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Correlating Critical Care Data from Different Resources to Predict an Effect: Related To a Domain Specific Treatment

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ABSTRACT: Disease treatment has different approaches to identify. Some will randomly identify through past experiences and some will do treatment based on the symptoms of the patient. But the research we are prescribing is disease relations and the relation between each variable we are considering for the prediction model. There will be connecting things between any two or more disease symptoms which are ignored by the practitioners in the hospital and here are designing an architecture based on the emergency department data in hospitals which are based on the different wing approaches. Each variable considered from emergency department and ICU is more valuable for designing any model and to perform some useful work in that domain. If we consider any practitioners normal treatment data we cannot get the apt information and the variables which are considering must be accurate and they should not degrade the model which we are designing. Critical care section will have highest accurate data from all domains and it will be helpful for identification of how much ratio of data is related to each other and how they are going to effect the patient and treatment which doctor is giving to that patient. Every minute part of data is valuable and countable in this kind of research for identification of percentage or ratio of each cause in the disease of the patient.

KEYWORDS: Machine Learning, Identification, Relations, Practitioners, Disease treatment, Emergency.

I. INTRODUCTION

Machine learning is a subfield of computerized reasoning (AI). The objective of machine adapting for the most part is to comprehend the structure of information and fit that information into models that can be comprehended and used by individuals.

Despite the fact that machine learning is a field inside software engineering, it contrasts from conventional computational methodologies. In conventional figuring, calculations are sets of unequivocally modified guidelines utilized by PCs to ascertain or issue tackle. Machine learning calculations rather take into consideration PCs to prepare on information data sources and utilize measurable examination so as to yield esteems that fall inside a particular range. Along these lines, machine learning encourages PCs in building models from test information with a specific end goal to mechanize basic leadership forms in light of information inputs.

Any innovation client today has profited from machine learning. Facial acknowledgment innovation enables online networking stages to enable clients to tag and offer photographs of companions. Optical character acknowledgment (OCR) innovation changes over pictures of content into mobile sort. Proposal motors, fueled by machine learning, recommend what films or network shows to watch next in view of client inclinations. Self-driving autos that depend on machine figuring out how to explore may soon be accessible to purchasers.

Machine learning is a constantly creating field. Along these lines, there are a few contemplations to remember as you work with machine learning philosophies, or examine the effect of machine learning forms.

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In this instructional exercise, we'll investigate the normal machine learning techniques for directed and unsupervised learning, and basic algorithmic methodologies in machine picking up, including the k-closest neighbor calculation, choice tree learning, and profound learning. We'll investigate which programming dialects are most utilized as a part of machine getting the hang of, giving you a portion of the positive and negative qualities of each. Also, we'll talk about predispositions that are sustained by machine learning calculations, and consider what can be remembered to keep these inclinations when building calculations.

Domain specific treatment is differed based on the disease we are considering to get treated and if we consider any chronic diseases the data using which we need to do predictions is very important. Consider Emergency department in hospitals and ICU data which will be recorded each and every single information of the patient treatment and health condition. Here there will be a correlation between the variables we are considering for prediction. For suppose one person is suffering with backbone pain and the reasons may be lifting heavy weights, doing over work than his body capacity etc. In other place another person also suffering with same backbone pain symptom and the reasons for his pain may be different. We need to identify the factors of which the disease is causing more[1-5]. Only some variables will show complete impact on the effect i.e., disease level that may be first level, or higher level. Based on the considerations of the variables and the present condition of the patient and the treatment given to the patient is also considered in the EHR based treatment data. EHR will be gathering information only about the one hospital information and will store information in the local repository or any other remote repository which have the high security measures, Because of the high confidential data regarding patient disease details and the treatment given to that patient, all the things needed to be encrypted even though the third party service provider should not be able to see the data.

