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MEDICAL DATA CLASSIFICATION USING ADVANCED COMPUTING TECHNIQUES: A SURVEY

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Abstract:
Electronic medical records (EMRs) were primarily introduced as a digital health tool in hospitals to improve patient care, but over the past decade, research works have implemented EMR data in clinical trials and omics studies to increase translational potential in drug development. EMRs could help discover phenotype-genotype associations, enhance clinical trial protocols, automate adverse drug event detection and prevention, and accelerate precision medicine research. Although feasible, data mining in EMRs still faces challenges. Existing machine learning tools may help overcome these bottlenecks in EMR mining to unlock new approaches in patient care. This paper will give comprehensives view on improving patient care while evaluating the viability and bottlenecks of their uses in data mining, machine learning and deep learning models. And also give analysis on EMR data classification models and their insights.

1. Introduction

Advances in Artificial Intelligence methods have skyrocketed in the past decade, especially in the medical space where the impact of healthcare reaches individuals across a broad spectrum of communities. In particular, machine learning (ML) researchers have gained access to a large quantity of high quality medical data, aggregated by health providers as a result of implementing hospital management systems. A crucial element of these management systems is electronic medical records (EMRs), which are rich in valuable real world data on patient, clinical and genomic data. An EMR is a digitized record of a medical occurrence documented either during or after an encounter by a medical professional in a medical environment. For example, the results of a blood test administered at a hospital may be part of an EMR. Clinical notes taken by the doctor in a routine check-up at a local clinic are also included in the EMR. EMRs can come in the form of structured data such as drug orders, medications, laboratory tests and diagnosis codes or unstructured data such as text-based clinical progress notes, radiology reports and pathology findings [1].

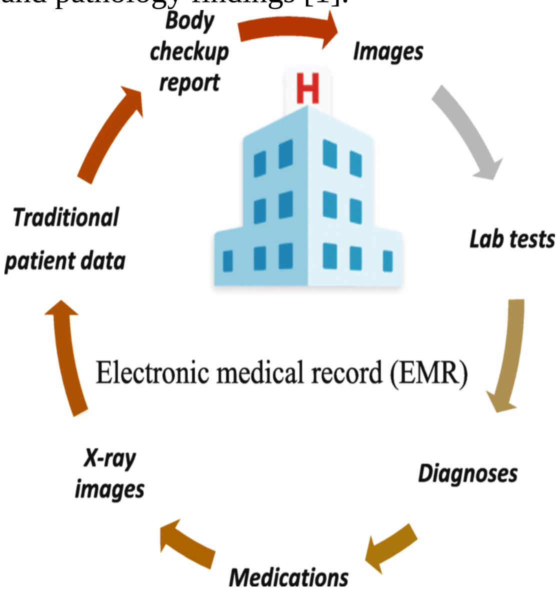

Fig-1: Electronics medical records

When EMRs are amalgamated to create a longitudinal overview of a specific patient, this larger unit of digitized records is called an electronic health record (EHR). Since EHRs contain historical data, they are used to track the health progression of patients over time. Although in some sources, the terms EMR and EHR are used interchangeably, or are sometimes referred to as the electronic patient record, for simplicity the above definitions are used here. Another digital record is the personal health record, which is the electronic medical data that the individual may choose to provide to the medical institutions or health providers, however issues of personal choice in volunteering data are beyond the scope of this chapter, so we do not consider the personal health record here.

Today, providers produce EMRs with the hope to provide a centralized source of medical data, which helps increase care coordination. With a standardized EMR system, if an individual decides to switch health providers, the medical data can seamlessly transfer to the new institutions. Furthermore, centralized medical data reduces duplication of records and identifies missing patient data, which reduces valuable time spent in clinical care. Compared to the traditional paperwork, EMRs significantly decreases disease identification time, making healthcare more time efficient and cost effective [2, 3]. In this sense, the EMRs improve quality of care.

In reality, there are issues in introducing EMRs into healthcare provider systems such as implementation and workflow disruptions. Implementation requires funding, necessary staff, and up to date digital technology. Institutions and geographic regions with ample resources will benefit from this implementation. However, for many smaller scale practices, implementation is not financially viable. For regions where institutions do not have access to technology that enables the production, storage and sharing of EMRs, this concept does not make sense. Furthermore, workflow is disrupted when clinicians and other medical professionals must alter their workflow in order to complete these documents. EMRs are notoriously unpopular in the medical community as it burdens professionals to constantly type on their computer instead of caring for their patients. Burdened professionals do not see the long term benefits and the reality in medical environments is that EMRs are primarily used for financial and administrative purposes. For example, although there are no global standards to what may be included in an EHR, it must always have billing codes, which are used for administrative purposes such as reimbursement or auditing reasons.

Despite these institutional challenges, EMRs are gaining traction in the biomedical space because there is potential to extract important biomedical conclusions from EMRs. As of December 2016, there are just under 2.1 million papers published on electronic medical records in drug development and research within google scholar [4]. Because EMRs are untapped and vast in quantity, researchers are particularly focused on testing ML methods on EMRs. EMRs also provide resources to carry out clinical trials at a lower cost and with reduced duration in terms of efficiency gained from automation and having better data sources. With a manual approach to identify and extract high value data, drug research on EMRs are not scalable and are extremely costly to employ domain experts for data extraction. The push for medical document digitization in conjunction with recent development in ML methods, such as natural language processing (NLP) that allows for machines to mimic human comprehension of written text, has allowed the outsourcing of these research tasks to machines and further facilitate drug research.

