2017

A Multi-model Approach in Developing an Intelligent Assistant for Diagnosis Recommendation in Clinical Health Systems

Christian E. Pulmano

Ma. Regina Justina E. Estuar
Ateneo de Manila University, restuar@ateneo.edu

Custom Citation

Christian E. Pulmano, Ma. Regina Justina E. Estuar, A Multi-model Approach in Developing an Intelligent Assistant for Diagnosis Recommendation in Clinical Health Systems, Procedia Computer Science, Volume 121, 2017, Pages 534-541, ISSN 1877-0509, https://doi.org/10.1016/j.procs.2017.11.071. (http://www.sciencedirect.com/science/article/pii/S1877050917322706)

Available online at www.sciencedirect.com

ScienceDirect

Procedia Computer Science 121 (2017) 534–541

Procedia Computer Science

www.elsevier.com/locate/procedia

CENTERIS - International Conference on ENTERprise Information Systems / ProjMAN - International Conference on Project MANagement / HCist - International Conference on Health and Social Care Information Systems and Technologies, CENTERIS / ProjMAN / HCist 2017, 8-10 November 2017, Barcelona, Spain

A Multi-model Approach in Developing an Intelligent Assistant for Diagnosis Recommendation in Clinical Health Systems

Christian E. Pulmano[a,b]*, Ma. Regina Justina E. Estuar[a,b]

Department of Information System and Computer Science, Ateneo de Manila University, Quezon City 1108, Philippines
Ateneo Java Wireless Competency Center, Ateneo de Manila University, Quezon City 1108, Philippines

Abstract

Clinical health information systems capture massive amounts of unstructured data from various health and medical facilities. This study utilizes unstructured patient clinical text data to develop an intelligent assistant that can identify possible related diagnoses based on a given text input. The approach applies a one-vs-rest binary classification technique wherein given an input text data, it is identified whether it can be positively or negatively classified for a given diagnosis. Multi-layer Feed-Forward Neural Network models were developed for each individual diagnosis case. The task of the intelligent assistant is to iterate over all the different models and return those that output a positive diagnosis. To validate the performance of the models, the performance metrics were compared against Naive Bayes, Decision Trees, and K-Nearest Neighbor. The results show that the neural network learner provided better performance scores in both accuracy and area under the curve metric scores. Further, testing on multiple diagnoses also shows that the methodology for developing the diagnosis models can be replicated for development of models for other diseases as well.

Peer-review under responsibility of the scientific committee of the CENTERIS - International Conference on ENTERprise Information Systems / ProjMAN - International Conference on Project MANagement / HCist - International Conference on Health and Social Care Information Systems and Technologies.

Keywords: artificial neural network; intelligent assistant; medical diagnosis; health intelligent systems

* Corresponding author. Tel.: +63917-561-7551
E-mail address: cpulmano@ateneo.edu

1877-0509
Peer-review under responsibility of the scientific committee of the CENTERIS - International Conference on ENTERprise Information Systems / ProjMAN - International Conference on Project MANagement / HCist - International Conference on Health and Social Care Information Systems and Technologies.
10.1016/j.procs.2017.11.071

1. Introduction

Medical diagnosis is an important task that requires a very accurate execution[1]. In recent years, challenges in accurate diagnosis have been more observable because of various factors such as increased number of elderly patients and, limited medical personnel and facilities. It is therefore now becoming more relevant to address this problem through development of innovative solutions that may help physicians in providing more accurate medical diagnosis[2]. Furthermore, more efficient solutions can be achieved by making available data more in influential in creating these solutions.

Healthcare institutions have already gained progress in the digitization of medical records[3]. The implementation of various clinical information systems has allowed health stakeholders to easily capture patient health data. However, insights from these data may not be easy to discover if there is no prior processing. Current technologies in the health ecosystem allow several patient records to be aggregated and analyzed[4] so that valuable and reliable information may be discovered.

Prior to this study, initial models were already analyzed to test on the idea of using Artificial Neural Networks for classification of unstructured clinical text data into a specific diagnosis[5]. This study focuses on improving on the previously analyzed models[5] for the development of an intelligent diagnosis recommender that can suggest possible diagnoses based on a given text input. Furthermore, it also focuses on its possible applications and integration opportunities into an existing clinical health system, more specifically, an Electronics Medical Records system.

