Optical Differential Diagnosis Process using Image Analysis

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***Abstract*— The human eye is a crucial component of our visual system, and regular eye exams are essential for maintaining good eye health. However, these exams can be time-consuming and expensive, mainly when performed by an ophthalmologist. A study proposes the development of an improved eye examination device that utilizes image processing and analysis technology to address this issue. The device employs the optical differential diagnosis process to provide a faster and more accurate evaluation of five commonly known eye diseases and assess healthy eyes. During the exam, the device takes and analyzes images to detect the presence of any disease or abnormalities, which reduces the time required to deliver results and provides a more convenient and cost-effective way to monitor and maintain eye health. After conducting several tests, the researchers found that the eye examination device had an overall accuracy of 92.49%.**

Keywords*—*Differential Diagnosis, Eyes, Diseases, TensorFlow, Image Analysis.

I. Introduction

The eyes are the most exposed yet fragile part of our body, and their importance is priceless. However, getting an optical check-up can be expensive and time-consuming, as it typically requires the expertise of professional doctors or exceptional optic nurses to perform the initial check-up or differential diagnosis. The proposed system aims to mimic the proper and ethical procedure of optical differential diagnosis performed by ophthalmologists and optic nurses.

In recent years, experts have suggested new techniques for image analysis based on artificial intelligence (AI). These techniques can overcome the shortcomings of the traditional methods used in industrial vision systems [1]. Deep learning algorithms have revolutionized the way computers process and interpret data. These algorithms can learn and improve independently by analyzing vast amounts of information, often surpassing human capabilities in various tasks. As a result of these advancements, fields such as image and speech recognition, natural language processing, and drug discovery have made significant progress [2] [3].

Several deep-learning algorithms have shown great promise in the field of medical imaging. Experts have designed these algorithms to analyze medical images, such as retinal images, and accurately classify or detect various disease conditions. With their high sensitivity and specificity, these algorithms have the potential to greatly improve the speed and accuracy of medical diagnosis significantly, leading to better patient outcomes [4] [5] [6].

Neural networks each have unique strengths for algorithmic approaches. TensorFlow, a popular library for machine learning and image analysis, includes various neural networks and commonly employs Convolutional Neural Networks (CNNs). While it requires minimal coding, TensorFlow relies heavily on large datasets for training. TensorFlow can provide a highly accurate output when appropriately used, surpassing a single neural network [7].

Three studies from the Philippines utilized image processing techniques to create a bimodal vein recognition system using a support vector machine [8]. The procedure uses two NoIR cameras connected to a multi-camera adapter mounted on a Raspberry Pi Model 3B+, which acquires images of the dorsal and palm veins exposed to infrared light. By using a support vector machine, the study was able to classify hand veins by 97.16%. Bumacod et al. conducted another survey on a digital goniometer that enables instantaneous measurement of the elbow and knee joint angles through pictures. The statistical analysis shows a 98.25% and 98.09% accuracy for the elbow and knee joints. Linsangan et al. [10] employed geometric analysis and (k-NN) to classify skin cancer in another investigation. The researchers looked at three types of skin lesions in their study: malignant melanoma, benign melanoma, and unknown. The functionality testing was 90% accurate due to the inquiry.

Neural networks can uncover critical details from massive amounts of data. In ophthalmology, the retina plays a crucial role in vision, and image processing technology can help detect retinal health [11]. Computer-aided diagnosis (CAD) systems provide precise, dependable, and efficient glaucoma diagnosis [12]. Recent advances in computational power capabilities have allowed the implementation of convolutional neural networks (CNN), facilitating autonomous classification of glaucoma based on complex features derived from thousands of available fundus images [13] [14]. By using neural networks to detect cataracts in the human eye, this study can aid in the early diagnosis of potential cataracts, which, if left untreated, may ultimately result in blindness [15].

Related to eye illness is jaundice. Modern technology also takes precautions against this illness and involves rehearsing the implementation of non-invasive detection for jaundice [16]. The accuracy of emergencies in a differential diagnosis is also high. A late-examined patient might already have a higher level of illness [17]. Diagnosing abnormalities in the eye are typically performed by ophthalmologists, specialists in identifying eye disorders and diseases, using sophisticated equipment. However, these devices can be prohibitively expensive and inaccessible in rural areas. This lack of resources can lead people to neglect eye disorders or attempt self-diagnosis, potentially exacerbating their condition. As such, there is a need for a cost-effective and easily accessible alternative that can be made available to those living in remote areas with limited medical knowledge [18].

In conclusion, this study is a big step toward getting this technology into clinical use. As future researchers focus on the final diagnosis, the conquest of differential diagnosis continues [19].

