An Intellectual Doctor Associate for Operative Treatment using Block chain Technique thereof

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Abstract:

A present- day mortal croakercannot recall all the information necessary to make a prompt but an accurate opinion. With the ultramodern cornucopia of handbooks, exploration papers and case studies, no croaker can master every aspect of medical care and recall every detail of the analogous cases. Yet, it's possible to feed an AI- grounded system with applicable data and let the computer sift through the expansivedatabase ratherof counting on the important furtherlimited mortal knowledge. So far, standard patient database for Two BD infrastructures stand out among so numerous, videlicet, the Lambda Architecture and the National Institute of norms and Technology (NIST) BD Reference Architecture. These offers update the Case information and transfer the same to different associations. In order to satisfy particular requirements, Lambda Architecture uses a system grounded on three main factors, videlicet, a batch sub caste, a serving sub caste, and a speed sub caste(for real- time data). Still, NIST BD Reference Architecture is rather an open tool (not tied to specific merchandisers, services, executions, or any specific results) to grease the discussion of conditions, structure designs, and operations that are essential in BD surroundings.

Keywords: ***block chain, Boston-based biopharma, BD environments, and patient management program.***

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I. Introduction

In India first step in diagnosis of illness is consulting doctor outside the Hospital. In the process of Treatment the doctor gives prescription including some drugs and tests based on his past experience. Sometimes this procedure may take more time to come to conclusion in some case, which may cause financial burden to the patient and in certain cases it may cost the life of the patient also. The available technologies help us to overcome the above problems to some extent. In order to help the both doctors and patient at outpatient consultation we propose to develop Application called intelligent doctor Assistant using Data mining and Machine learning. This application collects the prescription at various outpatients consulting in City and stores them into centralized Database. These data is initially preprocessed and kept ready to apply machine learning models which are developed as part of this application.

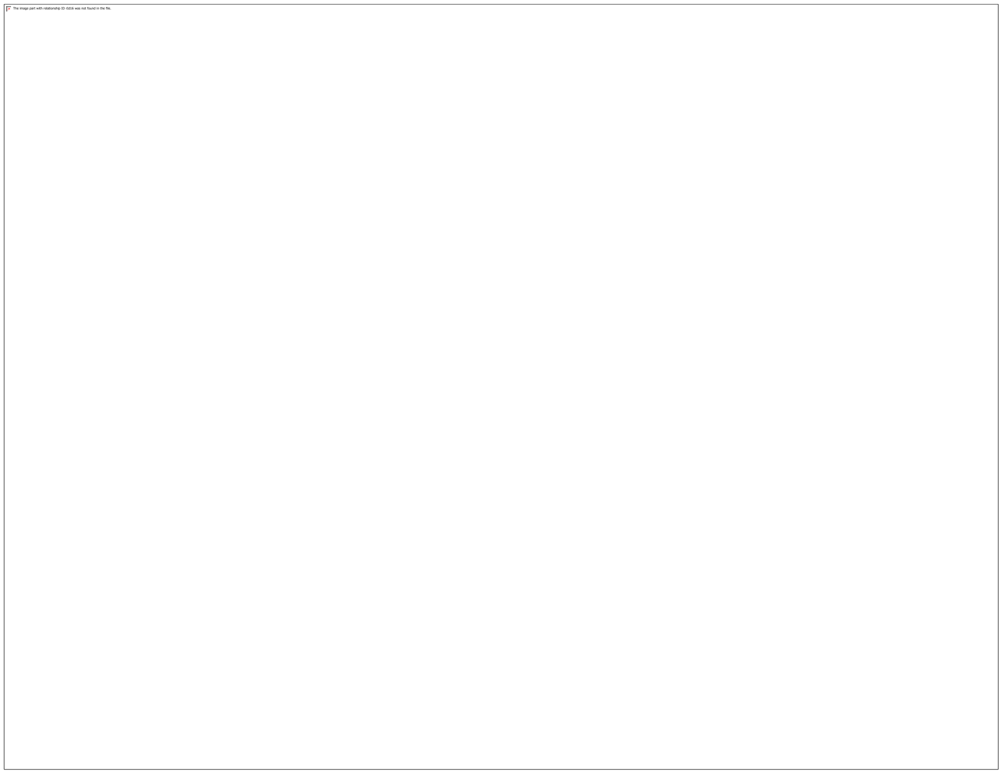

Figure 1: Architecture of Intelligent Doctor Assistant for effective diagnosis

Whenever a doctor checks patient he write a prescription (electronic prescription), which is submitted into centralized database. Immediately the doctor will get the most similar cases on his screen by pulling from the centralized database with help of machine learning models working on database. This app also allows the doctor to explore case into next level.

