Review

Artificial intelligence in medicine

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Introduction: Artificial intelligence is a branch of computer science capable of analysing complex medical data. Their potential to exploit meaningful relationship with in a data set can be used in the diagnosis, treatment and predicting outcome in many clinical scenarios.

Methods: Medline and internet searches were carried out using the keywords 'artificial intelligence' and 'neural networks (computer)'. Further references were obtained by cross-referencing from key articles. An overview of different artificial intelligent techniques is presented in this paper along with the review of important clinical applications.

Results: The proficiency of artificial intelligent techniques has been explored in almost every field of medicine. Artificial neural network was the most commonly used analytical tool whilst other artificial intelligent techniques such as fuzzy expert systems, evolutionary computation and hybrid intelligent systems have all been used in different clinical settings.

Discussion: Artificial intelligence techniques have the potential to be applied in almost every field of medicine. There is need for further clinical trials which are appropriately designed before these emergent techniques find application in the real clinical setting.

Key words: Artificial intelligence – Neural networks (computer)

Artificial intelligence (AI) is defined as 'a field of science and engineering concerned with the computational understanding of what is commonly called intelligent behaviour, and with the creation of artefacts that exhibit such behaviour'.[1] Aristotle attempted to formalise 'right thinking' (logic) through his syllogisms (a three part deductive reasoning). Much of the work in the modern era was inspired by this and the early studies on the operation of mind helped to establish contemporary logical thinking. Programs which enable computers to function in the ways, that make people seem intelligent are called artificial intelligent systems. The British mathematician Alan Turing (1950) was one of the founders of modern computer science and AI. He defined intelligent behaviour in a computer as the ability to achieve human-level performance in cognitive tasks, this later became popular as the 'Turing test'.[2] Since the middle of the last century, researchers have explored the potential applications of intelligent techniques in every field of medicine.[3,4] The application of AI technology in the field of surgery was first successively investigated by Gunn in 1976, when he explored the possibility of diagnosing acute abdominal pain with computer analysis.[5] The last two decades have seen a surge in the interest in medical AI.

Modern medicine is faced with the challenge of acquiring, analysing and applying the large amount of knowledge necessary to solve complex clinical problems. The development of medical artificial intelligence has been related to the development of AI programs intended

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to help the clinician in the formulation of a diagnosis, the making of therapeutic decisions and the prediction of outcome. They are designed to support healthcare workers in their every day duties, assisting with tasks that rely on the manipulation of data and knowledge. Such systems include Artificial neural networks (ANNs), fuzzy expert systems, evolutionary computation and hybrid intelligent systems.

Artificial neural networks

Judging by the volume of publication in the last two decades, ANN is the most popular AI technique in medicine.[6] ANNs are computational analytical tools which are inspired by the biological nervous system. They consist of networks of highly interconnected computer processors called 'neurons' that are capable of performing parallel computations for data processing and knowledge representation. Their ability to learn from historical examples, analyse non-linear data, handle imprecise information and generalise enabling application of the model to independent data has made them a very attractive analytical tool in the field of medicine.

McCulloch and Pitts (1943) invented the first artificial neurone using simple binary threshold functions.[7] The next important milestone came when Frank Rosenblatt, a psychologist, developed the Perceptron in 1958[8] as a practical model. Many variations of the basic Perceptron network have been proposed but the most popular model has been multilayer feedforward Perceptron (Fig. 1). These networks are made up of layers of neurons, typically an input layer, one or more middle or hidden layers and an output layer, each of which are fully connected to other layer. The neurons are connected by links, and each link has a numerical weight associated with it. A neural network 'learns' through repeated adjustments of these weights. One of the important characters of ANNs is that they can learn from their experience in a training environment. The use of multilayer feedforward Perceptron was restricted by the lack of a suitable learning algorithm until Paul Werbos (1974) a PhD student introduced 'backpropagation' learning.[9] Some of the other popular network designs include Hopfield networks,[10] Radial Basis Function[11] and the Self-Organizing Feature Map.[12]

