Course Project Report

Automated Detection of Corneal Ulcers Using ResNet: A Deep Learning Approach

Submitted By

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as part of the requirements of the course

IT for Healthcare [Jul-Nov 2024]

in partial fulfillment of the requirements for the award of the degree of

Master of Technology in Information Technology

under the guidance of

Dr. Sowmya Kamath S, Dept of IT, NITK Surathkal

undergone at

DEPARTMENT OF INFORMATION TECHNOLOGY

NATIONAL INSTITUTE OF TECHNOLOGY KARNATAKA, SURATHKAL

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C E R T I F I C A T E

This is to certify that the Course project Work Report entitled **"Automated Detection of Corneal Ulcers Using ResNet: A Deep Learning Approach"** is submitted by the group mentioned below -

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this report is a record of the work carried out by them as part of the course **IT for Healthcare (IT820)** during the semester **Aug-Dec 2024**. It is accepted as the Course Project Report submission in the partial fulfillment of the requirements for the award of the degree of **Master of Technology in Information Technology.**

(Name and Signature of Course Instructor)
Dr. Sowmya Kamath S.
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DECLARATION

We hereby declare that the project report entitled **"Automated Detection of Corneal Ulcers Using ResNet: A Deep Learning Approach"** submitted by us for the course **IT for Healthcare (IT820)** during the semester **Aug-Dec 2024**, as part of the partial course requirements for the award of the degree of Master of Technology in Information Technology at NITK Surathkal is our original work. We declare that the project has not formed the basis for the award of any degree, associateship, fellowship or any other similar titles elsewhere.

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Place: NITK, Surathkal
Date: December 7th, 2024

Automated Detection of Corneal Ulcers Using ResNet: A Deep Learning Approach

Sai Saketh[1], Charan Srinivas[2], Phaneendra Reddy[3], Sai Kiran[4]

***Abstract*— Abstract—Corneal ulcers are a major concern for eye health worldwide, often leading to severe complications if not diagnosed and treated promptly. Traditional methods of diagnosing these ulcers heavily depend on the expertise of clinicians and can sometimes result in delays or errors, potentially worsening the patient's condition. To address this challenge, we explored the use of deep learning, specifically the ResNet architecture, to automate the detection of corneal ulcers.Additionally, this study incorporates the U-Net model to segment corneal ulcers, providing detailed morphological insights alongside robust classification. This combined approach enhances the accuracy and utility of the automated diagnostic system. By training our model on a carefully selected dataset of corneal images, we evaluated its ability to classify cases with high accuracy, sensitivity, and specificity. The results highlight the potential of this approach as a reliable tool for early and precise diagnosis, reducing reliance on manual assessments. This study demonstrates how artificial intelligence can play a transformative role in improving eye care and patient outcomes, particularly in regions with limited access to specialized healthcare.**

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I. INTRODUCTION

Corneal ulcers are the most serious eye conditions that are among the first causes of dispread blindness in the world. It can develop due to infectious conditions or injuries resulting from other underlying conditions. However, it becomes very important that an individual patient diagnoses very promptly and accurately to avoid irreversible damage and complications in corneal vision (Alhajraf et al., 2020).

Most of the times, corneal ulcers would require the use of processes such as slit-lamp examination and microbiological analysis. These are proven methods but are highly time-consuming and require specific measures in terms of skills of trained eye care professionals. This means that facilities with limited healthcare resources or lacking ophthalmologists will fail to diagnose and treat a lot of ocular diseases in time, thereby making the risk of losing vision greater.

Recent years have brought to the fore all new promising opportunities for reinventing medical diagnostics, owing to advances in artificial intelligence and deep learning. Convolutional Neural Network, among many deep learning approaches, proves to be fast evolving technology with an impressive performance in image recognition and classification tasks. Learning and extraction of very complex patterns from images make them invaluable in medical imaging, especially in the field of radiology, dermatology, and ophthalmology.(Lyu et al., 2020)(Loo et al., 2020) (Wang et al., 2021b)

ResNet is a deep residual learning framework and has its own specialty among CNN architectures in terms of breaking down barriers such as overcoming the very deep network with a vanishing gradient. Thus, ResNet assures efficient learning even in very complex models via using shortcut connections and makes it better for applications requiring very high precision, as in medical diagnostics. The remarkable performance of ResNet in identifying diseases based on X-ray, CT, and other types of images points out such features(Mayya et al., 2021)(Wang et al., 2021a).

