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Dry Eye Disease Classification Using AlexNet Classifier

[1]Yuva Krishna Aluri, [2]B. Aruna Devi, [3]N. Alangudi Balaji, [4]Vidyabharathi Dakshinamurthi, [5]Ramesh Babu P., [6]Sivaram Rajeyyagari

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Abstract: Reduced tear production and/or quality are typical causes of dry eye disease (DED), also known as ocular surface disease. Its rapid progression to a chronic, treatment-resistant illness can be attributed to its multifactorial character, which involves multiple underlying illnesses that are intertwined with one another. For this reason, it is often recommended that many treatment modalities be employed simultaneously in order to achieve adequate management of DED. In many situations, the first line of defense is a topically applied artificial tear supplement, followed by the administration of therapeutically active eyedrops. However, the drops are quickly cleared from the precorneal region by the eye natural defensive mechanisms, reducing the drug potential to penetrate the eye. Commonly used excipients in eyedrops can be harmful to the eyes and exacerbate DED symptoms.

Keywords*: Tears, AlexNet, Dry Eye Disease, ocular surface disease, Classifier*

1. Introduction

A Multifactorial Disease of the contrast sensitivity, reduced spatial frequency, blurred vision, increased glare and tired eyes are common symptoms of DED, despite the fact that the condition rarely poses a threat to the patient vision [1]-[2]. Impairments in social interaction, physical functioning and overall health are common among patients with DED and contribute significantly to a reduction in quality of life.

Most cases of dry eye fall into one of two categories: evaporative dry eye (EDE), in which tear fluid evaporates too quickly, or aqueous tear-deficient dry eye (ADDE), in which the lacrimal glands are unable to or inefficient in producing tears (DED). Aqueous tear deficiency evaporation means dry eye. Most cases of ADDE involve a problem with the lacrimal functional unit, which may or may not have an autoimmune basis. The majority of persons with dry eyes suffer from evaporative dry eye syndrome (EDE) and is defined by a shift in tear fluid lipids, potentially compromising the integrity of the tear fluid [3]. The inability of the meibomian glands to perform properly is linked to EDE as well. Multiple sclerosis glomerulopathy, also known as MGD, is a renal disease that has multiple potential causes.

Some examples include inflammation, microbial infection, and a lack of lipids. Because of this, it is not uncommon for one DED subtype to eventually take on certain clinical symptoms of the other, creating a hybrid or mixed variant of the condition. Thus, the use of a combination of therapy approaches to address DED issues is relatively rare [4].

Many prescription medications, the vast majority of which are intended for topical use, are available for the treatment of ocular surface problems. This is because these drugs are easier to use and produce less systemic side effects. This makes it the only route for delivering drugs to the eye at sufficient quantities for treatment. It makes reasonable that eyedrops are the most prevalent route of administration for current ophthalmic formulations [5].

However, medication given topically is less effective due to the eye natural defenses, and eyedrops must be used often over long periods of time. The subsequent decrease in treatment efficacy is a direct result of this trend toward reduced patient compliance. When treating DED, it is often required to use multiple types of eyedrops at once, which might complicate the treatment and reduce the compliance of patients [6].

This study concentrates on the challenges associated with the production of topical formulations, with a particular emphasis on the ocular surface compromise that is

[1]*Assistant Professor, Department of Computer Science and Engineering, Prasad V Potluri Siddhartha Institute of Technology, Kanuru, Vijayawada, Andhra Pradesh, India.* ***yuva.aluri@gmail.com***
[2]*Professor, Department of Electronics and Communication Engineering, Dr.NGP Institute of Technology, Coimbatore, Tamilnadu, India.* ***arunadevi@drngpit.ac.in***
[3]*Professor, Department of Computer Science and Engineering, Koneru Lakshmaiah Education Foundation, Vaddeswaram, Vijayawada, Andhra Pradesh, India.* ***alangudibalaji@gmail.com***
[4]*Associate Professor, Department of Computer Science and Engineering, Sona College of Technology, Salem, Taminadu, India.* ***dvbharathi77@gmail.com***
[5]*Associate Professor, Department of Computer Science, College of Engineering and Technology, Wollega University, Nekemte, Oromia Region, Ethiopia.* ***drprb2009@gmail.com***
[6]*Department of Computer Science, College of Computing and Information Technology, Shaqra University, Shaqra, Saudi Arabi.* ***dr.sivaram@su.edu.sa***

frequently observed in DED. In addition, the formulations generally employed in DED care are discussed, with a focus on their ability to treat the aforementioned many underlying disorders. This article also discusses the advantages and unique features of various formulations.

