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Designing a Decision Support System using Electronic Health Records for Symptoms Faking Problem at Emergency Clinics

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Abstract— In today's fast era, people have no time for taking a good care of their health. People prefer taking painkillers for their routine problems and move ahead. This has resulted in increased use of such medicines. Many of them are taking such medicines for recreational purposes. In the eastern countries, such medicines are available only with valid prescriptions. Hence, these people try to do symptoms faking at the emergency clinic to get the required medicines prescribed from the medical practitioner. It is very difficult for the doctor to verify the authenticity of the symptoms. A decision support system for symptoms faking problem is proposed. This proposed system will be a multi-branch system using a concept of Electronic Health Record (EHR). The aim is to explain the overall architecture of the system along with the significance of each branch. The deep learning methodology will be suitable to perform learning of the systems used within the branch. The paper also contains the explanation of the aggregation of the branches to produce a result as symptoms faking alert flag.
Index Terms—deep learning, emergency clinics, multi-branch system, symptoms faking.

I. Introduction

In the current era, everyone is tied with a lot of activities. It is very difficult for people to address their health issues and have a course of treatment for the same. Many people prefer taking painkillers to keep the pain away from their daily routine. Many of the popular painkillers are widely used over the world. The other medicines like inhalers, cough syrups are also ahead in this race. Even though, the overdose of these medicines is dangerous to health, it is still fine if it is taken to subside the real issues. The main problem lies here. Many of the people are using these medicines for recreational purpose. They get addicted to such medicines and that can cause a serious problem to their health. Such medicines are getting used as opioids. In many of the eastern countries, all these medicines are not sold without a proper prescription. To get rid of this obstacle, such opioid users catch hold of emergency clinics. The doctor to patient ratio over there is very low and it is difficult for doctors to tend to each patient with full dedication. Taking advantage of the same, these opioid users do symptoms faking at the emergency clinic. With this, they easily get their required medicines prescribed from the medical practitioner.

We have decided to work on this problem. An additional help in deciding the authenticity of the symptoms provided by the patient. This led to the idea of a decision support system which will assist the medical practitioner to decide whether the patient is faking the symptoms or not. This system will not overrule the doctor's decision, but it would aid doctors in taking their decision more precisely.

Deep learning has emerged as one of the great techniques in the domain of predictive analysis. We have tried to propose a system where deep learning can play a vital role. The proposed system will be a multi-branch system. The electronic health record (EHR) is a digital storage of the patient's medical record [1]. Our proposed system uses patients' EHRs to generate patient profiling. This helps in identifying the possible symptoms the patient should ideally have compared to the symptoms he is complaining about [2]. The system analyses this situation from the different perspective and comes up with the value which represents the truth in the symptoms submitted by the patient.

II. Purpose

In most of the eastern countries, there is a marginal increase in the consumption of drugs. It is the narcotics drugs which is causing a lot of danger. But on the top of that the major problem is about the opioid drugs which are openly available over the counter. These are the drugs which can be easily prescribed by the doctors at the emergency clinics on the realization of the patients' need [3]. The problem is that some mendacious patients are using such drugs for the recreational activities. Such patients take the help of emergency clinic for getting their necessary prescriptions. The doctor to patient ratio is less in emergency clinics and hence less time is spent per patient. The opioid users take the advantage of this and come to emergency clinic with well fabricated symptoms [4]. These symptoms are so well selected that the doctor prescribes them the drug of their choice. Then such drugs are used for recreational purpose which causes danger to one's life. This is the main purpose of our proposed system. Our system is aimed at assisting medical practitioners at emergency clinic. Such medical practitioners required to attend to patients and listen to their symptoms. Based on the symptoms they are supposed to prescribe strong pain relief medicines to the patients. If this process is not done carefully then it may lead to creation of opioid users. Our proposed system is designed to help the doctors in this process. Based on its design, it performs certain computations and generates the alert flag for the symptoms submitted by the patients. This will support the doctor in taking the decision about whether to provide the prescription or not.