In this article we are focusing on the issues regarding the process currently EHR applications [6-10] are following and what are the modifications we can perform to get a great prediction models to get good accurate results in the prediction models. We are proposing a new architecture of gathering the data and storing the data in an efficient manner. In the further sections we are explaining about the present procedure of EHR data collection with sample, proposed approach to solve issues in current scenario, expected results of correlation and conclude with finite description.

II. EXISTING APPROACH

The Electronic Health Record (EHR)– at that point called the Electronic Medical Record (EMR) or Computerized Patient Record (CPR)– got it first genuine approval in an Institute of Medicine's (IOM) report in 1991 entitled "The Computer-Based Patient Record: An Essential Technology for Health Care.(www.nap.edu)" IOM drove home the EHR is expected to change the wellbeing framework to enhance quality and improve security.

The claim to fame of family pharmaceutical has additionally expressed that the EHR is a center innovation for the eventual fate of family drug in the Future of Family Medicine Project. This venture traces "Another Model" of tend to family medication with the EHR as "the focal sensory system" of that model. The EHR turns into a device through which the family drug office can change practices to address its issues and the requirements of its patients. Upgraded work processes and access to data make the act of prescription more proficient for doctors and their staff. Choice help and computerized updates enable the training to convey more secure and higher quality care to patients and the group.

The EHR is about quality, security, and proficiency. It is an extraordinary apparatus for doctors, yet can't guarantee these Excellencies in disengagement. Accomplishing the genuine advantages of EHR frameworks requires the change of practices, in view of value change approaches, framework and group based care, and confirmation based solution.

Suppliers who utilize EHRs report substantial changes in their capacity to settle on better choices with more exhaustive data. EHR appropriation can give human services suppliers:

Exact and finish data about a patient's wellbeing. This empowers suppliers to give the most ideal care, in the case of

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amid a normal office visit or in a restorative crisis, by giving the data they have to assess a patient's present condition with regards to the patient's wellbeing history and different medicines.

The capacity to rapidly give mind. In an emergency, EHRs give moment access to data about a patient's restorative history, sensitivities, and drugs. This can empower suppliers to settle on choices sooner, rather than sitting tight for data from test comes about.

The capacity to better organize the care they give. This is particularly critical if a patient has a genuine or ceaseless restorative condition, for example, diabetes.

An approach to impart data to patients and their family parental figures. This implies patients and their families would more be able to completely participate in choices about their medicinal services.

The fundamental objective of well being IT is to enhance the quality and security of patient care. The guarantee of completely acknowledged EHRs is having a solitary record that incorporates the majority of a patient's wellbeing data: a record that is avant-garde, finish, and exact. This places suppliers in a superior position to work with their patients to use sound judgment.

EHRs can likewise hail conceivably unsafe medication cooperation's (to endorse specialists investigate choices before an issue happens), check solutions and doses (to guarantee that drug specialists apportion the correct medication), and decrease the requirement for possibly dangerous tests and methods.

Human services is a collaboration. Shared data bolsters that exertion. Patients, their families, and suppliers all advantage when all colleagues can speak with each other viably and effectively. The Nation's wellbeing and economy advantage also. Electronic wellbeing record (EHR) selection requires a speculation of time and cash, however the advantages regularly exceed the expenses, and budgetary motivating forces are accessible to enable suppliers to make the progress.

More than 144,000 installments totaling $7.1 billion have just been issued to experts and healing facilities by the Centers for Medicare and Medicaid Services (CMS)

An expected $22.5 billion will be paid from 2011 – 2022 to qualified suppliers who receive EHR innovation.

As restorative practices and advances have propelled, the conveyance of complex, top notch therapeutic care has come to require groups of social insurance suppliers— essential care doctors, pros, medical attendants, professionals, and different clinicians.

Every individual from the group has a tendency to have particular, constrained associations with the patient and, contingent upon the colleague's specialized topic, a fairly extraordinary perspective of the patient. Essentially, the social insurance group's perspective of the patient can wind up noticeably divided into detached certainties and bunches of side effects. Social insurance suppliers require less divided perspectives of patients.

