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 data 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 hypothesizes 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 for the description and diagnosis of disease are a major challenge for 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; and other methods.

3. PROPOSED MODEL

Inconsistent due to variations in speech style/vocabulary for the description and diagnosis of disease are a major challenge for 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; and other methods.

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
deemed. 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

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

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
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 hypermetropia 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

<table>
<thead>
<tr>
<th>Model</th>
<th>Correctly Classified Instances</th>
<th>Incorrectly Classified Instances</th>
<th>Kappa Statistics</th>
</tr>
</thead>
<tbody>
<tr>
<td>ANN</td>
<td>86.92%</td>
<td>15.29%</td>
<td>0.8511</td>
</tr>
<tr>
<td>FFNN</td>
<td>82.64%</td>
<td>19.58%</td>
<td>0.8011</td>
</tr>
<tr>
<td>BPNN</td>
<td>87.74%</td>
<td>14.47%</td>
<td>0.8611</td>
</tr>
<tr>
<td>RNN</td>
<td>87.09%</td>
<td>15.13%</td>
<td>0.8211</td>
</tr>
</tbody>
</table>

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

<table>
<thead>
<tr>
<th>Model</th>
<th>Mean Absolute Error</th>
<th>Root Mean Squared Error</th>
<th>Relative Absolute Error</th>
<th>Root Relative Squared Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>ANN</td>
<td>0.0401</td>
<td>0.1315</td>
<td>20.80%</td>
<td>45.49%</td>
</tr>
<tr>
<td>FFNN</td>
<td>0.0491</td>
<td>0.1592</td>
<td>26.91%</td>
<td>55.66%</td>
</tr>
<tr>
<td>BPNN</td>
<td>0.0344</td>
<td>0.1171</td>
<td>16.92%</td>
<td>40.16%</td>
</tr>
</tbody>
</table>

Table 4. Comparison of Classification Accuracy

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

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.

REFERENCES


