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Chapter

Application of Artificial Intelligence in Modern Healthcare System

Sudipto Datta, Ranjit Barua and Jonali Das

Abstract

Artificial intelligence (AI) has the potential of detecting significant interactions in a dataset and also it is widely used in several clinical conditions to expect the results, treat, and diagnose. Artificial intelligence (AI) is being used or trialed for a variety of healthcare and research purposes, including detection of disease, management of chronic conditions, delivery of health services, and drug discovery. In this chapter, we will discuss the application of artificial intelligence (AI) in modern healthcare system and the challenges of this system in detail. Different types of artificial intelligence devices are described in this chapter with the help of working mechanism discussion. Alginate, a naturally available polymer found in the cell wall of the brown algae, is used in tissue engineering because of its biocompatibility, low cost, and easy gelation. It is composed of α-L-guluronic and β-D-manuronic acid. To improve the cell-material interaction and erratic degradation, alginate is blended with other polymers. Here, we discuss the relationship of artificial intelligence with alginate in tissue engineering fields.

Keywords: artificial intelligence (AI), machine learning (ML), natural language processing (NLP), medical imaging, SVM

1. Introduction

Artificial intelligence (AI) technique is the most effective technology used in the modern healthcare area. The rapidly growing accessibility of healthcare medical data and also the advances of big data diagnostic techniques has completed the potential of the current successful uses of artificial intelligence (AI) in healthcare system. With the help of important medical questions, potential artificial intelligence (AI) techniques can disengage healthcare-appropriate information secreted in the huge quantity of data, which can maintain healthcare decision-making. Modern healthcare technology in various medical areas has spread to the several pioneering startups in the world, which helps people in healthier and longer lives. The advances have initially been determined by the beginning of mobility and software, permitting the health sector to digitize several of the pen- and paper-based processes and operations that are presently held up service release. Nowadays, computer software has become far more intelligent and autonomous. These new abilities are discussed under the same cover of machine learning (ML) and artificial intelligence (AI), which are accelerating the tempo of improvement in healthcare. The applications

of machine learning (ML) and artificial intelligence (AI) in healthcare region have allowed the area to employ some of its major challenges in particular domains like drug discovery, personal genetics, and disease identification and management. Every time an innovative technical tool comes into the healthcare system, it also faces several challenges. Most of the common issues of artificial intelligence (AI) technique in healthcare system are regulatory compliance requirements, patient and provider adoption, and also lack of data exchange. The Artificial intelligence (AI) has moved from all of these concerns, reducing the areas in which it can accomplish something. The purpose of artificial intelligence (AI) and machine learning (ML) in healthcare system is redesigning the industry and creating what was once impracticable into a real truth. For artificial intelligence (AI)/machine learning (ML) to take its place in the healthcare system, sustained access to appropriate data is necessary to succeed. Artificial intelligence (AI) can be used to analyze and identify patterns in large and complex datasets faster and more precisely than has previously been possible. It can also be used to search the scientific literature for relevant studies and to combine different kinds of data, for example, to aid drug discovery. Artificial intelligence (AI) health apps have the potential to empower people to evaluate their own symptoms and care for themselves when possible. Artificial intelligence (AI) systems that aim to support people with chronic health conditions or disabilities could increase people's sense of dignity, independence, and quality of life, and enable people who may otherwise have been admitted to care institutions to stay at home for longer. Artificial intelligence (AI) depends on digital data, so inconsistencies in the availability and quality of data restrict the potential of artificial intelligence (AI). Also, significant computing power is required for the analysis of large and complex datasets. Clinical practice often involves complex judgments and abilities that artificial intelligence (AI) currently is unable to replicate, such as appropriate knowledge and the ability to read social cues. With the help of machine learning process, structured data like genetic data, electro physical data (EP), and imaging data are properly investigated. Machine learning makes the information analytical algorithms to extract characteristics from the input data. Input data generally in machine learning algorithms involve with patient's natures as well as the intermittently apprehension healing effects. A patient's nature generally includes bottom line data, such as gender, disease history, age, gene expressions, electrophysiological data (EP) test, analytical imaging, idea test results, and medicinal symptoms. Support vector machine was also applied in cancer diagnosis. Even supposing complicated data, machine learning represents the support for artificial intelligence (AI). At this moment in time, an innovative advancement is happening in the subfield of neural networks. This has created notable interest in various domains of healthcare science, in addition to drug analysis and also the area of public health. Deep neural networks can implement in addition to the most exceptional human clinicians in specific diagnostic tasks. Also, artificial intelligence techniques are already promising in healthcare-based apps, which can be performed by any network machine like modern smart mobile phone. Artificial intelligence has the ability to address imperative health challenges, but it is limited due to the unavailability of good health data. Employing artificial intelligence (AI) involves some ethical issues including the probable for artificial intelligence (AI) to make mistaken assessments and then the question of responsibility occurs.