Electronic Health Records are the cloud based and desktop based applications using which all the treatment data regarding the patients in that specific hospital is gathered and maintained for the further evaluation and utilization if needed by any research scholars. The actual procedure of the these applications is to identify the domain of the patient that is to which section of the department the patient belongs and the personal information of the patient regarding the disease, hobbies, food habits, age, work nature, what are the symptoms he is feeling and since how many days he is suffering with this symptoms [11-15].

Originally diseases are divided into two parts. Genetic and Congenital. If the patient got any disease like heart attack, diabetics, BP etc, these are considered as genetic disorders because they got this from their family members like

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inheritance. All the symptoms of few of the same of their parents or grandparents will be seen in this patient and we can treat him according to the symptoms he is feeling. The issue here is there is a lot of correlation between the things in the EHR [17-18] data which the researchers can work on and we cannot avoid that without implementation and in this current architecture of EHR this kind of implementation is missing. The Congenital Disorders are by birth issues caused to the patients and they can be identified by birth or after some duration after the birth. These are said to be chronic diseases and there is a lot of correlation between the data and this identifications will be minute and we cannot even expect the relation between the variables we gather.

The table below can be considered as the sample of collection of data in the EHR data. We can get a clear idea on what are the things we can get from these records and how can we tabulate those for further designing of the prediction models using machine learning. The main scenario here is to implement machine learning algorithms in an efficient manner using which we can give better treatment for the patients for the different diseases and for the different scenarios. The main idea is to identify the correlation of the components in the data set and need to know about how we can improve the dataset with the efficient variables and relation between those.

Data	Type	Characteristics	Examples
Vitals	Numerical, Temporal	Typically measured every second/minute within ICU and every few hours outside ICU	Blood Pressure, Respiration Rate, Heart Rate
Lab Tests	Numerical	Typically measured a few times, investigation depends on patient's condition and diagnoses	Blood Glucose, Uric Acid
Medication Orders	Numerical, Temporal	Physician orders of prescribed medications	Insulin, Aspirin
Procedures	Numerical, Temporal	Medical/surgical procedures performed on the patient	Craniotomy, endoscopy
Diagnoses	Numerical, Temporal	Diagnoses of past and current conditions	Sepsis, Diabetes
Nursing Notes	Text, Temporal	Assessment of patient's condition including subjective observations	See Figure 3
Radiology	Image, Text	Radiology images accompanied by reports from the radiologists	X-Ray, CT Scan
Demographic	Numerical, Static	Demographic details of the patients	Age, gender, ethnicity

Figure 1: Tabular content of the components of tests in the dataset formed using EHR application

III. PROPOSED APPROACH

Here we are proposing a new concept of correlating one dataset to another dataset which is used for designing better prediction model. There are few steps to be followed to gather the data and correlate. They are as follows:

a. Based on the keyword of the disease gather the variables and form the dataset
b. Separate each and every dataset based on the domain that is department.
c. Plot all the symptoms into a separate file. Then we can get clear idea that how many times that specific symptom is recorded in whole treatment of that patient and also complete patients list
d. Based on the keyword count plot the graph for identification of the impact of symptoms. Based on this graph, impact of a specific symptom is recorded in a separate dataset. In that dataset we can identify the weightage of each symptom in the list.
e. Based on the list form a neural network.
f. Like the same way gather all the information from other EHR applications and form the same networks so that we can estimate which is the more correlated to all the diseases and what is the most case of happening that disease.

