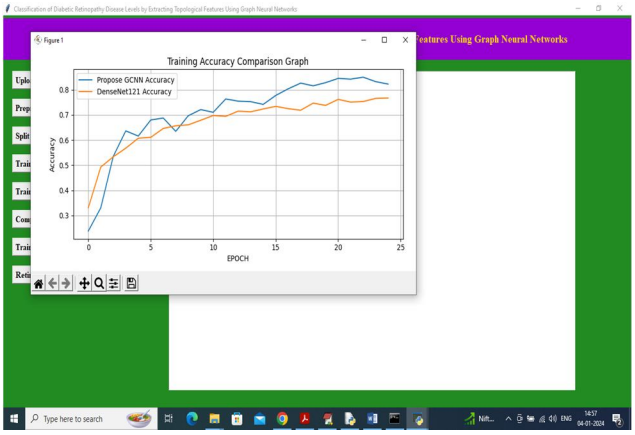
IV. RESULTS AND DISCUSSION



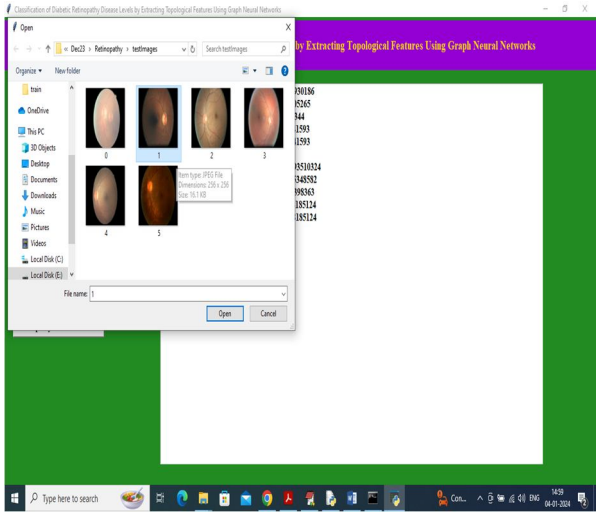
To upload the dataset to the program, click on the "Upload EyePacs Dataset" button on the above page. Once uploaded, you will see the results below.



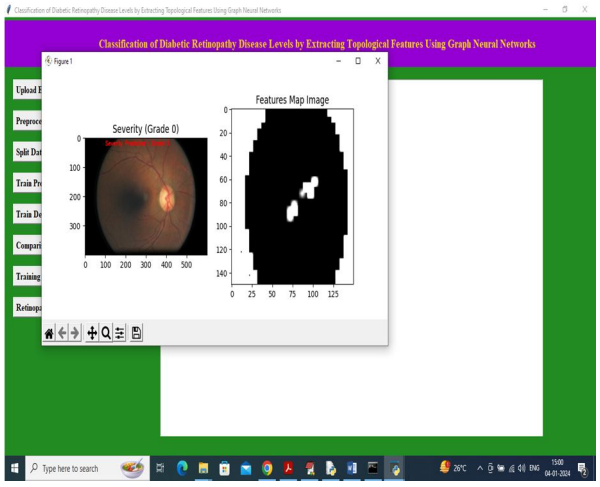
You may load the EYEPACS dataset by going to the previous screen, choosing the folder, and then clicking the "Select Folder" button. This will take you to the page below.