2. Background

A multifactorial ocular disease is described as a vicious spiral of tear film instability and hyperosmolarity by the Tear Film Ocular Surface Society. Inflammation, damage, and changes in neurosensory function can result from a disruption in ocular surface homeostasis. Without therapy, DED can worsen to the point that it permanently damages the eye surface [7].

According to the criteria set by the TFOS DEWS II, insufficient tear production leads to aqueous deficient dry eye (ADE), while meibomian gland dysfunction (MGD) is a major contributor to evaporative DED. The most frequent form of dry eye is caused by a lack of aqueous. Actually, the vast majority of individuals will exhibit symptoms that are common to both diseases. Since DED worsens over time, prompt identification and therapy are crucial for patients to avoid the disease from becoming a chronic, incurable condition. Despite the DEWS II criteria success in drawing attention to DED multifaceted nature, diagnosis remains difficult and time-consuming even in normal clinical settings. Until the symptoms have progressed significantly, DED is rarely detected [8].

An updated set of DED diagnostic categories was presented in a recent consensus report that detailed the findings of an clinical expert panel. Three disease types were identified in the research, with the pathological severity and impact on visual disturbance increasing in ascending order. This study was included in a wider initiative that aimed to summarize the results of a panel of clinical experts [9].

The Nominal Group Technique (NGT) and the Delphi technique were used to develop these definitions. Type I of Dry Eye Syndrome (DED) is mild and short-lived; type II of DED is episodic but mild; and type III of DED is chronic, persistent, and very severe. This is a crucial aspect of illness classification, as it indicates that the disease has progressed to a point where the chronic inflammation is being maintained by processes that cannot be stopped [9].

The primary goals of treating DED are to limit the risk of complications and ease any discomfort the eye may be experiencing. First-line therapies for dry eye disease often consist of lid hygiene, counseling on trigger avoidance or control. Ocular surface modulators, multiple-action, and wetting agents are some of the alternative terms proposed by expert consensus committees to characterize tear substitutes [10].

Tear replacements have been around for a while, and they mimic the lubricating effects of real tears by either completely replacing or supplementing the watery component of the lacrimal film. In most situations, they do nothing to alleviate inflammation or support healthy eye function. A lack of tear replacement retention at the ocular surface reduces the treatment efficacy. This is considered true than usual for low-viscosity compositions [11].

Multiple routes of action in tear replacement therapies have been shown to improve tear film quantity and quality. Oil-in-water nano-emulsion formulations can improve the TFLL thickness and stability. Therefore, the drug would remain in the eye for a longer period of time. Medication that maintains healthy epithelial cells and returns balance to the ocular surface is an example of a treatment known as an ocular surface modulator [12]-[14].

3. Proposed Method

The primary objective of this research is to empirically evaluate image preprocessing and classifier enhancement approaches to boost the precision of early DED identification using fundus images.

At a high level of abstraction, Figure 1 depicts the use of this method as a pipeline. In this study, we compared the results of three distinct pre-trained models applied to the raw retinal fundus dataset. After applying standard image processing methods to our raw fundus images, we trained this dataset using the model that had the greatest results in the previous experiment. In addition, we preprocessed data with a CNN that we custom-built and used it to train the CNN. At last, we compared the outcomes to find out if pre-processed images improved the model accuracy.

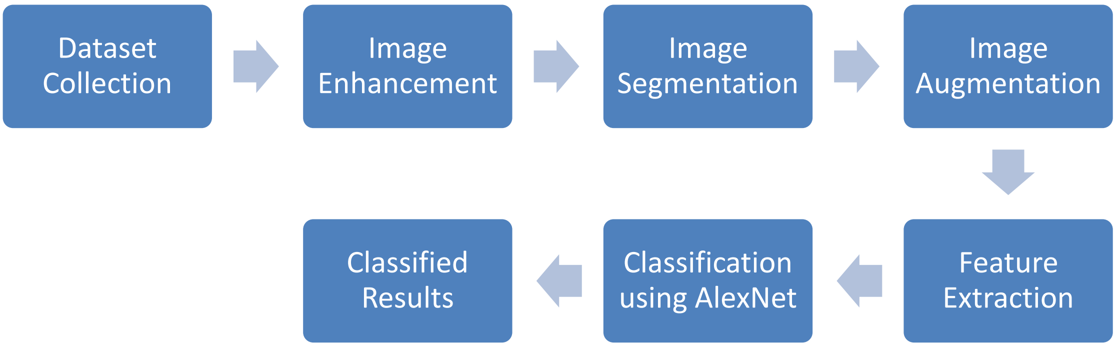

Fig 1: Architecture of AlexNet based architecture

Image Pre-processing

In the initial step of image processing, called preprocessing, noise and variation are reduced to enhance the image clarity and contrast of the retinal fundus. Images can be normalized and adjustments made for non-uniform intensity variations in addition to boosting contrast and minimizing noise during the preprocessing step. Both of these steps improve the accuracy of subsequent steps by reducing artifacts. Fundus image DED characteristics are also identified, retrieved, and segmented so that previously trained models can be applied to them.