II. RELATED WORK

The field of corneal ulcer detection and segmentation has seen significant advancements over the years, with researchers exploring various machine learning, image processing, and deep learning techniques to address the challenges associated with accurate diagnosis and segmentation

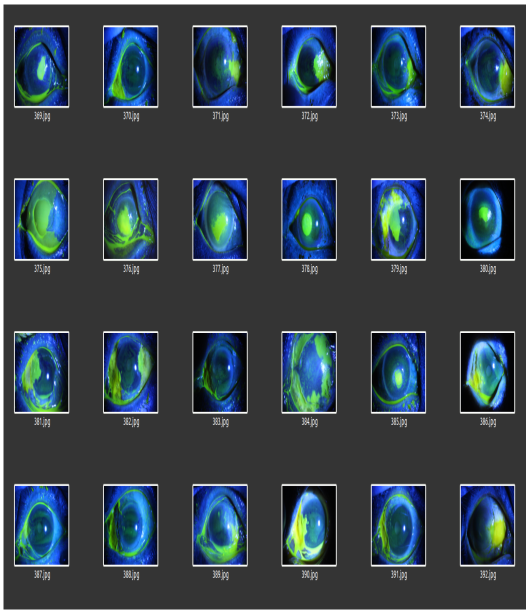

Fig. 1: Dataset images

A. Machine Learning and Image Processing Approaches

In an effort to achieve a fully automated pipeline for segmenting flaky corneal ulcers in 2019, Zhenrong Liu et al.(Liu et al., 2019), in combination with the Gaussian Mixture Model (GMM), processed data with Otsu thresholding in HSV color space, thus obtaining a Dice similarity coefficient of 0.88 validated on 150 images, stressing automated segmentation effectiveness. In 2020, Jessica Loo et al. presented to the world an automatic segmentation algorithm designed to identify biomarkers for microbial keratitis called SLIT-Net. SLIT-Net is able to segment multiple pathological regions of interest across different light modalities by analyzing slit-lamp photographs of 133 eyes. The performance of the model is convincing in terms of Dice coefficients ranging from 0.62 to 0.95 across different ROIs using sevenfold cross-validation to make them robust(Loo et al., 2020). In the same year, Pablo Lima et al. sought a semiautomatic segmentation method based on supervised machine learning approaches. The authors evaluated several algorithms including multi-layer perceptron, SVM, K-nearest neighbors, and random forest. Among these, random forest was the best algorithm, achieving Dice similarity of 0.85 and accuracy as high as 99.08.(Lima et al., 2020)

B. Deep Learning Advancements

Since the arrival of deep learning approaches, it is gradually replacing the traditional methods towards achieving better results for medical image segmentation. In 2020, Junyan Lyn et al. proposed a transformative transfer learning model in corneal segmentation based on the encoder-decoder architecture. The model utilizes an Xception feature extractor along with atrous spatial pyramid pooling, and achieved the state-of-the-art results with a Dice score of 0.9582, an accuracy of 97.63 and a sensitivity of 95.37 during testing on SUSTech-SYSU dataset.(Deng et al., 2020) In 2021, Veena Mayya et al. came up with an MS-CNN architecture for corneal segmentation, which was further used by the authors with ResNeXt for differentiating. Their work could identify fungal keratitis very effectively with an accuracy of 88.96 on a dataset created by Jessica Loo et al.(Mayya et al., 2021) Likewise, Tingting Wang et al. came up with CU-SegNet, a Ushaped encoder-decoder network designed for segmenting corneal ulcers of any shape and size in fluorescein images. The CU-SegNet model showed signs of impressive performance on the SUSTech-SYSU dataset, with a Dice coefficient of 0.8914.(Wang et al., 2021b)

III. Dataset

In this current study, the SUSTech-SYSU Dataset is used, which was open-developed for the task of segmentation and classification of corneal ulcers. The dataset comprises 354 high-resolution images with annotated information by qualified ophthalmologists on both the presence and severity of corneal ulcers.