Data collected from clinical health systems are utilized to create an accurate intelligent assistant. Automatic recommendation of possible diagnoses based on observable signs and symptoms is a promising solution in medical diagnosis, especially in the context of developing regions like the Philippines, where there are still a lot of shortcomings in the health ecosystem. It is important to note, however, that the diagnosis recommender is not meant to replace human decision-making, but rather, to help with physicians in making more informed decisions.

This article is organized as follows: in section 2 we present a review of previously conducted researches, and literature related to our study; in section 3 we identify the materials and methods used in the study; in section 4 we present the results and analysis of the initial models; and in last sections we state the conclusion and enumerate recommendations for further studies.

2. Related literature

2.1. Clinical Health Systems

Clinical health systems can be implemented in many forms which include, but are not limited to, Hospital Management Information Systems (HOMIS), Laboratory Information Systems (LIS), and Electronic Medical Records (EMR) systems. In this study, we focused more on EMR systems. EMRs are characterized as digital medical records used within a health facility[4]. It is believed to be at the center of any clinical information systems as it serves as the foundation for ICT-integrated routine clinical workflow. EMRs can replace paper-based medical recording, provide a single point of access for data, automate report generation and track information trails, thus, improving the clinical healthcare delivery[5,6].

An example of an operational Electronic Medical Record in the Philippines is SHINE OS+. SHINE (Secured Health Information and Network Exchange) was launched in 2011 to address the need for an integrated health information referral system. Its four main features include 4 Rs: recording patient health and medical information, reminding patients of appointments and medication schedules, referring patients to other health facilities, and producing aggregated and summarized reports[5,7]. Other existing EMR systems in the Philippines are CHITS, WAH, SegRHIS, iClinicSys and for mobile-based platforms, eHATID LGU. EMRs offer great potential for data analysis because of its capacity to collect large amounts of patient health data and its important contributions to the construction of patient electronic health records (EHR)[5,8].

2.2. Diagnosis Prediction using Artificial Neural Networks

Several studies have already explored the use of Artificial Neural Networks (ANN) in disease risk prediction. For example, one study used a feed-forward back-propagation network for diagnosis of acute nephritis and heart disease. The model predicted with 99% accuracy for acute nephritis disease while 95% accuracy for the diagnosis of heart disease[9]. In another study, an agent implementing a Multilayer Perceptron with Backpropagation Algorithm was developed to recognize a pattern for diagnosing and predicting five blood disorders. Results showed that it yielded low percent errors, therefore, accurately identifying patterns[10]. The described studies presented promising results in disease prediction which suggests the viability of the computational potentials of ANNs in the health and medical field[9,10,11,12]. ANN is a desirable tool for medical purposes because of its high parallelism, robustness, generalization and noise tolerance[11].

3. Materials and methods

In this section, we describe the materials and methods used for the study. The goal of the study is to build an intelligent agent that can identify possible diagnoses based on a given health-related text input. The intelligent agent follows a multi-model approach such that for each analyzed diagnosis in the dataset, an individual model was constructed. The goal is to iterate over all the models and return all diagnoses that positively classifies the text input. All models were developed using a Multi-layer Feed-forward Neural Network with Backpropagation trainer.

3.1. Data Retrieval

De-identified data were gathered from SHINE OS+. The dataset used only consisted of data encoded in the following fields: chief complaint (TEXT), and diagnosis (TEXT). Initially, there were 83,148 records of consultation data which were gathered from January 2011 to October 2016. However, after filtering the data to remove records that did not have either a `complaint' or `diagnosis' value, there were only 34,680 records left. This was used as the final dataset for the study. Ten diagnosis cases were focused for the study which also means that ten individual diagnosis models were produced. The diagnoses used and the number of records for each diagnosis in the dataset are shown in Table 1 and examples of chief complaint and diagnosis text data in Table 2.

3.2. Pre-processing

The goal of the pre-processing phase is to ensure that the dataset is transformed into a corresponding numerical equivalent. This step is required since Artificial Neural Network classifiers only accept numerical inputs. The text features were tokenized, with stop words and punctuations removed, to create a vocabulary of all the possible unigram tokens. Aside from the unigram tokens, bigrams and trigrams were also considered. Term Frequency- Inverse Document Frequency (TF-IDF) was used the term-weighting method. The resulting TF-IDF matrix was further standardized wherein each feature have zero unit variance.

