Application of Neural Networks in the Medical Field

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Abstract

The field of computer technology has seen remarkable advancements, which has led to a surge in interest in the possible applications of "Artificial Intelligence," or AI, in the fields of medicine and biological research. The field of artificial intelligence known as "Artificial Neural Networks" (ANNs) is one of the most promising and intensively researched subfields in AI. ANNs are, in their most fundamental form, the mathematical algorithms that are generated by computers. ANNs are taught using standard data and are able to comprehend the information that is imparted by the data. ANNs that have been trained come extremely close, on a basic level, to replicating the functioning of small biological neural clusters. They are the digital model of the biological brain, and they have the ability to discover complicated nonlinear correlations between dependent and independent variables in a data set, something that the human brain may be unable to do. These days, ANNs are employed extensively for medical applications in a variety of subspecialties within the field of medicine, particularly cardiology. Diagnostics, electronic signal analysis, medical image analysis, and radiology are just few of the fields that have found considerable use for ANNs. Many researchers have made use of ANNs for modelling purposes in the field of medicine and clinical research. Both pharmacoepidemiology and medical data mining are experiencing increasingly more applications of artificial neural networks (ANNs). The author of this paper provides an overview of the many different applications of ANNs in the field of medical science.

Keywords: Artificial Neural Networks (ANNs), Artificial Intelligence (AI), Convolutional Neural Network (CNN), Electronic Health Record (EHR), Deep Neural Networks (DNN).

1 Introduction

Challenges in refining the structure and administration of healthcare sector, such as better integrating procedures in healthcare provision for patient-centered chronic disease management, arise as healthcare systems in developed countries shift towards a “value-based, patient-centered model of care delivery”. Emerging innovations, including artificial intelligence, have the ability to solve non-traditional patient care, the changing healthcare environment and workforce, the introduction of new and diverse health information systems, and much more (Chaurasia and Culurciello, 2017). There are many potential solutions to all these health-care management challenges, especially given the widespread adoption of

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AI to make ever-more-complex decisions across industries; however, there is a dearth of words of wisdom on how to choose methods that are particularly well-suited to the health care sector.

Increase in the number of elderly people and the complexity of their diseases, as well as the success of emerging therapeutic procedures, the increasing cost of labour, as well as the growth of the health care business, are all factors that will push up global health care spending to $8.7 trillion by 2020. It has been observed that many healthcare institutions are unable to affordably upgrade their aged infrastructure and legacy technology (Che et al., 2017). Decision-makers, in an effort to transition to value-based care, are reportedly shifting their attention to issues such as population health management, such as assessments of developments in quality, health, and cost, and also the adoption of advanced delivery models to enhance procedures and care coordination.

Due to the numerous system interdependences, like evolving external factors and conflicting interests, which can make the procedure of decision-making more difficult, health care organisations are being forced to become more strategic in their approach to management. This trend is expected to continue (Chen et al., 2016a). When it comes to making high-risk choices without the assurance of high-return, decision-makers in the health care industry may confront challenges linked to technology, culture, and risk. As per economic theory, the majority of companies want to minimise their risk tolerance.

According to a white paper that was issued by IBM, as increasing amounts of health care data is being captured and digitised, health care organisations are beginning to make use of the opportunity to analyse big sets of regularly obtained digital information in order to enhance their services and bring down their costs. Instances include assessing financial, clinical, and operational data to address issues pertaining to the efficacy of programmes as well as generating predictions pertaining to patients who are at danger (Chen et al., 2016b). In 2015, the worldwide market for healthcare predictive analytics was estimated to be worth USD 1.48 billion, and its value is anticipated to increase at a pace of 29.3% by the year 2025. In a related vein, it is anticipated that worldwide revenue, which now stands at $811 million, would climb by 40% by the year 2021 owing to the AI industry for applications in health care (Cheng et al., 2016a). “The machine learning as a service industry is a branch of artificial intelligence that is projected to hit $5.4 billion by 2022”. The healthcare sector is a major key driver of this market.

