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Research Article

An Economic Decision-Making Model for Drugs Using Big Data and Convolution Neural Network in Healthcare

Jinqiao Yuan

School of Business Administration, Northeastern University, Shenyang, 110819 Liaoning, China

Correspondence should be addressed to Jinqiao Yuan; 1410477@stu.neu.edu.cn

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Incorporating health big data (HBD) and observational real-world patient-level genomic and clinical data in several subpopulations into drug economic analysis of precision medicine has the potential to be beneficial ion various ways. However, health economists encounter practical and operational difficulties when using HBD in this framework. On an individual patient level, the “big data” age represents an exciting opportunity to use strong new sources of information to reduce clinical and drug economic uncertainty. Health big data is a very important resource in the field of medicine. It is an irresistible trend to rationally utilize the advantages of health big data to serve medical care and clinical medicine. Health big data will play an irreplaceable role in pharmaceutical research and development, disease diagnosis and treatment, health risk factor analysis, public health emergency management, residents’ health management, and precision medicine. However, the application of health big data in the field of medicine also faces some challenges, such as irrational drug use in primary medical and health institutions. This paper builds a drug economic decision-making model based on health big data and uses a convolutional neural network to study the model. This research is conducted to realize the understanding of drug demand, which is conducive to the country’s understanding of drugs. It also allows people to better seek medical treatment. Artificial intelligence’s new advancements in the big data era have prepared the way for future rational drug modeling and evaluation that will have a huge influence on drug discovery methods which ultimately have better impact on public health.

1. Introduction

Human and disease genetics, which have unlocked the capacity to target the medicines to be the most beneficial for the patients, have long been identified with personalized medicine [1]. Medicine is a specialized entity that is used to diagnose, prevent, and treat illnesses. The application and cost of medicines accounts for a large proportion of medical and health services, with the gradual increase in the public’s understanding and awareness of the concept of health and the improvement of the public medical service system [2]. Therefore, in addition to reliable efficacy and high safety, the cost of treatment approaches has become a significant indication of medical and health services in the basic selection principle of drugs [3]. But at the same time, the information asymmetry between doctors and patients is an inevitable reality in the process of traditional medical and healthcare services. Medical and healthcare service institutions have obvious information advantages, which can easily lead to induced demand and moral risk in the process of implementing medical services. Advise patients to experience unnecessary tests or purchase additional medications [4, 5].

Over the years, a lot of money has been put into achieving the promised benefits of big data. China, for instance, has put millions of dollars into Big Data Knowledge Centers. Several proposals and projects under the Horizon 2020 program in Europe have focused on using big data to enhance healthcare (i.e., AEGLE, OACTIVE, and Big Mediatic). All of the programs obtained \$290 m in financing in 2018, intending to personalize healthcare using a variety of data sources (such as genetic data, monitoring data, and electronic health record data) from 1 million Chinese citizens. The commercial sector’s investments in “big data technology” considerably outnumber those made by governments [6, 7].

Economic evaluations can be used to assess the (potential) return on investment of novel technologies to make the best use of limited resources. Drug economic evaluations are comparison analysis of the costs and benefits of different treatment options. Drug economic evaluations that give information on a technology's health and economic influence can assist with decision-making and support additional investments required to fulfill a technology's potential. Even though big data analytics has the potential to reduce costs, it is unclear if this claim is backed up by concrete evidence. As a result, we wanted to see how big data analytics may support clinical decision-making in terms of health and drug costs. We begin by determining how analytics influenced clinical practice due to the absence of a clear concept for big data. Then, we assessed which of these analysis fit within the category of big data analytics [8].

Since my country's health service costs, especially the raised prices of drugs, are increasing year by year, the problems of limited health resources in the country and the growing demand for health services have become increasingly acutely. The problem with low ability is a significant concern. As a result, the new pharmacoeconomics technique aims to achieve the best possible results. In my country, the exploration and practical work of enhancing health effects with limited drug resources has spread quickly and extensively, and more and more medical institutions and scientific research institutions have begun to try this exploration and practical work [9]. At the same time, with the rapid development of information technology, the Internet has become an important channel for people to obtain medical service information.

Through the information channel, patients can improve their understanding of their own health status. Patients believe that they can and are responsible for their own daily disease management. In this form, medical institutions are required to improve the quality of medical services and make information on diagnosis and treatment and medication transparency, which can avoid moral hazard and adverse selection caused by information asymmetry to a certain extent.

The following are some of the research contributions of this paper.