In the context of ML methods, EMRs pose problems such as how EMRs do not have a standardized formatting, how minorities could be underrepresented, and how EMRs contain human errors. Today in the healthcare space, EMRs exist in abundance but were not originally created with a large scale data-mining vision [5]. Rather, providers replaced paper-work with electronic records to keep up with the technological pace of the 21st century.

Such digitization of the traditional paperwork was done on an ad-hoc basis and many healthcare institutions independently regulate EMRs to create a highly heterogeneous data set [6, 7]. This heterogeneity makes data pre-processing for ML methods time consuming and financially costly if domain experts are required for this task. Another difficulty stems from the issue of institutions and geographic regions not having access to technology or financial resources to implement EMRs. The lack of EMRs in particular communities means those individuals are not electronically visible. In this sense, EMRs will not be able to sample certain populations in the world. These underrepresented populations will not have as much benefit from the biomedical success of EMRs as those represented in the sample populations, increasing the inequality of medical care. Lastly, basic human error in the EMRs will affect analysis performed on these data sets, if they are not corrected. In addition, the EMRs come from different institutions, which may enter their data differently. Without a standardized requirement for EMRs, some parts will be missing core information and the operation is not scalable.

2. Electronic Health Records

The best known form of clinical data is the electronic health record, which contain lots of important information. An electronic health record is the digital version of a person's medical information and history that is maintained overtime by a healthcare provider.

Medical data found in an electronic health record can include:

- General numerical information, such as vital signs like heart rate, respiratory rate, and temperature.
- Diagnostic-related information, like laboratory test results from blood tests, genetic tests, culture results, and so on. It can also include imagery like x-rays.
- Treatment information. For instance, is the person receiving any medication? If so, how much (what dose) and how often?

Other Clinical Data

Other forms of clinical data include:

- Administrative data, non-clinical research data focused on record-keeping surrounding a service, such as hospital discharge information. This can be part of an electronic health record as well.
- Claims data, which is information regarding insurance claims.
- Patient/disease registries, which are systems that help collect and track clinical information of defined patient populations.
- Health surveys, which can help evaluate or tally statistics like say, the most common chronic illnesses a nation faces.

Characteristics of medical data:

When I survey restorative records as a lawful medical attendant specialist, I locate that specific attributes of the record influence my examination.

- **Accuracy of the medical record**

The precision of the information alludes to the accuracy of the information gathered. It ought to mirror the information given by the real source. Exactness of data contained in the medicinal services record can be influenced by: the patient's physical and passionate wellbeing at the season of information gathering, meeting and archiving aptitudes of the social insurance specialist, access to the patient's past records, unwavering quality of gear utilized for indicative purposes, the remaining task at hand of the suppliers in charge of graphing, familiarity with an awful or unforeseen result, and the trustworthiness of the electronic frameworks used to gather, scatter, and store data.

- **Accessibility of the medical record**

Openness identifies with the simplicity of recovering information, and can be influenced by a few things. The manner in which the therapeutic records are sorted out and printed has a gigantic effect. A few records I get are photocopies with the front of the page having no relationship to the back of the page. At the end of the day, a doctor request might be supported by a nursing note. This disconnected stream influences the capacity to pursue the string of the data.

- **Comprehensiveness of data**

Every single required datum parts ought to be caught in the record, and suggests that the outline is finished. Missing pages or records moderate the advancement of audit.

- **Consistency of information in the medical record**

The consistency of a medical record alludes to the way that the data are solid and that the uprightness of data has not been debased paying little mind to how regularly or how the data have been recovered, seen, put away, or prepared. Once in a while I discover bits of another patient's medical records inside a diagram. This makes me wonder if the data was embedded into the graph while the patient was accepting consideration or when the diagram was being arranged.

- **Timeliness of information**

The planning of recording the data is a key part of data. Medicinal services records ought to reflect current data that is reported as near constant as could be allowed. Inability to keep up a present and auspicious record can impact the consideration and treatment recommended for the patient. Late sections ought to be investigated for self-serving remarks after a terrible result.

- **Relevancy of the medical records**

Are the medical records pertinent to the risk issue related with the case? It is our activity as lawful attendant specialists to enable the lawyer to comprehend the need and advantages for requiring explicit medical records. This helps with getting the law office's collaboration in acquiring the data.

4. Medical data classification methods:

Previously there are many research work on medical data classification in order to get the insights of medical data. Here we give an overview about different types of medical data classification mechanisms.

4.1 Data Mining

Data mining applications are widely used in different domain. Health care sector also used Data mining techniques in different zone like blood bank, Polio and HIV. We know that most of the data related to this disease are available in the form of\ unstructured or semi-structured. Through Data Mining we can focus on target data. We can describe Data mining in various forms that is filter out unwanted information and get desired information and convert this information to knowledge by performing some techniques. In the modern day's data being generated in most of organizations is measured in huge volume and it will be gigabytes or terabytes. Medical sector also have huge number of information and it is growing day by day. When we are looking for information from several terabytes of information it can be difficult to search such similar information from large volume. This shows the necessity for intellectual use of technology to be step ahead which is helpful for society and medical sector.

