**SEGMENTATION OF RETINAL BLOOD VESSELS USING CONVOLUTIONAL NEURAL NETWORKS**

**A PROJECT REPORT**

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BONAFIDE CERTIFICATE

Certified that this project report “SEGMENTATION OF RETINAL BLOOD VESSELS USING CONVOLUTIONAL NEURAL NETWORKS” is the bonafide work of “SAI KRISHNA R (212714104129), SIVA SUBRAMANIAN P A (212714104146), SUDHARSHAN K (212714104155)” who carried out the project work under my supervision.

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INTERNAL EXAMINER EXTERNAL EXAMINER

**ABSTRACT**

Retinal Fundus images have been widely used by ophthalmologists to diagnose and treat various diseases like Glaucoma, diabetic retinopathy, hypertension, arteriosclerosis and other cardiovascular diseases. To find the exact cause of the disease with the retinal fundus image for the ophthalmologists is difficult at times as the root cause of the disease can be found at the very end of the blood vessel which tends to be minute and slender. Moreover, due to the presence of liquids and gels like Aqueous Humor and Vitreous Humor, the visibility of the vascular tree gets reduced and the chances of error by humans while detecting the cause of the disease gets increased. To achieve a level of accuracy that aims at a patient’s faster diagnosis and treatment, a computer aided diagnostics and machine learning techniques such as Convolutional Neural Networks is used to segment the blood vessels or the vascular tree from the retinal fundus images to show a clear cut picture of the segmented vascular tree thereby increasing the chances of the ophthalmologists to detect the disease and provide the necessary treatment.

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**LIST OF ABBREVIATIONS**

**MIC** Medical Image Computing

**ANN** Artificial Neural Network

**CNN** Convolutional Neural Network

**OCT** Optical Coherence Tomography

**SVM** Support Vector Machine

**DRIVE** Digital Retinal Images for Vessel Extraction

**RGB** Red Green Blue

**HDF** Hierarchical Data File

**TP** True Positives

**FP** False Positives

**TN** True Negatives

**FN** False Negatives

**CPU** Central Processing Unit

**GPU** Graphic Processing Unit

**CUDA** Compute Unified Device Architecture

**SVM** Support Vector Machine

**ReLU** Rectified Linear Unit