Office Scanning/Filing Systems:

Alphabetical Indexing
Numerical Indexing
Current, Active, and Inactive Case Record Files
Subject File
X-Ray Files
Tickler Files
Reminder Calendars
Follow-up Files
Filing Philosophy

The most simple alphabetical indexing method uses three units. Unit 1 is the last name, Unit 2 is the first name, and Unit 3 is the middle name or middle initial. There is little difficulty in assigning the correct alphabetical position in the file to each patient’s record when indexing is done in the unit method.

Unit 1	Unit 2	Unit 3
Jones	John	J.
Jones	John	L.
Jones	Mary	P.
Jones	Mary	W.

A more detailed type of alphabetical indexing uses five units. Unit 1 is the last name in capitals, Unit 2 is the patient’s title, Unit 3 is the first name, Unit 4 is the middle name or middle initial, and Unit 5 is the nickname or name by which the patient prefers to be called.

Unit1	Unit 2	Unit 3	Unit4	Unit5
JONES	Mr.	John	J.	Johnny
JONES	Dr.	John	L.	Jack
JONES	Mrs.	Mary	P.	Mary
JONES	Miss	Mary	W.	Mary

Two difficulties sometimes arise within the three unit system. First, family chart errors are difficult to avoid; and second, confusion results when patients have the same last, first, and middle initials. The five unit system allows a married woman to use her formal name (eg, Mrs. John J. Jones), which would distinguish her from another Mary J. Jones. It also allows patient differentiation by title (Mr., Dr., Mrs., Miss), and shows the name by which the patient prefers to be called. This system greatly reduces the risk of having two files labeled identically.

1.1 Disease Identification/Diagnosis:

A present-day human doctor cannot recall all the information necessary to make a prompt but an accurate diagnosis. With the modern abundance of textbooks, research papers and case studies, no doctor can master every aspect of medical care and recall every detail of the similar cases. Yet, it is possible to feed an AI-based system with relevant data and let the computer sift through the extensive database instead of relying on the much more limited human knowledge.

Disease identification was brought therefore at the forefront of ML research in medicine. Key players on the market were among the first to join the quest for the precise diagnosis, particularly in much-needed areas like oncology. To name only some of them, Boston-based biopharma company Berg applies AI to research and develop diagnostics and therapeutic treatments in multiple areas, including dosage trials for intravenous tumor treatment. The joint effort aims to find the early symptoms of visual problems caused by diabetes and age-related sight degeneration. ML technologies will analyze more than one million eye scans and find out the first signs of visual degeneration which may be missed by most experienced doctors.

1.2 Health Records

Closely connected to personalized medical treatment is the area of health-related documentation. Document classification using support vector machines, as well as optical character recognition, i.e. transforming handwriting into digitized characters, are both essential ML-based technologies in the field of collection and digitization of electronic health information. The domain includes such big players as MATLAB with its ML handwriting recognition technologies and Google offering Cloud Vision API for optical character recognition.

1.3 Treatment gives base on the record

Personalized medicine, which can provide for a more effective treatment based on the individual health data paired with predictive analytics, is also a hot research area. The dominant research method in this domain is so far supervised learning, which allows physicians to select from more limited sets of diagnoses and to estimate the given patient's risk based on the similarity of symptoms and genetic information.

II. Novelty In Proposed Methods:

So far, standard patient database for Two BD architectures stand out among so many, namely, the Lambda Architecture and the National Institute of Standards and Technology (NIST) BD Reference Architecture. In order to satisfy particular needs, Lambda Architecture uses a system based on three main components, namely, a batch layer, a serving layer, and a speed layer (for real-time data). However, NIST BD Reference Architecture is rather an open tool (not tied to specific vendors, services, implementations, or any specific solutions) to facilitate the discussion of requirements, structure designs, and operations that are inherent in BD environments.

- ***Hospital length of stay.*** Hospital length of stay was reported in days and was determined by subtracting the date of hospital admission from the date of hospital discharge.
- ***Discharge destination.*** Discharge destination is the location the patient is residing immediately post hospital discharge and can include: home, other hospital, rehabilitation facility, other supported residential facility (including retirement villages, supported residential services, respite and transitional care), low level care (hostel), high level care (nursing home) or death.

Figure 2: Lambda Architecture

Beyond the processing capabilities of Map Reduce, another option for large scale number crunching is General Purpose GPU Programming (GPGPU), such as Nvidia CUDA and OpenCL framework. Another solution, based in Hadoop, is Mahout Library, which is an ML and Statistics library able to work in distributed application environments. However, the MapReduce key-value approach prevents the implementation of many ML algorithms. Other interesting libraries related to BD are: MLPACK, a state-of-the-art, scalable, multiplatform ML library that provides cutting [15] e.g., algorithms whose benchmarks exhibit far better performance than other leading ML libraries. This architecture used to upload and share patient information, between different doctor's servers.

