Article

Data Driven Approach for Eye Disease Classification with Machine Learning

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Abstract: Medical health systems have been concentrating on artificial intelligence techniques for speedy diagnosis. However, the recording of health data in a standard form still requires attention so that machine learning can be more accurate and reliable by considering multiple features. The aim of this study is to develop a general framework for recording diagnostic data in an international standard format to facilitate prediction of disease diagnosis based on symptoms using machine learning algorithms. Efforts were made to ensure error-free data entry by developing a user-friendly interface. Furthermore, multiple machine learning algorithms including Decision Tree, Random Forest, Naive Bayes and Neural Network algorithms were used to analyze patient data based on multiple features, including age, illness history and clinical observations. This data was formatted according to structured hierarchies designed by medical experts, whereas diagnosis was made as per the ICD-10 coding developed by the American Academy of Ophthalmology. Furthermore, the system is designed to evolve through self-learning by adding new classifications for both diagnosis and symptoms. The classification results from tree-based methods demonstrated that the proposed framework performs satisfactorily, given a sufficient amount of data. Owing to a structured data arrangement, the random forest and decision tree algorithms' prediction rate is more than 90% as compared to more complex methods such as neural networks and the naïve Bayes algorithm.

Keywords: Machine Learning; Classification; Framework; Eye diseases; ICD codes

1. Introduction

Artificial intelligence (AI) plays an important role in assisting medical experts with early disease diagnosis. There are a large number of AI-based disease detection and classification systems combining medical test results and domain knowledge [1–6]. However, correlating the actual symptoms and clinical observations with the corresponding diseases is missing in most of these systems. This is perhaps owing to the variety of observation recording methods by medical experts. For example, some use symbols for diagnosis, whereas others give a textual description; hence, there is no standard method. Therefore, this data should be manually converted into a standard format so that machines can use it for analysis. This limits the size of data used in any analytical study, which is the main cause of current gaps in human-knowledge-based diagnosis and machine-intelligence-based predictions.

Commonly, ophthalmic diseases are not life threatening; however, progress over time can have significant impact on the patient's life. Physical examinations are performed using ophthalmological instruments and a comprehensive interpretation is used for diagnosis. Therefore, any machine-based solution should concurrently consider observations, symptoms and standardized test results for

predictions. Furthermore, the use of a standard description for clinical data and medical test results can be the key to success. The first step toward this is the use of health records in electronic form. Maintaining patient information as digital data has several potential benefits, including rapid retrieval along with timely data transmission among multiple medical experts [7]. Moreover, the use of standard taxonomies for patient data recording can further improve its quality, accuracy and consistency.

This study focuses on developing a general framework for the standardized recording of patient symptoms and clinical observations, thus assisting medical experts in keeping up with the exponential development of medical knowledge arising from clinical trials and logical advancements in the field. Similarly, medical cases solved in the past may greatly contribute to the training of machine-learning agents for accurate diagnosis [8]. This is also important because machine-learning algorithms can analyze the large number of features required for diagnosis more effectively than humans. Accordingly, intelligent agents, using a carefully designed multi-agent-based classification model, can outperform humans by efficiently analyzing all the features along with previous information [9].

The rest of the paper is organized as follows. In Section 2, existing machine-based solutions for medical diagnosis are briefly described. In Section 3, the proposed methods for data modeling and pre-processing are explained, as well as the framework designed for analyzing and predicting eye diseases. In Section 4, the results are described and the paper is concluded in Section 5.

2. Related Work

A large amount of research has been conducted on developing medical expert systems to automate diagnostic processes [2,4,10–12]. These expert systems can produce accurate responses based on pre-defined rules; however, the use of static rules results in restricted learning and therefore failure to respond to new situations. With the advancement in machine learning algorithms, the focus shifted toward machine learning through training data. Hence, almost all medical fields, in particular ophthalmology, are now experiencing rapid growth in machine-based research activities. A brief review of related work will now be provided.

In References [4,13–16], textual and numeric data was used for certain eye problems, namely, dry eye diseases, refractive error, esotropic eyes and progression in glaucomatous visual field defects. Moreover, probabilistic classifiers such as naïve Bayes and support vector machines were used. In 2011, research on cataract disease was conducted by the Electronic Medical Records and Genomics Network. ICD-9 (International Classification of Diseases) [17] codes and current procedural terminology codes were used for cataract diagnosis in patients without surgery. Furthermore, natural language processing (NLP) and intelligent character recognition (ICR) were the machine-learning techniques used to identify cataract cases and their type. Specifically, written documents were scanned and after ICR and NLP were performed, they were used in the diagnosis process [18,19]. In 2014, a study was conducted to analyze clinical data for finding the relationship between signs and diagnosis of dry eyes disease [20]. The dataset was obtained from 344 patients and the analysis was based on independent component analysis (ICA) and Pearson correlations. The highest correlations were found between conjunctiva and corneal staining. Furthermore, each component of the ICA mixing matrix exhibited minimal residual information. Consequently, no consistent relationship was found among the most frequently used signs and symptoms.

Moreover, a number of studies focused on analyzing image data for direct conversion into diagnostic data. In 2018, research was conducted into blood vessel segmentation [21] using image-processing methods based on machine-learning methods. Vessel segmentation process is divided into four categories including vessel enhancement, machine learning, deformable models and tracking. Reference [21] also provides a recent survey of the methods that can be used in this type of research and Reference [22] provides an earlier such survey. The most common disease leading to blindness is glaucoma [1], for which image-based detection was relatively more efficient than for other diseases. In References [3,23–25], algorithms were used for the detection of abnormal retina along with the classification of a normal retina. Furthermore, multiple diagnostic images of the retinas were

used along with patient clinical records. In Reference [26], a survey of various computer-based ocular disease identification methods was presented. Multilayer perceptron, support vector machines and linear and quadratic discriminant classifiers were found to be more successful in identifying different eye problems.

As previously mentioned, the most common but dangerous eye disease is currently glaucoma. Optical coherence tomography (OCT) images are used for its diagnosis and therefore they should be classified for computer-aided glaucoma detection [1,6,27–31]. Similarly, in Reference [32], imaging data was used for identifying intraocular lenses and refractive surgery. EyeView was used to optimize vision quality. Furthermore, computing solutions have been presented for identifying specific eye diseases such as age-related macular degradation [33], for the auto-detection of a diabetic retina [34,35] and for automatic localization of the optic disc using image classification with support vector machines [5].