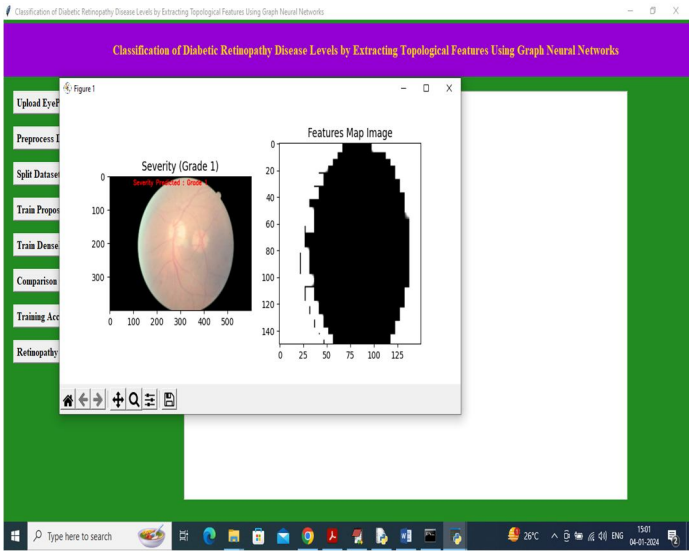
Propose GraphCNN outperformed Existing DenseNet121 in terms of accuracy, as shown in the accuracy graph above. The x-axis displays the number of training epochs, while the y-axis displays the accuracy. As shown in the following graph, both algorithms' accuracy drew closer to 1 with each passing epoch, while GraphCNN obtained a much greater accuracy. Simply click the "Retinopathy Grade Detection" button to submit your test photo and get your findings. Image of a feature map along with the severity of each grade



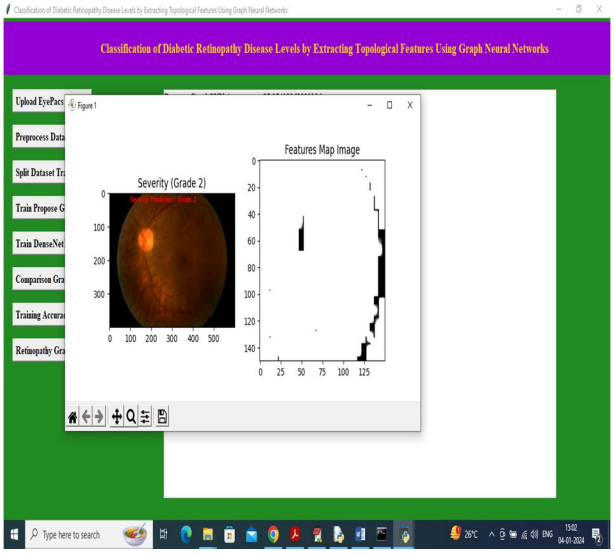
After choosing and uploading the "1.jpg" picture in the previous screen, click the "Open" button to get the following result.



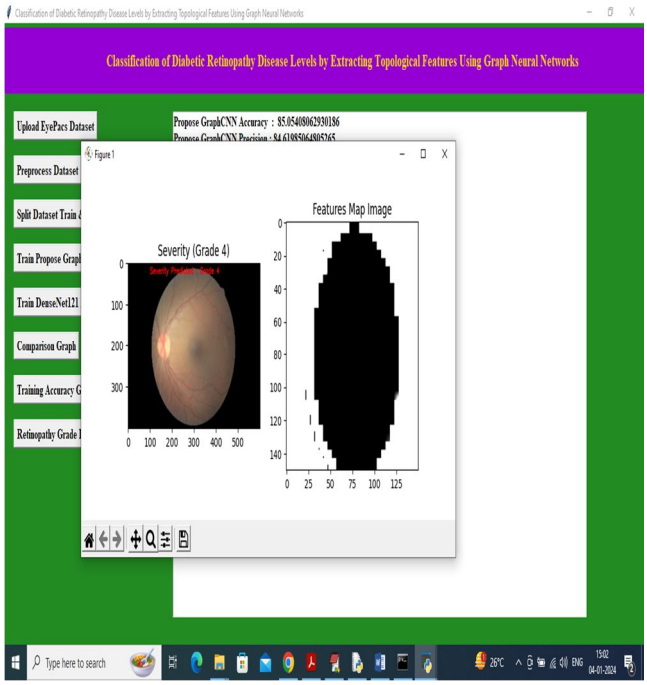
The red text in the first picture above shows the Grade Severity prediction as 0, the features map image is taken from the Graph CNN, and the additional test inputs are below.



In above image predicted Grade is 1



As seen in the previous panel, the grade is 2.



You may submit and evaluate other photographs in the same way; the one above has a grade of 4.