2. Artificial intelligence (AI) devices

Basically, artificial intelligence (AI) devices are categorized by two main types: the first one is machine learning (ML) category [1], which generally analyses the

structured data, for example, electrophysiological data (EP), genetic data, and imaging data. For healthcare applications, the machine learning (ML) processes try to gather patients' individuality or understand the possibility of the disease effects [2]. The second type of artificial intelligence (AI) device is the natural language processing (NLP) technique [3], which can take out the information from free or unstructured data such as medical observations or health journals to enhance structured health check data. The natural language processing (NLP) processes objects at revolving contents toward the machine-understandable structured records and can then be considered by machine learning (ML) procedures [4]. **Figure 1** explains the road plan from medical data making, during natural language processing (NLP) data improvement and machine learning (ML) data investigation, to medical judgment creating. In this figure, the road plan starts and ends with medical activities. As dominant as artificial intelligence (AI) procedures, they can be inspired by medical/healthcare troubles and also be practical to help out the medical performance at the end.

2.1 Machine learning (ML) processes

Machine learning (ML) builds the data investigative algorithms to extort characteristics from the data. Inputs to machine learning (ML) algorithms consist of patient 'characters' and occasionally therapeutic effects of concern. A patient's characters generally contain bottom line data, for example, gender, age, disease history, and also disease explicit data, for instance, gene expressions, analytical imaging, electrophysiological data (EP) test, objective test results, medication, and medical symptoms. In addition to the attributes of the patients medical results are frequently composed for medical investigation. These contain syndrome pointers, patients' endurance periods, and quantitative syndrome stages such as the size of tumor. Here j^{th} characteristic of the i^{th} numbers of patient is denoted by P_{ij} and Q_i is representing the effect of concern. Regarding whether to integrate the results, machine learning (ML) algorithms can also be separated into two main types: supervised learning and unsupervised learning. One more type is also available

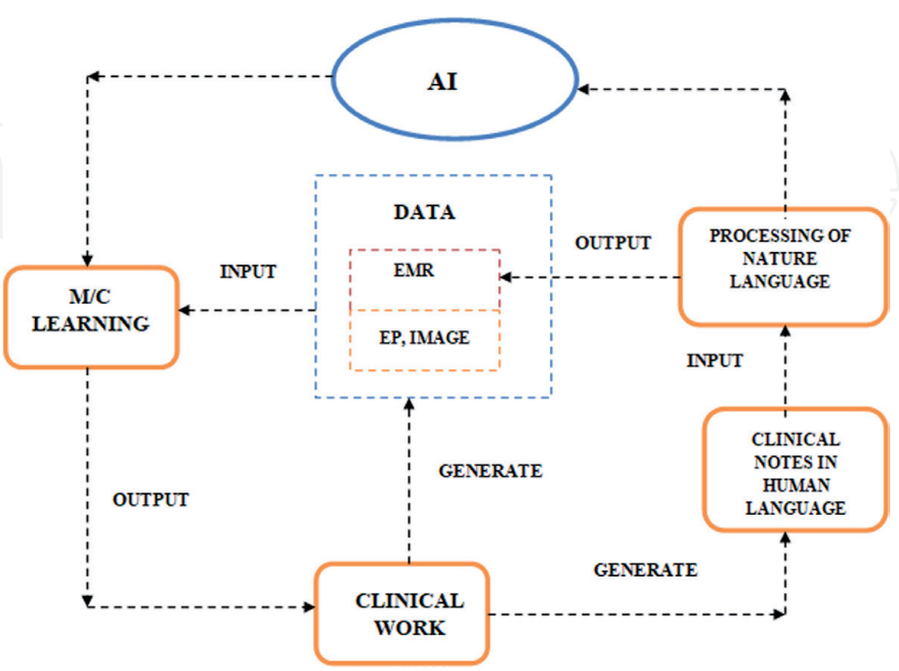


Figure 1.
The road plan from generation of medical data, during natural language processing (NLP) data improvement and machine learning (ML) data investigation.

named as semisupervised learning. **Figure 2** represents all these three types of learning procedures. Unsupervised learning is also identified for feature removal, whereas supervised learning is appropriate for analytical representation by constructing several interactions involving patient individuality (input) and result of concern (output). In recent times, semisupervised learning has been projected as a hybrid involving supervised learning and unsupervised learning, which is appropriate for circumstances wherever the effect is omitted for definite issues.