A current assessment of artificial intelligence uses in health care showed utilisation in important problem areas like cancer or cardiology, including ANN as a frequent ML technique. The survey also found that machine learning is a popular use of AI. Clinical diagnosis, speech recognition, the probability of cancer, the prediction of length of stay, image interpretation and analysis like automated electrocardiographic (ECG) interpretation used to detect myocardial infarction, and drug discovery are all examples of emergence of (ANN) in the field of medicine. Uses outside of clinical settings have included things like improving health care organisational administration and making predictions about important metrics like cost or facility use (Cheng et al., 2016b). In order to give health care professionals and the whole health care system with cost-effective responses to the issues of resource and time administration, ANN has been employed as part of decision support models.

2 Neural Network

Learning about neural networks may be a very challenging task. Admittedly, many people consider the applications of artificial intelligence in the medical profession to be something out of the realm of possibility at this point.

“**Neural Networks** are a computational approach which is based on a large collection of neural units loosely modeling the way the brain solves problems with large clusters of biological neurons connected by axons. Each neural unit is connected with many others…These systems are self-learning and trained rather than explicitly programmed…” According to Wikipedia.

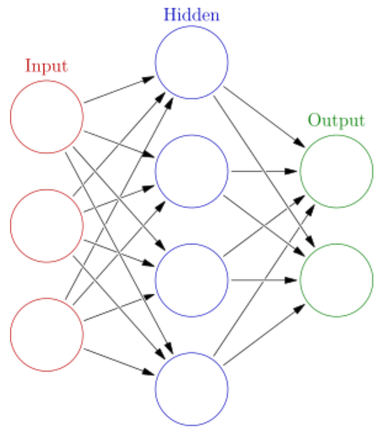

Figure 1: Artificial Neural Network

Suppose that a doctor wishes to make a forecast about a patient's well-being, such as whether or not she or he is at danger of suffering from a certain ailment. One approach to think about it is as follows: How would a physician be able to determine that particular piece of information? In most instances, it would include doing blood tests, taking tests of the patient's vitals, and other types of examinations in order to uncover characteristics of patients that have been shown to be reliable health predictors (Choi et al., 2016a). But what if physicians are only aware of a small number of the risk factors for a particular disease? Or, even worse, what if they are unaware of any of the risk variables at all? It is not practical to make any forecasts at this time.

In the field of medicine, ANNs are helping to make predictions that traditional medical professionals simply couldn't handle on their own. They are effective at times when they are able to acquire data, but they are not yet aware of which specific aspects of that data are of the utmost significance (Choi et al., 2016b). Because of this, these abstractions are capable of capturing complicated interactions that may not be readily evident, which ultimately leads to improved prediction for healthcare system.

The advantages of artificial intelligence and neural networks may be divided into two categories the benefits to patients, and the benefits to physicians and other medical professionals. Deep neural networks, also known as DNN, are able to assist in the interpretation of medical scans, such as electrocardiograms and endoscopies. A special focus is placed on radiology, namely the use of neural networks to the interpretation of X-ray images (Çiçek et al., 2016). The results of Google's use of algorithms to interpret chest images resulted in the company making 14 distinct conclusions, ranging from pneumonia and heart hypertrophy to lung collapse and collapsed lungs. DNNs are able to identify a variety of diseases, including some forms of cancer, fractures, haemorrhages, skin lesions, retinopathy, and many more. By monitoring the course of depression, neural network algorithms may improve the effectiveness of medical practises across a wide range of specialties, including dermatology, cardiology, ophthalmology, and even psychotherapy. The fact of the matter is that the majority of the research and reports are still only available as preprints. Preprints have not been reviewed by appropriate reviewers nor have they been published (Cicero et al., 2017). In preprints, algorithmic procedures are evaluated based on their correctness, which is not the same thing as clinical efficacy. In most cases, efficacy is verified by time-consuming and costly clinical studies.

The development of algorithms that patients can employ on their own takes a lot longer than the development of algorithms that professionals use. "The Smartwatch algorithm for identifying arrhythmias was granted approval by the Food and Drug Administration (FDA) of the United States in 2017". And as a result of that, in 2018, Apple was granted clearance from the FDA for the algorithm that is utilised in the Apple Watch Series 4. The sensors on a watch are able to determine the wearer's heart rate as well as the heart beat experienced during exercise (Dai et al., 2018). The user will get a notification to begin recording an ECG via the watch if the watch detects a significant divergence from the predicted value. The findings are given an interpretation by the algorithm after that.

