Identifying a Medical Department based on Unstructured Data
A Big Data Application in Healthcare

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Abstract: Health is an individual's most precious asset and healthcare is one of the vehicles for preserving it. The Indian government's spend on healthcare system is relatively low (1.2% of GDP). Consequently, Secondary and Tertiary government healthcare centers in India (that are presumed to be of above average ratings) are always crowded. In Tertiary healthcare centers, like AIIMS, patients are often unable to articulate correctly their problems to the healthcare center's Reception staff for these patients to be directed to the correct healthcare department. In this paper, we propose a system based on Big Data and Machine Learning to direct the patient to the most relevant department .We have implemented and tested parts of this system wherein a patient enters his symptoms and/or provisional diagnosis; the system suggests a department based on this user input. Our system suggests the correct department 68.05% of the time. Our system presently makes its suggestions using gradient boosting algorithm that has been trained using two information repositories- symptoms and disease data, functional description of each medical department. It is our informed assumption that, once we have incorporated medicine information and diagnostics imaging data to train the system and the complete medical history of the patient, performance of the system will improve significantly.

1 INTRODUCTION

Everyone strives to be healthy and stay away from hospitals but occasionally one must visit a healthcare facility. Healthcare in India is a three-tier system; Primary care is the first line of contact, often between a patient and a doctor. Secondary and Tertiary healthcare centers require a referral from a Primary healthcare center. Tertiary healthcare centers cater for complicated medical conditions and require specialized medical consultations.

A sample referral is shown in Figure 1. The referral has the name of a patient, provisional diagnosis and the hospital name to which the patient has been referred to but more often without the details of the department within the hospital. The Tertiary healthcare centers such as AIIMS (All India Institute of Medical Science) have multiple departments, with near unique capabilities in each department for treating ailments. Even medically literate patients often have difficulty in identifying the correct department. The healthcare center's Reception staff is often the first port of call and these staff often quickly browse through the medical documents of a patient to identify the appropriate department; this is not fool proof and mistakes are often made, leading to inconveniences caused downstream to all parties concerned. This is a major bottleneck, especially as the system must deal with many thousands of patients each day.

People who have access to the Internet, and have the required skill sets, can collate information about each department before making an online appointment. However, for many people in India, they do not even have access to the Internet and/or not literate enough to make an online appointment.

Irrespective of the channel used for booking, all walk-in patients face very similar challenges of identifying the correct department to proceed to. We have therefore focused on the walk-in process where most of the errors have been noticed. It was our conclusion that we need to first augment the manual appointment booking process to identify the correct department, thereby make the overall booking process easier and error free for the patients. In this work, we propose a system that will automatically

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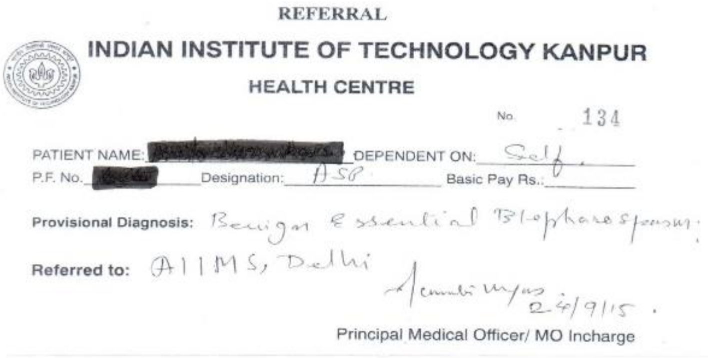
REFERRAL

INDIAN INSTITUTE OF TECHNOLOGY KANPUR

HEALTH CENTRE

No. 134

PATIENT NAME: [redacted] DEPENDENT ON: Self

P.F. No. [redacted] Designation: ASR Basic Pay Rs.:

Provisional Diagnosis: Benign Essential Blepharospasm

Referred to: AIIMS, Delhi

24/9/15

Principal Medical Officer/ MO Incharge

Figure 1: A Sample referral to a tertiary healthcare system.

recommend an appropriate department to the patients by looking at their medical documents.

We have reviewed the related work in §2 and presented a formal model of our proposed system in §3. An implementation of our system has been detailed in §4. Results and conclusions have been presented in §5.