There are two major unsupervised learning techniques available such as (i) principal component analysis (PCA) technique and (ii) clustering technique. Principal component analysis is basically for element reduction, mainly while the characteristic is documented in a huge number of elements, such as the number of genes in a genome-mixt connection revise. Principal component analyses (PCA) project the data on a small number of principal component (PC) guidelines, without trailing in excess of information regarding the issues. Occasionally, PCA is used to decrease the element of the data, after which clustering technique is used to fraction the issues. All these fraction issues with related characteristics are gathered together, without applying any result information. This algorithm's result output helps the cluster tags for the patients throughout maximizing as well as minimizing the parallel of the patients and also involving the clusters. These accepted clustering algorithms contain (i) Gaussian mixture clustering, (ii) K-means clustering, and (iii) hierarchical clustering. Alternatively, supervised learning reflects on the topics' outcomes in cooperation with their characteristics and goes via a definite training procedure to find out the finest outputs connected through the inputs, which are nearby the standard outcomes. Generally, the formulations of output contrast through the concern outcomes. Such that, the outcome can be the possibility of receiving an exact clinical result, the projected value of a disease stage or the projected endurance time. Evaluated by unsupervised learning and supervised learning, which offers extra clinically applicable results; therefore Artificial Intelligence (AI) relevance in healthcare system most regularly apply supervised learning. Unsupervised learning may be applied as a component of the preprocessing stage to or find out subgroups or decrease dimensionality, which consecutively makes summarizing supervised learning stage more capable. Appropriate methods contain logistic regression, linear regression, decision tree, naïve Bayes, random forest, discriminate analysis, nearest neighbor, neural network, and support vector machine (SVM). Neural network and SVM are the most accepted supervised learning methods in healthcare applications [5]. The mechanisms of neural networks and support vector machine (SVM) techniques process together with relevant examples in the cardiovascular disease, neurological disease, and cancer.

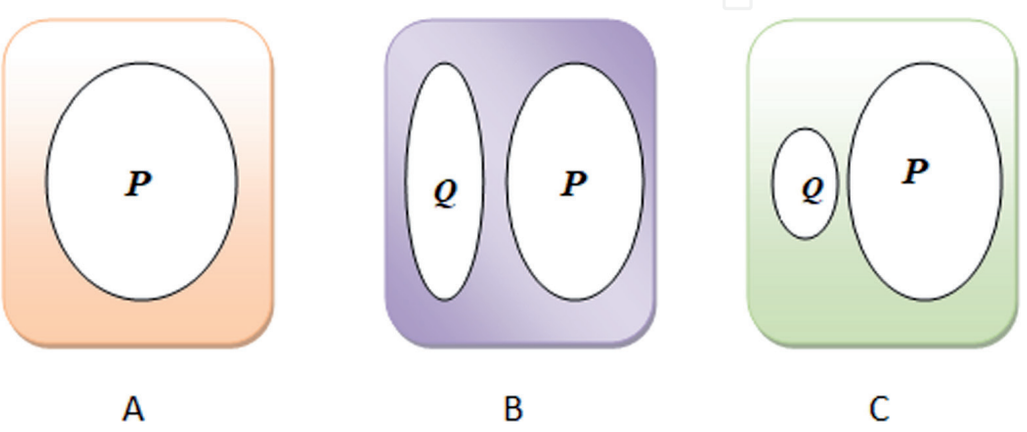


Figure 2.
Representation of (A) unsupervised learning, (B) supervised learning, and (C) semisupervised learning.

2.2 Neural network

Neural network is basically known as the expansion of linear regression for confining the difficult nonlinear relationships dividing the input parameters and outcome data. In this neural network, the relations involving the input parameters and the outcome are represented throughout the multiple unknown layer grouping of preindividual functional. The aim is to calculate approximately the weights via input data and also the outcome data so that the average error involving the outcome and their calculation is reduced. Here, this technique is described via following some examples. Neural network was used in stroke diagnosis [6], where the input parameters were given as Xi_1, ..., X_{ip} and $p = 16$ stroke-related symptoms, together with acute confusion, problem of vision and mobility, paresthesia of the leg or arm, etc. Y_i represents the binary outcome, where $Y_i = 1/0$ represents that the i^{th} patient has or does not have stroke. The output factor of importance is the possibilities of stroke (a_i), which represents the equation given below:

$$a_i = h\left\{\sum_{K=1}^{D} w2l\, fk\left(\sum_{l=1}^{p} w1l\, X_{il} + w_{10}\right) + w_{20}\right\} \tag{1}$$

In this equation, w_{10} and w_{20} are not equal to zero, where X_{ij}, $fk = 0$; fks and h are prespecified functions, which indicate that the weighted grouping influences the disease threat as a whole. **Figure 3** represents the neural network system.

The instruction's aim is to find out the weight of w_{ij}, which can minimize the calculation in accuracy given by $\Sigma_{i=1}^{n}(Y_i - a_i)^2$. The minimization can be done via standard optimization algorithms, for instance, local quadratic estimate or gradient decline optimization, which are integrated in both R and MATLAB software. The latest data were issued from the similar population and the results of w_{ij} are also applied to calculate the outcomes rooted in their particular characters [7]. This is the same as methods have been applied to identify cancer treatment [8], where the input efforts and outcomes are the principal components (PC) predictable from 6567 genes and the tumor groups. A neural network was applied to identify breast cancer, where the inputs represent the surface information from mammographic images and where the outcomes are tumor indicators [9]. Another problematical neural network model was analyzed to identify Parkinson's disease derived where the input parameters are motor and nonmotor indications and neuroimages [10].