III. Literature Survey

We have studied some significant technical papers regarding the identification of opioid users.

Zhengping et. al., 2018 talk about deep learning solutions for classifying patients on opioid use [5]. The paper focuses on the rise in the usage of opioid by in appropriate users leading to substance abuse. In the recent times, deep learning has done a remarkable job in the filed of learning. We also have a significant amount of data represented as Electronic Health Record. This has triggered the idea of classifying the opioid users using a model consisting of deep learning and recurrent neural network. The paper explains the use of deep learning algorithms on a dataset made up patients' medical history in the form of electronic health record. This has helped for the identification of opioid users and their groups. It is being evident that the newly defined models using deep learning have shown significant improvement over the classification models used with traditional approach. It has helped in identifying crucial features for long term users and opioid dependent users. This has proved that the efficiency can

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be achieved in the clinical investigations using the progressive deep learning models.

Xinyu Dong, et. al, 2019 [6] has proposed many prediction models in this paper. These models are useful for the assessment of the opioid poisoning in the upcoming years with probability. These models have used records from electronic health records as well as some data from claim records. Significant sized datasets were used to identify traits related to toxicity in opioids. Along with this, the other various things analyzed includes diagnosis, prescriptions, test results, patients' medical records and associated clinical events. Decision Trees, Random Forest, Logistic Regression were some of the models tested with the different datasets. It was observed that the performance of Random Forest model outperformed others.

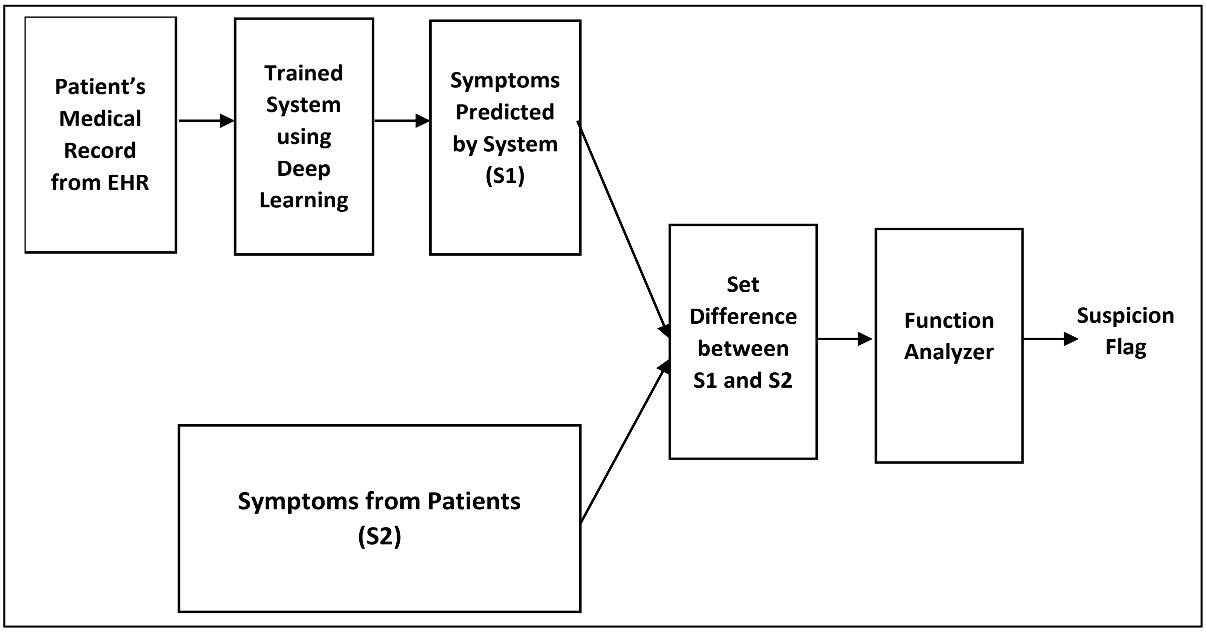

Fig. 1. State Transition Diagram for

This certifies that a decent level of accuracy can be achieved for automated prediction at the clinical level for deep learning-based approaches. This opens newer opportunities for the creation of deep learning-based prediction systems to assist medical practitioners for fighting problems of opioid users.