Image Enhancement

Standard image improvement techniques, such as increasing the contrast and brightness, were utilized to improve the overall quality of the images before any further processing was performed.

Contrast enhancement:

To make image more readable, the CLAHE method (contrast limited adaptive histogram equalization) is used. The CLAHE algorithm is a variant of the AHE method with the same ultimate goal of achieving histogram equality.

The transformation function is calculated after the enhancement function has been applied to all of the neighboring pixels. The lower contrast sets this apart from AHE. To increase contrast, CLAHE applies contrast limited histogram equalization (CLHE) to data sections the size of tiles rather than the complete image. Then, we employ bilinear interpolation to perfectly rejoin the tiles that were previously separated. Grayscale retinal images were obtained using CLAHE. Cliplimit is a tool for minimizing image noise. Generating a clipped histogram and a grayscale mapping. By dividing the entire number of pixels by the total number of grey levels, we may determine the median number of grey pixels in a region.

$$n_{avg}=(n_{CRxp}*n_{CRyp})/n_{gray}$$

Where,

where (n_{avg}) is the average number of vertical and horizontal pixels and (n_{gray}) is the average number of grayscale levels in the scene.

The number of pixels in the x-direction of the contextual region is denoted by the notation n_{CRxp}.

n_{CRyp} is a count of the number of pixels along the y-axis of the context region. Afterward, you must determine the precise clip restriction.

$$n_{CL}=n_{CLIP}*n_{avg}$$

When used to biological images, CLAHE is a valuable technique since it simplifies the process of determining the main observable elements. Because of this, CLAHE is a very helpful method.

Illumination correction

The goal of this preprocessing method is to mitigate the negative effects of retinal images with poor lighting.

$$p'=p+\mu_D-\mu_L$$

In this case, the original pixel size, p, has been replaced by the new pixel size, p', while the target average intensity, μ_D, and the actual average intensity, μ_L, are both taken into account. This method facilitates the growth of retinal microaneurysms.

Image Segmentation

The study is successful in developing a classification system for diagnosing mild DED that is based on deep learning, we will need to take into account the significance of both the network design and the input data. This is necessary if we are going to be able to develop a system that is accurate. The final outcome is significantly impacted by the level of photographic excellence of the images that are uploaded. There are a lot of factors that contribute to the variability of retinal fundus images. These factors include the brightness and contrast levels, as well as the number of photographs taken. In addition, anatomical characteristics play a part in this heterogeneity. Because of this, the value of the images that are used for classification can be raised through the process of feature segmentation, which eventually leads to improved accuracy.

Elimination of the Circulatory System and Blood Vessels Blood vessels are one of the most essential anatomical features to look for when attempting to diagnose early stages of DR through retinal imaging. As a result, the following techniques are considered to be part of the category known as retinal blood vessel segmentation: Image enhancement, and the Tyler Coye algorithm are the three methods that can be utilised to further increase the quality of the improved image after it has already been enhanced. Operations based on morphology are one of the approaches that can be used.

Since the green channel of the RGB colour scheme exhibits a stronger contrast between the vascular network and the background, we made use of such ways in order to improve the image. Our goal was to provide a clearer representation of the subject. Gradations can be seen in a fundus image brightness and contrast levels, as the backdrop has both of these characteristics. Following the adjustment of the brightness and contrast levels, a threshold level is figured out with the assistance of the ISODATA algorithm that is a part of the Tyler Coye method.

The application of morphological processes results in an additional polishing of the surface (elimination and expansion). As a direct result of combining these two vital tactics, we are in a position to get rid of the background noise and fill in the details that are in the foreground. The equation that follows exemplifies the process of erosion, which can be utilised to either remove the border of the region or spike it, depending on the situation.

$$A \ominus B = \{p | B_p \subseteq A\}$$

Dilating a image refers to the process of enlarging the border of an image, which can be done regardless of whether the border is in the foreground or the background of the image. The following equation is one that a lot of people use when attempting to define a space that has been filled in this fashion.

$$A \oplus B = \{x | B_x \cap X \neq 0\}$$

In order to make the image pixels appear more closely spaced, it is necessary to begin by carrying out the dilation process, and then proceed to the erosion operation. This process can be characterised by the following mathematical equation:

$$A \cdot B = (A \oplus B) \ominus B$$

Where,

$\oplus$ - dilation;

$\ominus$ - erosion;

A - element and

B - dilation erosion.