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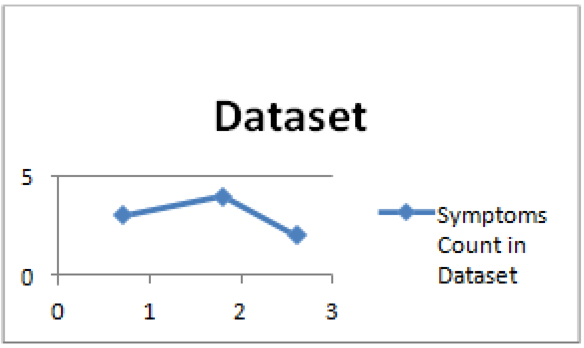

Chart 1: Sample Dataset which will plot the count of specific symptom in the current data set

In chart 1 we can see the plot of the estimated count of each symptom in the dataset.
Like the same way we need to gather the all datasets from every EHR and correlated everything to estimate the main reason for causing a specific disease.

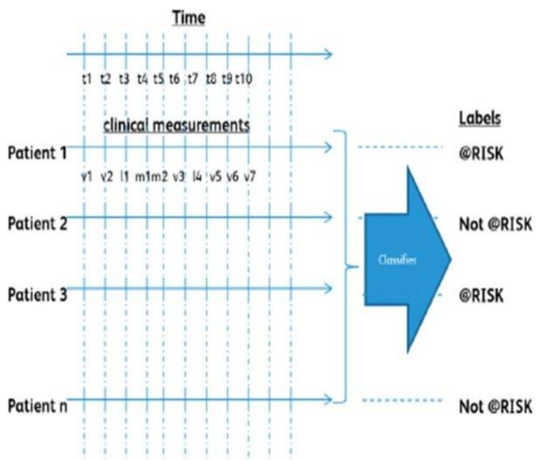

Figure 2: Time series and Risk Management architecture.

The about architecture is based on the time series management and risk factor identification. The risk management is for identifying which symptom is playing a major role in the making risk for the patient. And based on that we need to give the treatment to the patient.

There are few things we need to consider to use this architecture. When the patient is suffering with one disease then we have chance to predict the treatment or we can try to predict the future treatment and medication based on correlating the variables. These variables are the list of symptoms.

IV. ADVANTAGES AND DISADVANTAGES OF PROPOSED SYSTEM

There are list of advantages and disadvantages of this architecture. They are as follows.

a. Data correlation helps to predict the disease treatment of the patient.
b. Data can be in multiple formats and we need to convert the format of the data to respective format which supports the model. If the data is in the form of object in the dataset then we need to convert them to float value or

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integer value.
c. If suppose MRI data or CT scan data is available then we need to convert that string variables to Integer values with the dummy variables like constants. We should not take more dummy variables for the model. Because they may create clumsy in the model. We can use limited amount of variables for the model and they are well sufficient for developing and designing the model.

d. This models is used for predicting the future treatment of the patients with specific disease or group of issues.

As we have advantages we need to discuss about the disadvantages too for this architecture.
a. Availability of multiple disease data may be creates problem because of unavailability of the proper data.
b. Researchers must have coding and medical knowledge before implementing prediction models using the variables using machine learning methodologies.
c. Correlating the variables may create mess in creating and implementing algorithm as we may or may not have proper knowledge on considering the proper variables for correlation.

VI. FUTURE SCOPE

The future work is simple and implementation is difficult because we need to combine multiple EHR applications at a time and need to get common dataset from the combined applications. For this kind of application implementation we need a hybrid architecture of cloud computing. In this hybrid architecture we need to host all the EHR applications [19-22] in one zone and the extraction of data from the repositories has to be done immediately after uploading the data into the applications. For suppose patient 1 data is uploaded into the server and then extracted datasets will be transferred to another isolated host in different region. The backup is stored in another locations and cold backup will be done parallel without any delay. Using those correlated data we can utilize better machine learning models and design a prediction model for better identification of diseases. If there is any possibility we can connect the personal EHR devices like bands, watches etc to the cloud service through a mobile application and we can even take them as samples for implementation.

VII. CONCLUSION

In this architecture we need to consider a cloud based host and different free access EHR applications and using those applications we need to gather the treatment details and the medication details. We also need to consider the symptoms details of the patient in every EHR application. If the architecture is more implemented in connected with personal EHR applications it could be much better for implementation and accessibility of the correlation of data.

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