Journal of Population Therapeutics & Clinical Pharmacology

RESEARCH ARTICLE
DOI: 10.53555/jptcp.v30i18.3175

DIAGNOSIS AND CLASSIFICATION OF OCULAR DISEASES USING SPATIAL CORRELATION NETWORKS

Sayyid Kamran Hussain[1*], Sadaqat Ali Ramay[1], Madiha Sarwar[2], Tahir Abbas[1], Muhammad Kaleem[2]

[1]Department of Computer Science, TIMES Institute, Multan, Pakistan.
[2] Department of Information Technology, University of Sargodha, Sargodha, Pakistan.
Email: kamran.hussain@tu.edu.pk; drsadaqatali@t.edu.pk ; madiha.sarwar@uos.edu.pk; drtahirabbas@t.edu.pk; muhammad.kaleem@uos.edu.pk

***Corresponding Author:** Sayyid Kamran Hussain
*Department of Computer Science, TIMES Institute, Multan, Punjab, Pakistan,
Email: kamran.hussain@tu.edu.pk

Abstract: Ocular diseases, ranging from diabetic retinopathy to glaucoma, pose a substantial global healthcare challenge, demanding accurate and timely diagnosis. The conventional manual interpretation of ocular imaging, while practiced with expertise, is subjective and labor-intensive. This research addresses the pressing need for automation in ocular disease diagnosis and classification through the innovative application of Spatial Correlation Networks (SCNs).

Our objectives encompass the development of a dedicated SCN framework, comprehensive dataset collection, standardized annotation, and the automated detection and classification of ocular diseases. Performance evaluation considers accuracy, sensitivity, specificity, and computational efficiency, alongside the potential for clinical integration. Ethical and regulatory dimensions are thoughtfully explored. The author has developed a patient-level multi-label OD (PLML_ODs) classification model based on a spatial correlation network (SCNet). This model takes into account the patient-level diagnosis by combining data from both eyes and performing multi-label ODs classification. The PLML_ODs model comprises three key components: a backbone convolutional neural network (CNN) used for feature extraction, specifically DenseNet-169; the SCNet for capturing feature correlations; and a classifier for generating classification scores.

DenseNet-169 is responsible for extracting two distinct sets of attributes, one from each of the left and right CFI. Subsequently, the SCNet records correlations between these two sets of features at a pixel-by-pixel level. After the attributes have been analyzed, they are integrated to create a patient-level representation. This patient-level representation is utilized throughout the entire process of ODs categorization.

To evaluate the effectiveness of the PLML_ODs model, a soft margin loss function is applied to a publicly accessible dataset. The results demonstrate a significant improvement in classification performance when compared to several baseline approaches.

Keywords: Ocular disease, spatial correlation network, CNN, eye disease.

1. Introduction

The escalating prevalence of vision-threatening ocular disorders (OD) such as age-related macular degeneration (AMD), diabetic retinopathy (DR), cataracts, and uncorrected refractive errors, alongside trachoma, has prompted worldwide concern. Recent research by the World Health Organization (WHO) emphasizes the alarming rise, with over 2.2 billion individuals globally affected by visual impairments. Sadly, a substantial portion of these cases remains unremedied or preventable[1].

The increasing occurrence of blindness and visual impairments attributed to conditions like trachoma, cataracts, and uncorrected refractive errors raises an urgent need for intervention [2]. Notably, AMD and DR significantly contribute to global blindness statistics [3]. The number of individuals suffering from these conditions is predicted to escalate [3]. With the global diabetes population projected to exceed 366 million by 2030 [4], the likelihood of diabetic-related visual impairments also surges [5]. Early diagnosis and treatment are crucial to prevent irreversible vision loss [6]. Diagnostic imaging methods, like confocal fluorescence imaging (CFI) and optical coherence tomography (OCT), play a pivotal role in the early detection of ODs [7]. However, the complexity of data analysis, scarcity of qualified personnel, and the need for enhanced precision necessitate automated models [8,9]. Convolutional Neural Networks (CNNs) have demonstrated exceptional promise in medical imaging [10], yet limited research addresses multi-label OD classification using CFI [11].

1.1 Problem Statement

In the field of ophthalmology and medical image analysis, there is a pressing need for accurate and efficient methods to diagnose and classify various ocular diseases from imaging data such as retinal scans and fundus photographs. Traditional approaches often rely on manual interpretation by trained experts, leading to subjective results, high workload, and limited scalability. To address these challenges, this research aims to develop a novel solution using Spatial Correlation Networks (SCNs) for the automated diagnosis and classification of ocular diseases.

1.2 Research Gap

Our study will address the challenge of diagnosing multi-label ODs using CFI-based patient-level data. We introduce the Spatial Correlation Network (SCNet) as the core component of our Patient-Level Multi-Label OD (PLML_OD) model. This novel model incorporates CFI data from both eyes to predict the likelihood of different ODs. The model includes a backbone CNN module for feature extraction, a SCNet module for feature correlation and fusion, and a classification module for outcome prediction.