The aim of this morphological process is to fill in these gaps so that the blood vessels are entirely covered in all of the regions where it is needed for them to be.

AlexNet

Because of its remarkable results in the 2012 ImageNet Large-Scale Visual Recognition Challenge, the AlexNet framework was conceived. Although inspiration was drawn from LeNet, this framework is significantly more complex, using roughly 60 million parameters. It was one of the top five entries with the highest error rate (15.3%), however it was far lower than the second-place entry error rate (26.2%).

AlexNet is a deep neural network architecture that consists of five convolutional layers and three fully linked layers which is shown in Figure 2. The RELU activation function has been selected as the optimal solution. During the training of a network, we make use of the MaxPooling layer, local response normalization, and several GPUs. When filtering an input image with a resolution of 224x224x3, the first convolutional layer uses 96 kernels with size of 11x11x3 at a stride of 4. The response and pooled output from the first convolutional layer are normalized before being passed on to the second. 256 kernels, each measuring 5x5x48 units, were used to implement the filters.

There is neither a normalizing layer nor a pooling layer between the connections of the second and third layers. There are 384 32x56-size kernels in the third convolutional layer. The fourth convolutional layer employs a total of 384 kernels, each of which is 33192 bytes in size. In the fifth convolutional layer, each of the 256 kernels is 3x3x192 pixels in size. Up to 4096 neurons can fit in each fully linked layer. A softmax is fed the output of the most recent fully connected layer. There are now a thousand unique labels representing the various categories.

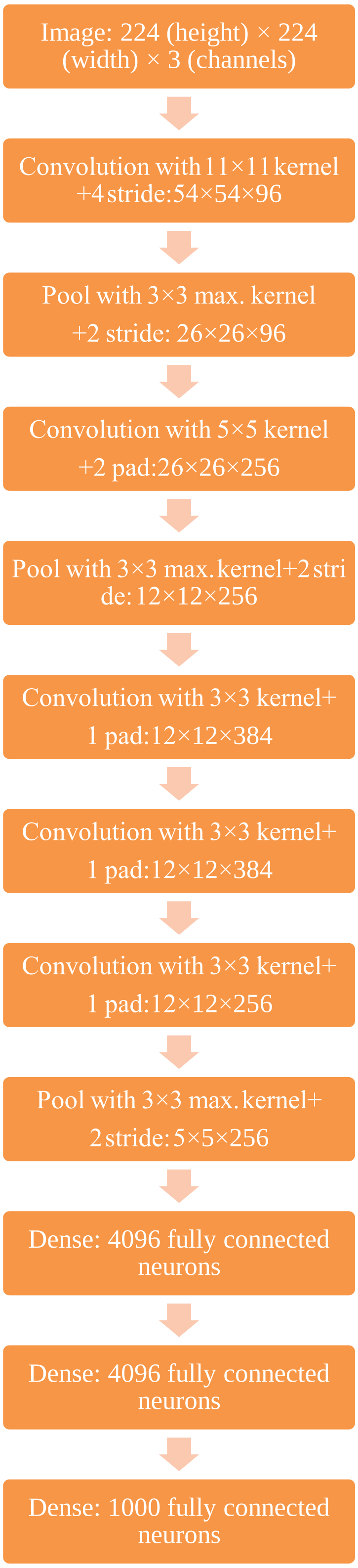

Fig 2: AlexNet Architecture

The RELU layer was inserted after the first 5 convolutional layers had previously been applied. After fixing the ReLU nonlinear behavior, the local response must be normalized. More generality is achieved by adding these normalizing layers on top. The equation for the normalized response activity is as follows:

$$b_{xy}^{i} = \frac{a_{xy}^{i}}{\left(k + \alpha \sum_{j=\max\left(0, i-\frac{n}{2}\right)}^{\min\left(N-1, i+\frac{n}{2}\right)} \left(a_{xy}^{j}\right)^{2}\right)^{\beta}}$$

The outcome of applying the i^{th} kernel to the current position, denoted by b, after regularization (x, y). Applying the i^{th} kernel to the location denoted by yields the neuron activity (x, y). There are exactly N kernels in the current layer, where N is the total number of kernels. The hyper-parameters α, β, k, and n, can be optimized with the use of a validation set.