Some mobile applications for smartphones make use of neural networks to keep track of and manage medicine use. For instance, AiCure requires its patients to record themselves taking a selfie video while simultaneously ingesting a medication. In order to prevent hypoglycemic episodes in diabetic patients, algorithms may monitor and evaluate changes in the patients' blood glucose levels (Esteva et al., 2017). With the use of the applications, common chronic diseases like depression, hypertension, and even asthma may be better treated.

3 NN in the Medical Field

Artificial neural networks, often known as ANNs, are better than statistical classification approaches in many fundamental ways. The usage of ANNs is appropriate in situations in which standard classification techniques are ineffective as a result of noisy or insufficient data. In multivariable classification situations characterised by a high correlation degree, neural networks may also be useful. The process of making a diagnosis of an illness is an excellent illustration of such difficult categorization issues (Fauw et al., 2018). This dependency may be broadened if the appropriate application of artificial neural networks is made in this field in order to get the interdependence of symptoms and an accurate diagnosis. On the basis of this extended model, researchers are then able to identify input patterns that reflect different illnesses and their symptoms. On the other hand, it is not essential to define the algorithm or in any other way identify the ailment throughout the application procedure. Only input patterns are required for the application. The following flowchart is an outline of the whole of the disease diagnosis process that occurs in clinical settings (Fig. 2).

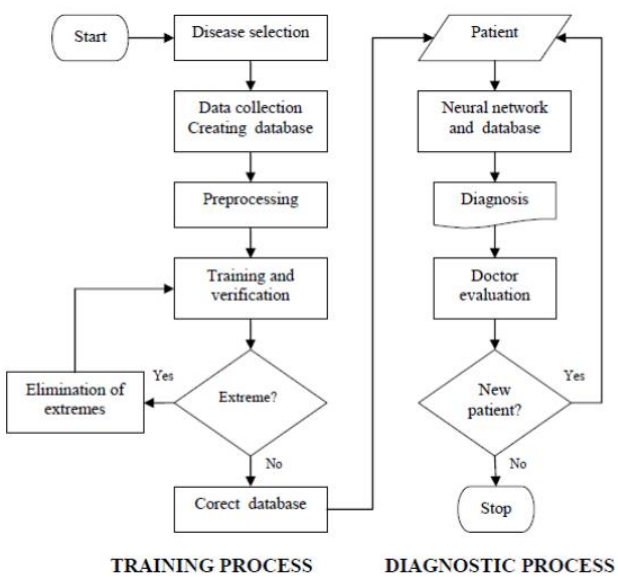

Figure 2: A Flowchart Showing how Physicians Diagnose Patients

The whole procedure of diagnosing diseases may be separated into two distinct parts: the training portion and the diagnostic component. In most cases, the process of training starts with the selection of target disorders, which is connected to the fact that the classification issue will be related to such diseases. After making the correct selection of a condition, the next step is to recognize the particular symptoms, measurements, and test findings that comprehensively characterise the nature of the illness in question. In the subsequent stage, a database is formed using this data (Finnegan and and Song, 2017). This database then needs to be checked, and any extreme numbers that are outside of the acceptable range need to be removed. This database is used to train the neural network, and also the results gained from this procedure are checked later. In the event that the outcomes of the trained neural network correspond to reality, then the neural model may be implemented in clinical settings. The process of diagnosis starts here with this first step. The information about the patient is sent into the neural network, which then makes a determination on the most likely diagnosis (Gao et al., 2020). The attending physician then verifies this finding to ensure its accuracy. The physician's judgement, which is based on his or her personal experiences and evaluation of all elements of the condition, as well as the outcome of neural network categorization, is ultimately what determines the diagnosis.