(1) Proposes a computational model for drug economic decision making based on health big data

(2) This paper uses the convolutional neural network algorithm to construct and study the drug economic decision-making model

(3) The proposed model uses a multiple hidden layers with standard learning processes to deal through in the given data. The performance of testing of the CNN prediction model is better than the other conventional models

(4) To propose intelligent model with a general understanding, people can get better medical treatment that can help in reduction of some burdens

The rest of the paper is organized as follows: Section 2 gives related work, Section 3 gives health big data, Section 4 provides us model construction of drug economic decision-making based on health big data, experiment and applied analysis are discussed in Section 5, and conclusion is given in Section 6.

2. Related Works

For several healthcare organizations (HCOs), the use of big data in people management operations has been a significant motivator in the past years. Since it has improved data processing speed, satisfaction results, and other different tests in support of people management activities and processes [10], the healthcare industry is increasingly moving away from disease-centered models and toward leaner patient-centered models, as well as toward a more data capacity value-based healthcare performance model [11]. Improved insights and understanding from leaders towards employees result in better selection of the appropriate people at the right time. Finally, some of the main reasons to develop in big data to support people management operations have included a better knowledge of the organizational culture and the ability to make sense of a variety of data sources and data types [12]. Applying big data provides for the evaluation of a larger variety of awards and compensation programs, distribution methods, employee interactions, and nonmonetary arrangements. Big data and reward computation algorithms can play a significant role in medical system planning and production [13].

Data scientists have a hurdle in integrating and implementing a large volume of medical data acquired across disparate platforms. As a result, it is argued that a healthcare revolution is required to take bioinformatics, health informatics, and analytics together to encourage personalized and more better clinical outcomes [14]. Future HT management is presented in this theoretical model as an accessible manner of hypothesizing patients' futures to positively change their behavior. The model's efficacy to impact positive healthcare decision-making and enhance patient outcomes should be demonstrated using real-world data from EHR databases [15]. This research aims at the ethical issues that may arise when system medicines become more widely used in clinical medicine. These include epistemological problems for clinical decision-making, the usage of big data-optimized scoring systems, and the risk of substantial growth in incidental and secondary findings [16]. While some ethical concerns are still theoretical, we must take use of the opportunity to predict challenges to avoid potential predictable errors when system medicines finally make its way into every day's treatment.

3. Health Big Data

Healthy big data is a new term that has emerged with the digital wave and information modernization. In recent years, it has come to mean the collection of health data that cannot be captured, maintained, or analyzed by conventional software tools in a reasonable amount of time. It includes huge, constantly increasing, and various data assets that require new processing techniques in terms of improving decision-making, awareness, and process optimization [17]. Health big data includes data on lifestyle, environment, and behavior that have an impact on an individual's health. The continuous advancement of innovative digital health devices and applications provides a unique environment for personal health data to be used for personal care. On the one hand, health big data enables patients to play a more active role in self-health management, and on the other hand, it greatly enhances doctor's clinical insights into patients' lives. Health big data can be mainly divided into personal health records, social media health data, and potential health data [18].

Personal health records (PHRs) mainly include continuous health data collected by personal self-tracking devices and wearable devices, etc. Personal health records can be used to track ongoing treatment or self-monitoring and to understand how well an individual is managing their health through professional healthcare providers. It also contains patient self-managed health data, such as food tracking, daily activities, and blood pressure monitoring. Personal health record equipment can capture multiple clinical data points in a long-time range, can improve the limitations of clinical settings, and is a powerful supplement to clinical personal health data. Doctors can verify and adjust diagnosis and treatment plans in a timely manner based on health monitoring data. In telemedicine, self-tracking data such as physical activity data has potential for research such as identifying potential patients [19].

Social media data is health data provided by health groups that is not available in any other source, including health data generated by communication tools such as email, social tools, and text messages. In addition to traditional social media, more and more specific medical and health-related social media sites provide healthy groups with a platform to receive information and emotional support. In recent years, many research efforts have used these data to extract information such as adverse drug reaction monitoring, and some studies have begun to use social media platforms to carry out various health interventions.

Potential health data mainly includes information related to personal health such as socioeconomics, compliance, environment, and lifestyle risk factors [20], such as relationship, purchase behavior data, and third-party payment data. Potential personal health information linked to system-oriented biomedical research can provide continuous, cross-cutting communication between biomedical research and individual healthcare [21].

In this section, we will discuss basic components of health big data system and development of convolutional neural networks in detail.