III. Proposed Methods:

The prevalence of prescribing faults and prescription errors has been quantified in prospective and retrospective cohort studies. Internal or external reviews of prescriptions, performed mostly by experienced pharmacists, or direct interviews or voluntary reports from prescribers have been used as sources of information [4, 5]. Depending on the reference parameters used, the observed incidence varies greatly. It is usually higher in process-oriented studies, which evaluate the presence in the prescription of potentially harmful errors, than in outcome-oriented studies, which mostly evaluate the incidence of preventable adverse drug effects. Prescription errors account for 70% of medication errors that could potentially result in adverse effects. A mean value of prescribing errors with the potential for adverse effects in patients of about 4 in 1000 prescriptions was recorded in a teaching hospital. Such errors are also frequent in ambulatory settings [4–6]. However, given the inconsistency of the criteria used to identify errors and the various definitions used, it is not surprising that a recent meta-analysis showed that the range of errors attributable to junior doctors, who are responsible for most prescriptions in hospitals, can vary from 2 to

514 per 1000 prescriptions and from 4.2 to 82% of patients or charts reviewed. The purpose of this study was therefore to determine the completeness of capture and level of agreement between three different data collection approaches in measuring length of stay and discharge destination. These were:

i. Observational data manually collected from ward-based sources by a research assistant
ii. retrospective administrative data extraction from an electronic patient management program (i.PM), and
iii. Retrospective review of scanned inpatient medical records post discharge from hospital (gold standard).

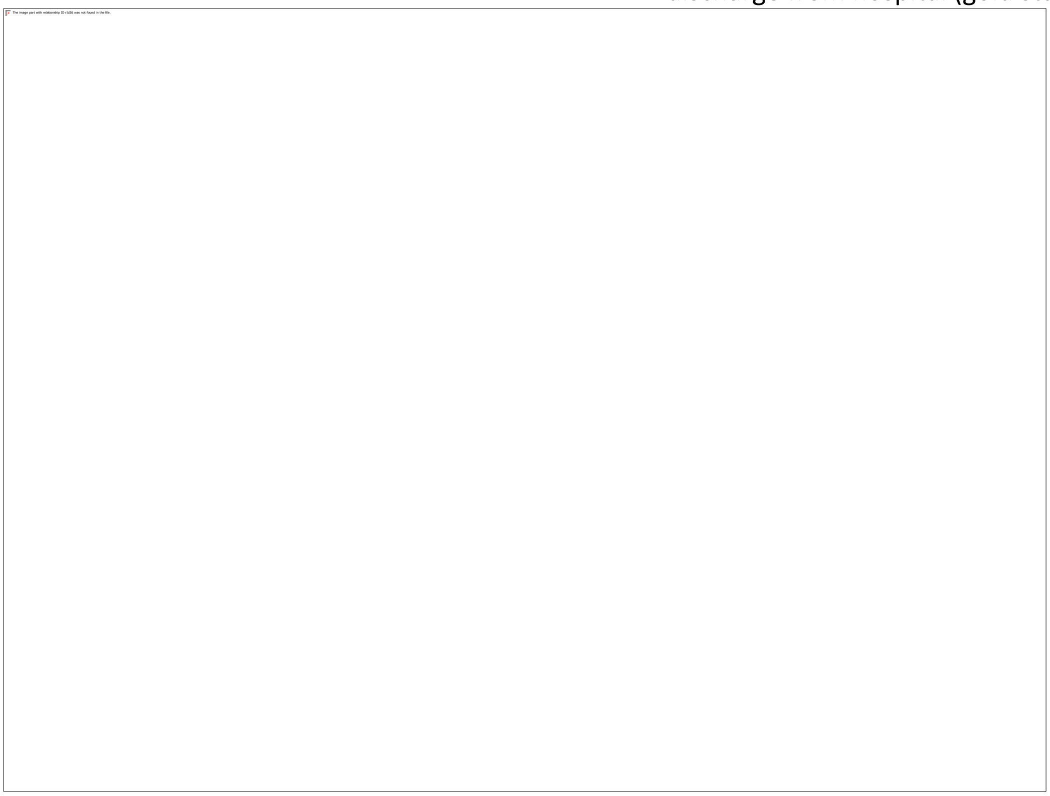

Figure 3: Prescription Reporting and Review by Doctors.