Data mining states to use variety of techniques to identify and filter out information or knowledge in data, and extracting these data for different areas like decision support, prediction etc. Through data mining, medical sector and Government can extract valuable information about trend, individuals, and segments from the mass amount of data. Data mining involves the use of statistical and mathematical techniques such as cluster analysis, predictive modeling and neural networking. Data mining is the procedure of analysis of source data from different viewpoint and categories it into valuable information which is useful for many people of society. Data mining is a technique of finding patterns and generates models from dataset. The several kinds of patterns that can be discovered which is highly depending upon the data mining tasks employed. Data Mining has been found increasing reception in business areas which need to analyze huge volume of data to discover knowledge and such knowledge converted into useful information. Data mining provides good results in the cases of time dimension procedure to get evolution of the present data and their relations need to be observed. The main purpose or reason that data mining is getting increasing attention in the present era because of wide range of availability of massive amount of information and using such process need to be turning it into knowledge. Great number of research work has been done using data mining techniques on medical sector throughout world.

4.2 Machine learning in medical data analysis:

The capacity to learn is a standout amongst the most basic qualities of insightful conduct. Machine learning is a subfield of AI concentrating computational strategies that can improve execution on some assignment by learning[8]. The point of machine learning exploration might be intellectual, specialized or theoretical[9]. Subjective points look to show human learning at some dimension. Mechanizing the procedure of learning obtaining for information based frameworks is a case of a specialized point. Hypothetical examination considers, for instance, qualities of learning strategies, for example, their degree and confinements. Like AI, machine learning is an intrinsically interdisciplinary recorded. Measurement, for instance, is generally used in the field of ML.

Machine learning techniques can be characterized based on different criteria, for example, fundamental learning procedure, portrayal of information, or application area. Langley and Simon[10] discovered five noteworthy standards in the field of Machine learning: Neural systems, Instance based learning, Genetic calculations, Inductive learning and expository learning. These standards share the shared objective of improving the exhibition of some errand, which is normally accomplished by finding and abusing regularities in preparing data.

Information procurement and data mining are significant application zones of Machine learning. Machine learning techniques have been used in a wide assortment of use areas, for example, Visa extortion location, manually written character acknowledgment, discourse acknowledgment, showcasing investigation, quality control in assembling, aircraft seating allotment, sustenance and synthetic equation enhancement and programmed grouping of heavenly objects[11].

The medical spaces wherein ML has been utilized are analysis of intense a ruptured appendix [12], conclusion of dermatological malady [13], determination of female urinary incontinence[14], analysis of thyroid diseases[15], discovering qualities in DNA[16], result forecast of patients with serious head injury[17], expectation of metabolic and respiratory acidosis in children[18], just as relating clinical and neurophysiologic evaluation of spasticity[19], among numerous others.

As medical data frameworks in present day emergency clinics and medical establishments become bigger and bigger, it causes extraordinary troubles in separating helpful data for choice help, particularly when conventional manual data examination has turned out to be wasteful and strategies for proficient PC based investigation are fundamental. Along these lines, presentation of a cutting edge, proficient and successful PC based strategy in medical investigation for choice help is justified. Medical examination utilizing machine learning systems has been executed throughout the previous two decades. It has been demonstrated that the advantages of bringing machine learning into medical investigation are to increment symptomatic precision, to lessen costs and to decrease HR. For instance, "Dementia because of Alzheimer's infection and different dementias comprise the fourth most regular issue among the older and have a complete expense in the USA of $100 billion every year. Legitimate treatment can diminish this expense by up to 25%[31].

Machine learning includes utilizing PCs to discover standards, or PC models that best portray issues from an electronic database. Machine learning systems are partitioned into two classifications: regulated learning and unsupervised learning. As the name may recommend, administered learning is a machine learning procedure that finds the best portrayed PC model from a database with the right class variable. The class variable is the variable of a database that the PC model needs to arrange.

In the present examination we utilized various types of machine learning methods: Neural networks[32], Decision trees[33], Bayesian networks[34] and Genetic algorithms[35] and so on. Besides, there are two distinct stages in any machine learning procedure: preparing stage and testing stage. The preparation stage is the point at which a PC model is actuated from a lot of tests in the database. In the testing stage the fabricated PC model is tried from a lot of inconspicuous examples in the database

Applying Machine Learning (ML) to physiological data represents a few difficulties. While ML can be adequately used to display well-characterized frameworks, applying it to a framework as mind boggling as the human body directs a considerably more cautious methodology.

Clinicians comprehend when an incessantly sick patient requires consideration by checking fundamental signs, just as several different highlights. The human body is made out of a few frameworks that influence one another, each with its very own goals and control instruments. In our models, every framework can be displayed with a vector of highlights and indispensable signs that portrays its state and a control model, (for example, an input circle). For instance, the mind controls dimensions of CO2 in the blood by expanding or diminishing breath.