ANNs have already found a wide variety of applications in the real world. Their ability to classify and recognise patterns accurately has attracted researchers to apply them in solving many clinical problems. As we realise that diagnosis, treatment and predicting outcome in many clinical situations is dependent on a complex interaction of many clinical, biological and pathological variables there is a growing need for analytical tools like ANNs which can exploit the intricate relationships between these variables.
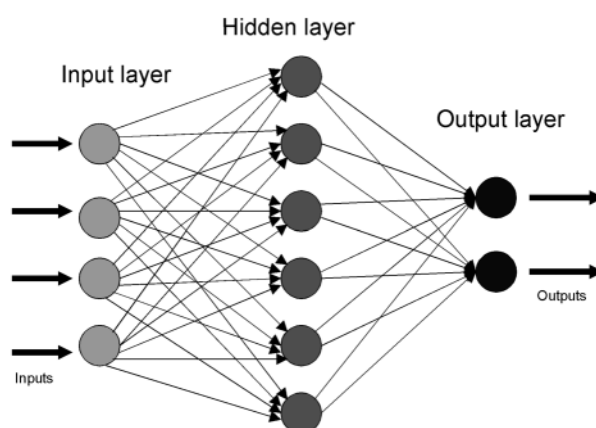

Figure 1 Multilayered feedforward artificial neural networks.

Baxt was one of the first researchers to explore the clinical potentials of ANNs.[13] He developed a neural network model which accurately diagnosed acute myocardial infarction and latter prospectively validated his work with similar accuracy.[14] Since then, ANNs have been applied in almost every field of medicine.

Diagnosis

ANNs have been used in the clinical diagnosis, image analysis in radiology and histopathology, data interpretation in intensive care setting and waveform analysis.

Stamey *et al.*[15] developed a neural network derived classification algorithm called ProstAsure Index which can classify prostates as benign or malignant. This model which was subsequently validated in prospective studies had a diagnostic accuracy of 90%, with a sensitivity of 81% and specificity of 92%. Some of the other surgically relevant diagnostic applications of ANNs include abdominal pain and appendicitis,[16] retained common bile duct stones,[17] glaucoma,[18] and back pain.[19]

ANNs have also been used in diagnosing cytological and histological specimens. PAPNET, a computerised automated screening system based on neural networks, has been developed to assist the cytologist in cervical screening and is one of the few ANN models which was promoted commercially.[20] Breast,[21] gastric,[22] thyroid,[23] oral epithelial cells,[24] urothelial cells,[25] pleural and peritoneal effusion cytology[26] have all been subjected to analysis by neural networks with varying degree of success. In radiology, it is possible to use both human observations and direct digitised images as inputs to the networks. ANNs have been used to interpret plain radiographs,[27] ultrasound,[28] CT,[29] MRI,[30] and radioisotope scans.[31]

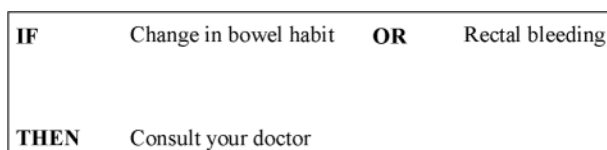ANNs pattern recognition ability has been used to analyse various wave forms including the interpretation

IF	Change in bowel habit	**OR**	Rectal bleeding
THEN	Consult your doctor		

Figure 2 A typical fuzzy rule system.

of ECGs to diagnose myocardial infarction,[32] atrial fibrillation,[33] and ventricular arrythmias.[34] Analysis of electro-enchalograms (EEG) by neural networks has led to its application in the diagnosis of epilepsy[35] and sleep disorders.[36] They have also been trained to analyse electromyographic (EMG)[37] and Doppler ultrasound[38] wave forms as well as haemodynamic patterns in intensive care patients.[39]

Prognosis

Prognostication is extremely important in planning appropriate treatment strategies and follow-up. Accurate identification of high-risk patients may facilitate targeted aggressive adjuvant therapy which may help cure the disease and prolong survival. ANNs with their ability to exploit non-linear relations between variables are particularly suitable to analyse complex cancer data. It has been demonstrated that neural networks can predict survival in patients with breast and colorectal cancer.[40,41] ANNs have also shown to perform better than consultant colorectal surgeons in predicting outcome in patients with colorectal cancer.[42] The authors of this paper have demonstrated the generalisability of ANNs, once trained on a particular data, the networks were able to predict outcome for patients from an independent institution with out retraining. ANNs have also been used to predict outcome in lung[43] and prostate cancers.[44] They have been applied to predict outcome in intensive care unit and have performed better than APACHE II severity of illness scoring system.[45]

Fuzzy expert systems

Fuzzy logic is the science of reasoning, thinking and inference that recognises and uses the real world phenomenon – that everything is a matter of degree. Instead of assuming everything is black and white (conventional logic), fuzzy logic recognises that in reality most things would fall somewhere in between, that is varying shades of grey. It was popularised by Lofti Zadeh (1965) an engineer from the University of California.[46] It uses continuous set membership from 0 to 1 in contrast to Boolean or conventional logic which uses sharp distinctions, *i.e.* 0 for false and 1 for true. Medicine is essentially a continuous

domain and most medical data is inherently imprecise. Fuzzy logic is a data handling methodology that permits ambiguity and hence is particularly suited to medical applications. It captures and uses the concept of fuzziness in a computationally effective manner. Zadeh wrote in 1969 that: 'the most likely area of application for this theory lies in medical diagnostics and, to a lesser extent, in the description of biological systems'.[47] Fuzzy expert systems have the structure of a series of 'if – then' rules for modelling (Fig. 2).

