



e-ISSN: 2319-8753 | p-ISSN: 2347-6710

IJRSET

International Journal of Innovative Research in
SCIENCE | ENGINEERING | TECHNOLOGY



INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN SCIENCE | ENGINEERING | TECHNOLOGY

Volume 13, Issue 5, May 2024

ISSN INTERNATIONAL
STANDARD
SERIAL
NUMBER
INDIA

Impact Factor: 8.423

9940 572 462

6381 907 438

ijirset@gmail.com

www.ijirset.com

Automated Glaucoma Detection

Rajarajeshwari Barathkumar

Post Graduate, Department of Data science and Machine learning, IIT Madras, Tamil Nadu, India

ABSTRACT: This project seeks to address the pressing need for improved glaucoma detection by developing an automated system using deep learning and retinal fundus images. The core objective is the creation of a tool that can aid ophthalmologists, enabling faster, more accessible, and potentially cost-effective glaucoma screening, with a strong focus on early detection

KEYWORDS: Automated Glaucoma Detection, Deep Learning, Retinal Fundus Images, Ophthalmology, Early Detection, Vision Loss Prevention, Glaucoma Screening, Diagnostic Tools, Medical Imaging, Optic Nerve Damage.

I. INTRODUCTION

Glaucoma: A Leading Cause of Vision Loss, its a group of eye diseases, progressively damages the optic nerve, the crucial connection between the eye and the brain. If left untreated, glaucoma can result in irreversible vision loss and eventual blindness. The silent nature of its early stages underscores the vital importance of early diagnosis and prompt intervention. Glaucoma stands as a major public health concern affecting millions of individuals globally. 64 million people were living with glaucoma in 2016 and that it will increase to 95 million by 2030. Worryingly, the number of people affected by glaucoma is projected to increase substantially in the coming years, highlighting the growing need for effective diagnosis and management.

1. Early Detection: Key to Preventing Vision Loss

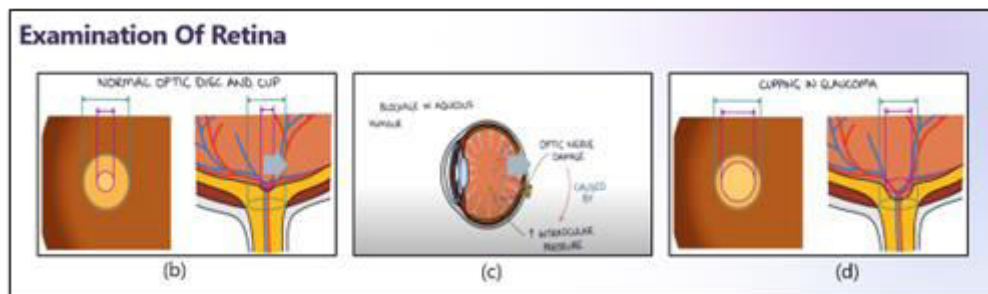
The insidious nature of glaucoma lies in its often-asymptomatic early stages. This makes regular eye examinations crucial for its detection. Early diagnosis and initiation of treatment can significantly slow or even prevent further deterioration of vision, preserving a person's sight.

2. Challenges in Current Diagnostic Methods

Traditional glaucoma diagnosis relies heavily on subjective evaluations and specialized equipment, requiring considerable expertise and potentially leading to delays in detection. Moreover, the growing demand for glaucoma screening necessitates the development of more accessible, efficient, and reliable diagnostic tools.

3. Project Focus:

This project specifically focuses on the analysis of fundus images, photographs of the eye's interior, for automated glaucoma detection. It aims to calculate the Cup-to-Disc Ratio (CDR), a valuable diagnostic metric, for accurate and efficient classification. The following explains Optic Nerve Damage and Cupping:



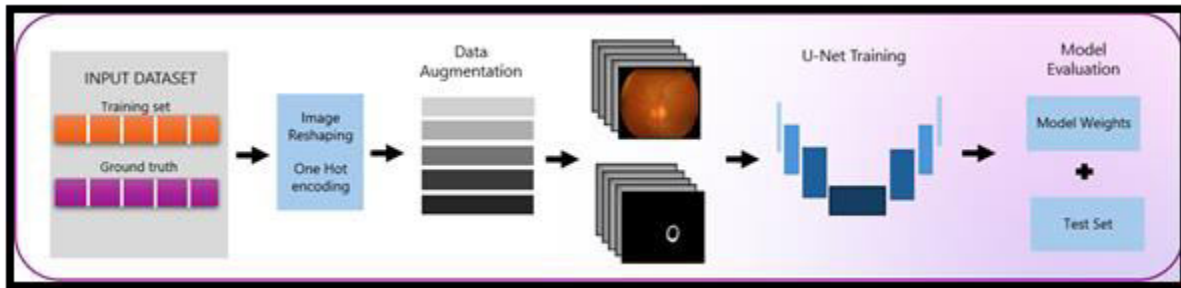
A. Cupping in a Healthy Eye: The optic cup, a central depression within the optic disc, typically occupies a small relative area in a healthy eye.

B. Cupping in Glaucoma: In glaucoma, elevated intraocular pressure and subsequent damage to nerve fibers causes a visible enlargement of the optic cup. This enlarged cupping is a clinical sign of potential glaucomatous damage.

II. PROBLEM STATEMENT

1. Optic disc-cup segmentation

Current glaucoma diagnosis methods can be time-consuming, resource-intensive, and prone to subjectivity. To address these challenges, this project aims to develop a deep learning-based system for automated glaucoma detection using retinal fundus images. The proposed system aims to offer a potential solution for improving the efficiency, accessibility, and accuracy of glaucoma diagnosis.



2. Automated Glaucoma Diagnosis using Deep learning:

Develop a U-Net-based segmentation model to accurately delineate the optic disc and optic cup in retinal fundus images. This segmentation model will form the foundation for precise glaucoma classification.

Implement a classification system that utilizes Cup-to-Disc Ratio (CDR) calculation to distinguish between glaucoma-positive and healthy images. The CDR serves as a crucial diagnostic indicator for glaucoma detection.

Thoroughly evaluate the proposed system's performance on the DHRISTI-GS1 dataset using relevant metrics. Comprehensive evaluation will ensure that the system meets performance standards for potential real-world application.

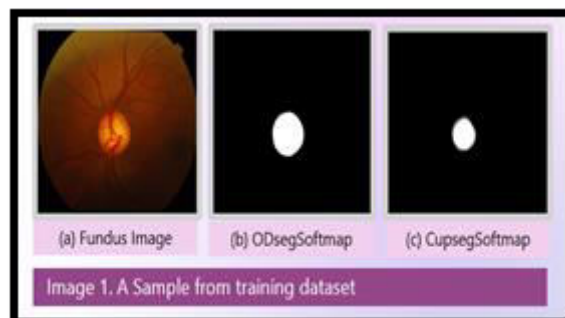
III. METHODOLOGY

A. Dataset for model Development

This project utilized the DHRISTI-GS1 dataset, a publicly available collection of retinal fundus images. The dataset comprised 101 fundus images, including both glaucoma-positive and healthy examples.

	Glaucomatous	Normal
Train	32	18
Test	38	13
Total	70	31
TOTAL SAMPLES	101	

Table 1. Distribution Of Dataset



The ground truth for each image also has information on

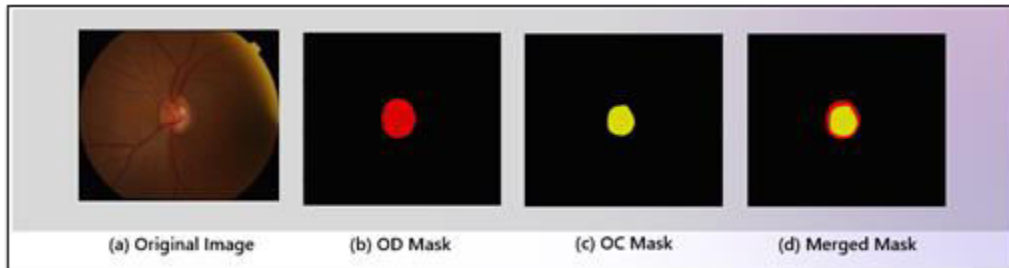
Region Boundary: Average boundaries for both OD and cup region are derived from the manual marked boundaries.

Segmentation Soft map: Manual segmentations obtained from four experts are fused together to generate a soft map for both OD and cup region.