In the paper published by Ramya Vunikili [7] the patients were classified into eight distinct groups based on the prescription for opioid drugs. This was done by using the current age of the patient at the time of writing prescription. Also, the side effects were identified by examining individual patient's diagnosis to determine the symptoms associated with the overdose of the drugs. For the purpose of classification, they have used two models like Logical Regression and Gradient Boosting. The base model using Logical Regression has given a decent accuracy. But the advanced model using Gradient Boosting as given much better accuracy.

IV. Proposed System

The proposed system is a decision support system for weeding out drug seeking behavior at the emergency clinic. The system contains two main branches, and the result is computed by the aggregation of the results from two branches. The first branch is mainly concerned with the patient's symptoms faking. It will try to generate the symptoms the patient ideally must have,

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using the available knowledge and then it compares these symptoms with the set of symptoms the patient is complaining about. The second branch deals with the patient's involvement in substance abuse [8]. It uses a well learnt system to decide whether the medical record of the patient hints towards the patient being an opioid user. It helps in strengthening the fact that the patient is doing symptoms faking. Let us try to understand each branch in detail and later we will discuss about the aggregation process.

A. Branch 1: Symptoms Faking by Patients

The Electronic Health Records (EHRs) are processed using Deep Learning methods for the prediction of set of probable symptoms [9].

It is used to generate a general space containing the symptoms the patient is likely to have. The novelty detection method can be employed to find the degree of patient's symptoms faking.

Fig 1 shows the flow structure of branch 1 which focuses on identifying the symptoms faking by the patients. As the first step, the patient's medical record is being taken from EHR which will be containing the patient's history. Deep learning is used to train a system with EHR dataset so that the
system becomes capable of predicting the possible symptoms the patient should have based on the EHR of the patient [10]. Using the medical history from EHR, we can get the diseases that the patient had in past. Each of the disease has some set of symptoms.

Using this correlation, the system will be able to generate the possible set of symptoms. So the current patient's EHR is fed to this trained system which produces the set of symptoms in the form of key-value pair. If the disease is taken as key, each disease will have a collection of symptoms which can be considered as value. A rule-based elimination system can be employed to reduce this set further. There can be some symptoms which are induced due to family history, age, environmental factors, and gender [11]. All such symptoms can be eliminated. This set is represented as S1, and it can be viewed as a normal space for patient symptoms.

