TEKNOFEST

AVIATION, SPACE AND TECHNOLOGY FESTIVAL

BIOTECHNOLOGY INNOVATION COMPETITION

PROJECT DETAIL REPORT

TEAM NAME

Tech Joyriders

PROJECT NAME

DESIGN AND IMPLEMENTATION OF OPHTHALMOLOGICAL DIAGNOSES OF EYE DISEASE USING OPTICAL COHERENCE TOMOGRAPHY MACHINE AND IMAGE PROCESSING

REFERENCE ID

#52573

Category

BIOTECHNOLOGY INNOVATION COMPETITION

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Project Summary (Project Description)

Diseases are a part of nature, that is they occur naturally due to different causes when we become careless. Similarly, eye diseases also occur naturally i.e., the diversify ocular disorders in which Cystoid Macular Edema (CME) has occurred, is strongly associated with the vision loss. Optical Coherence Tomography (OCT) allows screening of the retina to diagnose a particular disease, but the flaw of OCT scans is that they contain artifacts, blur edges and speckle noise, which creates difficulty in identifying retinal fluid i.e. CME regions. Our work includes 4 main image processing steps i.e. Minimum filtering, Block-Matching and 3D filtering (BM3D), A Richardson-Lucy deconvolution technique and contrastsetting which are applied to eradicate noise and other degradation effects to improve the quality of OCT scan. It provides a better visualization of the OCT scan to the clinicians. Furthermore, we mainly focused on developing an automated method based on deep learning to detect the presence and progression of retinal fluid i.e. CME. The performance of our algorithm was evaluated for accurate identification of retinal fluid localization and compared with manual segmentation of fluid by experts, which are highly correlated. The automated detection of CME by an enhanced algorithm achieves better performance and assists the clinician to easily monitor the progression of CME and its severity level. This method has the prospective to enhance the efficiency of Diabetic Retinopathy (DR) screening, and in this manner, the loss of vision in the case of Diabetic Macular Edema (DME) is prevented. This integration of knowledge from ophthalmology and artificial intelligence (AI) can revolutionize the current diagnostic procedures for eye diseases and modify its clinical procedures to improve the field of medicine in the upcoming days

SOFTWARE AND ASSEMBLY:

The project is implemented on Spyder IDE using Python programming language (Python3) to conduct various experiments on three major steps sequentially. In the first step, we performed Image preprocessing, statistical calculation, analyzing and visualization graphs by utilizing these outstanding libraries as shown:

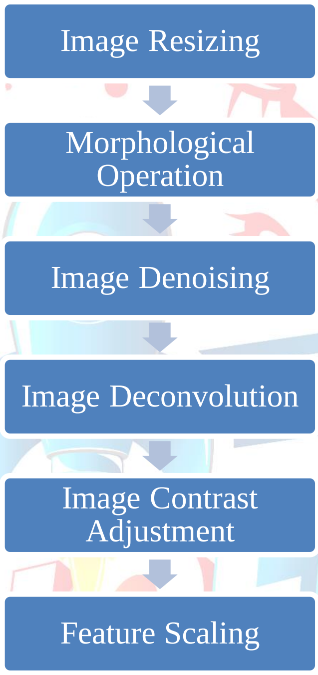
Library Name	**Purpose of Usage**
OS	For dealing with the operating system
Numpy	To deal with arrays and their operations
Scipy	For performing scientific computation
Skimage	For image processing related libraries
Sklearn	
PIL	
CV2	
BM3D	
ImQuality	To calculate BRISQUE score
DOM	To estimate sharpness score
Seaborn	For visualization of plots
Matplotlib	

In the second step, the U-Net model has been trained using Keras with a Tensorflow backend. For visualization of graphs related to accuracy and loss of training, the Tensorboard comes to play.