There are numerous methods by which data may be collected for research and hospital administrative purposes. Observational length of stay and discharge destination data can be manually collected from ward-based sources including; nursing handover records, paper-based ward discharge/transfer records, paper-based inpatient medical records, direct observation by experienced personnel, and 24hour recall of key hospital personnel (e.g. Nurse Unit Manager).

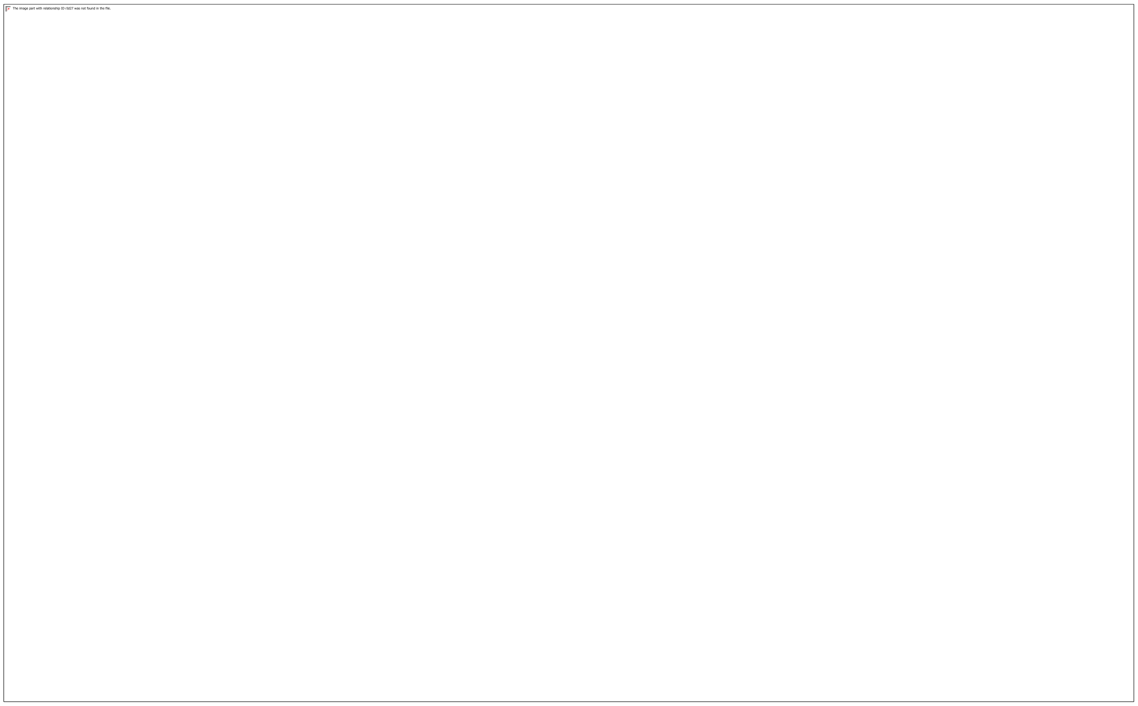

Figure 4: Sharing Prescription Database

However this is a time-intensive data collection method which is difficult to fund in the current environment where research funding is increasingly more competitive. Retrospective data may be collected via review of scanned inpatient medical records post hospital discharge. While this approach has previously been used as a gold standard measure for multiple outcomes, transforming medical records into research data is resource intensive and requires exceptional knowledge and skill in medical context and research. An alternative to these traditional methods of hospital data collection has been to extract electronic administrative data. Retrospective hospital administrative data has become a commonly used source of inexpensive and readily available information. Administrative data is not normally entered specifically for research purposes, with previous literature indicating the use of administrative data in adverse events and coding for billing purposes may result in inaccurate data.

In this Approach Doctors are from different Locations, where each one has their own Server called Node. Any doctor can access the patient information and examine the condition of the patient. Any doctors can update the case sheet as per the querying status of the patient. Doctors has to login to the sever and update. Patient data can be shared to the different associations like insurance corporations and government officials along with the authenticated doctors. Research aspirants also can use the patient data for their upcoming researches.