With our group of ML specialists and biomedical designers, we distinguished a few key regions of center in our journey to display physiological procedures. In a portion of these territories, the ends we came to were outlandish.

4.3 Deep learning in medical data analysis:

Healthcare associations all things considered, types, and claims to fame are winding up progressively keen on how man-made consciousness can bolster better patient consideration while diminishing expenses and improving efficiencies.

Over a moderately brief timeframe, the accessibility and advancement of AI has detonated, leaving suppliers, payers, and different partners with a bewildering cluster of devices, innovations, and procedures to browse.

Simply learning the dialect has been a top test for some associations. There are inconspicuous yet critical contrasts between key terms, for example, AI, machine learning, deep learning, and semantic figuring. Seeing precisely how data is ingested, broke down, and came back to the end client can bigly affect desires for exactness and dependability, also impacting any ventures important to get an association's data resources ready. So as to proficiently and adequately pick between seller items or contract the correct data science staff to create calculations in-house, healthcare associations should feel sure that they have a firm handle on the various kinds of computerized reasoning and how they can apply to explicit use cases.

Deep learning is a decent spot to begin. This part of man-made brainpower has in all respects rapidly turned out to be transformative for healthcare, offering the capacity to break down data with a speed and accuracy never observed.

In any case, what precisely is deep learning, how can it contrast from other machine learning procedures, and by what method can healthcare associations influence deep learning systems to comprehend the absolute most squeezing issues in patient consideration?

5. Literature survey

5.1 Medical imagining using Data mining:

Picture mining is plainly unique in relation to low-level PC vision and picture handling strategies. This is on the grounds that the focal point of picture mining is the extraction of examples from a huge assortment of pictures, while the focal point of PC vision and picture preparing systems is understanding or potentially separating explicit highlights from a solitary picture.

Ordonez et al [1] presented another concentration for data mining which is worried about information revelation in picture databases for discovering affiliation. This methodology introduces a data mining calculation to discover affiliation leads in 2-dimensional shading pictures and it doesn't depend on an area information. The exploratory outcomes show that the picture mining is practical and recommends a few bearings for future work around there. The vast majority of the ongoing written works on picture mining are dedicated to information disclosure, for example, grouping and mining affiliation rules. The issues of looking through the areas of exceptional visual consideration or fascinating examples with regards to a huge arrangement of picture are likewise managed.

Hsu et al [2] acquainted the picture mining with consequently extricate semantically significant data (information) from picture data. It has checked on that the picture mining can be utilized for biomedical applications. Perner has exhibited an instrument and a technique for data mining in picture-documenting frameworks. It is planned to find the significant information for picture investigation and conclusion from the data base of picture portrayals. Information Building techniques are utilized to acquire a rundown of traits for representative picture portrayals. A specialist portrays pictures as indicated by this rundown and stores portrayals in the data base.

Agrawal and Srikant et al [3] have announced that the therapeutic data mining has incredible potential for investigating the shrouded examples in the data sets of the medicinal area. These examples can be used for clinical determination to give a user-oriented way to deal with novel and concealed examples in the data. The effects of data mining methods remembering fake neural systems for restorative diagnostics have likewise been inspected. Have introduced the Apriority, Apriority Tid and Cross breed calculations for finding all huge affiliation manages between things in a huge database of exchanges.

Stanchev et al [4] have introduced another technique for picture recovery utilizing significant level semantic highlights. It depends on extraction of low-level shading, shape and surface qualities and their transformation into significant level semantic highlights utilizing fluffy creation rules determined with the assistance of picture mining procedure. Data mining advancements have additionally been widely applied on clinical data so as to remove new medicinal information as helpful and non-paltry example have presented the new looking through calculation in picture databases to dodge comprehensive pursuit utilizing staggered signature document ordering procedure. This system doesn't cause any obvious expulsions and the mark parameters can be chosen to limit the bogus drop likelihood. Prior investigations uncover that the various tissues/organs of premium can be characterized utilizing the anatomical structure present in the pictures. Notwithstanding, the pixel-based surface methodology has been liked to characterize the areas of intrigue. This methodology fuses different surface highlights and choice trees to achieve tissue grouping in ordinary CT pictures.

Kaus et al [5] have built up the robotized division apparatuses to make division of X-ray pictures by supplanting manual laying out proposed a strategy for the recognition of masses in mammographic pictures that utilizes Gaussian smoothing and sub testing activities as pre-handling steps. The mass district is fragmented by building up force joins from the focal parts of masses into the encompassing territories. It is utilized to order the districts portioned as kind masses or threatening tumors by processing surface measures in versatile strips of pixels encompassing the mass areas.

Liu et al [6] have proposed a structure to incorporate characterization and affiliation rule mining. The calculation was created to produce all class affiliation rules (Vehicles) and a precise classifier. Afterward, Antonie considered the affiliation rule mining to manufacture PC supported frameworks to help medicinal staff in restorative consideration offices. Serhat and Yulmaz have detailed a mechanized framework for distinguishing masses in mammogram pictures. This framework has been actualized thinking about districts of intrigue (return for money invested) and rule-based grouping.