In the third step, we evaluate the trained model and statistically quanitfy the predicted Oct images with the ground truth with Tensorflow and Tensorboard libraries respectively.
The experimentations have been conducted on two platforms, one with the personal laptop: Dell Inspiron 5379 with **Intel® Core™** i5-8250U CPU at 1.60 GHz (8 CPUs, 6 MB cache) and 8 GB RAM. It took 4 and a half hours to fully train the model on Laptop. The other one uses Google collab with GPU as it has outstanding processing speed and it took only 3 minutes to train the whole U-NET model.

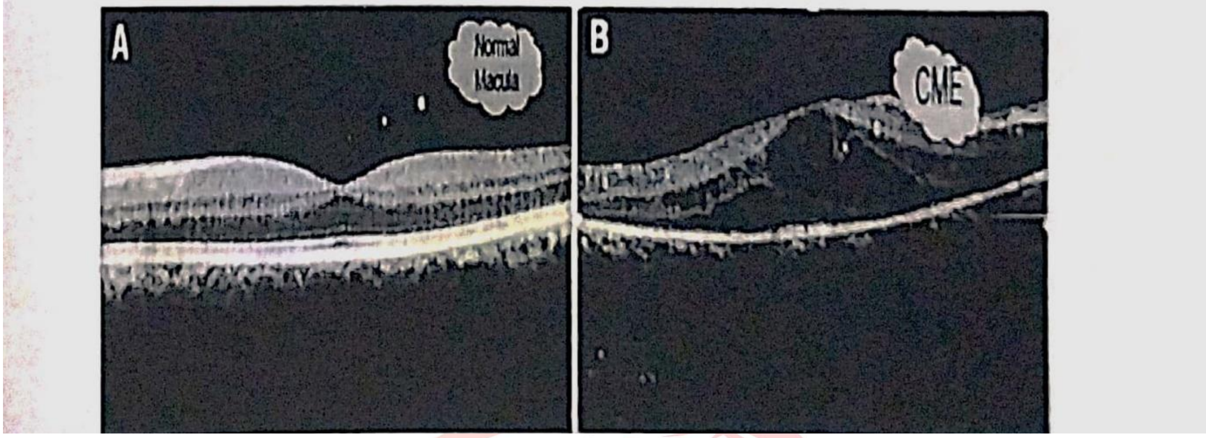
DESIGN:

The complete flowchart for all the steps required in designing the image preprocessing is shown in the figure:



2. **Problem:**

Diabetic retinopathy (DR) remains a major microvascular problem to a person affected with diabetes and therefore is a major reason for irreversible vision. Almost one in every 11 adults are affected globally, and remaining DR patients, suffer from diabetic macula edema (DME). It still remains the common vision losing source in patients with DR, activated by the gathering of fluid inside the macula, causing the macula to swell and it may arise at any stage of the diabetic retinopathy and it can be distinguished by growth of blood vessels from choroid towards the macular region. Therefore, primary detection and medication of DME plays important role. The OCT Machine image of a normal macula is shown in the diagram and the cystoid macula edema (CME) occurring with DME is a tough job because of a high quantity of cysts, severe touching of cysts, random variation of cysts sizes etc. Like most commercial OCT-apparatus, the retinal borders are detected and give overall macula width, but with no calculable knowledge about pathological parameters. Therefore, analysis of the area of fluid areas is also a crucial addition to the useful diagnostic matrix. Traditional diagnostic methods of ophthalmology rely on the trained skills and understanding of physicians, which can arise high chances of misdiagnoses, so a step must be taken to produce the most effective and accurate results. Moreover, most commonly found OCT in the hospitals/clinics is available in its older version that is the time domain OCT which lacks in several functions reducing the chance of earlier detection of DME.