2 RELATED WORK

Over the years, several computational systems for decision making have been used in healthcare. These have either helped humans in reducing their workload or helped in decision making or both. Expert systems built to diagnose a disease (Naser et al, 2010; Tenorio, 2011; Rahman and Hossain, 2013; Ibrahim, 2014) have faced a challenge in clearly representing medical history of a patient. Supervised learning techniques such as decision trees, Bayesian classifiers, artificial neural networks, support vector machines and k-nearest neighbors have also been used in building expert systems. A decision support system can also be rules or fuzzy rules based (Rahman and Hossian, 2013). These systems are used for diagnosing the presence of a disease, or predicting adverse effect of a drug (Fosamax), or predicting the onset of a disease (Ibrahim, 2014; Ephzibah and Sundarapandian, 2012; Jain and Raheja, 2015).

Another line of research led to the development of systems that helped patients in managing their diet and medicines (Caballero-Ruiz et al, 2017; Goethe and Bronzino, 1995); some helped Health Insurance Providers with pre-authorization of insurance requests (Araújo, 2016); others helped doctors in identifying the best possible treatment for a given disease (Delias, 2015) or even recommending pathological tests (Alonso-Amo, 1995); or check the efficacy of an ongoing treatment (McAndrew, 1996). All these systems require a vast amount of data (Davenport, 2014) and with the advent of Big Data (Aruna Sri and Anusha, 2016), a new set of possibilities in healthcare have emerged (Schultz, 2013). Prevention strategies and treatment recommendations are all based on vast amount of data (Saravan, 2015). The medical world has not yet evolved a standard terminology to describe medical conditions and medical departments. Work is being carried out to create a standard medical language to be used across applications and platforms (Handerson, 2016).

We extensively searched for an application or a system that can provide a description of all diseases and respective departments of hospitals that treat these diseases. To the best of our knowledge, no such application exists. Such an application or a system can help a patient identify the appropriate department of a hospital for a specific treatment. We spoke with the doctors in Secondary and Tertiary healthcare facilities, and they all confirmed that patients are often directed to the wrong department by the Reception staff. Sometimes, patients are not even able to describe their problems. Often the Reception staff are unable to decipher the medical reports/documents provided by the patients. A patient often therefore ends up wasting his own time; the hospital also ends up wasting its own resources if the patient ends up at the wrong department. We have, hence, decided to build a system that will direct patients to the most appropriate department of the healthcare facility. Our system is based on Big Data techniques and is described next.

3 THE PROPOSED MODEL

The block diagram of our proposed system is given in Figure 2. When patients walk into a Tertiary healthcare center, their documents can be scanned including:

- previous prescriptions from doctors
- medicines taken
- diagnostic reports & medical images

The scanner would then digitize the documents. The digitized documents would then be used by the Digital Utility Module (referred to as DUM). The DUM would pre-process and extract the information presented in the documents and images. The images will then be processed, extract metadata if available, to identify the organs and other relevant details available in the images (Filipovych and Davatzikos, 2001; Kucheryavski, 2007; Antoio at al, 2001). Prescriptions, reports, bills etc. will be processed by OCR and ICR engines to convert them into searchable and editable text (Ciregan, 2012; Patel et al, 2012).

The extracted information will then be passed to the next module, called DIRECT. The DIRECT module will recommend a hospital department based on the input. DIRECT is at the heart of our system, has the knowledge base and processes the inputs provided by patients to recommend an appropriate department. DIRECT employs a machine learning model that is trained and validated offline. The training process involves the following steps that we explain next.

- Data Cleaning & Preprocessing
- Scalable Model Building
- Model Validation & Selection
- Preprocessing & integration for updates

Data Cleaning and Preprocessing

We need a labeled dataset to train the system. For instance, we can train the system to learn the disease that each hospital department treats by using data containing diseases mapped to an appropriate hospital department. This process includes creating a profile for each disease based on its symptoms, medicines, and diagnostic reports and then mapping each disease profile to a department. This includes extracting the useful parts of the text, purging the stop-words from the text (Ullman and Rajaraman, 2011), converting the words into a common form by using stemming (Lovins, 1968), feature extraction from the texts (Guyon and Elisseff, 2003) and converting the data into a vector space model (Ripley, 1996). The challenging part of the problem is that apart from text data, there are also image data to deal with. According to data types, we have loosely three classes of extracted features – the symptoms or disease name, the medicines taken and processed images. While training, the model will learn to assign weights to each class of features.