The patient's clinical state must be accurately described in the data while building a database for neural network training. Consideration should not be made of any data that provides extraneous or incorrect information concerning the patient's diagnosis. The doctor's job is to choose the best characteristic data. The most of the time, these data consist of fundamental details about the patient's condition, the findings of biochemical tests, symptoms, as well as other data that aids in making the right diagnosis. All of these data from one patient that were gathered and assessed correspond to one neural network input pattern. The input patterns employed throughout the training process have a significant impact on the capacity to generalise the discovered relationship between symptoms and diagnosis. Consequently, the database should include a significant number of reliable patterns that define the diagnosis (Grinsven et al., 2016). In order to generalise in patient diagnostic instances, even for cases that are not in the training data, this will allow the neural network to approximatively detect hidden dependencies in the data set. The database structure includes a table or matrix that contains data on the diagnoses and general health of the patients.

The multi-layer perceptron networks are ANNs that are most often used in medical diagnostics. Figure 3 illustrates the fundamental concept of the medical diagnostic using the MLP as well as its structure. The logical sigmoid function was used in both the hidden and output layers of the network's structure. MLP was used to implement categorization depending on this data, and system inputs were expressed in the database as normalized medical variables with a range of 0 to 1. Each output of the network had a number between (0, 1) that represented the percentage of groups in the output (Gulshan et al., 2016). A set of hidden neurons' number was determined experimentally. The selection with insufficient hidden neurons resulted in a poor approximation of the relation examined. If there were too many hidden neurons, the neural network would closely resemble the sought relation in the training data and lose its capacity to generalise.

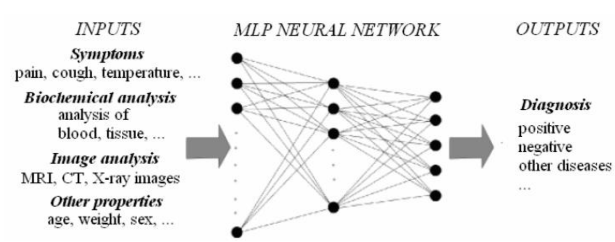

Figure 3: MLP Medical Diagnosis

In order to train the MLP neural network, researchers used normalised data from the database pertaining to the diagnosis of patients. The information on the patient's diagnosis was standardised to range (0, 1). It is required to split the data appropriately into training, testing, and validation data in order to ensure that the neural network is trained correctly. This is done in order to ensure that each group (diagnostic) has an equal amount of representation in the data. Apart from these following applications are there of NN in the medical field:

3.1 Medical Image

The medical image is an essential component in the process of medical evaluation and treatment since it provides a crucial foundation for comprehending a patient's illness and assisting clinicians in reaching therapeutic conclusions. Increasingly more medical image data, like computed tomography (CT), magnetic resonance imaging, and other types of imaging, are being produced as medical technology advances at a quick pace and the field of medical health continues to see explosive job growth. If specialists reviewed large volumes of medical imaging data on their own, the process would take far more time. In addition, the specialists who conduct the evaluation of medical imaging data may have variable degrees of experience, expertise, and other relevant aspects, which may lead to the production of conclusions that are incorrect or biased (Gupta et al., 2018). To a certain degree, machine learning algorithms are able to aid professionals in automatic detection; nevertheless, it is possible that these algorithms will not be able to process and attain a high level of accuracy when presented with such large amounts of data and difficult challenges.

Deep learning has been shown to be effective in the area of image processing. This kind of learning examines pictures in order to complete a variety of tasks, including image classification, target identification, and target segmentation. In recent years, there has been a growing tendency in the field of medical research toward the use of deep learning strategies in the process of analyzing medical images. The technologies of artificial intelligence were employed by researchers to assist medical professionals in making correct diagnoses and judgments. These responsibilities include a wide range of facets, including, but not limited to, the diagnosis of retinopathy, skin cancer, and bone aging. The results of deep learning are on par with those of an expert in these fields (Haenssle et al., 2018). One of the most effective approaches to DL is the CNN. The idea of translational invariance as well as limit sharing is followed by the convolutional neural networks, which makes them particularly well suited for automatically extracting image information from the source picture.