Moreover, to predict cataracts, visual quality was determined using contrast sensitivity in Reference [32]. Then, Fageeri et al. [16] diagnosed refractive error based on the spherical, cylindrical and axis values of wearing glasses. The model was based on decision tree, naïve Bayes and support vector machine classification algorithms and used four classes of patients suffering from hyperopia astigmatism, myopia (nearsightedness), myopia astigmatism and hyperopia (farsightedness). The analysis was conducted using the Waikato environment for knowledge analysis and the proposed model was used for disease classification and for determining the relationship between symptoms and diagnosis with accuracy up to 98.75%. In Reference [36], a gene network was designed to define disease expression involving the determinants corresponding to nodes.

Table 1 presents some recently published research work in medical or related domains using different machine-learning algorithms. Mostly researchers focused on using sophisticated machine-learning methods such as Naïve Bayes, SVM and Deep Learning algorithms to improve classification accuracy. However, no effort has been directed towards data modeling, which, however, can improve the classification or prediction of results. Therefore, this requirement has become the basis of the current study.

Table 1. Recently published medical research into the classification of diseases using machine-learning approaches. These studies have not used a structured coding scheme for data representation and, therefore, are unable to give any general framework for classification.

	before and 2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Deep Learning												[37]
Convolution Neural Network											[38]	[39,40]
Neural Network	[41]	[42]			[35]	[6,43]						[44]
Support Vector Machine (SVM)	[28]			[15]	[31]	[26]	[5]			[16]	[45]	
Naïve Bayes	[28]				[31]					[16]	[44–46]	
Random Forest					[31]						[45]	[39]
Decision Trees			[14]							[16]	[44]	
Regression Analysis					[31]							
Optimization Algorithm						[43]		[33]		[47]		
Customized Algorithms	[4]		[18,34]	[19,30]		[20,25]						
Years	before and 2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019

3. Methodology Adopted

The literature review demonstrated that almost all existing studies are disease based and, thus, the algorithms developed or used were tested for specific eye diseases, for example, glaucoma disease prediction in Reference [13] and refractive error classification in Reference [16]. Accordingly, no general solution is available. This is primarily due to the lack of standardization in recording medical information, a major difficulty that has hindered general automated solutions. A critical challenge in applying machine-learning methods to data obtained by multiple experts is inconsistencies owing to differences in expression style/vocabulary for disease description and diagnosis. Hence, a standardized framework is required to facilitate direct data entry by experts as efficiently as possible, which in turn may facilitate classification, as shown in the results section of this paper (Section 4). Overall, the following are the innovative contributions this paper makes:

- Automatic conversion of data into a structured format directly collected from medical experts using ICD coding;
- State-of-the-art data modeling for fast and accurate disease classification;
- Support for features selection in classification;
- Dynamic updating of codes to incorporate new symptoms and clinical observations; and
- Improved classification results using conventional machine-learning methods.

3.1. Data Modeling

To resolve the ambiguity caused by variations in medical language when representing the same concepts, controlled terminologies have been established, ensuring effective communication across health care entities and information systems. These terminologies map synonyms of medical terms to a common concept so that similar objects can be grouped together, thereby providing the infrastructure to support powerful features such as retrospective data analysis, prospective clinical trials and evidence-based practice [7]. Various standards in medical terminologies are available, such as the 10th version of International Classification of Diseases (ICD-10), Systematized Nomenclature of Medicine, Clinical Terms and Medical Entities Dictionary [7].

In ophthalmology, multiple factors are considered, such as illness history (including general health information), anterior eye examination (through a slit lamp) and posterior segment examination (through a specialized lens). Therefore, data from slit lamp examination and posterior segment examination are combined for diagnosis, as shown in Figure 1. ICD-10 [17] is also based on structured hierarchies for eye-related disease diagnosis. Therefore, these examinations were used for AI-based learning and were arranged in a hierarchical structure similar to the physician decision tree shown in Figure 2. After rigorous analysis and discussion with experts, the most suitable hierarchical structures of ICD-10 coding for eye diseases were adopted. Diagnosis consisted of multiple levels, according to the existing eye problem. There were a maximum of six levels involved in the definition of any symptom. However, for flexibility, less than six hierarchical levels were required for cases where the disease is at a premature stage. Therefore, in the proposed framework, the definition of a symptom varies according to the situation. An example of a symptom identified from slit examination can be seen below.
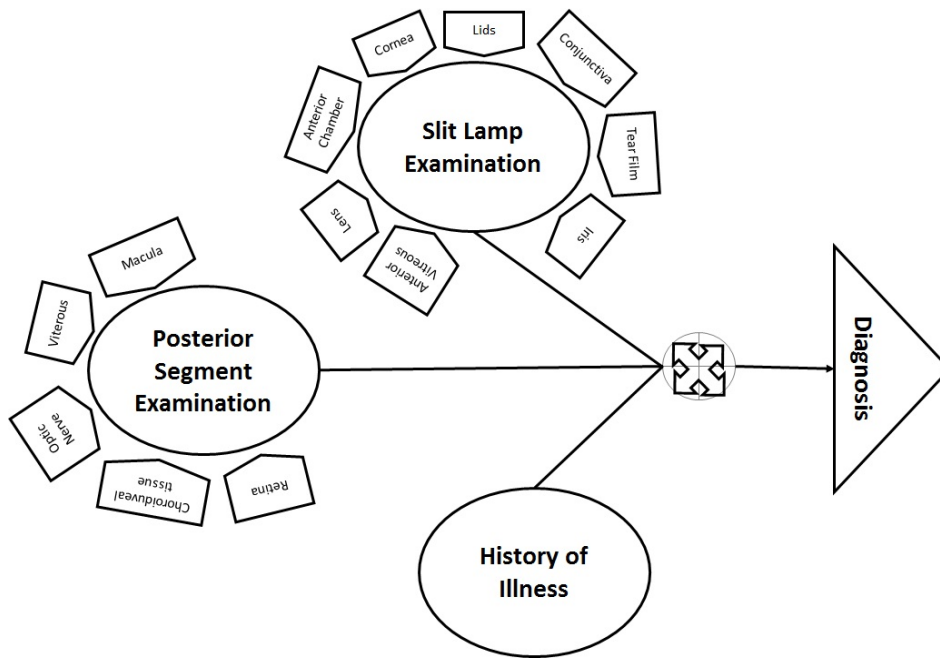
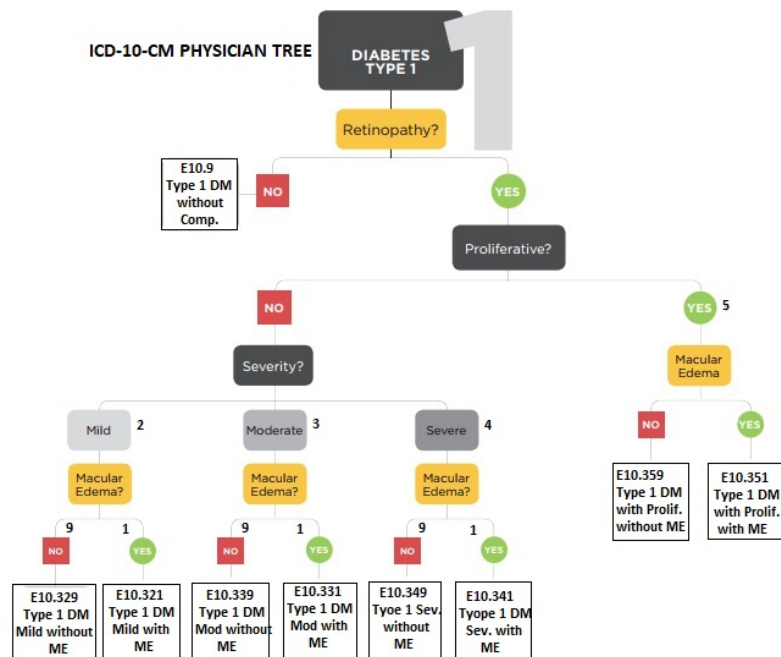**Figure 1.** Eye disease diagnosis mechanism.