In this study, we are more focused on developing individual models for each diagnosis rather than creating a large multi-class model. This is achieved by using one-vs-rest binary classification technique wherein when analyzing a diagnosis, positively diagnosed records are labelled as `1' while the rest are labelled as `0'. However, following this procedure poses a class imbalance problem. For the analysis of a diagnosis, the dataset gives an unequal number of positive and negative samples, with the latter always having an enormously higher number. This problem causes the classification models to perform very poorly. Therefore, an under-sampling technique was implemented to create balanced datasets for each diagnosis.

The under-sampling procedure utilized the K-means clustering algorithm to select a subset of negative samples that is representative of the whole class. For each cluster, random samples were taken and were included in the final datasets. The reference formula used to compute for the number of clusters K is shown in Eq. 1. In this formula, K is dependent on the number of samples n that are included in the clustering[13].

$$K = \sqrt{(n/2)} \tag{1}$$

Table 1. List of diagnoses analyzed in the study and sample counts

Diagnosis	Count
Upper Respiratory Tract Infection Bacterial (URTIB)	4609
Bronchitis	3051
Hypertension	2653
Pneumonia	2230
Asthma	873
Acute Tonsillopharyngitis Bacterial (ATB)	476
Tuberculosis	444
Gastro-Enteritis	437
Urinary Tract Infection (UTI)	421
Influenza	334

Table 2. Examples of data being analyzed

Patient Complaint	Diagnosis
dizziness for 7 days + elevated blood pressure	Hypertension
fever for 3 days + cough for 3 days + runny nose for 3 days	Upper Respiratory Tract Infection Bacterial
fever for 4 days + loss of appetite + cough for 2 days	Bronchitis
fever with pain on the throat	Acute Tonsillopharyngitis Bacterial

All pre-processing activities were executed using programs built with Python. The final output for the pre-processing were sparse-matrices for each diagnosis consisting of the scaled feature values, with balanced positive and negative classes.

3.3. Processing and Analysis

The activities under the processing and analysis phase were accepting the sparse-matrices produced from the pre-processing phase and producing the actual diagnosis models. Also, included in this phase was validating whether the produced models were accurate. As mentioned earlier in this study, the main approach was to implement one-vs-rest classification technique to produce individual models for each diagnosis. The Artificial Neural Network models were compared with other classification algorithms, i.e., Naive Bayes, Decision Trees and K-Nearest Neighbors, to test whether it was appropriate and better to use for the problem. All models were built using the Scikit-learn classifier modules[14]. The same set of data was inputted to the different classifiers and the performance of each model was evaluated based on accuracy and AUROC scores from a 10-fold cross-validation procedure. Statistical differences among classifier performances were determined using One-Way Analysis of Variance (ANOVA) and the Tukey Honest Significant Difference (Tukey HSD) was used as the post-hoc test.

3.4. Artificial Neural Networks

The classifier uses a Multilayer Feed-Forward Neural Network with Back Propagation Training Algorithm. Its structure consisted of one input layer, one hidden layer and one output layer. The network was trained using a stochastic gradient descent solver, logistic sigmoid activation function, constant learning rate of 0.01, and momentum of 0.09. An optimal parameter grid searching algorithm was implemented to approximate optimal hidden layer size for each diagnosis model.

3.5. Integration into SHINE OS+

The diagnosis models produced were stored in a server and reloaded every time a new chief complaint input is encoded in SHINE OS+. A Python program was built to execute the diagnosis recommender. This program accepts a new text input and performs the same pre-processing procedure done with the training data. After cleaning the input, the program iterates over all diagnosis models and identifies which ones output a positive feedback. The program produces a list of diagnoses that are believed to be related with the given chief complaint input.

4. Results and discussions

To discuss the outcomes of the experiments, this section is divided into two parts: (1) Evaluation and comparison of neural network models with the other classification algorithms, and (2) Integration within a clinical health information system.