2.3 The support vector machine (SVM)

The supporting vector machine is mostly applied for categorizing the topics into two different clusters, where the result Y_i, $Y_i = -1$ or 1 indicates whether the i^{th} patient is in set 1 or 2 correspondingly. This procedure can be completed for circumstances with more than 2 sets. The fundamental hypothesis is that the subject matters can be divided into two different groups via a decision boundary distinct on the characteristics Xij, which can be represented as:

$$a_i = \sum_{j=1}^{p} w_j X_{ij} + b \tag{2}$$

where w_j represents the weight put on the j^{th} characteristic to mark edits' comparative implication on moving the outcome between the others. If $a_i > 0$, the i^{th} patient is categorized to group 1, that is, $Y_i = -1$; and if $a_i < 0$, the patient is categorized to group 2, that is, $Y_i = 1$. Furthermore, assuming that the new patients come from the same population, the resulting W_j can be applied to classify these new patients based on their traits. An important property of SVM is that the determination of the model parameters is a convex optimization problem so the solution

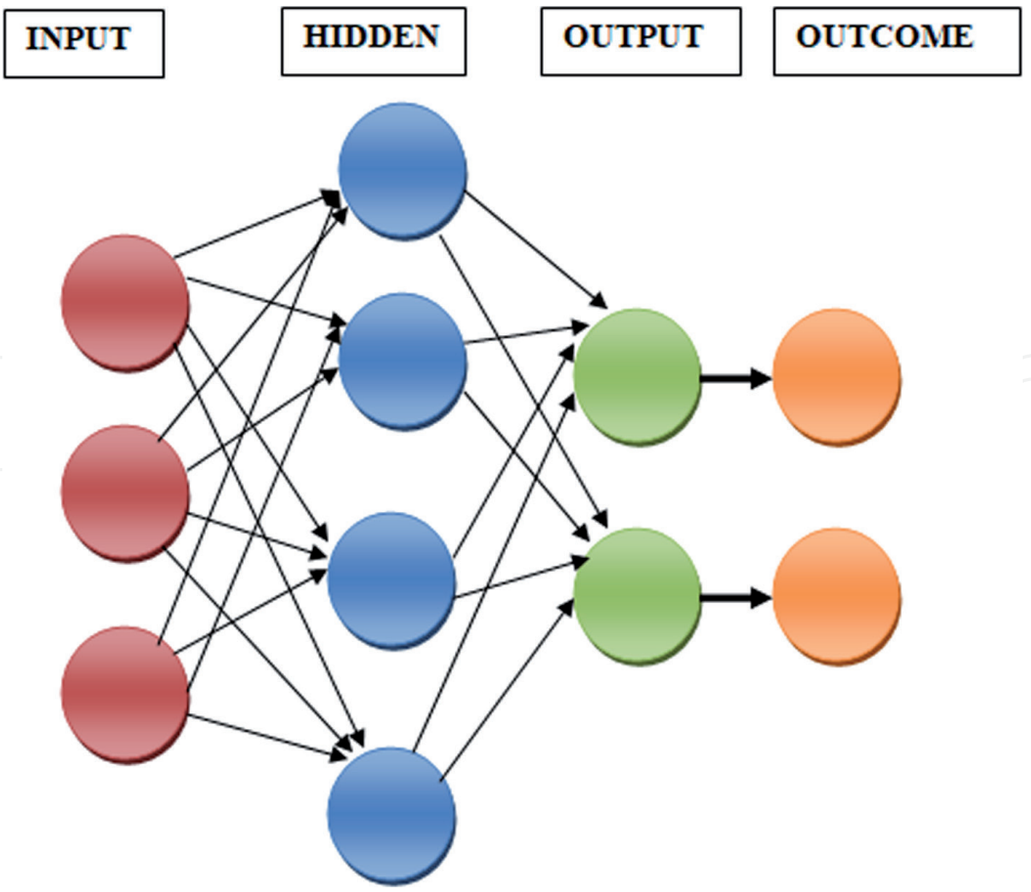


Figure 3.
Neural network diagram.

is always global optimum. Additionally, many obtainable rounded optimization technique applications are readily available for the SVM performance. SVM has been widely applied in healthcare research. For example, SVM was used to recognize imaging biomarkers of psychiatric and neurological disease [11]. SVM was also applied in cancer diagnosis [12]. SVM and other statistical methods can also be used to reach early detection of Alzheimer's syndrome [13]. SVM was applied to analyze the power of an offline human and device interface, which can control the upper-limb prostheses [14].

2.4 Deep learning method

Deep learning method is a contemporary expansion of the traditional neural network method. **Figure 4** represents deep learning like a neural network with multicovers.