Figure 2. ICD-10 physician decision tree for diabetic retinopathy [48].

Cornea → Endothelium → KPs → Fine → Site → Generalized

Moreover, recording data in this form is impossible during the examination, as the doctor cannot ignore the patient while writing down all required elements of a symptom. Therefore, a highly efficient method is required to ensure accurate data entry and, hence, an interface for web applications was developed so that the doctor or any other medical expert needs to click only three times (on average) to select the entire hierarchy of a particular symptom. Figure 3 shows the definition of a symptom using a graphical user interface. The mouse is pointed to the plus symbol of "Cornea" for either the right or the left eye and the next level of available options appears as a dropdown menu. When the user further hovers the mouse over "Endothelium" the next level of available options appears. Continuing further, multiple options appear for the final definition of the symptom. Finally, the last option is

selected and all the above levels are concatenated. In the example, when "Generalized" is selected, the complete hierarchy will be displayed.

Figure 3. Data entry of symptoms through selection: A symptom is added for the cornea of the right eye shown in the sign pane on the right side of the screen; if a symptom cannot be found, "Others" is the option where new symptoms can be added.

Furthermore, a graphical user interface was also developed for providing a diagnosis in standard format. This is achieved by introducing a search option in the diagnosis dropdown menu because it is difficult to scroll through all available options to reach the required diagnosis. After entering the keywords, the user clicks on the desired diagnosis in a standard format, as shown in Figure 4. This approach has the advantage of obtaining the same data format from all users.

Figure 4. Data entry of diagnosis through search engine: The initial letters of the diagnosis are entered and the system automatically suggests the related diagnosis, thus reducing the effort in typing or selecting multiple hierarchies.

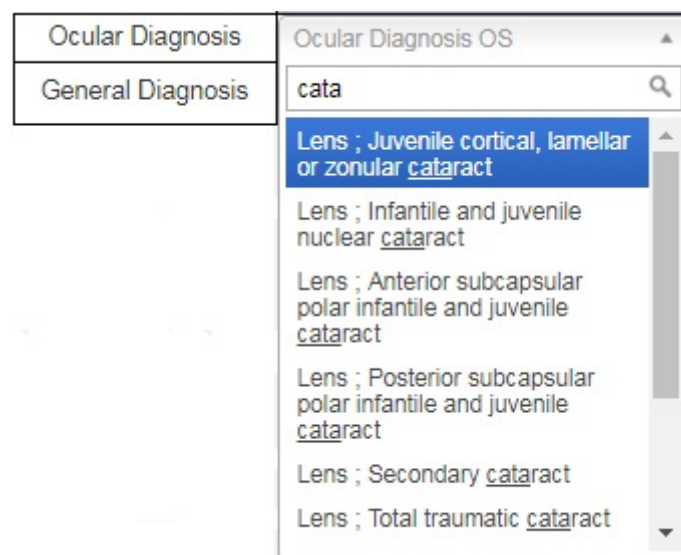Thereby, all the symptoms as well as the diagnosis are stored, providing the foundation for machine learning. Initially, the predicted results are compared with the actual diagnosis by medical experts. As shown in the results section, the predicted results may be as accurate as the expert opinion by increasing the amount of data.

Data recording does not end there. For machine-learning algorithms, searching is the most important step and the characters in a symptom are difficult to match efficiently and accurately. Furthermore, the selection order results in false matches. If, for example, lid swelling is selected as the first symptom, followed by three other symptoms but some other expert selects the symptoms in a different order, the machine considers that two separate eye problems are defined. Therefore, symptoms are stored as ordered numeric codes. Table 2 describes different symptoms and their corresponding codes, as recorded for a patient. Mathematically, the numbers 452,111 and 452 are considered to be far apart but, in the proposed system, they belong to the same hierarchy and should thus be grouped together. Therefore, to unify coding, zeros are appended to the symptom code so that all codes contain six digits, that is, 452,111 and 452,000 for the aforementioned case. The absence of a symptom is represented by six zeros.

Table 2. Example of data recording in the proposed system for a patient. Combined code for symptoms facilitates fast matching and efficient diagnosis. Blank cells indicate the absence of a corresponding symptom in a particular patient and, therefore, this is represented by zeros in the code.

Category	Selected Symptoms	Codes	Sorted Codes per Category
Lids	Lids ; Swelling ; Site ; Upper Lid ; Involving Medial Part	11111	111110-000000-000000-000000-000000
Conjunctiva	Conjunctiva ; Discharge; Purulent	241	214000-000000-000000-000000-000000
Tear Film	Tear Film ; Special tests ; Marginal tear meniscus ; <1 mm	3311	320000-331100-000000-000000-
	Tear file; Unhealthy	32	000000
Cornea			000000-000000-000000-000000-000000
Anterior Chamber			000000-000000-000000-000000-000000
Iris			000000-000000-000000-000000-000000
Lens	Lens ; Phakic ; Opacity; Sub-capsular ; Posterior	71212	712120-000000-000000-000000-000000
Anterior Viterous			000000-000000-000000-000000-000000
Combined Code	111110-000000-000000-000000-000000-214000-000000-000000-000000-000000-320000-331100-000000-000000-000000-000000-000000-000000-000000-000000-000000-000000-000000-000000-000000-000000-000000-712120-000000-000000-000000-000000-000000-000000-000000-000000-00000		

3.2. Data Collection and Description

The dataset used in the present study was composed of real-time data on which data mining techniques and classification algorithms were applied. Professional doctors directly recorded the data for research and development and confidentiality was assured. Table 3 shows the size and description of the dataset. There are 10 attributes, namely, age, gender, complaint, VA (left eye), VA (right eye), pinhole (left eye), pin hole (right eye), slit lamp exam, posterior segment exam and diagnosis. Among

these, only age is numeric, whereas all others are nominal and diagnosis is a class attribute with nominal values.