These annotations by experts ensure accurate and reliable labels thus making the dataset an invaluable source for training and evaluation of deep learning models. Images are collected under standardised conditions to provide a clear detailed representation of corneal ulcers. Then dataset was splitted 80 as training and 20, for validation into final preparations to train and test the U-Net and ResNet based detection model.This division resulted in 283 images to train and 71 images to Verification. The training set was used to teach the model to detect corneal ulcers, while the validation set helped assess the model's performance and fine-tune its parameters to improve accuracy and generalization.

The SUSTech-SYSU dataset has been widely recognized and used in previous studies, making it a benchmark for comparing the performance of various models. Its diverse collection of images captures ulcers of different shapes, sizes, and intensities, posing realistic challenges for segmentation and classification tasks. However, the dataset's relatively small size presents a challenge, requiring careful pre processing and the use of data augmentation techniques to ensure the model can generalize well and avoid over fitting.

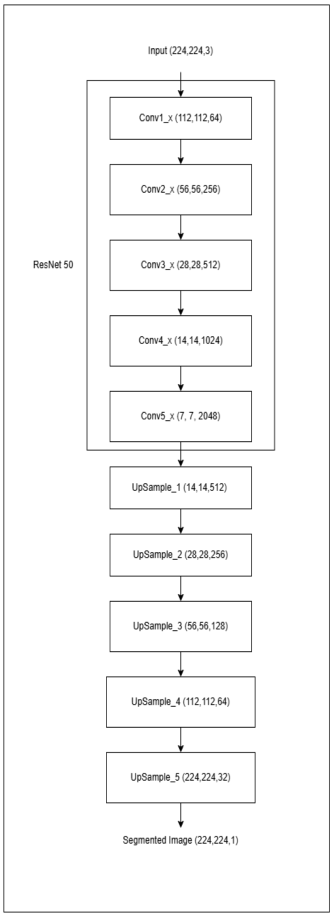

Fig. 2: ResNet50 model Architecture

IV. Problem Statement

Automated detection of corneal ulcers through deep learning techniques-U-Net and ResNet architecture is the hard-coded problem approach. Major causes of Vision impairment; Diagnosis must be done in time to Avoid very serious consequences, such as blindness. Traditional diagnostic methods are time-consuming and subjective, depending mostly on specialty ophthalmologists, and therefore are not as accessible in most resource-poor settings. It tries to develop an efficient, effective, and accurate diagnostic tool by training a ResNet model on annotated images from the SUSTech-SYSU dataset. Automated detection and classification as a part of corneal ulcers form into improving diagnostic accuracy and minimizing human error while being scalable. Early detection can be achieved through the clinical as well as the remote setting.

V. Methodology

The methodology for this study involves using deep learning techniques, particularly the ResNet architecture, for the automated detection of corneal ulcers. The process includes several key stages, from data pre processing to model training and evaluation.

A. Dataset Preprocessing

The first step in the methodology was to prepare the SUSTech-SYSU Dataset for training and validation. Additionally, image normalization was performed to standardize pixel values, making the images suitable for the ResNet model. The dataset was split into 80 for training and 20 for validation to ensure that the model's performance could be reliably evaluated. For U-Net training, the SUSTech-SYSU dataset was augmented with binary masks representing the ulcer regions. Images were resized to 256x256 to match U-Net's input requirements, and data augmentation techniques such as rotation, flipping, and scaling were applied to improve model generalization.