B. Dataset Preparation

a. Mask Processing

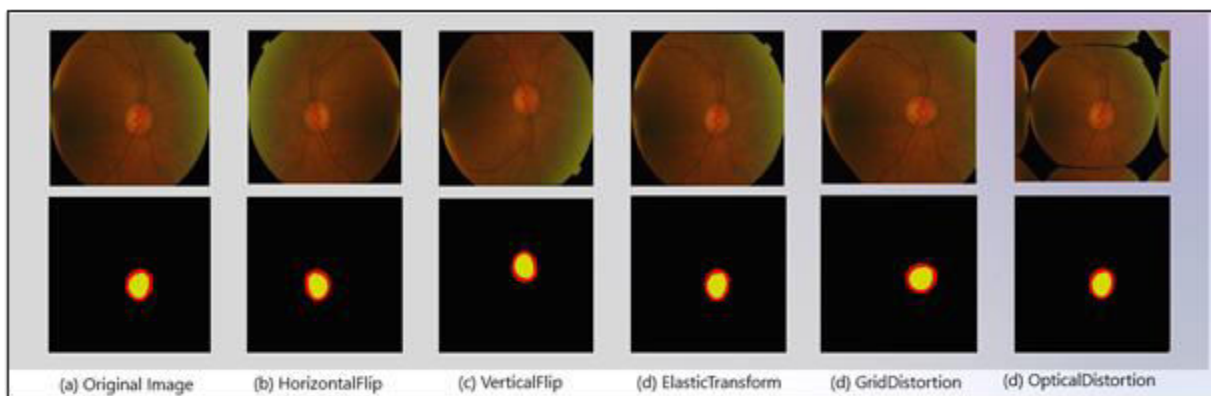
Merging Optic Masks: The separate optic disc and optic cup segmentation masks were combined to create a single mask for multi-class segmentation. This step streamlined the model's learning process by reducing the need to train two separate models for OC and OD. This merged mask is created from the segmentation soft map provided by the DHRISTI-GS1 dataset.



b. Augmentation

To combat the challenges of limited dataset size and inherent variations within retinal fundus images, data augmentation was employed. Augmentations artificially expand the training set, boosting the model's ability to generalize to new, unseen examples and reducing the risk of overfitting.

Data augmentation was employed using the Albumentations library. Albumentations offers a rich variety of image-specific transformations. By generating augmented versions of each input image and corresponding mask, the training dataset was expanded. This augmentation process significantly increased the available training data (240 samples) and validation data (60 samples), enhancing the model's ability to learn robust and reliable segmentation patterns.



c. Normalization

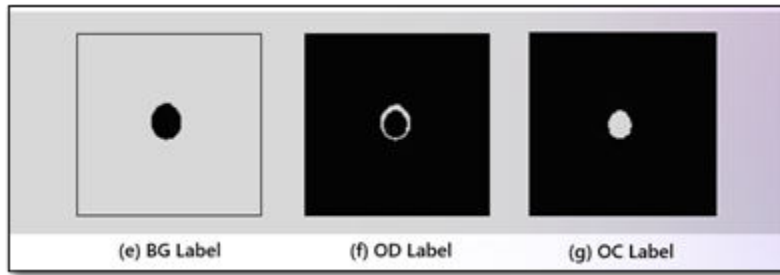
Ensuring Consistency: Images were normalized to ensure a consistent range of intensity values. This standardization step facilitates faster model convergence during training and enhances overall performance by preventing extreme pixel values from skewing the model's learning.

d. Resizing

Compatibility with Model: Images were resized to a uniform input size to align with the requirements of the chosen model architecture. This consistency ensures that all images are processed correctly by the model.

e. Label Generation

Preparing Ground Truth: Segmentation masks were transformed into numerical labels representing distinct classes (e.g., background, optic disc, optic cup). By providing these clear labels, the model can associate specific pixel patterns with the corresponding anatomical structures, enabling it to learn segmentation effectively.