Table 3. Dataset and attributes description

Dataset Ophthalmology data: Symptoms and Diagnosis	Number of Attributes 10	Number of Instances 3025		
S.No.	**Attribute Name**	**Attribute Type**	**Example**	**Attribute Description**
1	Age	Numeric	32	Patient age
2	Gender	Nominal	M	M/F
3	Complain	Nominal	Blurred Vision, Pain	Provides general health information and history of present illness
4	VA_OD	Nominal	20/50	Visual acuity of right eye to check if there is any problem in vision
5	VA_OS	Nominal	20/40	Visual acuity of left eye to check if there is any problem in vision
6	PH_OD	Nominal	20/25	Pinhole value of right eye denoting if vision abnormality improves on wearing glasses or not
7	PH_OS	Nominal	20/20	Pinhole value of left eye denoting if vision abnormality improves on wearing glasses or not
8	Slit Lamp Exam	Nominal	Lids; Swelling; Site; Upper Lid	Symptoms obtained from slit lamp examination of patient showing external exam of eye
9	Posterior Segment Exam	Nominal	Retina; Retinal Detachment; Rhegmatogenous detachment; Macula On	Examination of posterior segment of eye also outputs symptoms regarding macula, retina, optic-nerve vitreous and choroid-uveal.
10	Diagnosis Class	Nominal	Glaucoma ; Unspecified primary angle-closure glaucoma	Diagnostic class is diagnosed based on symptoms shown above for prediction of ophthalmology disease according to ICD-10 coding.

3.3. Data Pre-Processing

In order that machine learning be performed in accordance with medical rules, pre-processing is required that involves data cleaning and normalization, noisy data filtering and handling of missing values [16]. It is important to mention that data pre-processing highly affects the performance of machine-learning algorithms and, if not performed properly, it may produce biased output [49]. The Weka knowledge analysis tool provides various pre-processing and transformation algorithms.

Feature selection and extraction are aimed at a more robust machine-learning process by identifying and removing irrelevant attributes from the dataset to reduce dimensionality and improve performance. However, ignoring a small symptom may have serious consequences. Fortunately, standard taxonomies eliminate unnecessary data and, therefore, no feature is ignored in analysis and diagnosis.

Missing values may also adversely affect machine learning. In this study, two techniques were used for handling missing values, namely, deletion of records with more than 60% missing values and a two-step diagnostic method using segmentation, which will be explained later.

3.4. Methods

A number of classification algorithms are in use in the medical domain with the promise of increasing reliability and confidence [50,51]. One can easily select a classifier according to the data, whether parametric or non-parametric [52,53]. Tree based methods such as Decision Tree and Random Forest are non-parametric classifiers and, therefore, can be applied to the data whose distribution

in not know. As in the medical domain collecting normally distributed data is almost impossible, non-parametric methods are always helpful [54]. However, some other classifiers such as Neural Network, Naïve Bayes and Support Vector Machines have also been very popular in classifying diagnostic data but use assumptions to simplify the learning process and sometimes lead to a higher error rate. All the same, for some classes of disease, such as for cancers, Support Vector Machines can have a valuable role and to that end the reader is referred to Reference [55]. Herein, we have used a mix of both types of classification algorithms that include decision tree, random forest, naïve Bayes and neural networks. The purpose is to identify the impact of the proposed data modeling method upon classification accuracy. Weka [56] was used for model implementation in the data classification algorithms. The Weka workbench is a combination of various machine-learning algorithms and data pre-processing filters, whereby existing complex learning algorithms can be applied to new datasets. As in most related studies, the dataset used in this study (described in Table 3) was divided into two sets: (1) Training; and (2) Testing with 70:30 split. For validation a 10-fold cross-validation method was used in the classification algorithms. For general comparison of the algorithms, no manual tuning of the parameters was performed so that the model can adjust itself according to the data.

3.5. Model Description

The proposed model is based on real-time patient data from electronic health records. It uses multiple examinations and analyzes patient records from various perspectives, as medical experts do.

Figure 5 shows the entire process in detail. Initially, the visual function test is used to start the diagnostic process. If the visual acuity of a patient is observed to be perfect (i.e., measured to be 20/20 or 6/6), then there is no vision problem; however, the patient may have some allergic eye disorders. Thus, the first decision will be made on the basis of visual acuity. If it is not perfect, then the pinhole value is considered. If pinhole vision improves to 20/20 or 6/6 according to selected scales, then the patient will be prescribed glasses and the diagnosis, according to ICD-10, will be pediatric/strabismus $\rightarrow$ refractive error. More specifically, the diagnosis will be myopia for nearsightedness and hypermetropia for longsightedness. If pinhole vision is not improved to perfect values, then slit lamp posterior segment examination will be performed to reach a diagnosis. A Java code on the MyEclipse tool was developed that decides on the basis of visual acuity and pinhole values whether the patient requires further investigation or not.

If the problem is not refractive error, then the slit lamp examination and posterior segment examination will facilitate the prediction of the predefined diagnosis class. In this step, missing values are removed from the dataset. If the diagnosis is refractive error, then the anterior and posterior segment examination attributes will remain empty. Therefore, by removing those instances, complete data is passed to the classification module. Thus, after the first step, the data is divided into two parts: one for patients with refractive error and the other for all other diseases.