4.1. Evaluation and comparison of neural network models with the other classification algorithm.

The next step was to test whether the Artificial Neural Networks trainer was the best classifier for diagnosis recommendation. This was done by comparing the performance scores of dataset 1 with Naive Bayes, Decision Trees and K-Nearest Neighbor. Table 3 shows the mean scores for each classifier for the diagnoses. It can be observed that the Neural Network scores were consistently at the top two best performances. The Neural Network classifier gained the highest mean accuracy for diagnoses `Hypertension', `Acute Tonsillopharyngitis Bacterial', `Gastro-Enteritis', and `Urinary Tract Infection' with scores of 80.80%, 85.40%, 78.15%, 91.41%, and 82.18%, respectively. For the rest of the diagnoses, it produced the second highest mean accuracy scores of 74.97% for `Upper Respiratory Tract Infection Bacterial', 77.38% for `Bronchitis', 69.01% for `Pneumonia', 66.61% for `Asthma', and 76.05% for `Influenza'.

However, it can be observed from the results that there were only very minimal discrepancies between the scores of the top two performing models for each diagnosis. Given this observation, it may be presumed that it may not be statistically different. To test this presumption, a one-way ANOVA test was first applied to the accuracy scores to identify if there exist significant differences among the results from the four classifiers. Table 3 shows the p-value for each diagnosis. The resulting p-values suggest that there were significant differences for all the diagnoses except for Influenza. The Tukey HSD test was used to determine which classifier pairs produced significantly different performance results from one another.

Similar results of the Tukey HSD can be observed on multiple diagnoses, as shown in Table 4. For `Upper Respiratory Tract Infection Bacterial', `Hypertension', `Pneumonia', `Asthma', `Acute Tonsillopharyngitis Bacterial', `Tuberculosis' and `Gastro-Enteritis', the p-values suggest that there were no significant differences with the scores of Naive Bayes, Decision Trees, and Neural Networks. This implies that even though the mean score of one classifier was higher than the other two, the difference is not statistically significant. For `Bronchitis', the results show that the difference between the scores of Decision Trees and Neural Networks, and K-Nearest Neighbor and Neural Networks were insignificant. For `Urinary Tract Infection', the p-values suggest that only the scores of Decision Trees and Neural Networks were insignificantly different. Generally, it applies to all cases that there were no significant differences between the Decision Trees and Neural Network results which implies that both classifiers may produce consistently better performance in terms of accuracy for diagnosis classification.

Evaluating on the predictive capability of Neural Networks, eight of the ten diagnoses had accuracy scores above 75% while the other two acquired mean accuracy under 75%. Diagnosis recommendation for `Pneumonia' and `Asthma' may not be as reliable as the others having accuracy of only 68.84% and 68.16%, respectively. But for the case of `Gastro- Enteritis', the model that was produced provided the best score of 91.41% which implies that diagnosis prediction for this model will most likely produce the accurate result.

As a second measure, the models were also evaluated on their AUROC scores. Table 3 shows the mean AUROC scores from the 10-fold cross validation. For this measure, the Neural Network trainer produced the highest AUROC scores for all diagnoses. However, it can't be denied that there may also be insignificant differences against the scores of the other classifiers. It is therefore necessary to apply the same tests that was performed on the accuracy scores.

The one-way ANOVA test for difference in AUROC scores produced the same result as that of the accuracy scores, with all diagnoses having significant differences except for `Influenza'. The *p*-values are also shown in Table 3. Furthermore, Tukey HSD was applied to identify which classifier gave AUROC results that were not significantly different with those produced by the Artificial Neural Networks.

The *p*-values are displayed in Table 4. Based on the resulting p-values, the following classifiers are observed to have shown insignificant differences with that of the Artificial Neural Networks for each diagnosis: Decision Trees for `Upper Respiratory Tract Infection Bacterial', K-Nearest Neighbor for `Bronchitis', Decision Trees for `Pneumonia', Naive Bayes and Decision Trees for `Asthma', and Naive Bayes for Tuberculosis. However, the Neural Network classifier was the only one that consistently produced the best AUROC for all the diagnoses.

Table 3. Mean accuracy and AUROC scores for the classifiers and p-values for each diagnosis.