C. Segmentation Model

a. The Power of U-Net

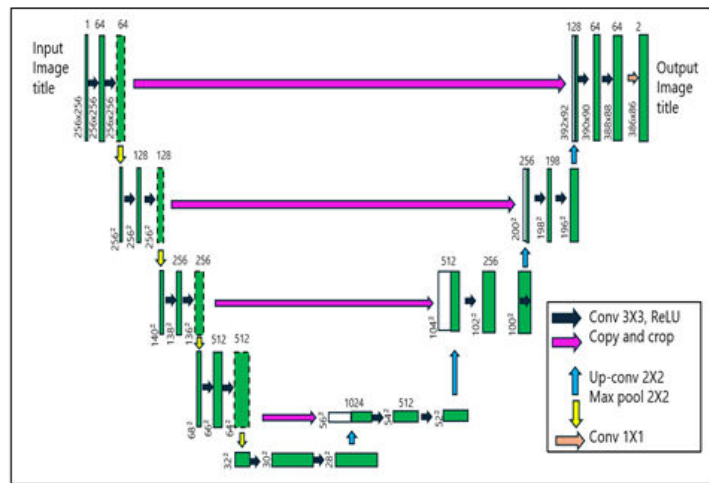
The U-Net architecture, proven effective in biomedical image segmentation tasks, was chosen as the backbone of the segmentation model. Its key components – the encoder, decoder, and skip connections – were instrumental in generating precise segmentation masks. The encoder progressively down sampled images, extracting features, while the decoder up sampled these features to recover spatial details. Skip connections seamlessly combined information from different resolution levels, critical for accurate boundary delineation.

b. Workflow

U-net takes Retinal fundus image as input.

Extracts features and generates a multi-class segmentation map.

Each pixel is classified as background, optic disc, optic cup.



c. Building Blocks

Skip Connections: Combine features from the encoder and decoder paths, aiding in pixel-level localization.

Convolutional Layers: Learn image patterns through repeated filtering operations.

Pooling Layers: Reduce dimensionality and increase spatial invariance.

Up-sampling/Deconvolution Layers: Increase feature map resolution in the decoder.

IV. OPTIMIZATIONS

Hyperparameter tuning aims to find the optimal model configuration for the best performance on the glaucoma detection task. Used Jaccard & Accuracy to measure model performance and guide hyperparameter selection. These metrics provided a comprehensive assessment of the model's ability to correctly segment the optic disc and cup regions, essential for accurate glaucoma diagnosis.

Key hyperparameters, such as learning rate, batch size, and optimizer, were tuned to attain optimal model performance. Filter size, and the size of the image was also tuned. Following figures provided best model performance.

Learning Rate = 0.0001

Batch size = 4

Epoch = 100

Optimiser = Adam

Loss = categorical loss entropy

Filters in Conv Blocks – Determine depth & complexity of features model can learn

Input Image Size – 256*256*3 directly affected computational complexity of the model

Training Enhancements – Keras Callbacks

During training, callbacks like ModelCheckpoint, ReduceLRonPlateau, and EarlyStopping were employed to save the best model, dynamically adjust the learning rate, and prevent overfitting.

EarlyStopping - Terminates training if performance stops improving for a specified duration, preventing overfitting.

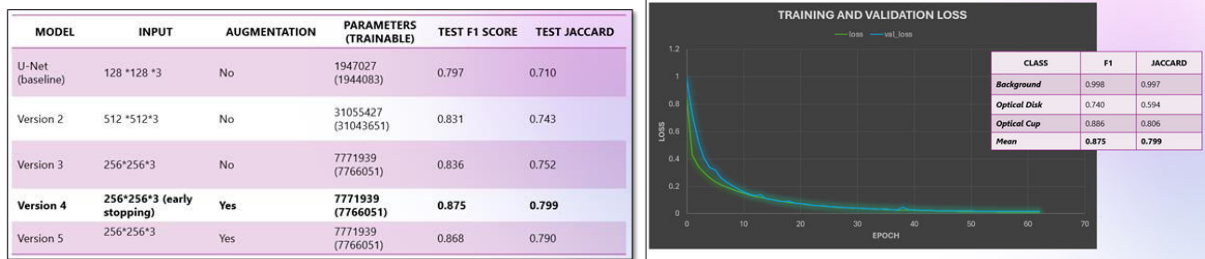
ModelCheckpoint - Saves the best performing model based on the evaluation metric

ReduceLRonPlateau - Dynamically adjusts the learning rate if improvement plateaus, promoting convergence.