To enhance training data without overfitting, we will employ Borderline Synthetic Minority Oversampling Technique (BL-SMOTE) and subsequently utilize SCNet to ensure accurate feature integration. This will enables assessment of various OD possibilities for each patient image. Performance evaluation employs a range of metrics and compares results against existing methodologies.

1.3 Research Objectives

The primary objective of this research is to develop and implement a novel spatial correlation module for the accurate classification of multi-label ocular diseases (OD) utilizing color fundus images (CFI). This objective aims to address the current limitations in the field of ocular disease diagnosis and classification, particularly the challenges posed by multi-label classification and the need for precise feature integration.

Spatial Correlation Module Development: Design and construct a spatial correlation module (SCM) that effectively captures the interrelationship of features extracted from both left and right CFI images. This module should facilitate the integration of information from bilateral images, enhancing the accuracy of multi-label OD classification.

1.4 Research Contributions
Our study brings several significant contributions:
Novel Model: We introduce a unique PLML_OD model based on SCNet, effectively leveraging bilateral CFI data to predict seven ODs.
For this study, a novel Deep Learning has been designed with the concoction of FL and CILF to classify the OHD disease. Combining these loss functions is an attempt to solve the issues of class imbalance and outliers present in the complicated OHD datasets.
Performance Boost: The proposed model will outperforms several baseline techniques, exhibiting exceptional classification accuracy.
Ablation Experiments: Through ablation experiments, we will demonstrate the superiority of our model over state-of-the-art methods.
Dataset Enhancement: We apply BL-SMOTE to address data imbalance and improve model performance.
Real-world Applicability: By providing patient-level diagnosis and considering bilateral CFI, our model offers practical relevance for ongoing surveillance of high-risk patients.

2. Literature Review
In this section of the work, we will discuss the numerous diagnostic approaches that are being utilized at the moment for OHD. In addition to this, we present a description of the restrictions that are now in place and highlight the key techniques and solutions that the proposed system has to offer to get beyond these limitations. Khan et al. [12] proposed a deep learning model named patient-level multi-label OD (PLML_ODs) for the classification of eye disease. They integrate DenseNet-169 with the PLML_ODs model and achieved an accuracy of 94.6% using fundus images. Ahlam et al. [13] proposed a hybrid model based on MobileNet and DenseNet-121 for the classification of eye diseases. Additionally, they used principal component analysis (PCA) to reduce the image dimensionality. Their proposed model achieved a significant classification accuracy of 94.85%. Yang et al. [14] designed a machine learning model such as a two-class boosted decision tree for the prediction of diabetic eye diseases using Microsoft Machine Learning Studio. They achieved 92.3% results accuracy in classifying eye diseases that happened due to diabetes. Combining random forest TL with VGG-19 was suggested by Choi et al. [15] for use in a CAD environment. To improve the system, this measure was adopted. With just a small sample size, they identified eight distinct types of eye diseases. They reasoned that with some careful consideration, the necessary number of categories might be cut down to three without sacrificing accuracy. Despite this, they revealed that increasing the number of categories to ten resulted in a reduction in accuracy of approximately 30%. The author intended to use a classifier ensemble that included TL, and the results of their efforts paid off with a 5.5% increase in accuracy. Because of the flawed and contradictory information, the authors were unable to improve performance enough despite the update. A novel CNN model was presented by Fan et al. [16] for the classification of glaucoma illnesses by the use of fundus pictures. They were successful in achieving 92.6% of the time. The authors of the study [17] used several preprocessing approaches with CNN to detect chronic ocular disease (COD) in images of the eye fundus.

3. Materials & Methods
3.1 Research Design
Our study address the challenge of diagnosing multi-label ODs using CFI-based patient-level data. We introduce the Spatial Correlation Network (SCNet) as the core component of our Patient-Level Multi-Label OD (PLML_OD) model. This novel model incorporates CFI data from both eyes to predict the likelihood of different ODs. The model includes a backbone CNN module for feature extraction, a SCNet module for feature correlation and fusion, and a classification module for outcome prediction.
To enhance training data without overfitting, we will employ Borderline Synthetic Minority Oversampling Technique (BL-SMOTE) and subsequently utilize SCNet to ensure accurate feature integration. This will enables assessment of various OD possibilities for each patient image.

Performance evaluation employs a range of metrics and compares results against existing methodologies.

3.2 Data Annotation

We recommend utilizing the PLML_OD model, which is instantiated through the utilization of a publicly accessible CFI dataset, as referenced in [11]. The Ocular Disease Intelligent Recognition (ODIR-2019) dataset, a component of the 2019 University International Competition, provides this dataset. The dataset encompasses eight distinct categorization groups, encompassing the normal control group (N) and seven groups associated with various illnesses, namely diabetes (DB), glaucoma (GL), cataract (CA), age-related macular degeneration (AMD), hypertension (HT), myopia (MP), and abnormalities (AB). Both the CFI and supplementary information, including the patients' ages, are employed in the formulation of patient-level labels. The initial release of the CFI comprises 5,000 examples, and 4,020 of these instances have been meticulously annotated and made accessible to the general public. The distribution of these 4,020 patient cases across the eight distinct categories is visualized in Figure 1.