Scalable Model Building

Gradient Boosting Machine (Click et al, 2017), Deep Learning (a multi-layer neural network model trained using back-propagation algorithm) (Candel et al, 2015) and Distributed Random Forest (H2O website) are the models that we have selected based on their potential and performance. Our main task is multinomial classification (Aly, 2005).

Model Validation & Selection

This is the process where we select a final model based on varying criteria like log loss (Collier, 2015) or misclassification rates among all the different models. There are many hyper parameters in each machine learning model that get tuned during this training.

Processing & Integration Updation

This process of the DIRECT module will enhance the accuracy of the system over time as it sees and learns from more and more real use cases. The predicted department and the inputs from the patients are pre-processed in the agreed format of our training data. It is then added to our knowledge base for continuous learning.

4 SYSTEM IMPLEMENTATION

We have implemented part of the proposed system called The Tertiary Healthcare Center Directing System. The complete system needs four information repositories for training: Symptoms & Disease Data (names of diseases and their symptoms), Departmental Functional Description, Drug & Medicine Information, Diagnostics Imaging Data. The form of Symptoms & Disease data is as follows.

<$symptom_1$, $symptom_2$, …, $symptom_n$> <$disease_1$>

Functional description of each department is represented as follows.

<$disease_1$, $disease_2$, …, $disease_m$><medical_deptt>

Drug & Medicine information consists of the following information.

<$drug_1$, $drug_2$, …, $drug_k$><$disease_1$>

Diagnostics and Imaging data has two components: Image and corresponding diagnosis. We have used Symptoms and Disease data as well as Departmental Functional Descriptions to train and test the system. We have not yet incorporated Drug and Medicines Information, Diagnostics Imaging data.

The data for training and validating the system is not available in the required form and requires pre-processing. Hence, the system implementation includes the following phases:

a. Finding a dataset that has disease information (possibly including their names, associated symptoms, types, synonyms etc.) and name of the concerned medical department.
b. Converting the above dataset into vectors.
c. Identify suitable machine learning models and train them.
d. Test the models and select the best performing model.

We created a labeled dataset using a disease-description dataset and a document on functional descriptions of hospital departments using heuristics. We used dataset from the Disease Ontology project called *doid-non-classified.obo* (DOID, 2017) (referred to as *disease_description*). Each disease has an assigned identifier, name, symptoms and some other details. We also created functional descriptions (referred to as *functional_description*) of healthcare departments from two different sources (Henderson, 2016; Mayoclinic Website, 2017). The datasets *disease_description* and *functional_description* contain information about 10612 diseases and 20 healthcare departments respectively. The system *compares* each disease description with all the departmental descriptions to assign each disease to a department. This is a challenging task and involves text processing. We had to remove stop words, perform stemming, used heuristics to handle synonymous, homonymous, etc. For instance, the pair of words *electrocardiogram* and *cardiomyopathy* are essentially the same whereas *hypertension* and *hyperbola* are totally unrelated. We used python to implement the preprocessing phase of the system.

We obtained a labeled dataset where each disease is mapped to a hospital department. The dataset is converted into a vector space model using term-frequency-index and document-frequency technique (tfidf). The labelled dataset presented as vectors have been used to train and test machine learning models.

Our problem is essentially a multinomial classification task (Aly, 2005). We had department names as our classes and the objective of our model was to learn a mapping between disease descriptions and departments. We split the datasets into two parts: 65% for training, 35% for testing. We trained three machine learning algorithms: Gradient Boosting Machine, Distributed Random Forest and Deep Learning. We implemented the system using an open-source big data analysis platform (H2O, 2016).