Based on research, the proponents of this study have found that optical differential diagnosis is expensive and time-demanding. This is because an ophthalmologist conducts the initial check-up with a professional license.

This research dramatically benefits optical medical institutions such as hospitals and clinics by lowering the cost of the initial check-up, resulting in a quicker process, and doing away with the necessity for an ophthalmologist during differential diagnosis.

This research aims to create a system that can determine the level or extent of various eye conditions such as keratitis, cataracts, uveitis, glaucoma, conjunctivitis, and eyes that are considered healthy. With the development of this system, the researchers aim to provide a more efficient and accurate method of assessing the seriousness of these eye conditions, thereby facilitating effective treatment and management.

This study's range of differential diagnoses only includes conditions including keratitis, cataracts, uveitis, glaucoma, conjunctivitis, and normal vision. Additionally, the external human eye is the sole subject of this investigation. Due to differential diagnosis requirements, the data will be presented in an aggregated manner.

II. Materials and Methods

Based on the literature reviewed for this study, a systematic application is being planned and constructed. The subject patient will be examined using the personalized slit lamp, and the computer will be able to view the patient’s eye. Upon a specific command, the application will capture a clear image of the patient’s eye and then undergo image analysis. The result will be an output indicating the probabilities of the patient’s eye disease, following the standards of differential diagnosis.

A. Conceptual Framework

Fig. 1 provides a visual presentation of the processes involved in detecting eye disease using an image captured through a macro camera. The input to the system is the image processed using a combination of TensorFlow and OpenCV. TensorFlow delivers highly accurate results by leveraging its embedded neural network known as CNN, while OpenCV is employed to extract relevant features from the image. The system outputs a list of possible eye diseases with their corresponding accuracy rate. The framework clarifies how the system's input, processing, and output components relate to one another.

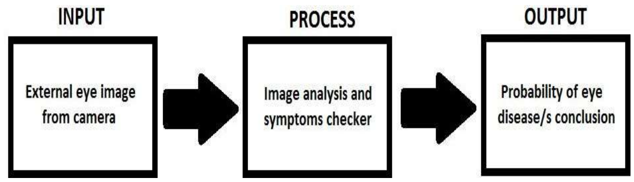


Fig. 1. Conceptual Framework

B. Software Resources

In this study, the software consists of an algorithm library of Google called TensorFlow. The core of this library now features an embedded neural network called CNN, which enables the library to perform advanced tasks such as image recognition and natural language processing with greater accuracy and efficiency. The resources implemented for computer vision will be OpenCV, a machine vision library.

C. Methods and Procedures

The algorithm and image analysis rely solely on software, computer vision, and other peripherals, such as the symptoms evaluator, to perform the necessary functions.

The software is composed of libraries, codes, and algorithms. Machine vision requires an OpenCV library, a standard library used to manifest camera captures and coding. TensorFlow's main library for machine learning provides many tools and functionalities for developing and deploying machine learning models. This powerful library will be able to give high-accuracy results with proper data sets. To implement the main algorithm for neural networks in this system, we will use CNN on top of TensorFlow and develop additional features, such as the symptoms evaluator, using Python code. The synchronized combination of each library, algorithm, and regulation will accomplish the needed functionality software-wise. Fig. 2 displays the block diagram of the CNN algorithm.

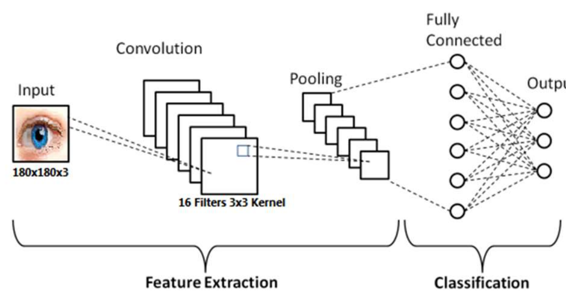


Fig. 2. Block Diagram of CNN Algorithm

The following algorithms for Kernel Convolution, Zero Padding, and Strided Convolution listed below were used in the CNN, respectively:

Kernel Convolution [eq. (1)] has *f* as the input image, *h* as the kernel, and *m* and *n* as the matrix's row and column indexes. Zero padding [eq. (2)], represented by *p*, has *s* equaled 1, with *f* being as filter dimension.