3.1. Basic Components of Health Big Data System. The health big data system mainly includes three parts: data detection terminal, data transmission network, and remote medical control center. The data detection terminal is mainly used to detect various physiological parameters of the human body. The important parameters included are the heart rate, respiration rate, body temperature, blood pressure, blood oxygen saturation, and other parameters. At the same time, the detected physiological data is sent to the data transmission network. The data transmission network is the carrier of data transmission, which receives the physiological data detected by the data detection terminal and sends it to the remote medical control center.

The remote medical control center receives information from the data transmission network and processes and screens it, thereby screening out abnormal data of physiological parameters for medical staff to process, diagnose, and store the received data in a large database for the purpose of coordinating with subsequent data comparing, as shown in Figure 1.

3.2. Development of Convolutional Neural Networks. The multilayer perceptron model was proposed in the 1980s, and the computer demonstrated great processing capacity in digital recognition. Due to the limitation of computer power at that time, especially the processing power of resources such as CPU, storage, and computer was limited. The data size was limited, and the model's capacity to represent itself was broad, and it was therefore typically incapable of dealing with complicated image problems. Hinton and Salakhutdinov introduced a technique for layer-by-layer network model pretraining in 2006 [22]. The artificial neural network with multiple hidden layers has a high feature learning performance by increasing the number of layers in the artificial neural network. They reduce the dimensionality of the neural network by encoding and training a multilayer neural network with low central layers to reassemble the high-dimensional input vector.

The complexity of deep neural network training is significantly reduced because of something like this. There are also new approaches for overcoming some of the challenges that come with training deep convolutional neural networks [23]. Since then, scholars have spent particular attention on the idea of deep learning and the fast development of convolutional neural networks. Many Internet technology organizations, such as Google and Microsoft, invested a lot of human and material resources in the research and development of large-scale deep learning systems in the early 21st century.

The convolution operation is characterized by each layer using a set of convolution kernels independently, which helps to extract useful features from locally related input points in a multilayer feedforward neural network model. The backpropagation algorithm is used by the CNN to learn throughout the training process. This backpropagation method optimizes an objective function that uses a response-based brain-like learning process. Backpropagation algorithms and convolutional neural networks have continued to succeed, leading artificial intelligence to a new level of development.

Deep architectures usually achieved better results that dominate shallow architectures when faced with difficult learning problems, especially after the fantastic performance of the LeNet convolutional neural network model [24]. On the Minst-dataset, followed by AlexNet [25], VGG [26], GoogLeNet [27], ResNet [28], Mobile Net [29] and other related network models, which have been widely used in medical image processing [30, 31], instance segmentation [32, 33] and other field applications.

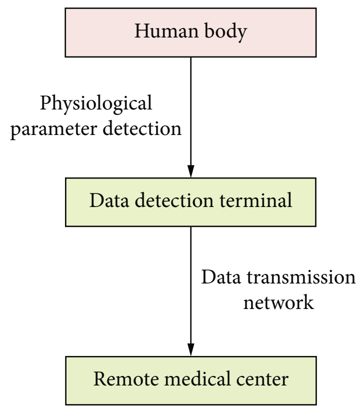

Figure 1: Basic components of a health big data system.

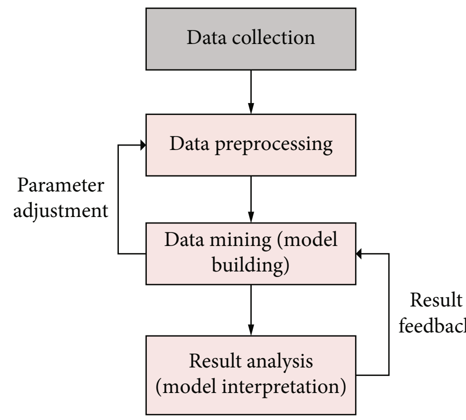

Figure 2: Health big data mining process.

4. Model Construction of Drug Economic Decision-Making Based on Health Big Data

This section discusses health big data mining process, convolutional neural network algorithm design, and health big data analysis model in detail.

4.1. Health Big Data Mining Process. A complete data mining process includes four main components: data collection, data preprocessing, data mining, and result understanding (see Figure 2). The mining of health big data is no exception, but the algorithms used in specific links are different.

This heading further discusses data collection for this research, data processing, data mining, and result analysis.

4.1.1. Data Collection. The main aim of data collection is to carry out data mining for the selected target, analyze all data related to it, and also include data information outside the target (such as weather, air, environment, and other external information that will affect certain medical behaviors) and to select data suitable for the mining target.