Another goal is to add general health data (illness history) as a contributing attribute for automatic disease classification. Accordingly, keyword selection was performed based on frequently presented complaints, such as decreased vision and watering eyes. It was observed that patients do not generally know or understand medical terms; therefore, they always use ordinary words to describe their problem, such as itching, watering or frequent blinking. Moreover, experts should be aware of other medical conditions, such as diabetes, hypertension, migraine or uveitis. Therefore, it is more convenient to compile a keyword list of history/health data and store it as the complaint attribute value.
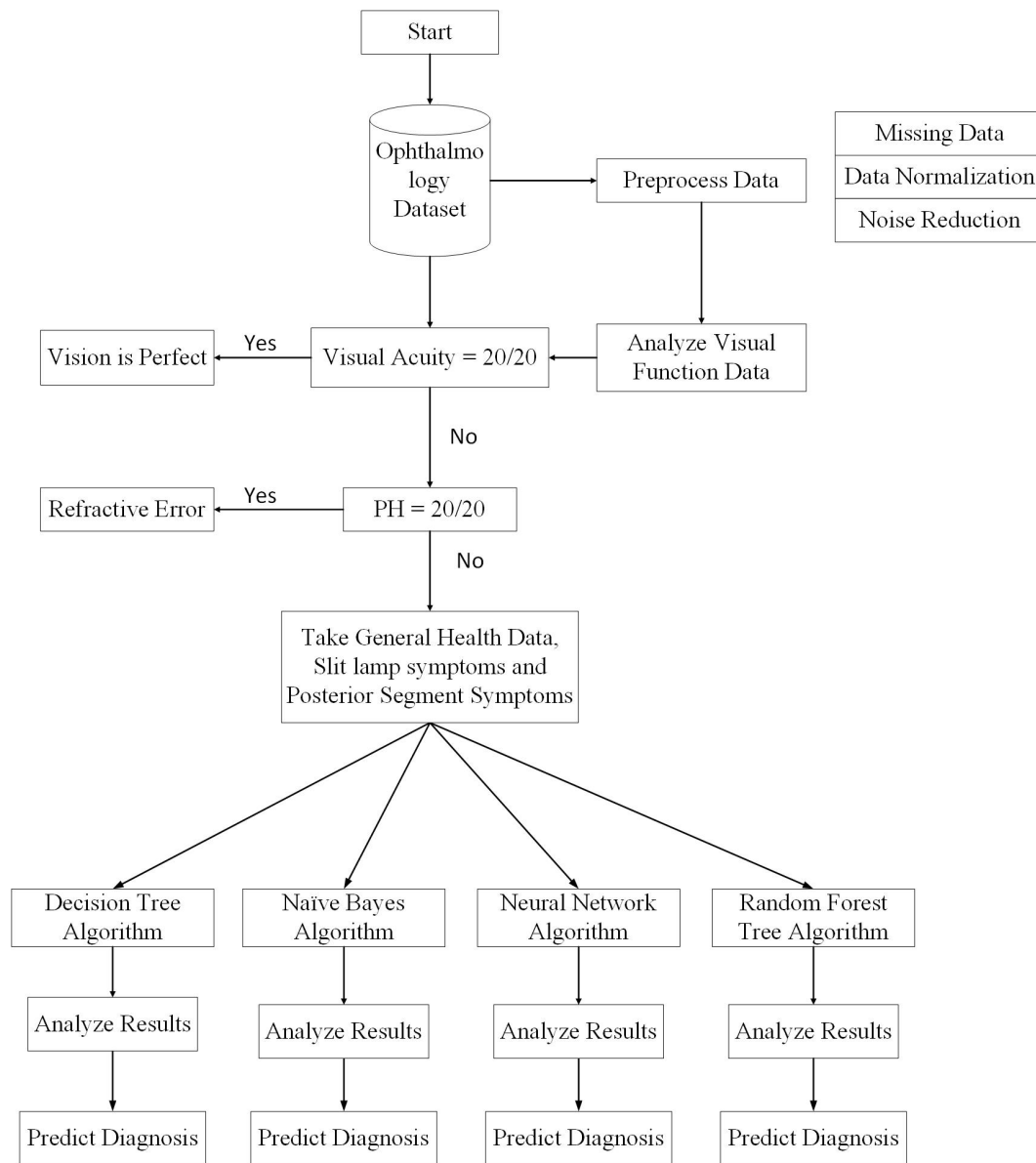
Figure 5. Framework for the prediction of eye diseases: Data are collected and its analysis is used for disease prediction by comparison with expert diagnosis for correct classification. Four different algorithms were used to authenticate the predicted results.

Data from the slit lamp exam is in the form of structured hierarchies written as textual values. The record of a single patient may contain one or multiple symptoms originating in the same or different parts of the eye. To handle this, a multi-label data mechanism is used for arranging multiple symptoms. In addition to symptoms from the slit lamp examination, there is another vital diagnostic test based on symptoms from the posterior eye segment that identifies disorders in macula, retina or the optic nerve. The machine-learning algorithm will then use the behavior learned from previous records available in the database and compare the current combination of slit lamp/external exam symptoms and posterior segment symptoms with those in the database to give an accurate diagnosis on the basis of all input attributes. Diagnosis is also in the form standard taxonomies defined by ICD-10 and maintained by the World Health Organization. Thereby, machine learning algorithms are used for decision making at various stages and they use their learning capabilities for the prognosis of eye diseases. Most of the data considered in this study were either in numeric or nominal/textual form.

Furthermore, classification algorithms were applied to classify given instances into one of the classes taken from ICD-10. The performance of each classifier was analyzed according to the number of correctly classified instances [16] and is discussed in the next section.

4. Results

A step-wise decision system generates the classification results presented in Tables 4 and 5. The performance of the classification algorithms was evaluated using several statistical measures, namely, kappa statistics, root mean squared error (RMSE), accuracy, precision, recall and the area under the curve (AUC) of receiver operating characteristics (ROC) graphs.

Table 4. Comparison of four different classifiers using statistical measures. The averages are for 10-fold cross-validation results of a 52 classes (diseases) classification.

Test Statistics	Decision Tree	Naïve Bayes	Random Forest	Neural Network
Correctly Classified Instances	85.81%	81.53%	86.63%	85.98%
Incorrectly Classified Instances	14.18%	18.47%	13.36%	14.02%
Kappa Statistics	0.84	0.79	0.85	0.81
Mean Absolute Error	0.029	0.038	0.0233	0.0779
Root Mean Squared Error	0.1204	0.1481	0.106	0.1857
Relative Absolute Error	19.69%	25.80%	15.81%	36.81%
Root Relative Squared Error	44.38%	54.55%	39.05%	57.25%

Table 5. Comparison of Classification Algorithms. The measures are averages of 10-fold cross-validation results produced from classifying 52 classes (diseases).

Performance Measures	Decision Tree	Naïve Bayes	Random Forest	Neural Network
Accuracy(%)	85.81	81.53	86.63	85.98
Precision	0.874	0.816	0.889	0.857
Recall	0.858	0.815	0.866	0.86
F-Measure	0.85	0.809	0.861	0.856
Computation time(seconds)	0.11	0.05	6.3	5.7

More than one measure is usually considered when classifiers are compared because one measure, for example, accuracy, considers only correct predictions, whereas others, for example, RMSE, consider only false predictions. However, some measures consider both correct and false predictions, for example, precision and recall but by a different proportion. Therefore, most of the commonly used performance measures were considered. As expected, tree-based methods performed better than probability-based methods (Naïve Byes). The kappa statistics demonstrated that both the decision tree and random forest algorithms performed better than the neural network. Similarly, according to the values of precision, recall and the F-measure, the random forest algorithm performed well. Conventionally, precision, recall and ROC are considered graphical measures, where curves are drawn to display the performance of an algorithm. For ROC curves, the true positive rate (TPR) is drawn against the false positive rate (FPR). However, to demonstrate the performance of the entire framework for predicting different classes (diseases), these performance measures for each class are shown in Figures 6–8.