Rapid growth of current computing allowed deep learning for constructing the neural networks along with huge amount of covers, which is impossible for traditional neural networks. Basically, this technique helps to investigate many critical nonlinear models in the information. One more cause for the recent acceptance of deep learning techniques is owing to the enhancement of the critical and volume of data [15]. Dissimilar to the traditional neural network, this process generally applies more hidden levels in order that the algorithms can handle critical data with different structures [5]. In the healthcare applications, the generally applied deep learning algorithms consist of recurrent neural network, convolution neural network technique, deep neural network, and deep belief network. Convolution neural network is the most accepted one in 2016. The convolution neural network is extended to analyzing the ineptitude of the traditional machine

learning algorithms when conducting high dimensional data, that is, data with a huge number of characteristics. Conventionally, the machine learning algorithms are considered to examine data when the number of characteristics is little. The image data are physically high dimensional because each image generally includes thousands of pixels as characteristics. One explanation is to present dimension decrease: primarily preselect an object of pixels as elements and then complete the machine learning algorithms on the ensuing lower dimensional traits. However, heuristic feature selection events may drop the information in the images. Unsupervised learning methods such as clustering or PCA can be applied for data-determined dimension decrease. The convolution neural network was first projected the high-dimensional image investigation [16], where the inputs for convolution neural network are the accurately regulated pixel values on the images. The convolution neural network then transmitted the pixel values in the image throughout weighting in the difficulty layers and variety in the subsampling layers instead. The ultimate output is a recursive purpose of the weighted input values. The weights are skilled to reduce the average error involving the predictions and the outcomes. The performance of convolution neural network has been incorporated in trendy software packages such as Caffe from Berkeley AI Research [17] and Tensor Flow from Google [18]. Recently, the convolution neural network has been effectively executed in the healthcare area to help disease identification. It is used to identify the congenital cataract disease throughout learning the ocular images [19], though it has over 90% accuracy on identification and treatment implication. Convolution neural network was performed to identify skin cancer from clinical images [20]. Convolution neural network is applied to identify referable diabetic retinopathy via the retinal fundus photographs [21]. The specificity and sensitivity of the algorithm are both over 90%, which expressed the usefulness of using the method in the analysis of diabetes. It is importance to declare that in all this type of applications, the presentation of the convolution neural network is competitive beside an experienced physician in the truthfulness for categorizes both usual and disease stages.

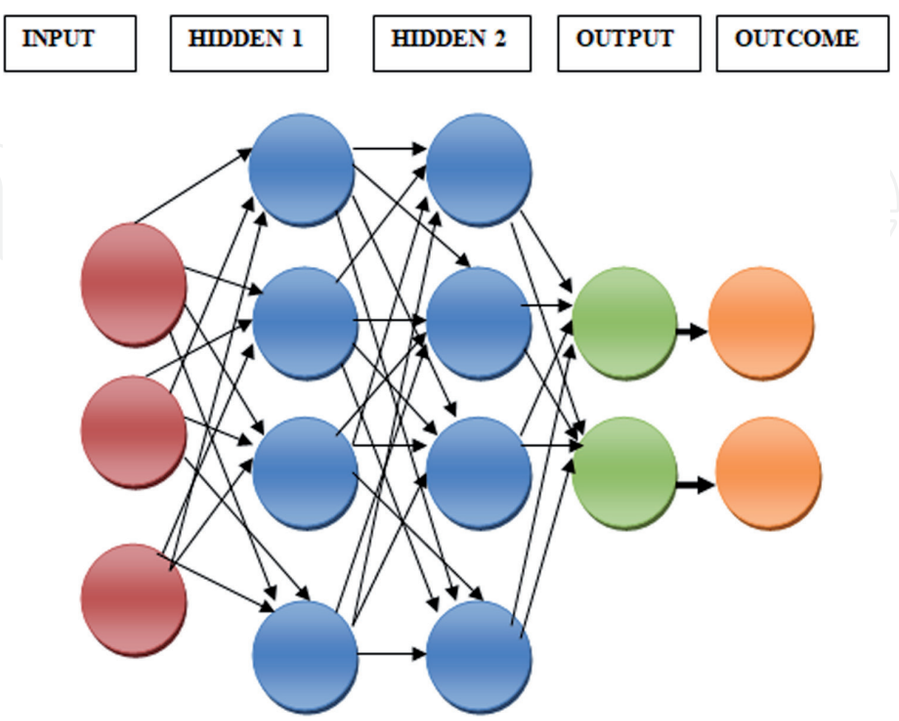


Figure 4.
Multilayer neural network.