3. Solution:

DL has been used to automatically detect abnormalities in eyes with significantly higher accuracies. In this project, the development, and validation of a fully data-driven artificial intelligence-based model is the aim, with unsurpassed convolutional neural network architecture U-Net which is used for fast, precise segmentation. And to screen Spectral-Domain Optical Coherence Tomography (SD-OCT) data obtained from diabetic patients for automatic identification and detection of multiple cyst-like (cystoid) areas of fluid gathering in the macula causes retinal swelling or CME in the most occurring eve disease like Diabetic Macula Edema (DME) with high reliability. Moreover, this project varies from weakly supervised methods. As it is able to learn automatically from retinal images without any manual pixel, or image-level labeling and without training a segmentation network before with other labeled datasets. It will also generate an automatic report which will highlight important abnormal regions, assist clinicians in monitoring, and a better understanding of IRC fluid development among diabetic patients to tackle this global disease. This suggested scheme can improve the application of intelligent diagnostic models to deal with the real-time diagnosis and it would help in decreasing the percentage of vision loss, allowing well-timed and precise diagnosis. Implementation of such an algorithm can expressively decrease the percentage of vision loss recognized as DME.

The suggested scheme is established in a challenging dataset employing data of Defected patients, which indicates that the suggested scheme performs better on OCT captured images with irregularly shaped edema and blurred boundaries.

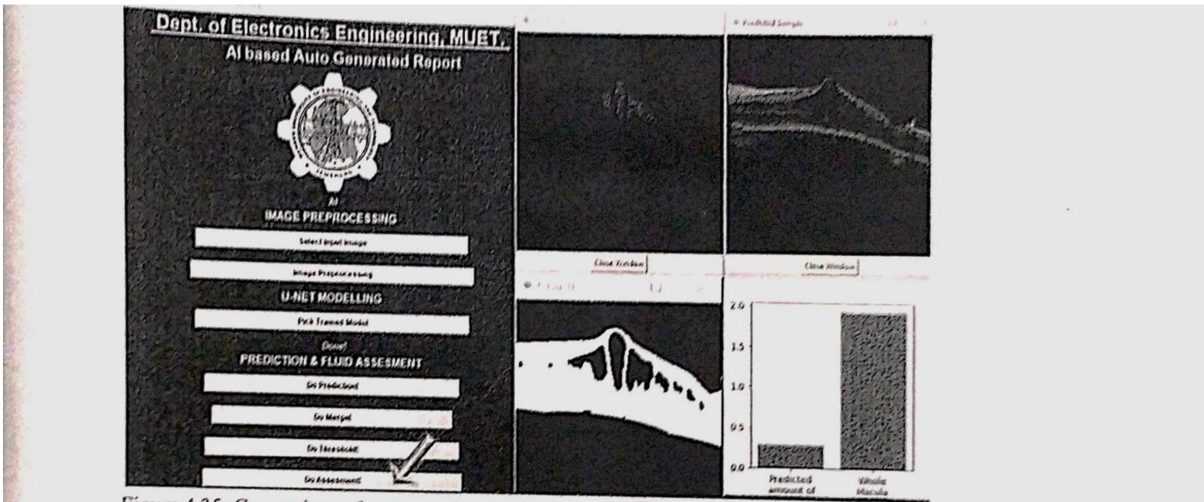


Figure 4.35: Comparison of segmentation size between the predicted and ground truth image.