Precision is a measure of relevance, whereas recall is the fraction of retrieved relevant instances over the total number of relevant instances (obtained usually in the range 0—1); therefore, high values for both measures indicate better performance. Similarly, FPR is the fraction of wrong true predictions and TPR or sensitivity is the fraction of correct classifications (for a classifier). TPR and FPR also range between 0 and 1 and high TPR and low FPR reflect good performance. Figure 8 shows that the random forest algorithm yields a high TPR for more classes (diseases) compared to the decision tree and naïve

Bayes algorithms. Although the FPR of the naïve Bayes algorithm has the lowest value, its TPR is also low for a number of classes.
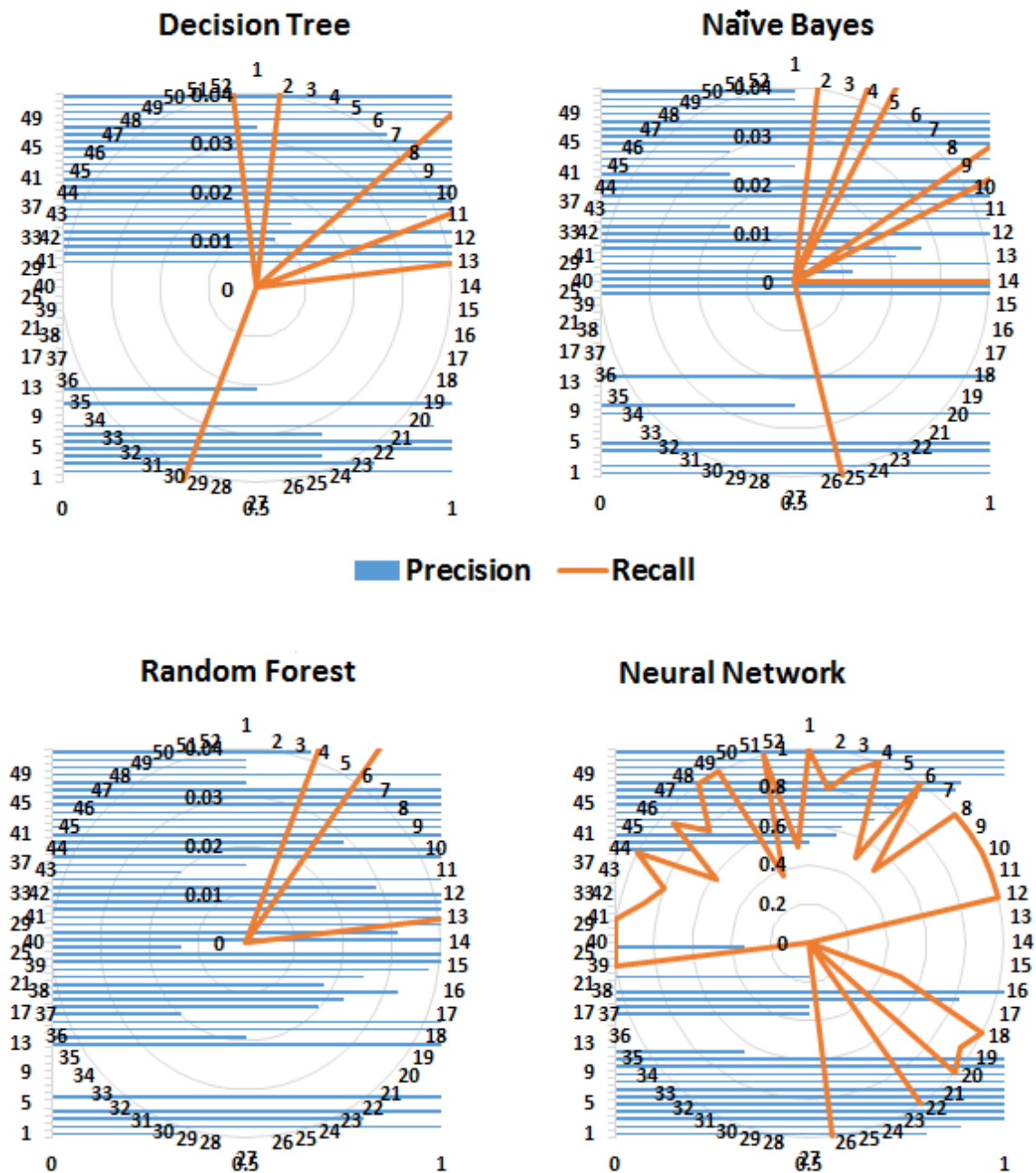

Figure 6. Precision analysis of classification algorithms for 52 classes (diseases) shown in Table 6. Precision and recall values decrease from the outermost (value 1) to the innermost circle (value 0). The curves lying on the outermost circle represent better classification results, such as those by the decision tree and random forest algorithms.

Table 6. Fifty-two different diagnoses (classes for classification) for which the data were recorded in the software by medical experts. The list has been sorted in alphabetic order for understandability.