Where: G = filtered image
f = original image
h = kernel
m, n = matrix row and column indexes
p = amount of zero padding
f = spacial extent
n_{in} = number of input features
n_{out} = number of output features
k = convolution kernel size
s = convolution stride size

$$G[m,n] = (f * h)[m,n] = \sum_j \sum_k h[j,k] f[m-j, n-k] \quad (1)$$

$$p = \frac{(f-1)}{2} \quad (2)$$

$$n_{out} = [\frac{n_{in} + 1p - f}{s} + 1] \quad (3)$$

Fig. 3 illustrates the flow of the system's algorithm and operation. The process starts when the camera captures an image of the patient's eye, which the computer receives for differential diagnostics. The system evaluates the idea of detecting specific diseases and calculates their accuracy or probability percentage.

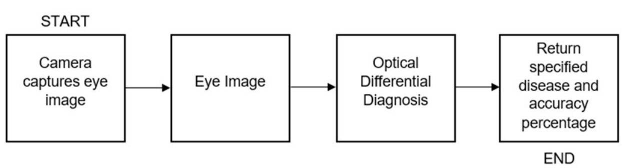


Fig. 3. System Flow

Fig. 4 shows the necessary step for diagnosing a patient with red eye, which involves conducting a patient history and eye examination to determine the cause. The patient history should include information about whether the redness is affecting one or both eyes, how long the symptoms have been present, what type and amount of discharge is current, any vision changes, the level of pain experienced, sensitivity to light (photophobia), any previous treatments received, the presence of allergies or systematic diseases, and whether the patient uses contact lenses.

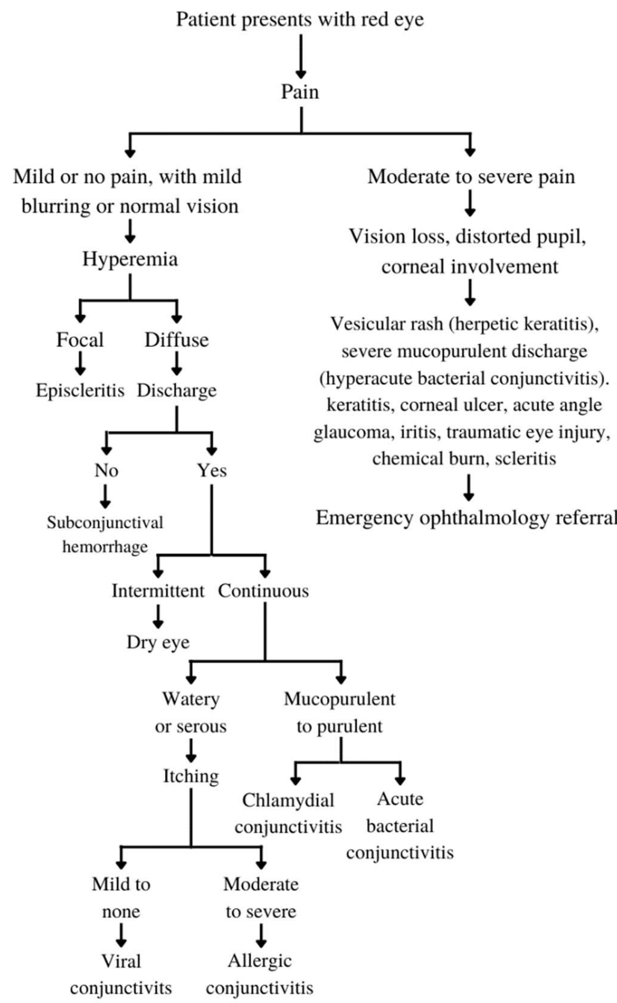


Fig. 4. Differential Diagnosis of Patient with Red Eyes
Source: Adapted from [20]

D. Step-by-step Procedure

This section illustrates the system process for the image processing procedures on the optical differential diagnosis.

1) Capturing Eye Image:

The device takes a picture of an eye, which is subsequently processed using TensorFlow and CNN algorithms. While processing the image, the system notes certain features of the picture.

2) Optical Differential Diagnosis Result:

As shown in Fig. 5, if any specific features are detected that correspond to any of the defined eye diseases, the system returns a list of possible eye diseases, which the symptoms evaluator then narrows down and evaluates. After that, the method returns the specified eye disease and its accuracy rate. The image indicates healthy eyes if the system finds no traits that could be attributed to any of the listed eye disorders.