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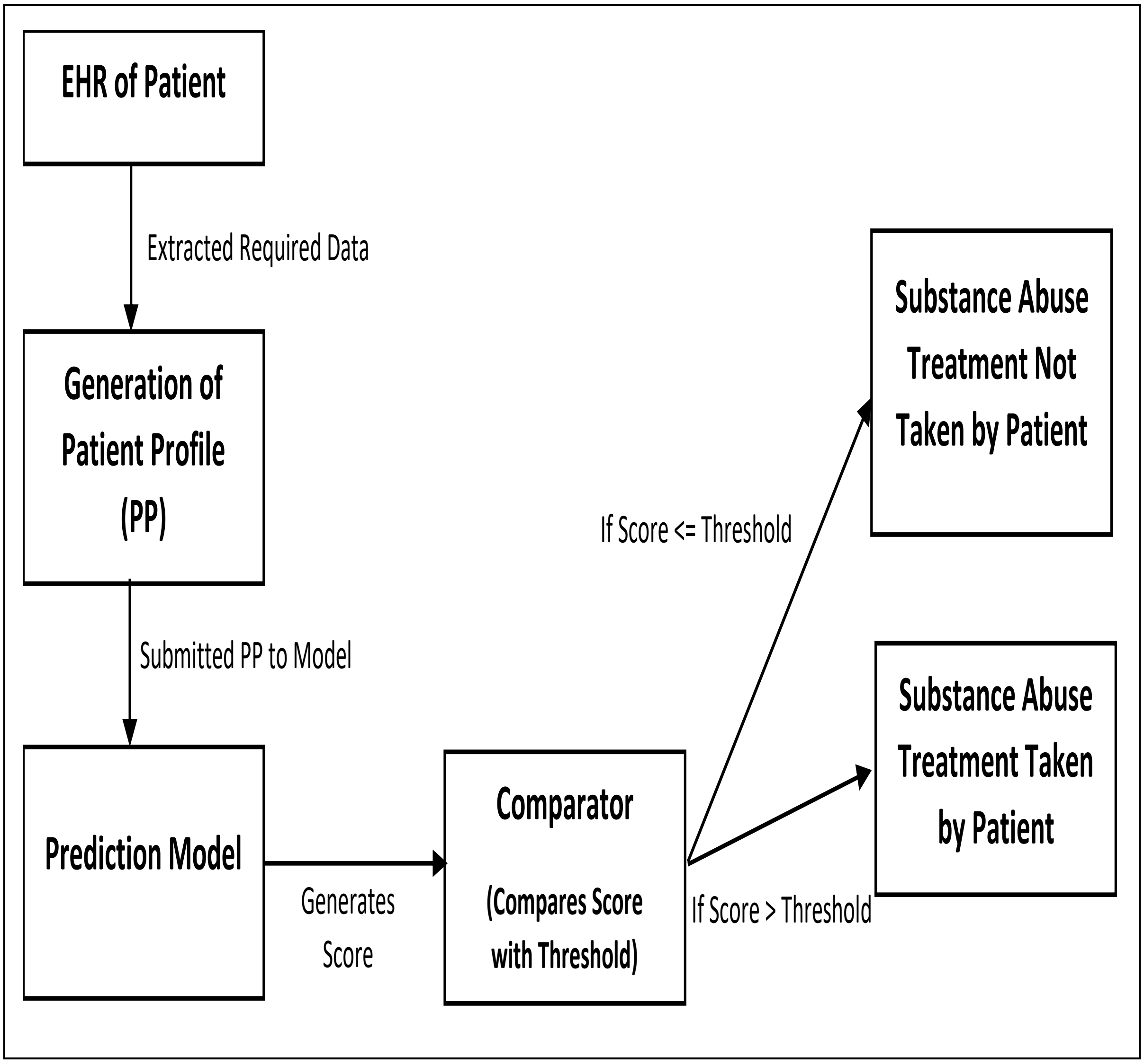

Fig. 2. State Transition Diagram for Branch 2

The other set of symptoms is represented as S2. This represents the set of symptoms that the patient is complaining about. This is the set which we must check for symptoms faking. Hence this set S2 must be compared with S1. We can see that in Fig 1 that we find the set difference between these two sets. The set difference can be visualised as the number of symptoms that the set S2 has which are not present in set S1. In other words, number of symptoms that the patient is complaining about, but they are not present in the set of predicted symptoms by the trained deep learning system. Then this set difference is fed to the function analyser as an input. It is expected to produce analytical result based on the symptoms.

The function analyser can have a separate logic to produce a positive suspicion flag or otherwise. It can be based on the level of symptoms. A trivial and less crucial symptoms like cold and cough may be given a less weight. Whereas a non-trivial and crucial symptom can be given more weight. A function analyser system can use a weighted average of these values to produce a combined value which when compared with threshold can result into generation of a suspicion flag.

B. Branch 2: Identification of Patient with Substance Abuse Treatment

The second branch focuses on the identification whether the patient has taken a substance abuse treatment.