V. CONCLUSION

In conclusion, the study " Disease Level Classification in Diabetic Retinopathy via Graph Neural Network-Based Topological Feature Extraction " combines medical imaging systems with graph-based deep learning concepts. This project's overarching goal is to use GNNs to improve our knowledge of disease phases in a way that will radically alter the DRD classification industry. Early intervention and individualized treatment plans will be made possible as a result of this.

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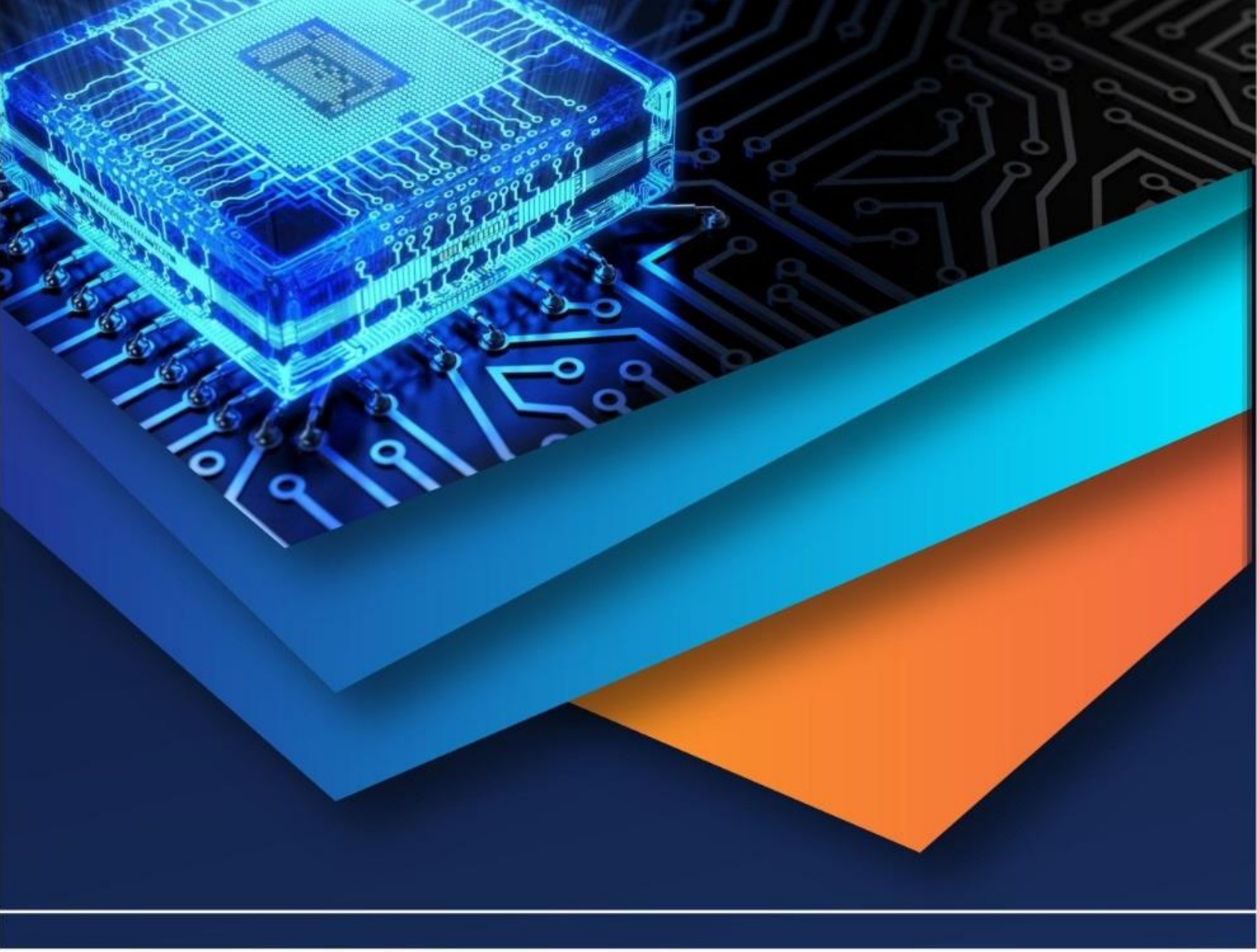

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