In order to improve its accuracy, AlexNet minimizes the overfitting that happens in fully linked layers. Many people have given up on the regularization method as a direct result of this. When the regularization procedure is initiated, the dataset extraneous details are learned. This includes things like incorrect data entries and noise. One aspect of this is getting into the nitty gritty. Overfitting occurs when a model is trained with an enormous dataset.

There is a risk that the model performance will decline when it is exposed to novel data, despite the fact that it may have performed well on the data it was trained on. Although the AlexNet model claims to be more accurate than the LeNet model, there are still open questions about how to handle an unbalanced dataset and how to improve the model for different data sets. Using the correct optimization strategy is crucial for producing optimal results from a CNN model.

Stochastic Gradient Descent (SGD) Algorithm

The stochastic gradient descent method involves making forward-looking adjustments to the model parameters. To achieve this, it adjusts the model parameters based on the gradient of the model computed for each sample used in the training phase. To do so, it compares the cost of computing one data point and its gradient to the cost of computing all the data points, which introduces uncertainty. The stages are updated in a short amount of time, and the bare minimum is met. As a direct consequence of this, it has rapidly emerged as one of the most widely employed optimization tactics. The training procedure for SGD is lengthy since it requires careful, incremental progress to a desirable goal.

As data must be frequently transferred between the GPU memory and the computer local storage when using GPUs for the calculations, efficiency is reduced. Equation (6) depicts the mechanism through which the transformation takes place. For each iteration, $f(x_k)$ represents the loss function, t_k represents the step size for that iteration, and i represents the iteration index. At step k+1, the model parameters are denoted by x_{k+1}. The loss function is calculated using the k^{th} example from the training set.

$$x_{k+1}=x_k-t_k\Delta f(x_k)^i$$

4. Results and Discussions

In this section, we validate the efficacy of the model against various existing optimisation methods that includes Batch Gradient Descent (BGD) Optimization and Root Mean Square Propagation (RMSprop). The proposed method is validated against the existing methods in terms of various metrics that includes accuracy, precision, recall and f-measure which shown and discussed in Table 1 to Table 4.

Table 1: Accuracy for Training/Testing

DED	Optimization Model with AlexNet	Training	Testing
Normal	BGD	62.36	61.83
	SGD	82.40	81.70
	RMSprop	58.06	57.57
Mild	BGD	63.59	63.05
	SGD	87.89	87.15
	RMSprop	52.99	52.54
Severe	BGD	64.96	64.41
	SGD	89.95	89.19
	RMSprop	82.46	81.76

Table 2: Sensitivity for Training/Testing

DED	Optimization Model with AlexNet	Training	Testing
Normal	BGD	68.64	68.06
	SGD	78.80	78.14
	RMSprop	73.18	72.56
Mild	BGD	66.59	66.03
	SGD	92.21	91.42
	RMSprop	89.45	89.58
Severe	BGD	87.81	87.06
	SGD	96.43	95.61
	RMSprop	78.89	78.22

Table 3: Specificity for Training/Testing

DED	Optimization Model with AlexNet	Training	Testing
Normal	BGD	59.42	58.92
	SGD	87.08	86.34
	RMSprop	55.17	54.70
Mild	BGD	61.47	60.95
	SGD	82.98	82.28
	RMSprop	52.25	51.81
Severe	BGD	60.26	59.75
	SGD	85.37	84.65
	RMSprop	86.06	85.33

Table 4: F1-Measure for Training/Testing

DED	Optimization Model with AlexNet	Training	Testing
Normal	BGD	44.05	43.68
	SGD	75.81	75.17
	RMSprop	98.35	97.52
Mild	BGD	53.27	52.82
	SGD	79.91	79.23
	RMSprop	28.69	28.44

Severe	BGD	97.33	96.50
	SGD	97.33	96.50
	RMSprop	77.86	77.20

The results of this study indicate that there is a link between the two etiological groups of dry eye disease and numerous socioeconomic and behavioral factors. Age, increased psychological stress, and a lowered self-perception of health are all linked to both aqueous-deficient and evaporative forms of dry eye syndrome. Researchers might reduce the prevalence of dry eye illness and improve patient outcomes by developing targeted screening and risk factor reduction programs that take into consideration the demographic and lifestyle risk variables identified in this study.

5. Conclusions

There has not been a lot of discussion on how to identify mild DED in everyday cases, but this study presents an approach for achieving just that. AlexNet has the added benefit of being able to automatically recognize certain types of data. This method will help you avoid the analytical and, at times, subjective nature of performing feature extraction by hand when limited by technology. The research also used multi-source data composites to gauge the system durability and responsiveness under real-world settings. The proposed AlexNet allows for the standardization of time-consuming eye-screening methods and provides a useful secondary diagnostic reference without relying on the subjectivity of humans.

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