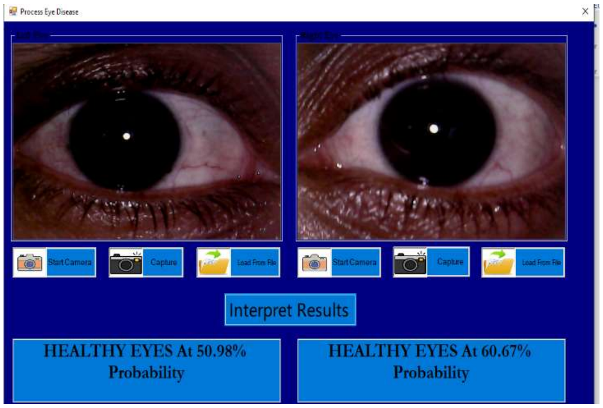


Fig. 5. Final Differential Diagnosis Result

III. Results and Discussions

This section of this study presents the findings of the image-based eye disease detection system. The system processes images of the patient's eye captured through a slit lamp examination, utilizing a combination of TensorFlow and OpenCV. The system's output provides a list of potential eye diseases and their accuracy rates, as detected by the system using the features extracted from the image. The results and discussion section highlights the performance and effectiveness of the proposed method.

A. Test Results

During the testing phase of the study, the researchers evaluated 1052 datasets and presented the results in Table 1.

A total of six different eye conditions were subjected to data collection throughout the system testing to obtain results. The accuracy rate rose because eye disease had a unique collection of data. These datasets were collected from a Kaggle online cache and eye photos provided by an ophthalmologist who prefers to remain anonymous during and after the study's implementation. Overall, the analysis accurately detected 973 out of 1052 samples, resulting in a 92.49% accuracy rate.

Table 1: Confusion Matrix Analysis

	N = 1052	PREDICTED DATA						
		K	C	U	G	Co	H	C.O
ACTUAL DATA	K	153	1	1	2	5	5	167
	C	5	160	5	5	5	3	183
	U	2	1	165	1	2	1	172
	G	2	5	3	175	5	2	192
	Co	2	3	1	3	135	2	146
	H	1	1	2	1	2	185	192
	T. A	165	171	177	187	154	198	1052
	C.A%	91.62%	87.43%	95.93%	91.15%	92.47%	96.35%	
	O. A	92.49%						

Where: N = Number of Sample
K = Keratitis
C = Cataract
U = Uveitis
G = Glaucoma
Co = Conjunctivitis
H = Healthy Eyes
T.A = Truth Overall
C.A = Classifier's Accuracy
O.A = Overall Accuracy
C.O = Classification Overall

$$Overall\ Accuracy = \frac{153+160+165+175+135+185}{1052}\ x\ 100\% \quad (4)$$

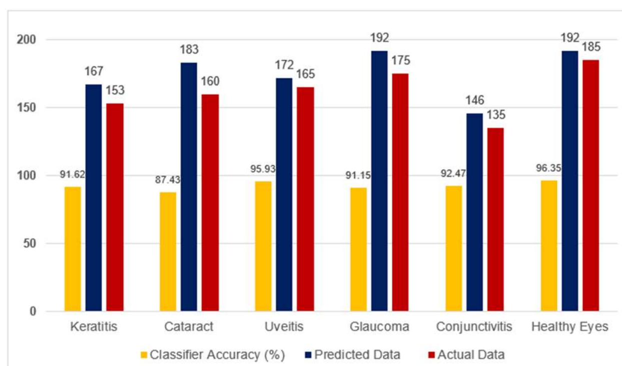
The system's overall accuracy was determined using equation 4; the system's accuracy rate is 92.49%.

B. Data Analysis

Out of the 1052 datasets tested, the results were tallied based on each eye disease's actual and predicted results.

Starting with Keratitis, 153 out of 167 samples were correctly identified, resulting in an accuracy of 91.62%. Out of 183 samples tested for cataracts, 160 were confirmed as true positives, resulting in an accuracy rate of 87.43%. Uveitis showed an impressive accuracy rate of 95.93%, correctly diagnosing 165 cases out of 172. The last two diseases, Glaucoma and Conjunctivitis, also achieved accuracy rates of 91.15% and 92.47%, respectively. Glaucoma had 175 correct identifications out of 192 samples, while Conjunctivitis had 135 accurate labels out of 146. Healthy eyes showed an accuracy rate of 96.35%, with 185 suitable markers out of 192 models. Table 2 compares the predicted and actual results of the eye disease diagnosis.

Table 2. Comparison between the predicted and actual results of each eye disease.



The blue columns show the predicted data, while the red columns indicate the actual obtained from the system. The yellow columns evaluate the accuracy of the results by measuring the discrepancy between the predicted and fundamental data.

IV. CONCLUSIONS AND FUTURE WORKS

This study created a system that utilizes the Optical Differential Diagnosis Process and images analysis to diagnose several eye diseases. Using a macro-lens camera, the researchers obtained more detailed images of patients' eyes for training and utilization of the system.

Expanding the number of eye diseases analyzed would be beneficial to enhance future studies. Additionally, incorporating x-ray imaging could improve disease detection, as this imaging technique may only make some illnesses visible.

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