2.5 Natural language processing

Genetic data and EP plus image are all machine-comprehensible, that is why the machine learning (ML) algorithms can be straightly presented after quality control processes or appropriate preprocessing. Though huge extents of medical data are like descriptive content, like a substantial examination, operative notes, and an experimental laboratory reports and release abstracts, these are formless and inconceivable for computer programming. Below this background, natural language processing (NLP) targets removing helpful data from the descriptive text to support the medical conclusion making [3]. A natural language processing (NLP) pipeline includes two main components: (i) classification and (ii) text processing. During text processing, the natural language processing (NLP) recognizes a sequence of disease-appropriate keywords at clinical remarks related to the past records [22]. After that, keyword subsets are preferred during analyzing their achievements in the arrangement in the normal abnormal cases. The authorized keywords then enter and enhance the controlled information to support medical choice making. The natural language processing pipelines have been developed to help the medical choice making on attentive treatment preparations and monitoring critical effects. For instance, it was showed that establishment of natural language processing, for analyzing the chest X-ray reports would help the antibiotic assistant system to aware physicians for the probable necessitate for anti-infective therapy [23]. Natural language processing was used to mechanically monitor laboratory-based difficult effects. Moreover, the natural language processing pipelines can also assist with disease analysis [24]. A recognized of 14 cerebral aneurysm disease-associated changeable during executing natural language processing (NLP), based on the clinical remarks [25]. Resulting variables are effectively applied for categorizing the common patients and the patients with cerebral problems, with 86% to 95% accuracy rates on the validation and training trials correspondingly. A natural language processing was implemented to extort the peripheral arterial disease-allied keywords from description clinical remarks. The keywords are then applied to categorize the common patients and the patients who have peripheral arterial disease, which reaches over 90% accurate [22].

3. Artificial intelligence (AI) applications in healthcare system

In spite of few limitations, artificial intelligence (AI) are applied in healthcare system. Researchers mainly focus on the region of major three diseases: cardiovascular disease, nervous system disease, and life-threatening cancer also. In cardiology, [26] explained the prospective uses of the AI system for making a diagnosis of the cardiac diseases with the help of cardiac images. Cardiac stroke is a natural and commonly stirring disease that has an effect on more than 500 million people all around the world. It is the most leading cause of death in world. It has also high medical expenses across the world nearly about US$ 689 billion, which causes serious trouble to patient families [27, 28]. For that reason, research on anticipation and medical treatment for stroke has a great impact. Recently, artificial intelligence (AI) processes have been used in additional and supplementary stroke-connected studies. In stroke-concerned cases, AI procedures help in the three main areas: before time for disease calculation and analysis, healing, and in addition to conclusion forecast and diagnosis assessment. About 85% of the time, stroke is caused by cerebral infarction, that is, thrombus in the vessel. For require of finding pre stroke indication, only some patients could obtain appropriate treatment. A movement-detecting device was developed for predicting early stroke [29]. For

model structure resolution, two machine learning algorithms like PCA and genetic fuzzy finite state machine are mainly used. The revealing method is attached with a patient human action detection phase and the starting of the stroke detection phase. Ideally, the typical model is remarkably different from the patient movement, and an attentive model that can detect stroke can stimulate and assess medical action and make it immediately feasible. Correspondingly, a device that is wearable was proposed for gathering data for regular and pathological steps for calculation of stroke [30]. The data can be removed and copied by SVM and unseen Markov models, and this algorithm could suitably organize 91% of information to the exact group. For some identification of the stroke, neuro-imaging processes like CT scan and MRI are also essential for disease estimation. Several studies have attempted to concern machine learning techniques to neuro-imaging data to support with stroke analysis. SVM was used in resting-state functional MRI data, where endophenotypes of motor disability behind stroke were classified and recognized [31]. This algorithm can precisely distinguish patients with a precision of 87.6%. T1-weighted MRI, [32] helps to rearrange the stroke injury. This effect is similar for human-proficient physical injury explanation. Kamnitsas et al. [33] attempted 3D CNN aimed at injury fragmentation in multisculpt brain MRI. It likewise used fully associated provisional casual field representation for ultimate postprocessing of the CNN's soft segmentation plots. With the help of Gaussian process regression method, stroke anatomical MRI images were analyzed,and also establish the vortex pattern performed well than injury load/area like the expecting elements [34]. Machine learning (ML) techniques are also useful to examine stroke patients with CT scans. A free-floating intraluminal thrombus can be created like injury post stroke, and this is complicated to discriminate by carotid sign in CT imaging. Three machine learning (ML) algorithms were used to categorize two quantitative types: shape analysis with linear classification analysis, SVM, and artificial neural network [35]. Machine learning is also used in expecting and evaluating the presentation for stroke cure. In a critical emergency phase determination, the result of intravenous thrombolysis (tPA) has a sturdy link for the diagnosis per durance rate. With CT scan, SVM can be used for expecting whether the patients by thrombolysis (tPA) cure can build up suggestive intracranial hemorrhage [36]. In SVM, complete brain images were used as input, which acted healthier than traditional radiology-based procedures. For improving the medical result making procedure of thrombolysis (tPA) healing, a stroke treatment model was proposed for investigating perform guiding principle, clinical trials and meta-analysis with Bayesian principle network [37]. The model consisted of 56 different types of variables and 3 decisions aimed at investigating the process for analysis, cure, and effective calculation. An interaction tree was used, where the subgroup investigated suitable thrombolysis (tPA) dosage as per patient individuality, taking into consideration the healing efficacy and the possibility of bleeding [38]. Several issues can influence stroke diagnosis and syndrome mortality. Evaluating with traditional methods, machine learning techniques have returns in progressing calculation activity. To enhance and maintain the medical assessment making procedure, a model was proposed for expecting a three-month healing outcome by examining the physiological considerations for the duration of 48 hours following stroke with logistic degeneration [39]. A database was observed with 107 patient's medical information through acute anterior stroke and also posterior stroke via intra-arterial therapy [18]. Here, the data were examined through SVM and artificial neural network and achieved calculation accurateness of more than 70%. Machine learning procedures was used to recognize the control effect in brain arterio-venous abnormality satisfied with endo-vascular embolization. Though typical degeneration analysis representation could only reach a 43%