Yu et al [7] have announced the different parts of highlight choice by presenting the two models to be specific a classifying structure and a binding together stage. They arrange the huge collection of highlight determination calculations, uncover future bearings for growing new calculations and to direct the choice of calculations for smart component choice. Another component choice calculation can be consolidated into the system as indicated by the three measurements.

Container et al [8] Picture mining manages all parts of enormous picture databases which infer that the ordering plan, the capacity of pictures and the recovery of pictures are all of worries in a picture mining framework the pictures from a picture database are first pre-handled to improve their quality. These pictures at that point experience different changes and highlight extraction to create the significant highlights from the pictures.

5.2 Medical imagining using machine learning:

Katarzyna Krupa, et al [9] summarized the artifacts in MRI and foreign bodies [medical implants, dental filling, cosmetics, tattoos, hair bands, surgical clips, labels on clothes, etc.] inside the patient body may confuse the pathology or may reduce the quality of investigations. The author says that the radiologists are often not told about the medical history of patient's and whether it is post-operative images or not. The author has presented images with different types of artifacts. The author proposed some methods of reducing artifacts but not discussed in detail the procedures to avoid or limit artifacts.

L J Erasmus, et al [10] in their review article has highlighted many different MRI artifacts and possible rectifying methods adopted by the radiologists. However, the author has not suggested any technique to remove artifacts by image processing techniques.

Sabine Heiland, et al [11] has explained a variety of artifacts that appear in MRI. The author state that the artifacts may degrade image quality and simulate or mask the pathologic abnormalities. He attracts the attention of personnel running MRI scanner to aware of the potential sources and also the physical origin of artifacts.

Mohana H S, et al [12] has discussed zipper artifact, presented and implemented a modified Gaussian technique to remove zipper artifact and they claim that the results are satisfactory.

Hayit Greenspan et al [13] implemented an automated segmentation algorithm to segment brain MRI images acquired under varying noise conditions using Expectation maximization (EM) and Gaussian mixture model (GMM). The authors claim that the algorithm was applied on different slices of T1 weighted images which were noisy and the algorithm gives superior results both visually and quantitatively.

M Usman Akram, et al [14], the authors applied global thresholding and morphological operations to remove false segmented pixels in the image and claims that the algorithm precisely segments and identifies the tumor from brain MRI images.

K Somasundaram, et al [15] the authors presented a fully automatic segmentation algorithm for extraction of tumor from axial plane T2 weighted MR images. They applied thresholding, morphological operations, largest connected component analysis and filter mask to extract the tumor. They conclude that the proposed method gave better results compared with other segmentation methods. the authors implemented a fully automatic segmentation algorithm using thresholding and mathematical morphological operators for detection of abnormalities in brain MR images and applied on different types of brain MR images for both visual and quantitative evaluations. They conclude that this method yielded promising and reliable results in a time frame of few seconds to attain accuracy of tumor detection, to identify the exact region and locations of tumor in the brain.

Mohammad Mahmudul Alam Mia, et.al [16] utilized back spread neural system effectively in numerous zones with amazing speculation results. Levenberg-Marquardt back-engendering calculation is used for preparing the system and recreates the picture. It is discovered that Marquardt calculation is essentially increasingly capable. Creator has decided the issue of number of neurons in each concealed layer and the number of shrouded layers required for high exactness.

Hari Babu Nandpuru, et.al [17] proposed a classification system using SVM by dissimilar seed purposes to recognize and classify the brain MRI images as usual and unusual. In this feature extraction is done by leaden ruler, regular and consistency structures. The authors conclude that the method gives more accurate results.

P. Mohanaiah, et. al [18] explained a texture feature extraction using GLCM. In this paper, author exhibited a utilization of GLCM to deliberate second request factual surface components for movement estimation of images.

M. Madheswaran, et. al [19] developed and presented an enhanced classification system for brain tumor classification from MRI images using association of kernels with support vector machine. Image segmentation is done using fuzzy-c means algorithm and image features are extracted using GLCM. The authors claim that the accuracy is found to be high for SVM classifier with GRBF kernel.

5.3 Medical imagining using Deep learning:

Deep learning is a kind of machine learning where a perfect statistic available in what way to achieve characterization projects frankly after movies, gratified or complete. Deep learning is normally actualized using neural scheme engineering. The term deep mentions to the amount of coatings in the scheme—the additional the coatings, the deeper the scheme. Usual neural schemes cover fair an insufficient coating, though deep schemes container consume hundreds.

Ciresan et al [20] utilized a deep CNN to recognize mitosis in bosom malignant growth histology pictures. Their systems were prepared to arrange every pixel in the pictures from a fix fixated on the pixel. Their strategy won the 2012 Global Meeting on Example Acknowledgment (ICPR) Mitosis Recognition Contest, outflanking different challengers by a huge edge. From that point forward, various gatherings have utilized diverse deep learning techniques for location in histology pictures.

Xu et al [21] utilized a SAE to distinguish cells on bosom malignancy histological pictures. To prepare their deep model, they used a denoising auto-encoder to improve strength to anomalies and clamors. Su et al. (53) utilized a SAE just as meager portrayal to recognize and section cells from tiny pictures.