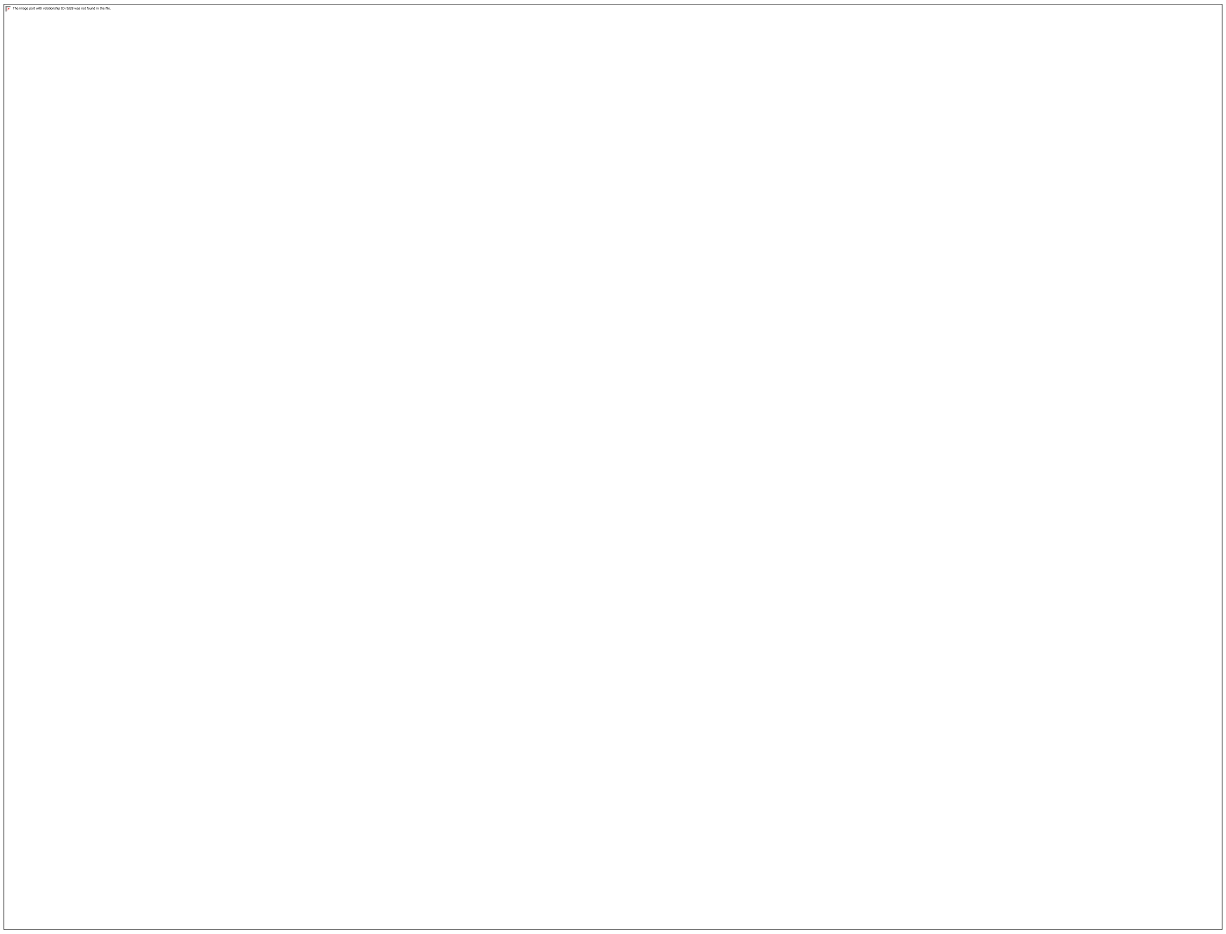

Figure 5: Patient treatment sheet updating procedure

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In the testing phase the data will go through different levels before the final output is achieved. In the first step in testing, the dataset for each dialect is gathered. Then the data pre-processing is done in a similar fashion as compared to training. After the pre-processing step Feature extraction is carried out in the testing phase. After this step likelihood score (β) for each dialect model is calculated and these scores can be noted as β1, β2, β3 and so on. The likelihood score acts a mark to decide on the dialect.

In various cases, there's a clear stage to give a base score to mappings, data and additionally to computations like joins or unions. Usually, the bottom score represents a confidence level, fixing to a node in stochastic process, author-authoritativeness score, or similarity live. In these cases, exploitation the given root age and feat the right theme for combining scores, we are able to mechanically derive a score for the derived information values, within the type of an observation. For example, we are able to mechanically acquire probabilistic event expressions or negative log likelihood scores (describing truth potentialities of a power within the joint event) from source information. Sometimes, similar quite score may become an access level. i.e., if the supply information is thought to own a selected group of access privileges related to them, we have a tendency to be also ready to mechanically verify that derived information ought to have a minimum of a similar quantity of protection. When scrutiny the chance scores with remaining others, the one with the most effective threshold is chosen and so the method involves Associate in nursing finish. When completion of the coaching and testing part we have a tendency to left with the non-standard speech that's known by the software package as spoken by the speaker.

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