Accuracy					
Diagnosis	**Naïve Bayes**	**Decision Trees**	**K-Nearest Neighbor**	**Neural Networks**	**p-value**
URTIB	73.93	75.17	68.71	74.97	1.17E-12
Bronchitis	72.83	78.93	76.53	78.01	1.47E-11
Hypertension	80.12	80.4	72.39	80.7	5.60E-15
Pneumonia	68.72	69.84	63	69.01	1.83E-08
Asthma	66.49	68.16	58.42	66.61	1.27E-07
ATB	79.62	85.2	72.24	85.4	2.68E-06
Tuberculosis	78.05	74.68	61.52	78.15	9.23E-11
Gastro-Enteritis	89.14	91.07	78.71	91.41	1.43E-09
UTI	76.01	81	61.76	82.18	1.01E-14
Influenza	74.99	78.33	72.38	76.05	7.38E-02
AUROC					
Diagnosis	**Naïve Bayes**	**Decision Trees**	**K-Nearest Neighbor**	**Neural Networks**	**p-value**
URTIB	0.7498	0.7772	0.7385	0.7951	9.30E-09
Bronchitis	0.75	0.7935	0.8085	0.8212	5.11E-11
Hypertension	0.812	0.8105	0.808	0.8634	3.08E-06
Pneumonia	0.697	0.7092	0.6925	0.7303	1.48E-03
Asthma	0.6902	0.6998	0.6065	0.7169	2.67E-07
ATB	0.8611	0.8646	0.8221	0.9092	1.65E-05
Tuberculosis	0.8138	0.7571	0.6612	0.8497	4.83E-11
Gastro-Enteritis	0.9125	0.9108	0.9	0.9612	5.39E-04
UTI	0.7765	0.8096	0.7319	0.8726	1.23E-06
Influenza	0.7723	0.7898	0.8012	0.8341	7.38E-02

The mean AUROC scores for the Neural Network models can be evaluated based on the traditional academic point system displayed in Table 5. Using this standard, it was observed that two models were rated as `Excellent', five models as `Good', and three models as `Fair'. The models for `Acute Tonsillopharyngitis Bacterial' and `Gastro-Enteritis' acquired excellent ratings with their AUROC scores of 0.9092, and 0.9612, respectively. This suggests that there is a high chance that predictions using these models will produce accurate results. The AUROC for the rest of the diagnosis models were rated as either fair or good, however, it is a fact that these models may not always produce the expected output, especially on diagnoses `Pneumonia' and `Asthma' which only scored AUROC of 0.7303, and 0.7169 respectively.

Based on the performed comparisons and evaluation, it can be implied that there is a higher chance that the Neural Network algorithm will perform better more consistently than the other classifiers. It is therefore a valid action to train the final diagnosis models that will be used by the intelligent assistant using Artificial Neural Networks rather than the other classifiers.

4.2. Integration within a clinical health information system.

Fig. 1 displays a sample integration of the diagnosis recommendation models in SHINE OS+. In this example, the chief complaint written is *"Dizziness for 7 days + elevated blood pressure"*. The clinical text data is encoded by the user via the `Complaints' text field. As soon as the user stops typing and transfers to a new field, diagnosis recommendation is activated and inputs the text data to the diagnosis recommender program. The program takes the text data input, performs the stemming procedure, loads the diagnosis models, iterates over all the diagnosis models, and identifies the diagnoses having probability estimates greater than or equal to 50.00%. A string in the form $diag_1$ $prob_1$, ... , $diag_n$ $prob_n$ is returned after processing. The recommended diagnoses and corresponding probability estimates are then displayed under the `Diagnosis' input field. Given the chief complaint stated above, the recommended diagnosis is Hypertension with 94.50% probability.

Table 4. *p*-values for the Tukey post-hoc test for significant differences between accuracy and AUROC scores of classifier pairs.