This factor can also play an important role in finalizing the symptoms faking of a patient. The prediction of substance abuse is possible by using EHR as an input. As shown in Fig 2, the patient's EHR selected from the database. This EHR contains lot of redundant information which is not significant to the current processing. Hence, this EHR is fed to the profiling system to create the patient profile. This system created the significant data from the EHR and outputs patient profile. This patient profile is then fed to our model which is ready to predict substance abuse. The logic uses the strongest predictors from the EHR which is responsible for substance abuse. Some of the important factors which are concerned with patient's profiling information includes education, age, living arrangements, employment status and gender.

The model takes these parameters and produces the score which is an indicative measure of the level of inclination the patient had to the substance abuse. As per the literature review and the consultation with medical practitioners, a threshold will be finalized which will be deciding factor for the system. A comparator is used to compare the score with the threshold. If the score is <= threshold, then it is concluded that the patient has not taken the substance abuse treatment. But if the score > threshold then it is concluded that the patient has taken the system abuse treatment.

C. Aggregation of Results from Both the Branches

The aim of proposing the multi-branch system for the problem was to do the analysis from the different angles. As stated earlier, the first branch checks whether the patient is providing the same set of symptoms that ideally, he should have as per the medical history. So if there is any deviation then there is some chance that patient is faking the symptoms. But still it can not be concluded with a strong support as there could be some reasons for deviation. In this scenario, the second branch will be very much useful. The second branch analyses the EHR to create a patient profile.

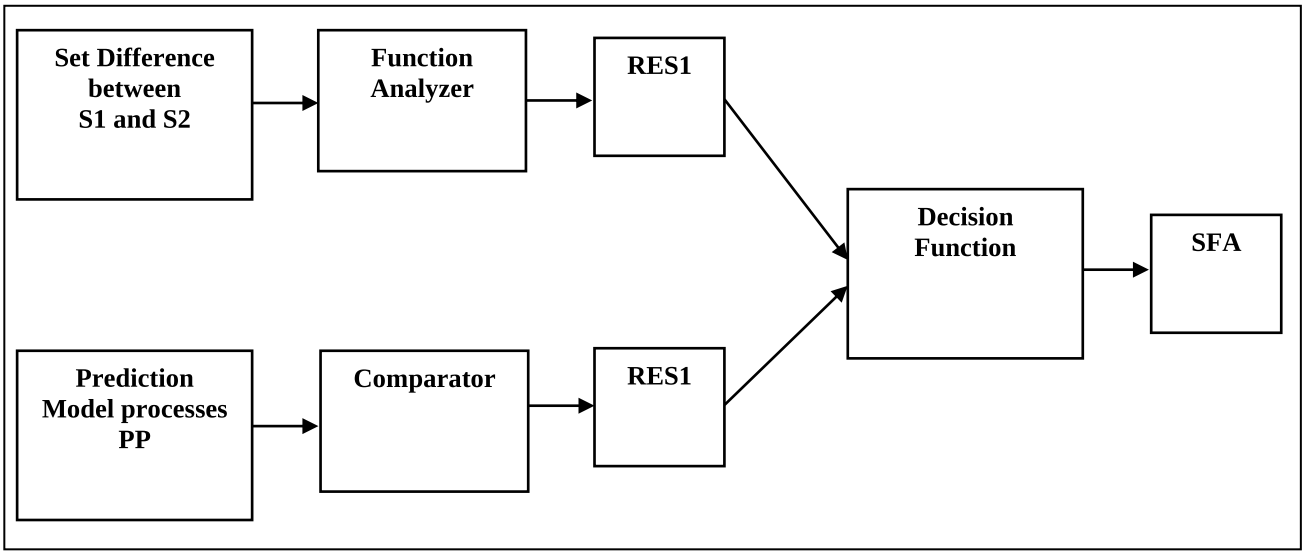

Fig. 3: Proposed Decision Support System

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This patient profile is fed to a trained system which tries to predict whether a patient has taken substance abuse treatment. There are lot of factors involved which help in predicting like living arrangements, age, marital status, education etc. Now if the second branch also predicts that the patient has taken substance abuse treatment then we get a strong support for the result of the first branch. It means the deviation in the symptoms is not justified and we can conclude that the patient is faking the symptoms.