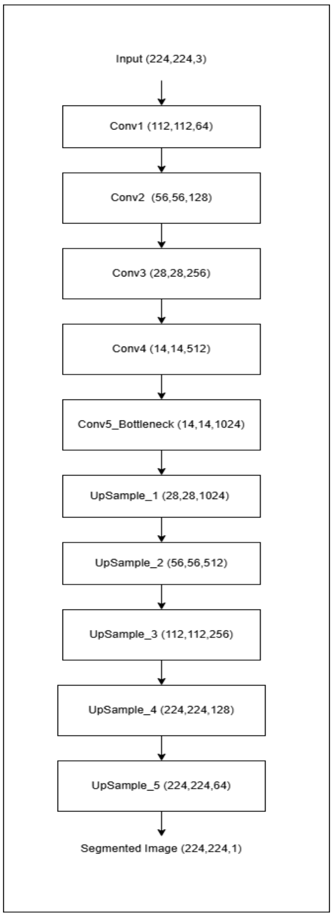

Fig. 3: U-Net model architecture

B. Model Architecture - ResNet50

The core of the model is based on ResNet, a deep residual network designed to overcome the vanishing gradient problem in very deep neural networks. ResNet's skip connections allow the model to learn residual mappings, improving its ability to train deep architectures. The architectural framework used in this study is a modified ResNet-50, pre-trained on ImageNet, It was fine-tuned by applying it to the corneal ulcer dataset. specific features of corneal images. The final fully connected layer is removed and output from encoder is passed to the decoder for upsampling the image.The network was designed to classify images into two categories: corneal ulcer or no ulcer.

C. Model Architecture - U-Net

U-Net has been used for pixel-wise segmentation of corneal ulcers. It has an encoder comprises of max pooling, and multiple convolutional layers for features collection at different levels. It has a decoder mirroring the structure of the encoder, to progressively reconstruct spatial details by transposed convolution. Skip connections link the encoder and decoder layers, so that the analysis preserves high-resolution features right before producing the binary masks for the output definition of the ulcer region.

D. Model Training

The above model has been trained on a dataset of 283 images from the training set. The binary cross-entropy loss function was used to guide learning for binary classification tasks. Adam optimizer, which becomes responsible to adjust it according to training conditions, such as convergence speed and efficiency, was used. To prevent overfitting, early stopping and dropout in the whole network layer were added. It was run for 50 epochs, and each epoch had validation to determine how well the model performed. It could be monitoring its accuracy and updating the hyperparameters if necessary.

U-Net architecture specifically designed for segmentation trained a model using a categorical cross-entropy loss more focused on pixel-wise accuracy. It used Adam optimizer with an initial learning rate of 0.001 and trained for 50 epochs with a batch size of 16. Therefore, segmentation performance is evaluated with the model in terms of Dice coefficient and Intersection over Union, thus developing these metrics into a comprehensive evaluation framework to ensure that the model predicts accurately the severity of corneal ulcers in images.

E. Model Evaluation

Model performance was determined by determining various metrics, such as accuracy, sensitivity, specificity, and F1 score. Accuracy is the degree to which the predictions of the model are correct overall and sensitivity or recall is a measure of positive identification of the model i.e. corneal ulcers.

Specificity indicates a negative identification of corneal ulcers, that is, its images, by the model. The F1 score, or harmonic mean of precision and recall, assessed the balance between these two metrics. Confusion matrix for further analysis of performance and class imbalance detection was used as well. Segmentation performance of the U-Net was measured using the Dice coefficient to evaluate joint prediction masks and ground truth while evaluating segmentation performance by using IoU. The measurements were done on training and validation datasets.

VI. Experimental Setup

The setup for this experiment encompasses the hardware and software configuration, as well as the procedure for the training and evaluation of a ResNet model, trained and evaluated for automated corneal ulcer detection. The major components of the experimental setup are detailed below. Hardware Configuration The experiments were conducted using a machine with the following hardware specifications: GPU: NVIDIA Tesla T4 (Kaggle Cloud) CPU: Intel i7 or equivalent RAM: 16 GB or higher Storage: SSD storage with at least 50 GB of available space for data and model storage The GPU acceleration cut down on the time taken to train and evaluate the model, letting it converge faster with larger images that can be handled more efficiently when training deep learning models.