precision rate, this technique's exertion is much enhanced with 97.5% exactness. An optimal algorithm was analyzed to calculate 30 days mortality test and gained additional exact calculation than surviving techniques [40]. Likewise, SVM was used to calculate the stroke mortality via discharge. Additionally, the application of the synthetic alternative oversampling procedure was proposed to decrease the stroke effect calculation prejudice reasoned among class inequality between several datasets. Brain images were examined for calculating the effect of stroke cure. CT scan data were examined through machine learning procedure for estimating the cerebral edema through hemispheric infraction [41]. A random forest was constructed to involuntarily recognize the cerebrospinal fluid (CSF) and examined the changes in the CT scan, and this is more precise and capable compared to the traditional procedures. Functional connectivity was extracted from magnetic resonance imaging (MRI) and practical magnetic resonance imaging (MRI) data, and ridge degeneration and multitasking intellect were also applied for cognitive deficit calculation following stroke [42]. A relationship was examined, which involved injuries extorted from magnetic resonance imaging (MRI) and the cure effect through Gaussian method regression technique [43]. The model was used to calculate the difficulty of cognitive damages during stroke and the way of retrieval in due course. In Arterys Cardio DL process, where artificial intelligence (AI) is help to make available programmed and also changeable ventricle segmentations related on traditional MRI of cardiac images [44]. In nervous system disease, an artificial intelligence (AI) method was developed [45] for repairing the regulation of body movement in quadriplegia patients. Farina et al. experienced the control of the offline man–machine edge, which applies the release timings for the spinal motor neurons for controlling the prosthesis of the upper limb. IBM Watson for the oncology diagnosis can be a consistent AI for cancer diagnosis from start to the end, which was explained by Somashekhar et al. [46] by a double-blinded validation study. A clinical image was examined for recognizing skin cancer subtypes [20]. The applications of these three types' diseases are not absolutely unpredicted. These three diseases are principal death causes; for that reason, analyzing the stages of the disease before time is vital to avoid worsening of the patients' health condition. Moreover, quick diagnoses can prospectively reach throughout recovering the analysis measures on electrophysiological (EP) or electronic medical record (EMR), imaging and genetic, and this is the major power of the artificial intelligence (AI) technique. Moreover, apart from the three main diseases, artificial intelligence (AI) system has been used in another disease too: to examine the ocular image data for diagnosing inherited cataract diseases [19]. A referable diabetic retinopathy was detected by the retinal fundus photographs [21].

4. Application of artificial intelligence in modern medicine

Artificial intelligence in modern medicine and medial area has been a mostly upcoming hot topic in current years. Although there is wisdom of excessive prospective in the use of artificial intelligence in modern medicine, there are also worries about the defeat of the 'human touch' in such an important and person-motivated work. Artificial intelligence in modern medicine denotes to the practice of artificial intelligence tools and programmed procedures in the identification and cure of patients who need care. At the same time as analysis and cure may appear like modest phases, there are numerous other circumstantial procedures that come to pass in demand for a patient designate properly taken to attention, such as:

i. Collecting information data from patient discussions and checks

ii. Treating and examining outcomes of result

iii. Applying several causes of information data to derive an exact identification

iv. Defining an applicable cure technique

v. Arranging and controlling the selected cure technique

vi. Patient observing

vii. Rehabilitation, continuation arrangements

Disagreement for enlarged use of artificial intelligence in modern medicine is that reasonably a various of the beyond could be programmed—computerization often means jobs are finished more swiftly, and it also help to frees up the time of a medical expert's when they could be acting other responsibilities, which cannot be computerized, and hence are appreciated as a more cherished practice of human wealth. For instance, technology application has improved in all regions of daily life. Now, there are unbelievable volumes of tools and robotics in association with modern medicine; all medical information is digitized, online appointments can be arranged, and with the help of different healthcare apps in smartphone, it can be easy to find out nearest medical clinics or any health centers. Artificial intelligence is already being used in healthcare modern medicine nowadays. As a medical assessment support system, DXplain [47] is an artificial intelligence system that can help to perform on a set of medical outcomes like symptoms, marks, laboratory files, etc. to make a hierarchical list of identification that can describe the medical indices. Germwatcher [48] is another artificial intelligent system that is considered to notice, and examine taints in needy patients. In medical robotic surgical technology, the "da Vinci robotic surgical system" [49] with defined movement, robotic arms, and magnetized visualization permits surgeons to perform surgery that is not possible through an exclusively manual method. The probable for enlarged artificial intelligence practice in modern medicine is not objective in a decrease of physical jobs and reducing doctor's time, growing proficiency and output-it also offers the prospect for healthcare system to change to further accuracy of modern medicine.