4.1.2. Data Preprocessing. There are usually chaotic, incomplete, and inconsistent data in the collected data, which is a common feature of data warehouses and large databases. Therefore, these data need to be preprocessed before mining to improve their quality and analytical capabilities. The specific steps are as follows:

(1) Data cleaning and processing (check the accuracy, legality, integrity, consistency, timeliness, and other aspects of the collected data in various ways and correct or even delete the data with poor quality)

(2) Data standardization (establishing a dataset standard for the collected data and converting and collecting the data format according to the standard)

(3) Attribute selection (using the corresponding algorithm to evaluate the data attribute value and select the attribute with high correlation with the result). The data preprocessing process is very awkward, often occupying about half or even 70% of the entire workflow

4.1.3. Data Mining. Also known as building a model, it is necessary to determine the algorithm and evaluation method of the model. There are two main ideas for mining health big data: one is to artificially establish mathematical models to analyze data based on previous experience, that is, traditional algorithms; the other is to use many sample data for training through artificial intelligence systems that have emerged in recent years, and let machines replace humans gaining the ability to extract knowledge from data, known as emerging algorithms. After the model is built, the model needs to be evaluated and optimized, and if necessary, it is necessary to return to the previous process for parameter adjustment.

4.1.4. Result Analysis. That is, the interpretation of the model, the actual application effect should be fed back to the established model, and the model should be adjusted according to the application effect.

4.2. Convolutional Neural Network Algorithm Design. When using the convolutional neural network algorithm to process medical and health data, it is first necessary to digitize each word included in the text data using the word vector method. The deep convolutional layer structure model is shown in Figure 3.

The designed convolutional neural network consists of 5 layers, convolutional layer 1, pooling layer 1, convolutional layer 2, pooling layer 2, and fully connected layer, which are used for word vector training of medical, healthcare data, and final disease risk assessment.

When performing word vector training, the higher the purity of the medical text data quantity required for training, the better; that is, the training data should have strong professionalism. This paper uses all clinical records extracted from a database of a tertiary hospital in the past 10 years as the original data for word vector training. During the training process, all the relevant parameters of CNN are defined as the set ϕ. The parameters in ϕ are firstly initialized randomly, and then, the parameters are updated by the gradient descent

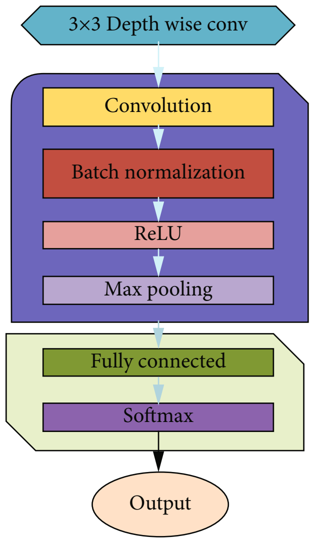

Figure 3: Depth convolution layer structure model.

method until the final parameter maximizes the corresponding log-likelihood function value. The resulting formula is shown in

$$\max\sum \log p(\text{class}/2A, \phi). \tag{1}$$

In the formula, 2A is the training sample dataset, and class is the correct classification of the training sample data. If γ is used to represent the learning rate, the formula for updating the parameters by the gradient descent method is shown in

$$\phi = \phi + \gamma \frac{\partial \log p(\text{class}/2A, \phi)}{\partial \phi}. \tag{2}$$

4.3. Health Big Data Analysis Model. The intelligent analysis model of health big data based on convolutional neural network is shown in Figure 4.

In this model, the database holds all the medical data of the hospital's diagnosis and treatment. Among them are the patient's self-reported condition, doctor's consultation, physical examination, various laboratory test results, medication, treatment plan, final diagnosis and results, etc. The model uses the historical medical text data in the database for continuous self-learning and optimization, and the final training model is used to realize intelligent analysis of newly incoming health data and disease risk assessment.