V. RESULTS

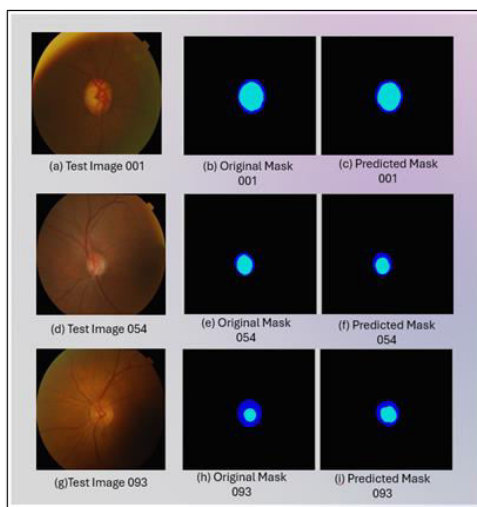
Model Comparisons

The models accurately segmented the optic disc and cup even in challenging cases with varying illumination. Version 4 achieved the highest segmentation accuracy, demonstrating its strength for glaucoma detection. Introducing augmentation strategies did significantly impact performance.



Segmentation Results and Observations

The proposed deep learning model achieved promising segmentation performance, particularly for fundus images with well-defined boundaries between the optic disc (OD) and optic cup (OC). This is evident in the sample images where the segmented masks closely adhere to the true anatomical structures.



Addressing Challenges with Healthy Eyes:

However, the model's performance was moderate for healthy eyes, where the boundaries between the OD and OC may be less distinct. The segmentation mask for the healthy eye exhibits less precise delineation around the optic disc, particularly compared to the segmentation in the glaucomatous eye. This observation is likely due to the less data samples of healthy eyes.

Potential Reasons:

Several factors could contribute to this variation in performance. One possibility is the imbalance between the number of glaucomatous and healthy images within the training dataset. Future work could explore incorporating techniques to address this class imbalance, such as oversampling or under sampling strategies. Additionally, investigating alternative model architectures or loss functions designed for imbalanced datasets might yield further improvements.

VI. CLASSIFICATION

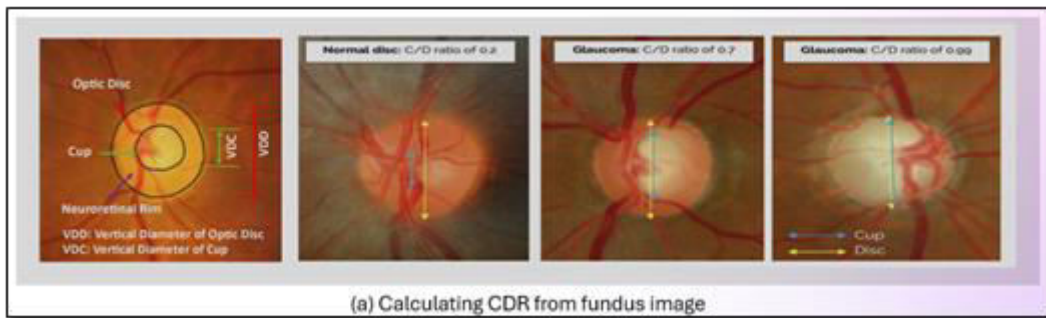
Utilizing Cup-to-Disc Ratio (CDR) for Glaucoma Detection

Following successful image segmentation, the next stage utilizes the segmented optic disc (OD) and optic cup (OC) regions to calculate the Cup-to-Disc Ratio (CDR), a crucial metric in glaucoma diagnosis. As shown in the below image, the CDR is calculated as the ratio of the vertical cup diameter (CD) to the vertical disc diameter (DD). In this case:

Vertical Cup Diameter (CD): Measure the vertical cup diameter based on the segmented image.

Vertical Disc Diameter (DD): Measure the vertical disc diameter based on the segmented image.

$$CDR = CD / DD$$



A high CDR can be indicative of potential glaucomatous damage to the optic nerve. By establishing a CDR threshold (e.g., 0.5 or 0.6), the classification system can categorize the image as either glaucoma-positive or glaucoma-negative. Below is the sample output on the unseen data. We can observe that, for healthy eyes, the probability for predicting the true label is less.