Sirinukunwattana et al [22] proposed a spatially obliged CNN (SC-CNN) to identify and group cores in histopathology pictures. In particular, they utilized a SC-CNN to appraise the probability of a pixel being the focal point of a core, where pixels with high likelihood esteems were spatially obliged to situate in the region of the focal point of cores. They additionally built up a neighboring group indicator combined with a CNN to all the more precisely anticipate the class mark of the distinguished cell cores.

Chen et al [23] planned a deep fell CNN by misusing the system of the full CNN, which replaces the completely associated layers with all convolutional portions. Based on the recovered applicants, they at that point made a fine segregation model by moving deep and rich element chains of importance learned on a huge normal picture data set to recognize mitoses from hard emulates.

Moeskops et al [24] concocted a multiscale CNN to upgrade heartiness in neonatal picture division and spatial consistency. Their system utilized different fix sizes and various convolution portion sizes to procure multiscale data about each voxel. Utilizing this strategy, the creators acquired promising division results for eight tissue types, with a Bones ratio6 averaging 0.82 to 0.91 more than five distinct data sets.

Zhang et al [25] planned four CNN designs to fragment Newborn child cerebrum tissues based on multimodal MRimages. On a lot of physically portioned is intense-stage mind pictures, these CNNs essentially beat contending techniques.

Nie et al [26] proposed the utilization of different completely convolutional systems (mFCNs) to section isointense-stage cerebrum pictures with T1-weighted, T2-weighted, and FA methodology data. Rather than basically joining three-methodology data from the first (low-level) include maps, they utilized a deep design to adequately intertwine significant level data from every one of the three modalities. They expected that elevated level portrayals from various modalities were correlative to each other. To begin with, the creators prepared one system for every methodology so as to successfully utilize data from numerous modalities; second, they melded different methodology highlights from the high layer of each system.

5.4 EHR data analysis using data mining:

Numerous doctors' question that electronic health records (EHRs) improve the nature of care. However, generally scarcely any practices are mining their EHR data to perceive how well they're doing or to refresh their consideration conveyance forms. Most are gathering data chiefly for outside announcing purposes, for the most part with the assistance of mechanized EHR highlights.

At the malady level, many chart-based SSL techniques were proposed. **Garla et al. [27]** applied Laplacian SVM as an SSL approach for malignant growth case the executives dependent on clinical content data. They extricated named elements from clinical content and spoke to each report utilizing a sack of-word portrayal, which brought about element vectors with in excess of 15,000 measurements. Their investigations demonstrated that the Laplacian SVM classifier outflanked the conventional SVM classifier.

Wang et al. [28] proposed a diagram-based SSL strategy that had the option to learn understanding danger bunches for tolerant hazard stratification. In view of the perception that hazard factors and their significance may change crosswise over various patient gatherings, they included their target work a gathering term that relegated patients into chance gatherings and a coordinating term that demonstrated the gathering task and mark expectation. Their proposed strategy beat traditional SSL technique, for example, GGSSL [99] on UCI datasets. They likewise exhibited six hazard bunches recognized by their strategy from a dataset with 1,296 Congestive Cardiovascular breakdown (CHF) patients.

Kim et al. [29] proposed a co-preparing diagram-based SSL technique for bosom malignant growth survivability expectation that used the supposed pseudo-marks. The calculation iteratively doles out pseudo-marks to unlabeled statistics once there remained an accord among the students. Their calculation originally built a bipartite chart that catches the connection between the marked and unlabeled occurrences. In light of the developed bipartite diagram, the closeness scores were processed with the end goal of order.

To catch the time part of the data, **Liu et al. [30]** developed a transient chart dependent on medicinal occasion groupings of potential patients for worldly phenotyping. They defined the learning issue as a grid recreation issue with an objective to limit the remaking mistake. The calculation learned chart bases as phenotypes and their loads. Their proposed transient phenotyping approach has been appeared to beat collected vector portrayal and other pack of-design portrayal for characterization.

Qian et al. [31] proposed an inquiry determination system that, rather than posing total inquiries, for example, names, the calculation requested that the human specialists answer the general similitude of the neighboring focuses to the questioned point by setting requesting on them. They planned the issue as a quadratic advancement issue that limits the reproduction blunder of a patient closeness lattice. The requesting gave by the master was encoded as the imperatives in the streamlining issue.

Herland et al. [32], With the overwhelmingly enormous healthcare data accessible, the pressing inquiry presently is the means by which to plan more astute instruments to investigate, break down, use, and bridle the data. In sustenance expressions, the arena of investigation is named Condition Informatics, which is an order that joins data discipline and software engineering inside the domain of healthcare with an objective to at previous improve the countryside of caution.

For lists intended for individual health status, **Yi et al. [33]** built up a bio-mark based framework to review individual health status. They likewise call it individual health list. The record is determined dependent on a direct mix of four lists, whose loads are dictated by master information. These four files are cardiovascular record, stress file, heftiness file, and the executive's file. Be that as it may, their methodology has the accompanying three hindrances: First, they don't consider the various long periods of data accessible for a similar individual, which shows a ceaseless improvement of an individual health status. Second, they don't go out on a limb (i.e., the passing) of an individual into represent foreseeing an individual's health status. Third, their calculation doesn't rank a person's circumstance against the entire populace. To summarize, the current methodologies of health file calculations are absolutely founded on master information and in this way just think about a restricted arrangement of elements. Scoring Frameworks Visualization has for some time been a typical practice for doctors. So as to limit human subjectivity and blunders because of idealism and weariness, diverse scoring frameworks have been presented.