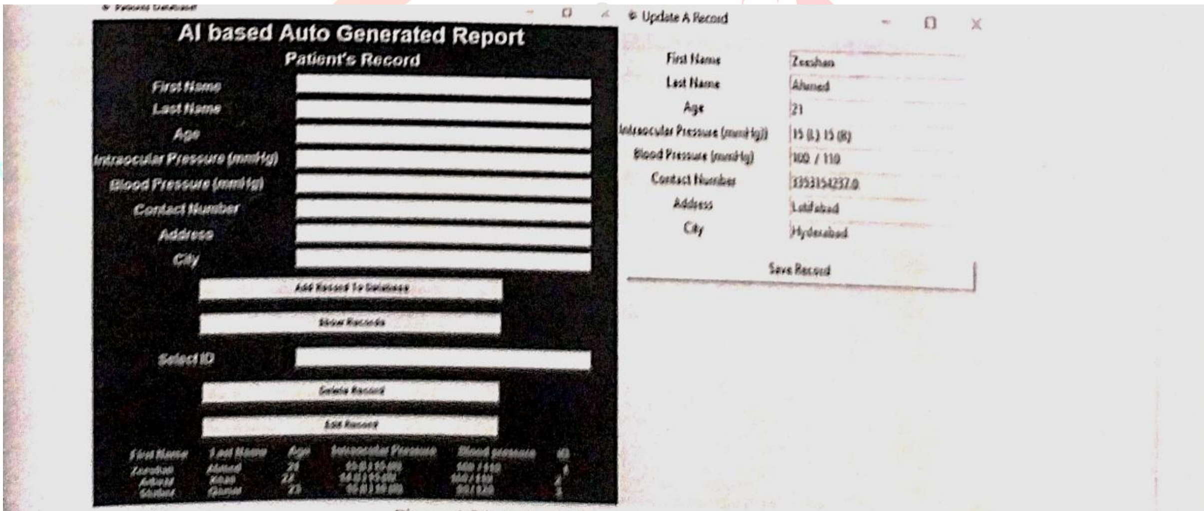


Figure 4.36: Patient's Record

4. Method

This AI-based project implements sequentially three major pipelines as follows:

- i) Image preprocessing
- ii) Model training
- iii) Model inference

In the first step, we enlightened how noisy is the OCT image. Moreover, these images are also containing certain degradation effects like artifacts and blurry edges. So this kind of degradation effects occurred in OCT images, needs to be eliminated. We followed a series of image processing steps to improve the quality of an image and utilized mainly Minimum filter (to enhance the dark pixels and remove outliers in OCT image), a denoising algorithm (BM3D: to grouped similar patches of a specific threshold and transform it to 3D, which then passed through hard- thresholding. Finally applied an inverse 3D transformation and aggregate all patch-wise estimation to construct a denoised image), a Richason-Lucy algorithm (to remove the blurry effects obtained after denoising algorithm with the help of iterations and PSF to recover fine and deblur image), and set contrast for better visualization. To ensure the improvement in the quality of images, we also used the image quality metrics to estimate the BRISQUE and sharpness score, With this inmage processing approach, we obtained outstanding results, which are then able to for the training of the U-Net model. In the second step, manual segmentation of fluid was performed by experts. The fluid related to CME in OCT images may vary in appearance and size, but also with respect to contrast and image quality, the OCT scans from different vendors sometimes differ greatly. Therefore, it is very time consuming and tough to examine CME regions for manual segmentation. The task of the manual delineation of CME structures was assigned to clinician experts, using an image segmentation app in MATLAB with the following tools: free-hand drawing and flood fill using MATLAB. We labeled 1 for the pixels set comprised of CME and 0 for the Non-CME pixels set, as ground truth labels. In the third step, the preprocessed OCT images and their corresponding ground truth labels were İnput to the U-Net model for the training and validation process. This U-Net model training can be done efficiently with small datasets and a lesser number of epochs, which save our great time The configuration of hyperparameters was chosen in such a manner to give optimal results over the entire process, as can be seen in chapter 4, all the performance metrics we utilized in oum experiments, achieved the best scores.

5. Innovative:

As previously explained in the Problems Section, older version of the OCT machine lacks in many grounds to give precise knowledge regarding DME. Our main aim is to implement a more better experimentation methodology with a mutual cooperation between an OCT machine and an AI based program. The existence of macular fluid signifies an essential clinical withdrawal standard for the supervision of patients suffering from macular disease, and assessment of fluid level through OCT has made an easy and accurate detection of several parameters required to detect any eye disease.

Our objective is to implement a better detection, quantification and analyzation of differences in retinal images with the help of a deep learning and image processing-based application to process OCT images and implement the best possible algorithm to predict Intra-Retinal Cystoid (IRC) fluid regions in DME eye disease.