As shown in Fig 3, the result of branch 1 is termed as RES1. It represents the probability that the patient is lying. It should be represented as a value between 0 and 1. If the magnitude of the RES1 is more it indicates that it is more inclined towards lying. Similarly, the figure shows that the result of branch 2 is termed as RES 2. It represents the decision whether the patient has taken the substance abuse treatment or not.

The aggregation of RES1 and RES2 is used for the generation of the final result. Designing the aggregation process itself can be a separate significant problem. Initially, we need to understand the relation between RES1 and RES2. A suitable machine learning model can be employed. It will help in finding the suitable weights for the aggregation process. Our final result can be represented as SFA Flag which indicates Symptoms Faking Alert flag. It can be a linear parameterized correlation between RES1 and RES2 as follows:

$$\mathbf{SFA = W0 + W1 * RES1 + W2 * RES2}$$

The initial learning of the system can take place by considering the doctor's decision as the result. Hence in the initial stage we will have the value of SFA as the decision taken by the doctor. This can be used to tweak the values of RES1 and RES2. Hence it results into a supervised learning problem. This mapping function can be improved upon learning by obtaining the optimal values for the weights used in the learning.

V. Proposed Algorithm

The overall system flow can be well explained by representing it in the form of the algorithm. Hence, we have proposed an algorithm to check whether the patient is symptoms faking or not. The proposed algorithm is as follows:

I/P: EHR of the patient and the symptoms submitted by patient as P.

O/P: Probability that the patient is faking the system.

Step 1:

Patient's EHR is submitted to Deep learning model.

Step 2:

It extracts the list of probable diseases the patient is suffering from.

Step 3:

It outputs the list of diseases that the patient is likely to have in the past.

Step 4:

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Each disease is associated with set of known symptoms. So performing union of these sets, we will be getting a set S_{Final} that represents the consolidated set of symptoms.

Step 5:
The input P represents the set of symptoms given by the patient. The confirmation of whether the patient is faking the symptoms can be done using the comparison of S_{Final} with set P.

DiffVal = Comparison_Function(S_{Final}, P)

Comparison_Function tries to find the similarity index between S_{Final} and P.

Step 6:
This is compared with a threshold of suspicion to generate the result of the first branch.

RES 1 = Calc_Relativity (DiffVal, Suspicion_Threshold)

Suspicion_Threshold is a hyper parameter that can be improved in the due course of development.

Step 7:
In the other branch, the patient profile (PP) is taken by a pre-trained model and outputs the probability that the patient has taken the substance abuse treatment.

RES 2 = Predictor_Model (PP)

Step 8:
Using the aggregation of RES 1 and RES 2 using an appropriate aggregation technique, the Symptom Faking Alert (SFA) can be raised. It will support the doctor in taking decision about symptoms faking by the patient.

VI. Conclusion

We have proposed a multi-branch decision support system for symptoms faking problem. The system has used the Electronic Health Record (EHR) data set for the training of learning models. It uses the EHR of the patient to generate patient profiling. The deep learning techniques are proposed to be used for extraction of significant data from the EHR. Further the machine learning techniques are efficiently used for processing patient profiling information and provide effective insights on the symptoms that the patient can have.

It is noteworthy to mention that the symptoms faking is not only being derived by merely the comparison of the symptoms given by patients with the symptoms derived from EHR. As the deviations might have some valid reason and circumstances. Hence, the additional support for this result is sought by adding an additional branch which deals with prediction of substance abuse by the patient. If the patient having deviation in symptoms also found to have taken substance abuse treatment, then it strengthens the claim for the symptoms faking of that patient.

In the recent era, the novel research has added learning from time-sequential and longitudinal data. It enables universal interpretation of data. This allows to add the insights using the continuation of time. The idea is to provide the overall perspective to the medical practitioner while taking decision using the recurrent neural network architectures like Long-Short-Term Memory Units and Gated Recurrent Units.

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