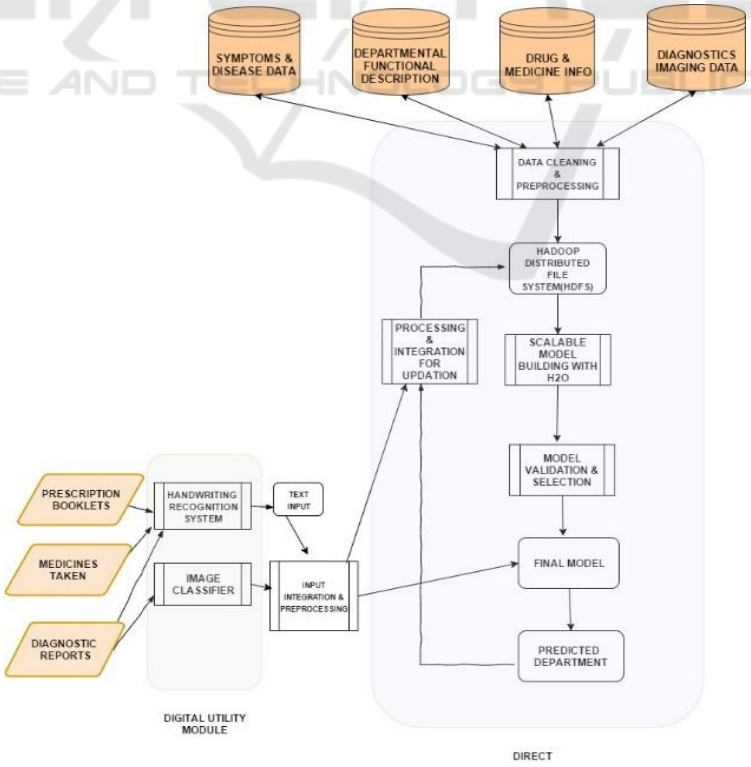

Figure 2: The block diagram of our system.

Table 1: List of medical departments in a hospital.

Serial No.	Department Name
1	Anesthetics
2	Breast Screening
3	Cardiology
4	Ear, nose and throat (ENT)
5	Elderly services department
6	Gastroenterology
7	General Surgery
8	Gynecology
9	Hematology
10	Neonatal Unit
11	Neurology
12	Nutrition and dietetics
13	Obstetrics and gynecology units
14	Oncology
15	Ophthalmology
16	Orthopedics
17	Physiotherapy
18	Renal Unit
19	Sexual Health
20	Urology

We choose the model with the lowest misclassification rate as our final model. The results from our model building, validation and selection phase have been discussed in the next section.

5 RESULTS AND DISCUSSIONS

We have used three machine learning models, namely Gradient Boosting Machine, Deep Learning and Distributed Random Forest. Each of these models require learning that essentially amounts to tuning some of the hyper parameters.

Random Forest hyper parameters include the total number of trees to grow, maximum tree depth and the number of predictors randomly sampled as candidates for each split.

Neural networks have variants such as *hyperbolic tangent* (Kalman and Kwasny, 1992), *rectifier* (Hahnloser et al 2000) and *maxout* (Goodfellow, 2013); each of these could optionally be paired with a regularization technique called dropout (Srivastava et al, 2014). There are many hyper-parameters to be tuned (Han and Kamber, 2001).

Hyper parameters of Gradient Boosting that need tuning include the number of trees to be constructed, the maximum depth of each tree, percentage of rows to be sampled per tree, and learning rate. There are certain guidelines for tuning these parameters (Friedman, 1999; 2002).

Table 2 summarizes the results that we have obtained from these three models. We trained all three machine learning models using 5 different settings of the parameters. After training the system, we tested using the same data. Column 2, 4 and 6 of Table 2 show false positive or misclassification for all 5 parameters settings for all three machine learning models on the training data. We then tested the three models with 5 different parameters settings using the validation data which is new to the models. The percentage of false positive is shown in columns 3, 5 and 7. The misclassification or false positives have been plotted for better perception of the three models with 5 different settings of hyper parameters and shown in Figure 3. As mentioned in the previous section, we have used 10,612 disease mapped to 20 hospital departments. It is obvious from the results that, using just the descriptions of departments and diseases, the system is able to suggest correct department 89.82% of the time using Distributed Random Forest on the training data. However, when we run Distributed Random Forest on validation data, it is able to suggest the correct department 60.19% of the time only. Amongst all models and parameters settings, the best validation performance is 68.05% of Gradient Boosting Model. The performance across all parameters settings and models is close to 70%.

It can therefore be concluded that the information contained in our dataset cannot give us a performance better than 70% true positives. Our system as shown in Figure 2 has many other sources of information that we need to incorporate for better performance as we explain in the next section.

6 CONCLUSION AND FUTURE WORK

We wanted to build a system that will help patients going to tertiary health care system identify the correct hospital department. We have implemented and tested parts of this system wherein a patient enters his symptoms and/or provisional diagnosis; the system suggests a department based on this user input. Our system suggests the correct department 68.05% of the time. To improve the performance further, we need to incorporate medicine information and diagnostics imaging data into our system as shown in Figure 2. The system should take user's past prescriptions and diagnostic reports into account when suggesting a medical department.

