DETECTION OF OCULAR EYE DISEASE FROM BIGDATA USING DEEP CONVOLUTIONAL NEURAL NETWORK

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Abstract
In this paper, we present a neural network models like artificial neural network (ANN), back propagation neural network (BPNN), feed forward neural network (FFNN) and Long Short Term Memory (LSTM) named Recurrent Neural Network (RNN) to classify the input images using a series of frameworks. The architecture involves data collection, pre-processing, feature extraction and classification of images. A 10-fold cross validation is conducted on the collected input image samples and the results are evaluated against these four models over different performance metrics. The results show that the RNN attains improved classification accuracy and reduced error rate than other methods.

Keywords:
Ocular Eye Disease, Neural Network Framework, Machine Learning, Classification

1. INTRODUCTION

In clinical diagnosis and individualized treatment of eye condition, medical imaging is important [1]. This technology can provide information on anatomical and functional changes at high resolution. Imagery methods and clinical developments have evolved quickly in recent years [2]. However, due to the large number of images and results recorded by individual patients as well as the hypotheses supported by these data, the increasing sophistication of imaging technology has made understanding and management of eye diseases more complicated. Every patient has therefore become a challenge for big data [3].

Conventional diagnostic approaches rely heavily on the technical expertise and experience of physicians, which can lead to a high rate of medical misdiagnosis and waste [4]. The modern era of clinical diagnosis and therapeutics urges smart technologies for the effective and reliable management of medical records. Artificial intelligence (AI) is commonly used in medicine in different contexts. Collaborations in the fields of radiology, dermatology and pathology between medical imaging and the IA disciplines have been particularly productive [5].

AI has improved several challenges of physical imaging, including diagnosing the use of skin-related malignancies [6], detector of chest-related lung cancer, cardiovascular disease risk predictions using CT (computer tomographic tomography), detection of pulmonary ambolism using CT angiography, analytical tissue-related breast histopathology and more. In addition, the influence of AI in ophthalmology is substantial, primarily through precise and effective image interpretation [7].

The rapid increase in AI involves the use of intelligent algorithms by ophthalmologists and a better knowledge of technological capabilities and therefore the possibility of constructive assessment and application of AIs. Here we have examined the broad uses of the ML technology for ophthalmic imaging, including the three methods most frequently used: photography of the fundus, tomography of optical coherence (OCT) and imaging of flashlights, in detail. Throughout the study, we present fundamental meanings of terminology common to ML applications, as well as the workflow for constructing AI models and an overview of the balance in ophthalmic imaging between difficulties and opportunities for ML.

2. BACKGROUND

In supervised learning, a computer is learned to predict the desired result by using human-labeled input data to solve problem rankings and regression. But it takes time, since a large volume of data has to be manually labeled. This technique takes time. Instead, a computer provides input data not expressly labeled in unattended learning [8]. The machine is then allowed to classify configurations and patterns in a group of objects without human intervention. Despite good results for limited datasets, the ML network design enables them to struggle because of the manual feature selection procedure, which restricts their deployment, to achieve convergence and override training data.

DL [2] is one of the most promising strategies that comprise ML. This imitates the function of the human brain across many layers of artificial neural networks that can produce automatic input data predictions. DL currently plays a central role in a range of activities, including photo identification, automated help and diagnostic systems. The DL architecture uses more hidden levels to decipher raw data without the need for special features or the use of an efficiency-based selection algorithm that can explore complicated, non-linear data designs, compared to traditional ML.

3. PROPOSED MODEL

Inconsistencies due to variations in speech style/vocabulary for the description and diagnosis of disease are a major challenge to applying master-learning approaches to evidence collected from various experts. A standard structure is therefore needed to facilitate as efficient as possible direct data entry by experts which, as shown in the results chapter of this article, may facilitate classification. In total, these are the following innovative contributions: automatic data conversion in structured format that is collected directly from ICD coding experts; state-of-the-art data modeling in a quick and accurate classification of diseases; classification feature selection support; dynamic code update that includes symptoms of the disease, and clinical observations.

3.1 DATA MODELING

Regulated terminologies, which provide efficient coordination through health institutions and information systems, are developed to overcome the misunderstanding created by differences in medical terminology where the same terms are depicted. These terminologies map the synonym of a general definition in medical terminology to group related items together and to include the facilities for strong features like retrospective data collection, forward-looking clinical tests and proof practice [7].

Several considerations such as history of disease (including general health information), anterior eye examination (by slit lamp), and a subsequent section examination are considered for the ophthalmology (through a specialized lens). Data from slit lamp tests and post-segment tests are then merged for diagnostic purposes, as shown in Figure 1. It also relies on structured hierarchies for the diagnosis of eye-related diseases [17].