Accuracy						
Diagnosis	**NB vs DT**	**NB vs KNN**	**NB vs ANN**	**DT vs KNN**	**DT vs ANN**	**KNN vs ANN**
URTIB	*0.2090	0.0010	*0.3498	0.0010	*0.9000	0.0010
Bronchitis	0.0010	0.0010	0.0010	0.0017	*0.4323	0.0844
Hypertension	*0.9000	0.0010	*0.8092	0.0010	*0.9000	0.0010
Pneumonia	*0.6110	0.0010	*0.9000	0.0010	*0.7849	0.0010
Asthma	*0.6310	0.0010	*0.9000	0.0010	*0.6771	0.0010
ATB	*0.0929	0.0150	*0.0776	0.0010	*0.9000	0.0010
Tuberculosis	*0.2983	0.0010	*0.9000	0.0010	*0.2730	0.0010
Gastro-Enteritis	*0.6116	0.0010	*0.4943	0.0010	*0.9000	0.0010
UTI	0.0208	0.0010	0.0030	0.0010	*0.8794	0.0010
Influenza	0.4409	0.6244	0.9000	0.0490	0.7093	0.3554
AUROC						
Diagnosis	**NB vs DT**	**NB vs KNN**	**NB vs ANN**	**DT vs KNN**	**DT vs ANN**	**KNN vs ANN**
URTIB	0.0038	0.4298	0.0010	0.0010	*0.0907	0.0010
Bronchitis	0.0010	0.0010	0.0010	0.1830	0.0028	*0.3142
Hypertension	0.9000	0.9000	0.0010	0.9000	0.0010	0.0010
Pneumonia	0.5723	0.9000	0.0067	0.3071	*0.1384	0.0017
Asthma	0.9000	0.0010	*0.3761	0.0010	*0.7030	0.0010
ATB	0.9000	0.0562	0.0122	0.0320	0.0225	0.0010
Tuberculosis	0.0269	0.0010	*0.2591	0.0010	0.0010	0.0010
Gastro-Enteritis	0.9000	0.7941	0.0077	0.8588	0.0056	0.0010
UTI	0.4173	0.1748	0.0010	0.0044	0.0265	0.0010
Influenza	0.8632	0.5921	*0.0538	0.9000	*0.2433	*0.4980

Table 5. Traditional academic point system for evaluating the Area under the ROC curve.

AUROC	Point System
.90 - 1	Excellent
.80 - .90	Good
.70 - .80	Fair
.60 - .70	Poor
.50 - .60	Fail

5. Conclusion and further recommendations

The goal of the study is to build an intelligent assistant that can identify possible diagnoses based on a given health-related text input. The intelligent assistant was integrated into a clinical information system to assist in the medical diagnosis process. For the development of the assistant, following a multi-model approach was believed to be a better alternative as compared to creating a large single multi-class dataset consisting of all the diagnosis samples. This is because a given set of symptoms may be related to multiple diagnoses.

Experiments were done to compare Artificial Neural Network models with Naïve Bayes, Decision Trees and K-Nearest Neighbor classification training algorithms to prove that it is in fact a viable trainer for the final prediction models that will be used by the intelligent assistant.

The experiments showed that the Artificial Neural Network learner provided one of the best performance scores in both accuracy and AUROC scores. The results of this study also show that the methodology proposed to develop individual diagnosis models can be replicated to produce more diagnosis models.

However, it is important to consider that the performance of models will always depend on the quality of data. It is understood that there will always be nuances in qualitative analysis, especially in the context of doctor's notes where there is a very wide range of possible entries. It is therefore relevant for intelligent systems to also have inputs from available health and medical standards. Further studies can focus on incorporating use of existing ontology for both medical and non-medical terminologies. This will help in properly defining what the tokens may mean. There are numerous terminology standards that are already available for use in health and medical purposes. Some examples are Unified Medical Language System (UMLS) and SNOMED CT. Future researches can also explore on the addition of structured data to improve on the relevant feature sets for the intelligent assistant. Health data consists of various types of data that can be helpful for creating predictive and prescriptive models for health decision support.