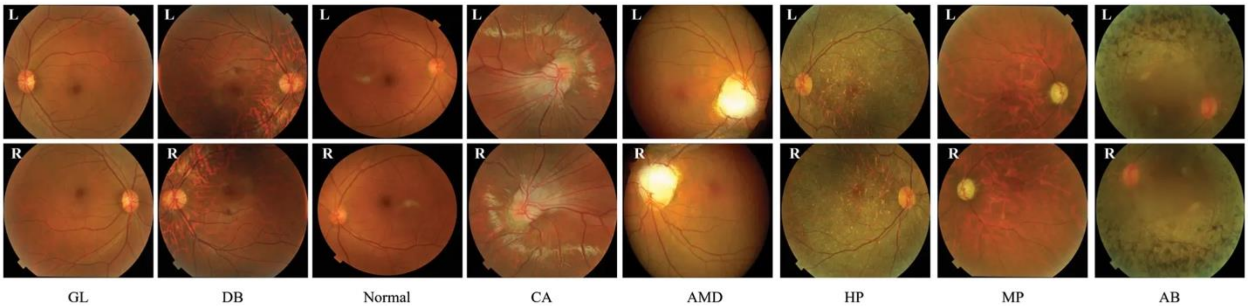

Figure 1. Sample of OD fundus images

Table 1: Summary of the OD dataset

Dataset	N	DB	GL	CA	AMD	HT	MP	AB	Total
Original	1100	1100	200	200	180	150	190	900	4,020
BL-SMOTE	1100	1100	1100	1100	1100	1100	1100	1100	8,800
Training (70%)	770	770	770	770	770	770	770	770	6,160
Validation (10%)	110	110	110	110	110	110	110	110	880
Testing (20%)	220	220	220	220	220	220	220	220	1760

4. Model Structure

The general structure of PLML_OD, as proposed, is depicted in Fig. 2. PLML_OD is composed of its principal constituent elements, namely the CNN backbone, the SCNet, and the ultimate classifier.

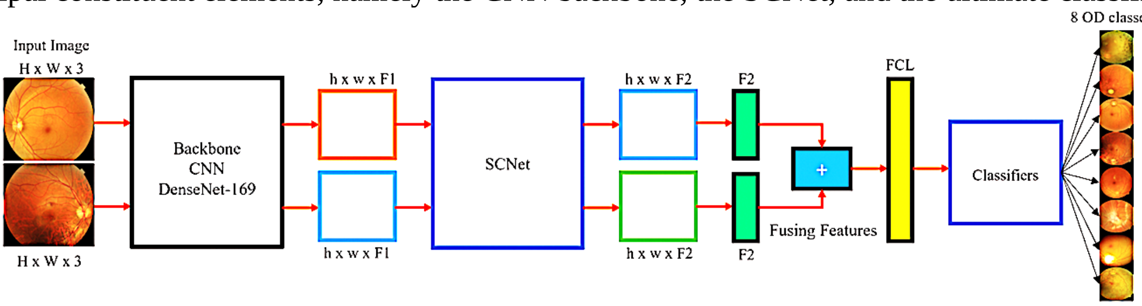

Figure 2. Architectural Design of the Proposed PLML_OD Model

5. Experimental Setup

The results of the training and validation are presented in Table 2, which breaks down the results by epoch. The baseline models, and the proposed CNN model, were run for as many as 200 iterations.

The highest level of accuracy that could be attained via training was 98.88%, while the highest level that could be reached through validation was 93.36%. These results suggested that the model learned well and was able to accurately classify GLU, CATR, and AMD in comparison to the baseline models.

Table 2: Results

Models	Training Accuracy	Training Loss	Validation Accuracy	Validation Loss
DenseNet-169	93.36%	0.13	91.04%	0.46
EfficientNet-B7	92.20%	0.34	93.80%	0.67
VGG-19	91.09%	0.79	88.90%	0.99
ResNet-101	94.09%	0.38	91.95%	
Inception-V3	88.90%	0.89	86.90%	
Proposed Model	98.88%	0.02	96.90%	0.02

6. Conclusion

This study bridges critical research gaps: the lack of automation in ocular disease diagnosis, limited utilization of spatial information, data standardization challenges, complexities in clinical integration, and ethical considerations. Successful completion promises a transformative impact on ocular healthcare, offering more accurate and scalable diagnostic tools while ensuring patient data privacy and regulatory compliance. By achieving these objectives, this research aims to contribute a sophisticated spatial correlation module that can significantly improve the accuracy of multi-label ocular disease classification using color fundus images. The developed module will be applicable in both clinical settings and ongoing surveillance of high-risk patients. The outcomes of this study are anticipated to advance the field of medical imaging, particularly in the domain of ocular disease diagnosis, and offer valuable insights into addressing multi-label classification challenges.

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