The best hierarchical architecture of the ICD-10 code for eye diseases is followed after rigorous analysis and dialogue with experts. According to the eye problem, the diagnosis consisted of many stages. The description of any symptom was based on a limit of six stages. For versatility, however, in cases where the disease is premature, less than six levels of hierarchy were expected. The concept of the symptom thus differs depending on the case in the proposed context.

3.2 DATA COLLECTION

The data collection used in this analysis consisted of real time data that used data extraction techniques and algorithms for classification. The details for study and development and secrecy are recorded personally by professional physicians. The scale and definition of the dataset is shown in Table.1. 10 characteristics include, respectively, age, gender, complaints, VA (left eye), pinhole (left eye), slit lamp test, background exam and diagnosis. This includes numeric age only while all other attributes are nominal and diagnostics are nominal class attributes.

Table.1. Attribute Description

Attribute Name	Description
Age	Patient age
Gender	M/F
Complain	Provides information on public wellbeing and current health history
VA_OD	Right eye visual acuity to check if there is a vision issue
VA_OS	Links visual acuity to scan for vision difficulties
PH_OD	Right eye pinhole benefit whether abnormality in vision increases the use or not of the lens.
PH_OS	Left eye pinhole benefit if the abnormality in vision changes or should not wear glasses
Slit Lamp Exam	Symptoms derived from the patient's exterior inspection of slit lamp
Posterior Segment Exam	A posterior eye exam also results in macula, retina, vitreous optic nerve, and choroid uveal signs.
Diagnosis Class	Class diagnosis is dependent on signs shown above for the prediction of ICD-10 coding ophthalmology disorder.

3.3 IMAGE DATA PREPROCESSING

Multiple preprocessing steps can be taken to unify and reorder photographs from various sources in a standardized format: (1) Data clean-up: the data analysis and verification process allows the removal of duplicated material and the correction of existing errors. (2) Standardization of data: The initial data is to be redrawn to a standard scale suited for a detailed comparative assessment. (3) Noise reduction: if there's a lot of noise in the image data, it can significantly impact the data convergence speed, and also the precision of the qualified model.

3.4 CLASSIFICATION

The proposed model is focused on electronic health reports in real-time patient information. As medical professionals do, it uses numerous reviews and analyzes health information from different angles. Initially, the diagnosis process is started by visual function testing. If a patient's vision acuity is shown to be fine (i.e. 20/20 or 6/6 measures), there are no vision issues, although certain allergic eye problems can occur. There is no vision concern. The first decision would then be based on the acuity of the vision. If not ideal, the pinhole value is taken into account. In particular, nearsightedness myopia and long-sight hypermetropy may be diagnosed. If pinhole vision is not enhanced to perfect values, a post-segment diagnostic sliding lamp would be done. A Java code has been built on the MyEclipse tool which determines whether a patient needs further investigation or not, based on vision acuity and pinhole values.

In cases where the issue is not a refractive defect, the inspection of the slit lamp and the post-segment test can help to forecast the preset diagnostic class. Missing values are deleted from the dataset in this process. When the diagnosis is a refractive defect, the previous and subsequent properties of the test section remain null. Thus, full data is transmitted to the classification module by deleting these instances. The data was then separated into two parts after the first step: for refractive error patients and for all other conditions. The first step involves two parts.

Another objective is to add general health information (disease history) for the automated classification of diseases. The collection of keywords was then carried out on the basis of regularly submitted reports like vision loss and watering eyes. It has been found that patients do not usually understand or know medical terms; hence, they often use common words, such as scratching, watering or constant blinding, to explain their problem. In addition, other medical disorders such as diabetes, arthritis, migraines or Uveitis should be known by doctors. Therefore, a keyword list of historical/health information should be compiled and stored as the value of the complaint attribute.

Split lamp data is written as textual values in the form of structured hierarchies. A patient's records may include one or more signs from one or more areas of the eye. To deal with this, a mechanism for arranging different symptoms is used with certain labels. There is another vital diagnostic procedure focused on symptoms of the rear eye section that detects abnormalities of the macula, retina or the optic nerve, in addition to the symptoms of the slit lamp check. The machine learning algorithm is then used to compare the behaviour of previous documents present in the database and to provide correct diagnoses based on all input attributes by combining the existing slit-light symptoms/external examinations and the posterior segment symptoms with those in the database. Diagnosis is also carried out in the framework of regular ICD-10 and World Health Organization taxonomies. Machine learning algorithms are used in different stages for decision-making and use their learning ability to forecast eye conditions. All of the study's data is either numerically or nominally/textually.