During the training process, several hyper parameters were fine-tuned, including the learning rate, batch size, and dropout rate. The optimum values were determined based on performance on the validation set. Additionally, the fine-tuning was done for the pre-trained ResNet model by adjusting the last layers of the network to better fit into the task of corneal ulcer classification. The training and testing process were carried out on Kaggle notebooks, utilizing the free GPU resources.

VII. Results and analysis

A. ResNet-50 Classification Results

The ResNet-50 model, trained and evaluated on the SUSTech-SYSU Dataset, demonstrated strong performance in detecting corneal ulcers. The model achieved an accuracy of 95.3 on the validation set, showcasing its ability to correctly classify images into ulcer and non-ulcer categories with high precision.

B. U-Net Segmentation Results

The U-Net model demonstrated excellent performance in segmenting corneal ulcers. After training and evaluation on the dataset, the model achieved a validation accuracy of 98.88 with a validation loss of 0.0278. The high accuracy underscores the model's capability to produce precise segmentation masks, effectively delineating ulcer regions.

TABLE I: Results

model	Accuracy	global acc	Sentitivity	Jaccard	Dice Sim
ResNet50	97.7	98.12	99.46	98.06	99.01
U-Net	98.88	98.87	99.68	98.82	99.40

We have also implemented the preprocessing model which we haven't succecced. Preprocessing techinique is not able to detect the ulcer in our approach as the green layer of ulcer is slowly decresing as we go far from the ulcer. So, We have not archieved our result in preprocessing approach.

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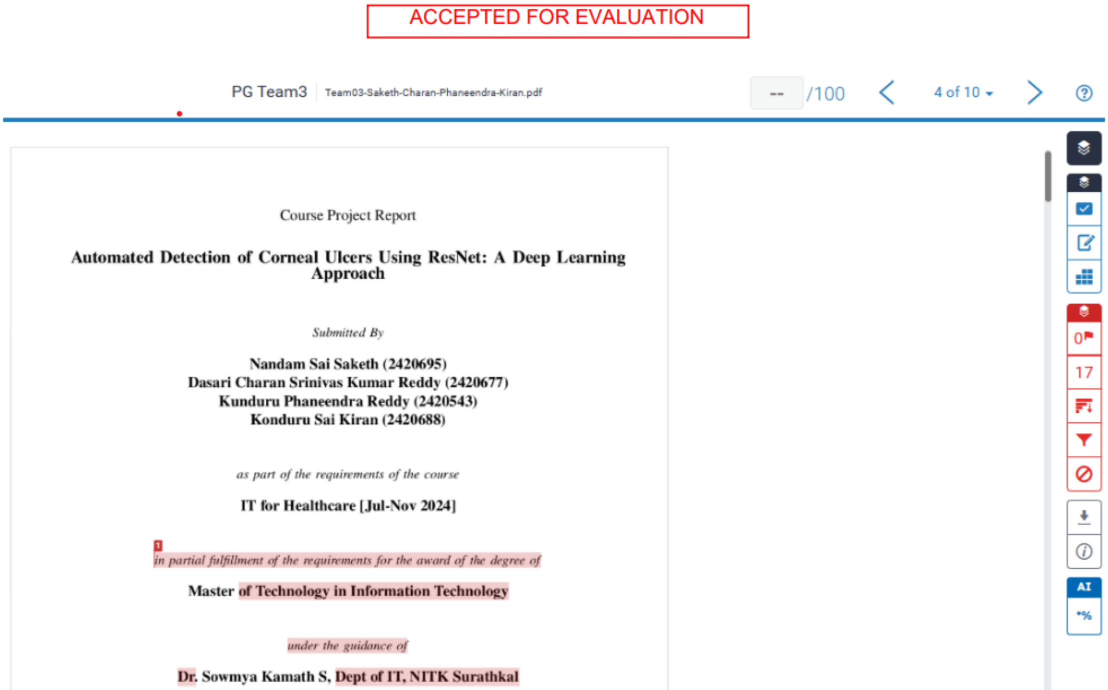
APPENDIX



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