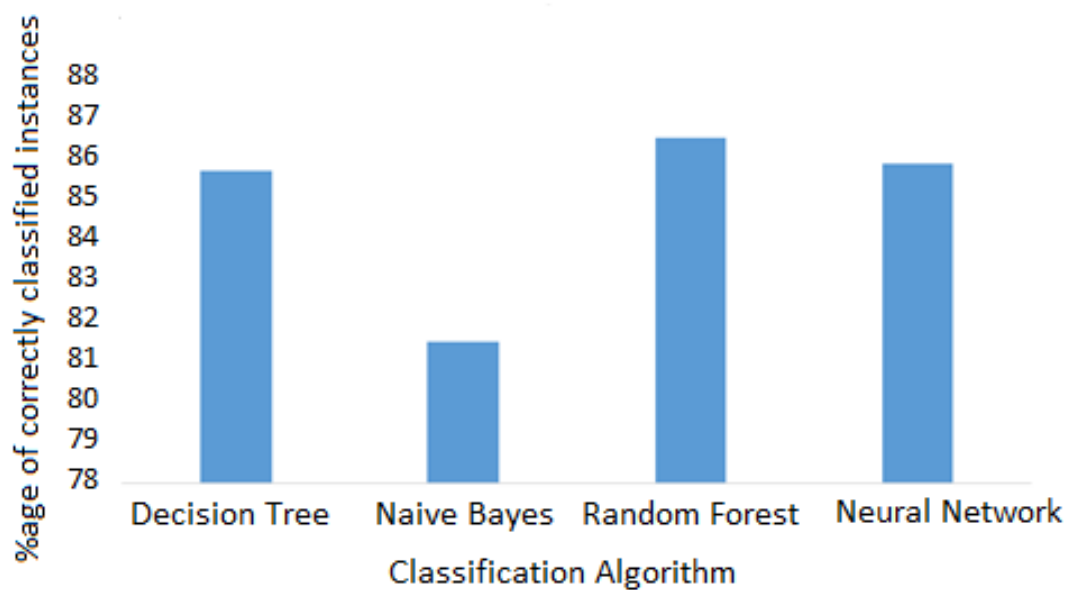| S.No	Diagnosis	S.No	Diagnosis
1	Conjunctiva → Acute atopic conjunctivitis	27	Glaucoma → Primary open-angle glaucoma
2	Conjunctiva → Adenoviral conjunctivitis	28	Glaucoma → Steroid responder
3	Conjunctiva → Chronic allegic conjunctivitis, unspecified	29	Glaucoma → Unspecified primary angle-closure glaucoma
4	Conjunctiva → Conjunctival hemorrhage	30	Lens → Phakic → Opacity → Cortical
5	Conjunctiva → Pingueculum	31	Lens → Phakic → Opacity → Cortical → Incipient
6	Conjunctiva → Viral conjunctivitis, unspecified	32	Lens → Phakic → Opacity → Cortical → Incipient → Vascular
7	Cornea → Corneal Edema/Opacity/ Degeneration → Bullous keratopathy	33	Lens → Phakic → Opacity → Nuclear → Grade 2
8	Cornea → Corneal Edema/Opacity/Degeneration → Keratoconus, stable	34	Lens → Phakic → Opacity → Sub-capsular → Anterior
9	Cornea → Keratitis → Exposure keratoconjunctivitis	35	Lens → Phakic → Opacity → Sub-capsular → Posterior
10	General Diagnosis → Bacterial conjunctivitis	36	Lens → Pseudoexfoliation
11	General Diagnosis → Blepharitis	37	Lens → Pseudo-phakic
12	General Diagnosis → Corneal Tear	38	Lens → Pseudo-phakic → Posterior Capsule → Opaque
13	General Diagnosis → Epithelial abrasion	39	Pediatric/Strabismus → Amblyopia → Strabismic
14	General Diagnosis → Incomplete PVD	40	Pediatric/Strabismus → Exotropia → Unspecified
15	General Diagnosis → Inferior oblique overaction-2	41	Pediatric/Strabismus → Eyelids → Chalazion
16	General Diagnosis → Leber Congenital Amourosis	42	Pediatric/Strabismus → Refractive
17	General Diagnosis → Lid fat deposits, upper and lower	43	Pediatric/Strabismus → Refractive → Astigmatism, irregular
18	General Diagnosis → Neovascular glaucoma	44	Pediatric/Strabismus → Refractive → Myopia
19	General Diagnosis → Normal eye exam	45	Pediatric/Strabismus → Strabismus → Other mechanical
20	General Diagnosis → Orthopic assessment	46	Retina → Degeneration of Macula and Posterior Pole → Central serous chorioretinopathy
21	General Diagnosis → Retinoblastoma	47	Retina → Degeneration of Vitreous body → Vitreous Hemorrhage
22	General Diagnosis → Sjorgen syndrome	48	Retina → Diabetes mellitus Type 1 → Without mention of complication
23	General Diagnosis → Stye	49	Retina → Hereditary Retinal Dystrophies → Pigmentary (e.g., retinitis pigmentosa)
24	General Diagnosis → Uveitis	50	Retina → Other retinal disorders → Hypertensive retinopathy
25	Glaucoma → Acute angle-closure glaucoma attack	51	Retina → Other retinal disorders → Other non-diabetic proliferative retinopathy
26	Glaucoma → Open angle with borderline findings, high risk	52	Retina → Retinal Detachments

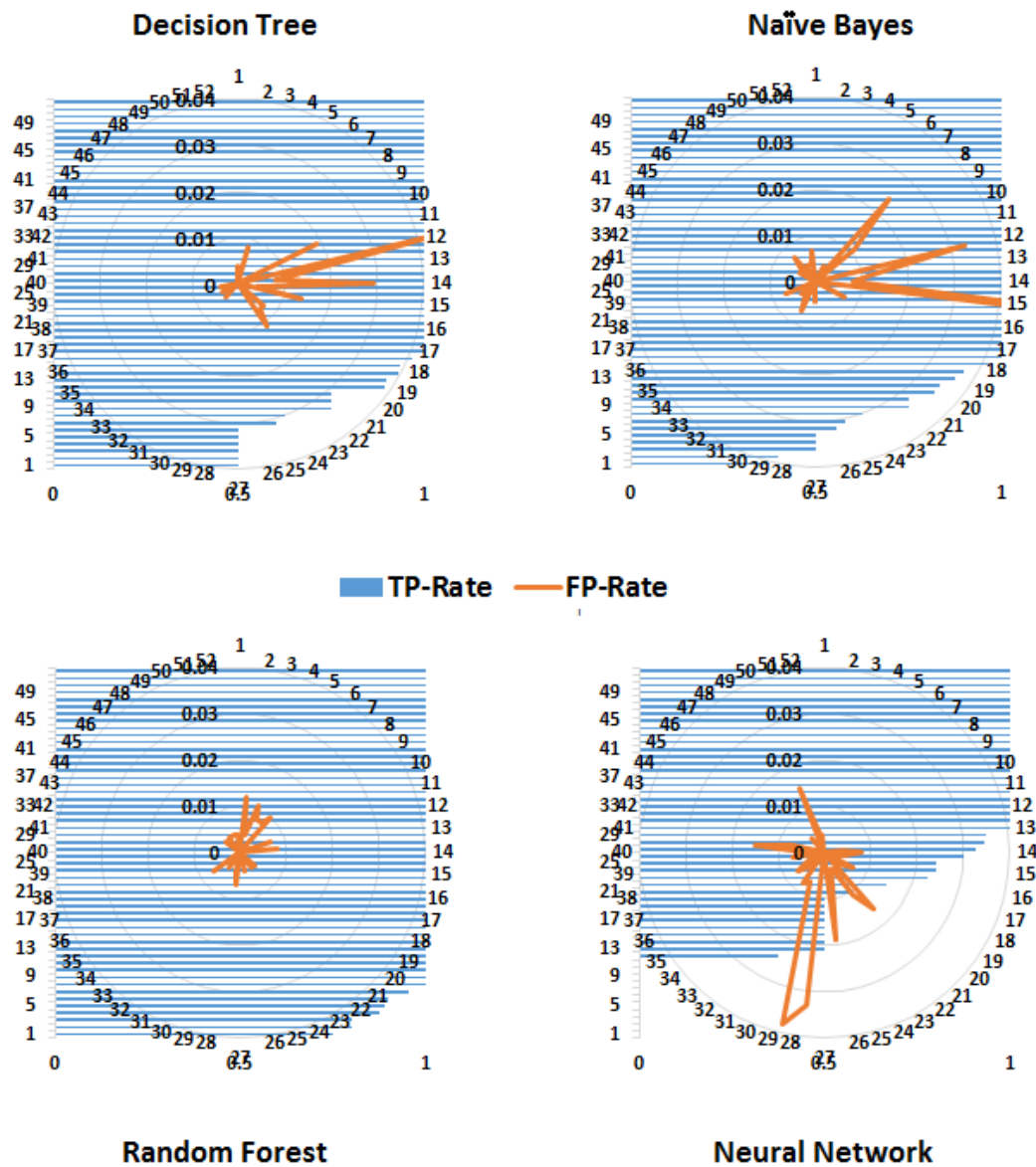**Figure 7.** Classification accuracy of algorithms.