The model is mainly composed of three modules: word vector training, CNN feature learning, and disease risk assessment. The word vector training module is responsible for preprocessing the professional medical historical data in the database and uses the processed data as quantity to digitally represent text data and train word vectors; the CNN feature learning module is responsible for inputting the trained word vectors into CNN In the analysis model, the learning and training of the analysis model is carried out, and finally the health big data analysis model with the best

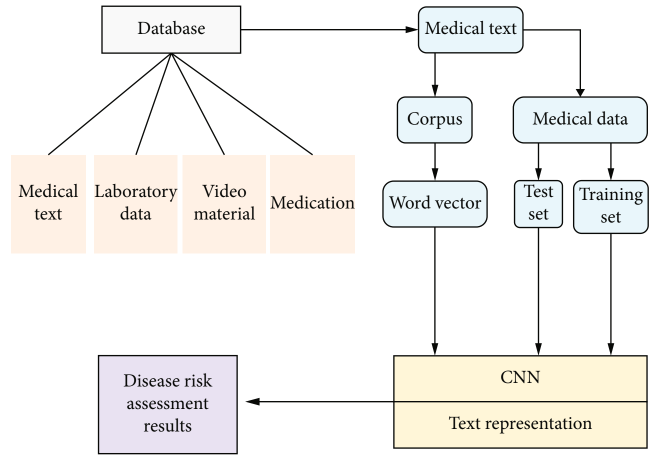

Figure 4: Health big data analysis model.

effect is obtained; the disease risk assessment module uses the trained model to perform health assessment on the new input data and outputs the final result.

5. Experiment and Applied Analysis

Drugs are classified in accordance with the standard of drug anatomy, therapeutics, and chemistry (ATC) classification system designated and regularly released by WHO Drug Statistical Methods Integration Center. The ATC code of carbapenem antibacterial drugs is J01DH, coded as J01DH02), biapenem (J01DH05), imipenem/cilastatin (J01DH51), and panipenem/betamirone (J01DH55).

The data comes from the use data of carbapenem antibiotics in hospitalized patients from January 1, 2018, to December 31, 2019, collected by the Hospital Information System (HIS) of a hospital in Weifang City, including the use of carbapenem antibiotics. Name, specification, usage, sales amount, average hospital stays of discharged patients, total number of discharged patients in the same period, etc. were divided into two groups. January 1 to December 31, 2018, is the pre-AMS management group, and January 1 to December 31, 2019, is the AMS postmanagement group.

Excel 2017 was used to input data, and SPSS 17.0 statistical software was used for analysis. Measurement data were expressed as $X \pm s$, and group t test was used for comparison between groups; enumeration data were expressed as rate, and x^2 test was performed. $P < 0.05$ was considered statistically significant. Before and after the implementation of AMS, the DDDs and AUD of total antibiotics in our hospital showed a downward trend, but the difference was not statistically significant. The DDDs and AUD of carbapenems showed a continuous downward trend, and the difference was statistically significant ($P < 0.01$). Before and after the implementation of AMS in our hospital, the total amount of antibiotics, the amount of carbapenems used, and DDC showed a downward trend, but the difference was not statistically significant ($P > 0.05$).

The results showed that a hospital in Weifang City effectively promoted the rational application of carbapenems by implementing AMS. After the implementation of AMS, the

DDDs and AUD of carbapenems showed a continuous downward trend, and the difference was statistically significant ($P < 0.01$), and the DDDs and AUD of total antibiotics showed a downward trend in general. In terms of drug economic burden, the total amount of antibiotics, the amount of carbapenems used, and DDC generally showed a downward trend. It is suggested that the management of carbapenem antibiotics and the rational use of antibiotics in our hospital have taken appropriate measures, and the effect is remarkable. It shows that the drug economic decision-making model based on health big data has a good effect under the combined action of convolutional neural network.

6. Conclusion

The development of large biological data with the possibility to influence health economic analysis of accuracy medication has accelerated in the recent years. Significant HBD relationship and motivational programs have determined the discipline onward. They are also helpful in providing health economics to analyze patients and patient subgroups on a micro level with the help of real-world data. While health economists are now faced with several challenges when utilizing HBD in economic analysis, potential solutions do occur, and they must be comprehensively tested in the upcoming years. Using convolutional neural network to study the decision-making model based on health big data for drug economy, the results show that the effect is still good, and it has potential value for promotion. As an important foundation and guarantee for improving the health of the people in China, medical and health services have accumulated various data resources of the Chinese people with the rapid development in the recent years.

These data materials, together with other relevant data information of the whole society, constitute the establishment of health big data that will promote the development of my country's medical and health services. Health big data has a variety of applications in my country's medical and health industries, including medical research and development, disease diagnosis, and treatments. Personalized medicine is utilized in areas such as health risk factor analysis, public health emergency management, resident health management, and precision medicine.

Data Availability

Upon request, the data used to support the findings of this study are available from the corresponding author.

Conflicts of Interest

The author declares that he has no conflict of interest.

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