DATA SAMPLE	TRUE LABEL	PREDICTED CDR	PREDICTED LABEL
Image_011	Glaucoma	0.88	Glaucoma
Image_003	Glaucoma	0.78	Glaucoma
Image_006	Normal	0.61	Normal
Image_078	Normal	0.76	Glaucoma

VII. CONCLUSION

The developed automated glaucoma detection system demonstrates encouraging results, offering a foundation for further research and improvement. Several key directions hold promise for elevating the model's performance and clinical applicability:

Dataset Expansion: Incorporating fundus images from diverse sources and populations would increase the model's exposure to a wider range of variations in image appearance, fostering greater robustness and generalizability.

ROI Extraction: Employing advanced Region of Interest (ROI) extraction techniques, such as Contrast Limited Adaptive Histogram Equalization (CLAHE), could enhance the delineation of the optic disc and cup in challenging images (e.g., with subtle variations or uneven illumination), bolstering segmentation accuracy.

Model Refinements: Investigating architectural variations of the segmentation model, exploring state-of-the-art deep learning models specifically designed for medical image segmentation, could yield further performance gains.

Data Imbalance: Addressing potential imbalances in the dataset between glaucomatous and healthy images is crucial. Techniques such as up-sampling, down-sampling, or specialized loss functions tailored for imbalanced data should be explored to optimize model performance for both classes.

Precise Boundary Marking: Developing or integrating techniques for meticulously marking boundaries within merged masks would directly enhance the accuracy of Cup-to-Disc Ratio (CDR) calculations, refining the glaucoma classification process.

VIII. FUTURE WORK

Accurate segmentation of the optic disc and cup plays a vital role in the early detection and management of glaucoma. This project successfully developed an automated glaucoma screening system utilizing deep learning analysis of retinal fundus images. The proposed system provides a promising foundation for assisting ophthalmologists, offering a potentially faster, more accessible, and cost-effective approach to glaucoma diagnosis.

While the current project demonstrates the power of deep learning for segmentation, there's ample room for further enhancement. Future work could investigate the integration of additional diagnostic parameters (e.g., IOP measurements) alongside deep learning features to potentially boost classification accuracy and provide a more comprehensive assessment. Moreover, adapting and extending the system to detect a wider range of eye diseases using retinal images would significantly broaden its clinical impact.

REFERENCES

4. Publishing Corporation Journal of Ophthalmology Volume 2015, Article ID 180972
5. Deng, Wei Dong, Richard Socher, Li-Jia Li, Kai Li, and Li Fei-Fei. : A large-scale hierarchical image database. In Computer Vision and Pattern , 2009. CVPR 2009. IEEE Conference on, pages 248–255. IEEE, 2009.
6. He, Xiangyu Zhang, , and Jian Sun. Identity mappings in deep residual networks. In European Conference on Computer Vision, pages 630– 645. , 2016.
7. Gao Huang, Zhuang Liu, Q Weinberger, and Laurens van . Densely connected networks. In Proceedings of the IEEE conference on computer vision and pattern recognition, volume 1, page 3, 2017.
8. S , , GD Joshi, A , et al. A comprehensive retinal image for the assessment of glaucoma from the optic nerve head analysis. JSM Biomedical Imaging Data Papers, 2(1):1004, 2015
9. P. H. , A. S. , and A. , “Optic cup using U-net architecture on retinal image,” Journal of Information Technology and Computer Engineering, vol. 4, no. 2, pp. 105–109, 2020.
10. L. Li, M. , H. et al., “A large-scale database and a CNN model for attention-based glaucoma detection,” IEEE Transactions on Medical Imaging, vol. 39, no. 2, pp. 413–424, 2020.
11. J. C. MacCormick, B. M. Williams, Y. et al., “, fast, data efficient and glaucoma with automated spatial analysis of the whole cup to disc profile,” One, vol. 14, no. 1, Article ID e0209409, 2019.
12. M. , S. Singh, N. et al., “Automated detection of Glaucoma using deep learning convolution network (G-net),” Multimedia Tools and Applications, vol. 79, no. 21-22, pp. 15531–15553, 2020.
13. Diaz-Pinto, S. Morales, V. , T. , M. Jose, and “ A. , “ for automatic glaucoma assessment using images: an extensive validation,” BioMedical Online, vol. 18, no. 29, pp. 1–19, 2019.



INTERNATIONAL
STANDARD
SERIAL
NUMBER
INDIA



INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN SCIENCE | ENGINEERING | TECHNOLOGY

 9940 572 462  6381 907 438  ijirset@gmail.com



www.ijirset.com

Scan to save the contact details