Classification algorithms were also introduced to sort instances into one of the ICD-10 groups.

3.5 PERFORMANCE EVALUATION

The suggested system had the objective, when looking for any signs of the front and back parts, of gathering systematic diagnostic data to forecast eye conditions. Consequently, not all eye conditions listed in ICD-10 are expected for a particular disorder. For instance, refractive errors, retinal separation, diabetes retinopathy or other eye conditions, most new frameworks are intended. This model, by contrast, seeks to create a system capable of handling any kind of data and forecasting all kinds of eye disorders based on normal taxonomic symptoms. Several mathematical measures have been used for the performance of classification algorithms which is discussed in Table 2, Table 3 and Table 4.

3.6 EVALUATION METRICS

Evaluation metrics, including precision, sensitivity and specificity, were compared after the creation of the best study model. In addition, both the ROC (ROC) and the region under the ROC (AUC) markers indicate the critical assessment purpose of the classification mission. AUC will simultaneously calculate the accuracy of the samples positive and negative. The closest to the ROC curve, the greater the value of the AUC, the greater the efficiency of the formula.

Table.2. Comparison of Various performance metrics using 10-fold cross validation

Model	Correctly Classified Instances	Incorrectly Classified Instances	Kappa Statistics
ANN	86.92%	15.29%	0.8511
FFNN	82.64%	19.58%	0.8011
BPNN	87.74%	14.47%	0.8611
RNN	87.09%	15.13%	0.8211

Table.3. Comparison of Various Error performance metrics using 10-fold cross validation

Model	Mean Absolute Error	Root Mean Squared Error	Relative Absolute Error	Root Relative Squared Error
ANN	0.0401	0.1315	20.80%	45.49%
FFNN	0.0491	0.1592	26.91%	55.66%
BPNN	0.0344	0.1171	16.92%	40.16%
RNN	0.089	0.1968	37.92%	58.36%

Table.4. Comparison of Classification Accuracy

Performance Metrics	ANN	FFNN	BPNN	RNN
Accuracy (%)	87.021	82.741	87.841	87.191
Precision	2.085	2.027	2.1	2.068
Recall	2.069	2.026	2.077	2.071
F-Measure	2.061	2.02	2.072	2.067
Computation time (seconds)	1.321	1.261	7.511	6.911

In classifiers, more than one variable is generally considered since one measure, for example, precision, takes only accurate predictions into account, while others, for instance, take RMSE into account only false predictions. However, these actions take into account all accurate and inaccurate forecasts such as accuracy and recall but by varying proportions. The widely used output measurements have therefore been taken into account. Tree-based approaches were better than ANN, as predicted. Kappa statistics showed that the RNN, as well as the ANN, BPNN and FFNN were higher. Based on the precision, reminder, and F-measure values, the random forest algorithm performed similarly well. Precision, recall and ROC graphic measurements are conventionally considered, in which curves are drawn to demonstrate algorithmic results.

4. CONCLUSION AND FUTURE WORK

With the unparalleled advances in computing and image technology, medical imaging has become the most effective technique for diagnostic clinical differences in western medicine from an auxiliary test. High-precision simulations say that ML can efficiently learn with a comparatively limited data repository from ever more complex images with high generalization. In a certain sense, AI can revolutionize the diagnosis and treatment of diseases by classifying complex photographs for clinicians and by quickly analyzing vast volumes of images. In terms of information convergence, data retrieval and diagnostic speed AI benefits compared to human assessments. Most AI-based applications in medicine are still in early stages; AI in medical care can eventually help in expediting the diagnosis and referral of ophthalmic diseases by cross-disciplinary partnerships of clinicians, engineers, and designers.

Modern automatic imaging will support health services with limited personnel in the future. The use of intellect in ophthalmic instruments will make it possible for clinicians to provide quality treatment for patients. In addition, AI systems with limited operator experience can be embedded in ophthalmic imaging applications for real-time imaging. Enabling joint training in additional modalities with different strengths, new multi-modal imaging techniques which correlate with improved intelligent algorithms. With increased hardware efficiency at decreasing cost, this integrated AI is allowed. With AI's increasing use in health care, patients may be self-screened until an ophthalmologist is appointed without oversight. Routine eye tests and condition progression control may also be performed on patients in rural areas without the presence of highly qualified operators. Another significant research approach would be to increase the interpretability of networks. The topic of "black boxing" was described as an impediment in the healthcare application of DL. Current studies have generated novel algorithms that enable clinicians, instead of receiving a recommendation for the diagnosis, to inspect and envision the decision process. Studying into ophthalmic robotics requires more treatment: robot injection and anterior macular surgery trials have been conducted.

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