6. Applicability

Under the current circumstances, we believe there is a dire need for prevention of eye loss rather than treatment since treatment requires more money and it could be extremely costly as it is a sensitive matter of vision loss from DME. Therefore, our idea should be converted to commercial use in local and private hospitals and eye clinics. Our project is entirely based on working of an AI intregrated model therefore it can be implemented in our areas of interest easily. The scientists, physicians and eye specialist could use our project and validate their results through different analytical approaches between computerised and physical eye checkups.

7. Estimated Cost and Project Scheduling

Project Calender:

S.No	Planning and Progress	Dates
1.	Project Preliminary Report	24/3/2021
2.	Project Detailed Report	14/6/2021
3.	To produce a software and computation environment	25/6/2021
4.	To do image preprocessing	29/6/2021
5.	To develop a detailed description of automated method	3/7/2021
6.	To produce a statistical evaluation of model	7/7/2021
7.	To perform further experimentations on clinical and automated methods	20/7/2021
8.	Application will be tested of our automated method	30/7/2021
9.	Final Testing	1/8/2021

Estimated Cost:

Our working software is Spyder IDE which available in Python programming languages and it is totally free and cost effective. It utilizes libraries which are very outstanding and are frequently used by engineers, data analysts etc. Other than that, our U-Net model has been trained using Keras with a Tensorflow backend. Just like Spyder IDE, Keras is entirely free and powerful, not to mention easy to use. Next platforms are required for our experimentation, As described in the SOFTWARE AND ASSEMBLY subsection, the given model of Dell costs 799$. Google colab 'colabotory' is used with the GPU is freely available to use. Thus, we can safely conclude that for our project to be implemented successfully, expertise in data handling and a working platform is required.

Project Idea Audience (Users):

The working audience for our project are the eye specialists, scientists and analyists having experience in the field of electronic apparatus in check ups of the eye. Therefore, our project is entirely based for the hospital staff and could be used for experimental purposes as well. With combined working of OCT machine and our AI model, eye specialists can treat the patients of DME and CME and prevent the eye loss before it occurs.

Risks

As, the Al model is trained with the retinal image dataset of the patients with DME and its mild to worst cases i.e, CME, where it also detects the accumulation of fluid in the macular region and the stages of CME based on the size and location of the cyst. Otherwise, there are also other commonly occurring diseases like Glaucoma, AMD (Age-related Macular Degeneration), etc., whose detection can be done similarly as discussed in chapter 1 that, the specific variations occurring in specific layers are used to denote the occurrence of one particular disease but the purpose of the project was to detect DME, fluid regions and measure the cyst in case of CME, which has been successfully and efficiently implemented.

Studies have shown that the designed algorithm's accuracy reduces when we tend to increase the number of diseases to be detected. And to more improve the applications of Al in the medical field, there is a need to design more intelligent systems that serve this purpose. Furthermore, one disease diagnosed through one imaging technique, not every time guarantees the accurate detection of a particular retinal abnormality (e.g. DR or glaucoma) in the medical field. So, Multimodal medical image data, such as visual field, angiography, fundus images, and optical coherence tomography images must be put togeher to design a general AI model for better results. A challenge faced by the authors in [32] is the limited accessibility of a big number of data for some rare kinds of diseases (like, Ocular Tumors, etc.) and there may occur some common diseases that are not imaged in routine in ophthalmology for example cataracts, etc

10. Project Team

Team Leader:

First Name Last Name	Task in a Project	School	With a project or a problem related experience
Abdul Haseeb Solangi Class 12th Pre-Medical	Team Leader, computation and report working	PakTurk Maarif Intl. Schools and Colleges, Boys Branch, Jamshoro	First time dealing with a problem related experience
Waqas Halepoto Class 12th Pre-Medical	Team Member, thesis provider and partner	PakTurk Maarif Intl. Schools and Colleges, Boys Branch, Jamshoro	First time dealing with a problem related experience

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