5.5 EHR data classification using Machine learning:

Access to patient outcomes is necessary to leverage EHR data within any machine learning system. Traditionally, outcomes are manually coded by physicians or trained coders. More recently, natural language processing-based systems have been used to automatically extract outcomes from clinical free-text data such as the physician's dictation.

The Physio net project **Goldberger et al [34]** a collaborative effort between MIT, Harvard's Beth Israel Hospital and Boston University created the first publicly available HER data repository for adult ICU data. They created a database called MIMIC that contains comprehensive EHR data from a single ICU visit. However, the identity of a patient is not tracked across multiple visits; thus, data across multiple visits for any single patient cannot be tracked. Most adult ICU patient visits last from a few hours to a couple of days so only short-term monitoring of health status is feasible using this data. The MIMIC database has spawned a body of work on physiologic signal processing from high granularity beat-to-beat heart rate data.

Peng et al [35] is a method for studying the fractal characteristics of beat-to-beat variability in the heart rate, measures correlations in the beat-to-beat signal over short- and long ranges. Altered correlation patterns have been found in signals from both patients with amyotrophic lateral sclerosis congestive heart failure and infants with intraventricular hemorrhage.

Syed et.al [36] have developed a method where beat-to-beat heart rate signals are windowed and similar windows are found using random projections. A frequency spectrogram of the resulting windows was found to be predictive of morbidity in patients with acute coronary syndrome within 90 days of a non-ST-elevation. A large amount of work has been done in the signal processing community related to electrocardiogram (EKG) data for examples). Overall, most approaches are not general purpose and tailored to a specific signal.

Stacey et.al [37] Techniques for constructing abstractions or lower-dimensional representations of multipara meter clinical time series data for the purpose of hypothesis discovery have been developed extensively. These methods typically manually identify characteristics of intervals that are clinically relevant for individual diseases. Alternately, they extract general purpose symbols (e.g., decrease, increase or constant) which are further abstracted to form strings of symbols to represent complex phenomena in the time series. These methods are work-intensive, and rely on clinical experts and heavy manual knowledge engineering (see for a survey).

Mietus et al [38] the majority of work on bedside monitoring has focused on generating alarms. Known clinically-relevant signatures (e.g., is the heart rate at the current time beyond the clinical norm or is the patient undergoing apnea are detected in real-time via online analysis of the continuously streaming measurements. Another line of work has focused on reducing false alarm rates by modeling false alarm events such as sensor drops or a blood sample draw. In both cases, the goal is of automation and not discovery.

Knaus et al [39] in the neonatal and adult population, risk prediction tools have been developed for measuring severity of disease. For example, in adults, the APACHE and APACHE II scores combine measurements such as temperature, heart rate, blood pressure and so on to make assessments in the first 24 hours about illness severity for patients in the ICU. Neonatal risk prediction scores of CRIB, SNAP and SNAPPE combine laboratory measurements and vital signs at 12 hours to quantify overall health. All of these scores require invasive tests and manual intervention. Outside the ICU, numerous other works have used clinical data and Bayesian networks for building expert systems for clinical decision support. More recently, clinical events from the EHR have been combined for predicting individual conditions.

Meystre et al [40] a different community of researchers has focused on using natural language process for information extraction from free-text data contained in the EHR. A popular approach here is to use a concept indexing system which seeks to map text to standardized concepts using terminologies such as those in the Unified Medical Language System (UMLS). The identified concepts are then used for a variety of extraction tasks for example, generating medication lists and patient problem lists, extracting coded data for decision support systems, or automatic detection of adverse events.

Goldacre et al [41] Recent efforts have been made to build large databases that consolidate data across multiple institutions for clinical discovery especially in relatively infrequent and complicated diseases Most studies on discovery are based on association rules between terms discovered in the free-text. These methods cannot be easily extended to incorporate domain knowledge or various types of clinical biases.

Gandhi et al [42] Automated extraction of patient outcomes from the rich EHR data source can improve quality of care. A recent article [in the New England Journal of Medicine emphasizes the importance of completed patient problem lists, its role in avoiding medical mistakes and a way of deriving comprehensive lists using automated extraction algorithms. Automated outcome extraction can also serve as infrastructure for clinical trial recruitment, research, bio-surveillance and billing informatics modules.

5.6 EHR data analysis using deep learning:

Late improvements in deep learning and artificial neural systems may enable us to address many of these difficulties and open the data in the EHR. Deep learning developed as the preferred machine learning approach in machine recognition issues extending from PC vision to speech recognition, yet has all the more as of late demonstrated valuable in normal language handling, grouping prediction, and blended methodology data settings.