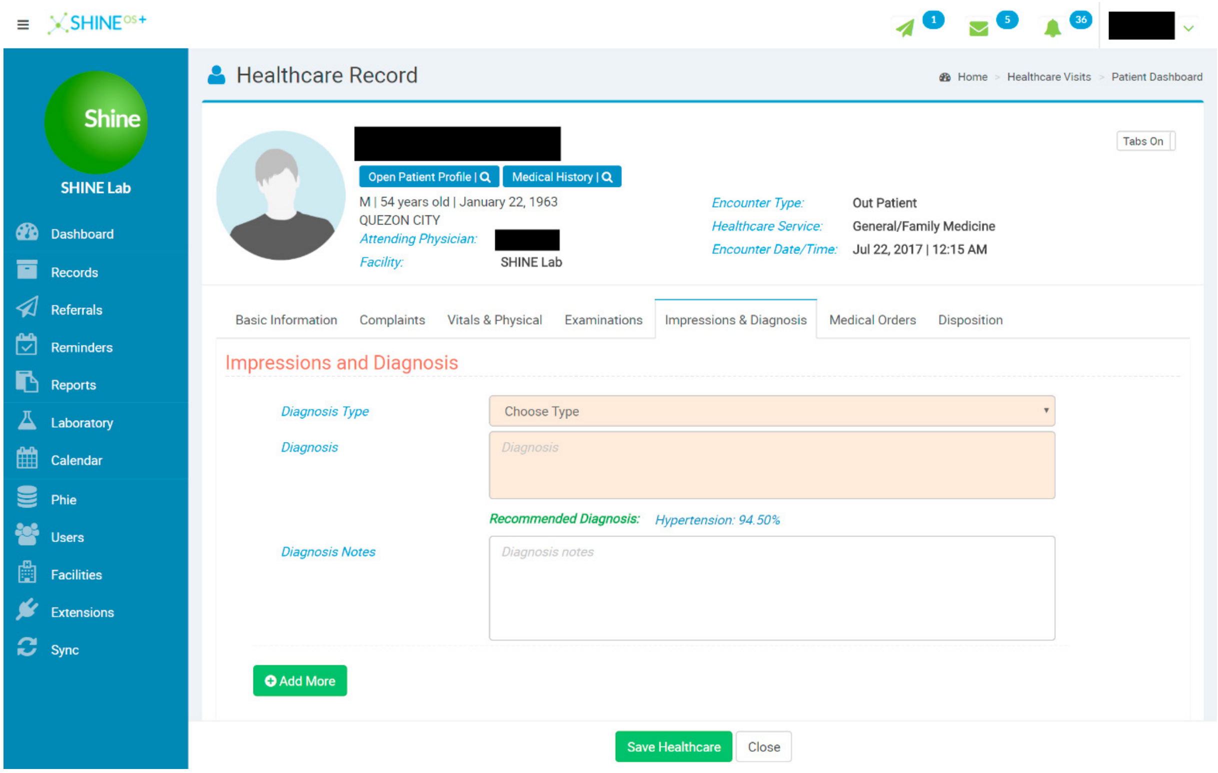

Figure 1. Intelligent assistant showing the list of recommended diagnoses and corresponding probability estimates.

References

1. J. Soni, U. Ansari, D. Sharma, S. Soni, Predictive data mining for medical diagnosis: An overview of heart disease prediction, International Journal of Computer Applications 17 (8) (2011) 43-48.
2. Y. Zhang, S. Liu, Z. Zhu, S. Si, Agent-based intelligent medical diagnosis system for patients, Technology and Health Care 23 (s2).
3. P. Groves, B. Kayyalli, D. Knott, S. Van Kuiken, The big data revolution in healthcare. Accelerating value and innovation, Center for US Health System Reform. Business Technology Office.
4. B. Marcelo, J. M. Cañero, Health information systems (2010).
5. C. Pulmano. Towards Developing an Intelligent Agent to Assist in Patient Diagnosis Using Neural Networks on Unstructured Patient Clinical Notes. Procedia Computer Science 100 (2016) 263-270.
6. R. Malakar, et al., Electronic medical records, Indian Journal of Dermatology 51 (2) (2006) 140.
7. SHINE OS+, SHINE OS+ about. URL http://http://www.shine.ph/about-2/
8. Hoerbst, E. Ammenwerth, et al., Electronic health records, Methods Inf Med 49 (4) (2010) 320-336.
9. Q. K. Al-Shayea, Artificial neural networks in medical diagnosis, International Journal of Computer Science Issues 8 (2) (2011) 150-154.
10. M. Payandeh, M. Aeinfar, V. Aeinfar, M. Hayati, A new method for diagnosis and predicting blood disorder and cancer using artificial intelligence (artificial neural networks), International Journal of Hematology-Oncology and Stem Cell Research 3 (4) (2009) 25-33.
11. F. E. Ahmed, Artificial neural networks for diagnosis and survival prediction in colon cancer, Molecular cancer 4 (1) (2005) 29.
12. L. Li, H. Liqing, L. Hongru, Z. Feng, Z. Chongxun, S. Pokhrel, Z. Jie, The use of fuzzy backpropagation neural networks for the early diagnosis of hypoxic ischemic encephalopathy in newborns, BioMed Research International 2011.
13. T. M. Kodinariya, P. R. Makwana, Review on determining number of cluster in k-means clustering, International Journal 1 (6) (2013) 90-95.
14. F. Pedregosa, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, J. Vanderplas, A. Passos, D. Cournapeau, M. Brucher, M. Perrot, E. Duchesnay, Scikit-learn: Machine learning in Python, Journal of Machine Learning Research 12 (2011) 2825-2830.