Table 2: Misclassification done by three different machine learning models with five different settings for hyper parameters for training and validation data (GBM: Gradient Boosting Machine, DL: Deep Learning and DRF: Distributed Random Forest, T: Training Data, V: Validation Data).

Parameters Setting	GBM (T)	GBM (V)	DL (T)	DL (V)	DRF (T)	DRF (V)
1	21.94	39.03	34.80	35.55	15.38	34.14
2	51.34	55.04	33.42	34.52	15.02	32.91
3	30.40	43.74	32.90	33.96	12.14	33.57
4	17.72	31.95	32.43	33.78	10.99	35.96
5	13.82	39.35	33.3	33.47	10.18	39.81

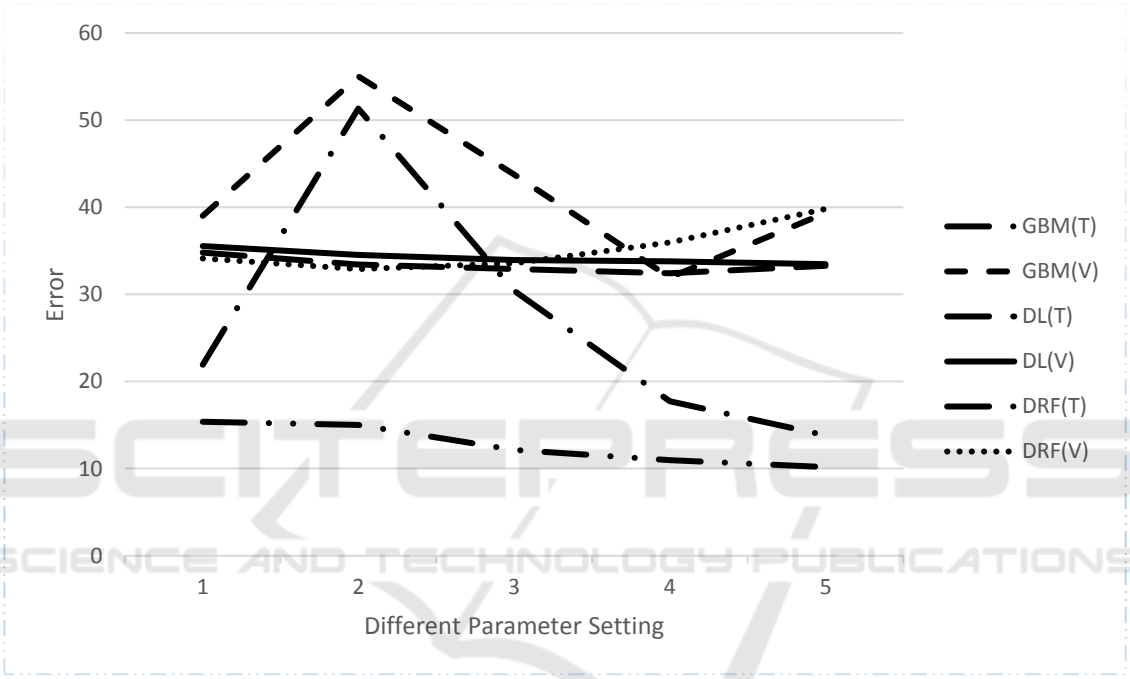

Figure 3: Misclassification done by three different Machine Learning models for five different settings of hyper-parameters with training and validation data; GBM: Gradient Boosting Method, DL: Deep Learning, DRF: Distributed Random Forest; T: Training and V: Validation.

Once we incorporate everything, the performance of this system will improve. We are now working on integrating diagnostic image data. We have experimented with image datasets of eyes and lungs. We have been able to classify the organ in the image with near 100% accuracy. We have yet to figure out a mechanism to integrate the diagnostic image data into the decision making process. We also want scan the past prescriptions and run them through OCR/ICR to convert them into text gain more information about the treatment that the patient has received. Again, this information must be integrated into decision making process. We may have to map branded medicines into generic medicines to be able to use this information in the deciding the hospital department. Perhaps, our knowledge base should contain a list of medicinal compounds and the common diseases which they treat, and a list of medicine names from different brands for the same compound.

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