5. Alginate and AI in biomedical fields

Smart biomedical and medical packaging with the application of polymers is a generally and rapidly growing area of interest for academia and industries. Among a variety of polymers such as alginate, many uses have been created such as in biomedical field, medicine, packaging, and food sector [50]. For example, in modern drug delivery systems, a mesh completed of nanofibers created by the electrospinning process is highly desired. Electro-spinning for biomedicine is based on the application of natural substances and biopolymers, along with the mixture of drugs such as sulfisoxazole, naproxen, and essential oils with antibacterial properties such as eugenol and tocopherol. In recent times, there has been an enormous thrust in the usage of biopolymers for a number of applications, especially in the biomedical and also in pharmaceutical areas [51, 52]. The functional effectiveness of the biopolymer molecules depends on the physicochemical properties, structural

features, and composition [53]. It is feasible to rationally design the structure and composition of the biopolymer to gain suitable useful features [54]. The internal structure of the polymer molecule determines many functional characteristics, for example permeability, integrity, and chargeability [55]. The strength of the biopolymer particles and their summative capability is influenced by the electrical characteristics. Molecules of biopolymers and their electrical properties influence the contact with other molecules present in the neighboring environment. Alginate is one of the most popular natural biopolymers and intensely studied [56, 57]. It is an anionic biopolymer consisting of units of guluronic acid and mannuronic acid in uneven blocks [58]. Guluronic acid and mannuronic acid are linked by glycosidic linkages [59, 60], whereas the guluronic acid forms α bonds (1 → 4) and β (1 → 4) bonds with mannuronic acid [61]. The stiffness of molecular chains is ensured by the rigid and bent conformations of guluronic acid [62]. Hecth et al. have recently discussed their study on the characterization of calcium alginate and sodium alginate with particular importance on their structure [63]. Different applications and properties of alginate have also been examined. Alginate characteristics used biomedical especially in biomedicine can be formed by adjusting the accessibility of their hydroxyl and carboxyl groups [64]. It influences the characteristics of alginates, such as hydrophobicity, solubility, and their biological activity [65]. Alginate hydrogels were formed by cross-linking polymer chains [66]. The chemical properties of alginate hydrogels were found to depend on the cross-linking density of the chain [67]. The cellular viability of MG-63 osteosarcoma cells was improved by blending alginate bioink solution with N-acetyl cysteine (NAC) [68]. One of the techniques used in the design of alginate hydrogels is intermolecular cross-linking, wherein only the alginate guluronan groups react with the divalent cation, most frequently the calcium used to gel the alginate [69].

6. Conclusions

Artificial intelligence (AI) in healthcare offered a variety of healthcare information results that artificial intelligence (AI) has examined and reviewed the most important types of diseases that artificial intelligence (AI) has arranged. Machine learning (ML) and natural language processing are two major groups of artificial intelligence (AI) devices. For machine learning (ML) process, two most accepted traditional methods are available, that is, neural network and SVM. A typical artificial intelligence (AI) system must have the machine learning (ML) component that can help for conducting the structured data such as EP data, images, and genetic data and another natural language processing (NLP) module for the deduction of unstructured works. The complicated algorithm requires to be taught during the healthcare results previous to the system which can support the physicians for the disease analysis and plans which should be required for treatment. This technique focuses on how computer-oriented assessment methods, within the same roof as artificial intelligence (AI), can help in improving health and clinical area. Even though sophisticated information and machine learning present the base for artificial intelligence (AI), at present, there are revolutionary progresses happening in the subfield of neural networks. This has produced remarkable enthusiasm in several fields of healthcare science, as well as drug analysis and public health. Deep neural networks can execute as well as the most excellent human clinicians in definite diagnostic responsibilities. Additionally, artificial intelligence (AI) tools are already emerging in health-based apps, which can be engaged in handheld, network machines such as smart mobile phones. The major obstructions to be defeated in building health and healthcare data information are the space between digital

data and human cognition. Data information regarding an entity patient is mostly gained in forms designed to be available to healthcare personnel. Typical data may consist of MRI or X-ray or ultrasound pictures of the patient, visual records of lung or heart function differing with time, or verbal similes of the patient as seen by the medical personnel. Alternatively, when data are accumulated in data information process and applied, in health research or to expand treatment procedures, it is regularly concentrated to statistical information that is mainly digital. The transfer of analog input into digital output is an oppressive task and may result in a defeat of important information, which would have been cooperative to the consumer.

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