The techniques of fuzzy logic have been explored in many medical applications. Schneider *et al.*[48] showed that fuzzy logic performed better than multiple logistic regression analysis in diagnosing lung cancer using tumour marker profiles. Similarly, the application of fuzzy logic has been explored in the diagnosis of acute leukaemia,[49] and breast[50] and pancreatic[51] cancer. They have also been applied to characterise ultrasound images of the breast,[52] ultrasound[53] and CT scan[54] images of liver lesions and MRI[55] images of brain tumours. Fuzzy logic has also been used to predict survival in patients with breast cancer.[56] Fuzzy controllers have been designed for the administration of vasodilators to control blood pressure in the peri-operative period.[57] They have also been used for the administration of anaesthetics in the operating room.[58]

Evolutionary computation

Evolutionary computation is the general term for several computational techniques based on natural evolution process that imitates the mechanism of natural selection and survival of the fittest in solving real-world problems. The most widely used form of evolutionary computation for medical applications are 'Genetic Algorithms'. Proposed by John Holland (1975),[59] they are a class of stochastic search and optimisation algorithms based on natural biological evolution. They work by creating many random solutions to the problem at hand. This population of many solutions will then evolve from one generation to the next, ultimately arriving at a satisfactory solution to the problem. The best solutions are added to the population while the inferior ones are eliminated. By repeating this process among the better elements, repeated improvements will occur in the population, survive and generate new solutions.

Most medical decisions can be formulated as a search in a very large and complex space. For example: a cytologist analysing a cytological specimen to decide whether they are malignant or not, is searching in the space of all possible cell features for a set of features permitting him to provide a clear diagnosis. Genetic algorithms exploit the mechanism of natural evolution to search efficiently in a given space. They are applied to perform several types of tasks like diagnosis and

prognosis, medical imaging and signal processing, and planning and scheduling. The principles of Genetic algorithms have been used to predict outcome in critically ill patients,[45] lung cancer,[60] melanoma[61] and response to warfarin.[62] They have also been used in computerised analysis of mammographic microcalcification,[63] MRI segmentation of brain tumours to measure the efficacy of treatment strategies[64] and for analysing computerised 2-D images to diagnose malignant melanomas.[63,65]

Hybrid intelligent systems

Each AI technique has its own strengths and weaknesses. Neural networks are mainly concerned with learning, fuzzy logic with imprecision and evolutionary computation with search and optimisation. The advantages of these technologies can be combined together to produce hybrid intelligent systems which can work in a complementary manner. Their synergy allows a hybrid system to accommodate common sense, extract knowledge from raw data, use human-like reasoning mechanisms, deal with uncertainty and imprecision, and learn to adapt to a rapidly changing and unknown environment. There are many different hybrid systems available and the popular ones are ANNs for designing fuzzy systems, fuzzy systems for designing ANNs, and Genetic Algorithms for automatically training and generating neural network architectures. Once again, the application of hybrid intelligent systems has been explored in many diverse clinical scenarios. Some examples include breast cancer diagnosis,[66] analysis of microcalcification on digital mammograms,[67] diagnosis of coronary artery stenosis,[68] assessment of myocardial viability,[69] and control of the depth of anaesthesia.[70]

Conclusions

There are many different AI techniques available which are capable of solving a variety of clinical problems. However, in spite of earlier optimism, medical AI technology has not been embraced with enthusiasm. One reason for this is the attitude of the clinicians towards technology being used in the decision-making process. Paradoxically, there is no qualm in accepting the biochemical results generated from an auto-analyser or images produced by magnetic resonance imaging. However, it is the obligation of researchers active in this field to produce evidence that these techniques work on a practical level. The need to undertake more randomised controlled studies to prove the efficacy of AI systems in medicine is, therefore, vital.

There is compelling evidence that medical AI can play a vital role in assisting the clinician to deliver health care efficiently in the 21st century. There is little doubt that these techniques will serve to enhance and complement the 'medical intelligence' of the future clinician.

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