Figure 8. True positive rate (TPR) and false positive rate (FPR) of classification algorithms for 52 classes (diseases) shown in Table 6. TPR is drawn as horizontal bars, whereas FPR is drawn on a circular scale. Although the naïve Bayes algorithm exhibits the smallest FPR, its TPR is also low for a number of classes. However, the decision tree and random forest algorithms exhibit better overall performance, with maximum horizontal bars approaching the maximum value of 1.

4.1. Hierarchical Prediction Accuracy

In Section 3.1, the data modeling was described, in which the diagnosis was also stored in a hierarchical structure and it was suggested that the classification could be performed at each level. For example, the diagnosis for Keratoconjunctivitis, generated by the system, is as follows:

Cornea → Keratitis → Neurotrophic keratoconjunctivitis

Here "Cornea" represents a first-level diagnosis, "Cornea → Keratitis" represent second-level diagnoses, whereas complete diagnosis will be considered "Cornea → Keratitis → Neurotrophic keratoconjunctivitis". To relate data frequency and to verify system reliability by prediction level, accuracies were calculated. This was important because in case of a rare disease, the system should be able to give a reliable diagnosis.

For example, if machine-learning algorithms are unable to give a complete diagnosis (e.g., *Cornea → Keratitis → Neurotrophic keratoconjunctivitis*), a second-level diagnosis, namely, *Cornea → Keratitis*, should be given or at least a first-level diagnosis, that is, *Cornea*. The advantage of this scheme is that if the system is unable to give a complete diagnosis, then it should at least specify a direction or the part of the eye in which the issue may exist, that is, partial but accurate diagnosis.

Performance measures for all classifiers are shown in Table 7. The random forest algorithm outperformed all others, followed by the decision tree and the neural network algorithms. However, accuracy dropped for second-level and complete diagnosis. This is obviously owing to the relatively low frequency of the data available for complete diagnosis. Overall, this demonstrates that the proposed framework is quite effective with data of sufficient frequency.

Table 7. Accuracy (%) for classification output at different levels of diagnosis.

Diagnosis Level	Decision Tree	Naïve Bayes	Random Forest	Neural Network
Level 1	90.79	87.21	91.57	89.12
Level 2	87.14	84.76	89.82	87.46
Complete Diagnosis	85.81	81.53	86.63	85.98

4.2. Discussion

The proposed framework was aimed at collecting structured diagnostic data for the prediction of eye diseases by considering all possible symptoms of the anterior and posterior eye segments. Therefore, it was not evaluated for a specific disease; rather, all eye diseases mentioned in ICD-10 were predicted. Most of the current frameworks are designed for a specific eye disease, for example, refractive error, retinal detachment or diabetic retinopathy. By contrast, the purpose of this model is to develop a framework that can handle any type of data and predict all types of eye diseases based on standard symptom taxonomies. However, comparing it with the data mining framework for the prediction of fatty liver disease in Reference [57], where a number of classifiers were used, tree-based methods yielded the highest accuracy, as shown in Table 8. Furthermore, as in Reference [36], the proposed method facilitated the identification of the correlations between attributes related to specific diseases by combining the observations related to different eye segments into one symptom. Recently published work for heart failure identification from unstructured data [58] exhibits good accuracy, although NLP techniques were used to first convert unstructured data into structured data that was subsequently fed into classification algorithms. The accuracy they achieved using the decision tree and naïve Bayes algorithms is significantly higher than that by the random forest and neural network algorithms but the results are based on only 14 patients' data. Therefore, reliability is questionable. In the present study, a substantially larger number of classes, hence more data, were considered, as compared to other studies. The comparison of the proposed method with existing solutions (shown in Table 8) demonstrated that this framework is capable of predicting eye diseases as accurately as analogous specialized frameworks presented for other medical diagnoses.

Table 8. Performance comparison.

Reference	Purpose	Performance
[4]	Expert system for eye diseases using if-else rules	positive response from patients
[14]	Pattern recognition in data	sensitivity 89–94% & specificity 37–42%
[57]	classification of liver disease using unstructured data	accuracy 93.3 %
[58]	Heart failure identification using unstructured data	accuracy 92%
Proposed method	eye disease classification using structured data	accuracy 93.5 %

The results demonstrated that classification by tree algorithms had better prediction accuracy. This is because data was arranged in hierarchical structure and therefore the decision tree and random forest algorithms made better predictions using step-by-step analysis of pruned trees. Moreover, tree algorithms had lower error rate than other algorithms. The neural network algorithm also performed well owing to the multiple hidden layers involved. The results by the naïve Bayes classifier were not as good as those of the others.

5. Conclusions

A general framework for improved classification of eye diseases was presented. It is based on symptoms recorded in the form of standard taxonomies directly by the medical experts. It can incorporate anterior and posterior segment signs along with general health data to correlate a disease with symptoms. Furthermore, a two-step diagnostic process was designed in which patient data related to refractive error was filtered out before analysis by machine-learning algorithms. Different classification algorithms were used, namely, decision tree, random forest, naïve Bayes and artificial neural network algorithms. Tree-based methods performed better than the artificial neural network. Furthermore, efficiency and accuracy were demonstrated to be positively correlated with the amount of available data. According to ICD-10 (used for diagnostic data), the highest accuracy was achieved for first-level diagnosis owing to a sufficiently large amount of data followed by second- and third-level diagnosis. Although the random forest algorithm appeared to be better than the artificial neural network, its execution time was slightly longer than that of the decision tree algorithm. However, as computer technology is advancing, this is expected to be resolved in the near future. Finally, the user interface developed for data recording is unique and has been greatly admired for its ease of use.

In the future, image-based test results will be directly translated into the symptom hierarchy for better disease prediction. Furthermore, nearest neighbor classification methods can also be used by converting codes into numerical data.

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