Esteva et al [43] gives a brief overview of how these are being applied to EHRs. It talks about how Convolutional Neural Networks (CNNs) are being applied for medical imaging, especially in radiology applications, giving very good performance. CNN being used with transfer learning methods, i.e., methods to learn CNN on very large datasets like ImageNet but usage of those models on medical imaging data has yielded very good results. In Natural Language Processing, deep learning is used in the form of Recurrent Neural Networks (RNNs), to learn features from the medical data as a time series. It can incorporate structured data like demographics and lab results, and also data from notes. Unsupervised learning methods like usage of autoencoders

Beaulieu-Jones et al [44] which is the practice of learning useful features from data by first reducing the dimensionality and then reconstructing unlabeled data, has also been prevalent in these applications. There has been active research on RNNs being used with very large (size of as big as 46 billion data points) medical datasets to combine both the structured data and unstructured (note) data, to give some very impressive results in in-hospital mortality prediction, 30-day readmission prediction, length of stay forecasting and final discharge diagnoses prediction.

In a slightly similar work**, Shickel et al [45]** does a detailed survey on the current deep learning methods that are being used in the notes in Electronic Health Records. The first application that it is primarily used in is information extraction, whether it is a singular medical concept (like disease, procedure, treatment), temporal event (a singular medical concept with respect bounded by time - like last week, last month, last 6 months), relations between medical concepts in notes, or expanding abbreviation with the help of free text available. The other applications include representation learning of ICD-9 codes, i.e., learning a real value vector representation of an ICD- code1 and mortality prediction, i.e., predicting whether the patient would die within their course of stay in the hospital (in-hospital mortality) or would die after a certain period of time after they get discharged (out-of-hospital mortality). Another very interesting application of notes in EHR is phenotyping, an active area of research in medicine, which can possibly give us more fine-grained subdivisions in types of diseases and give us better precision in specific diagnosis. This not only would improve how we would define diseases now, but it also gives us the possibility to discover new phenotypes. This is evident from the fact that Google's Deep mind was able to solve the protein-folding problem, something what medical researchers thought would be impossible to solve.

Another work, **by Lee et al [46]** shows how we can model notes into embeddings and use then in a feed-forward neural network to obtain named entities, which would help in dataset deidentification, and therefore it would be easy to share the dataset with people who would be interested in this research. The Sachan paper also performs a Biomedical Named Entity Recognition, but uses a labeled dataset instead of training on an unlabeled note.

Another very common project for medical word embeddings is the Graph-based Attention model or GRAM **Choi et al [47]** Like Med2Vec, GRAM also takes the set of all ICD codes and patient visits as its main inputs. But here the initial visit vector is not created straight away, and instead the codes are arranged in the form of a directed acyclic graph, with the more general concepts at non-leaf positions and the more specific codes at leaf nodes. Depending on the type of visit, the code is taken from one of the leaf nodes along with its parent nodes and then these codes are converted into the embedding space and combined together by using an attention mechanism. After passing this through a tanh activation, it returns the final visit vector. This vector after passing through a feed-forward neural network returns the predicted ICD code, which is seen to give a higher AUC score than the baselines.

An excellent example of how embeddings can be run on unstructured data (or notes) is given by **Zhu et al [48]** it first forms a contextual word embedding with ELMo, by using a corpus of clinical notes and wikipedia pages related to medicine. After the training is done, this trained embedding is run on different kinds of notes available in EHRs with the help of a bidirectional LSTM, and returns the precise clinical concepts related to a word or phrase in the input note. This technique achieves the best F1 score for clinical concept extraction and has a lot of uses in mortality prediction, diagnoses prediction and automated de-identification.

The paper by **Kiros et al [49]** provides a good introduction to this concept. That concept can be easily extended to note writing, especially for writing notes from radiology reports. The images can be given as inputs to the log-bilinear model defined in the paper to generate radiology report from the images. An implementation of generating radiology notes has been tried but can be extended to support this notion of modality. There are some machine learning methods that have been used for general applications in which prediction needed to be made from data coming from various sources. An example of this is the paper, which introduces a topic model called Scholar, which takes as input the text documents, and then uses a modified version of Latent Dirichlet Allocation, after which the intermediate representation is passed onto a Variational Autoencoder [50], which can also take as input any word embedding of the metadata available with the document, and then predicts the final document label. The system when tested on a news articles, imdb and yahoo datasets returned the highest accuracy compared to other linear models and topic model baselines.

6. Conclusion:

In the past decade, EMRs have become a vital data source in advancing healthcare. In the context of AI, EMRs are highly attractive because there is a vast quantity of rich and variable data types which cannot be processed manually. In the context of biomedical research, EMRs have exciting potential for impactful medical applications, but only if actionable biomedical conclusions can be accurately extracted. In the clinical context, EMRs were introduced to replace the traditional paperwork but were not intended for data-mining research; they were never intended to perform anything that paper documents were not designed to do. Having been introduced in a time before the phrase "machine learning", digitization of medical records has far surpassed the imagined benefits of this transition. Envisioned as a direct replacement of paper records, EMR history has been fraught with difficulties: implementation costs, workflow disruptions and cyber-attacks to name a few. Harnessing EMRs for research purposes marks a milestone in translational biomedical medicine. It is the intersection of basic science, data-driven methods and clinical research where healthcare is transformed: every hospital visit improving human knowledge of diseases one EMR at a time.

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