A CNN structure for using chest X-ray images to identify pneumonia is shown in Figure 4. The pooling layer, convolution layer, as well as the entirely linked layer make the CNN. A convolution layer's filtering window will first iteratively traverse across the image to extract local features. Next, to decrease parameters and overfitting and boost network performance, the pooling layer will test the learned features. The ultimate results will be generated by these characteristics via the fully connected layer.

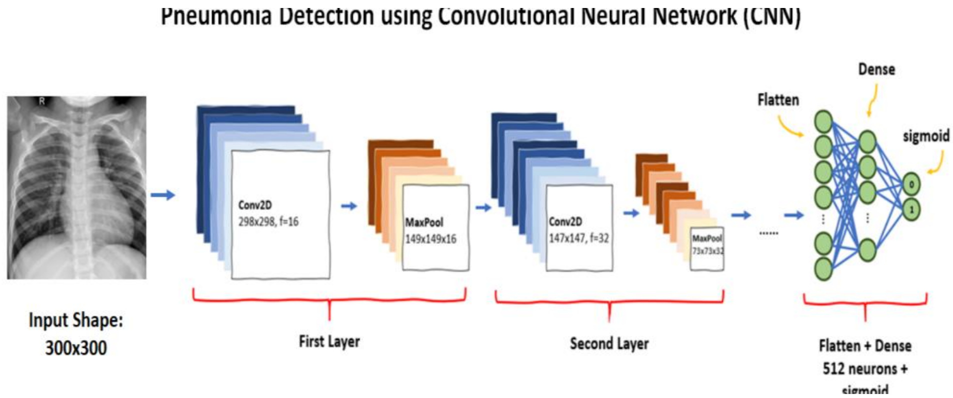

Figure 4: Chest X-ray for Pneumonia Detection using CNN

There are often many convolution layers in a CNN so that the bottom layer can learn the local characteristics of the image and the top layer can combine these local data to determine the overall features. The position and form of lesions or tumours are often varied for the same symptom in various images, making analysis highly challenging. Convolutional neural networks have the benefit of being able to automatically extract local characteristics from pictures and incorporate them into feature sets. CNNs are thus ideal for processing medical image data.

3.2 Electronic Health Record

Many deep learning neural networks have been successfully used in the field of natural language processing, including the one-dimensional CNN, GRU, LSTM, recurrent neural network (RNN), and others. Such networks are good for processing data that is connected to sequences, such as time series, sentences, voices, and so forth. In a similar vein, computational medicine employs natural language processing technologies to handle electronic medical records using neural networks.

The EHR has drawn considerable attention in recent years. The treatment information for patients is kept in an EHR. The data consists of structured data on demographics, structured data on diagnoses, medications, structured data on procedures, structured data on experimental test findings, and structured clinical writing. Exploring electronic health records may enhance medical progress by increasing the accuracy and effectiveness of diagnosis. For instance, it uses data mining to forecast illnesses in electronic health records to provide patients timely treatment, or it examines the hidden connections between medications, diseases, and pharmaceuticals in electronic health records to assist clinicians in making decisions (He, et al., 2016). In brief, using electronic health records may help individuals better understand their physical state and illness status, and using them can also assist medical personnel better diagnose issues and provide effective treatments.

Data from electronic health records are often analysed using machine learning. The characteristics must often be manually extracted before being included into the model. Finding the hidden connection in the data using this feature extraction approach may be challenging since it often rely on the extractor's expert subject knowledge. The quality of the manually derived features, then, influences the model's prediction outcomes. In addition, this strategy wastes a significant amount of time and resources and impairs research effectiveness.

The drawback of standard machine learning, which requires manual feature extraction, is solved by deep learning. However, there are significant issues when employing the deep learning approach to deal with EHR data because of its uniqueness and complexity. The EHR, which are a source of data, include several therapeutic concepts. These ideas are coded, for example under the categories of sickness, medicament, and diagnostic coding (Hitaj et al., 2017). Different medical ontologies define the coding standards as well as the meanings they stand for. Doctors also document these clinical ideas in chronological sequence. Furthermore, by only recording the patient's state, it is impossible to identify and investigate the connection between these ideas.

One hot coding with a dimension equal to the number of medical ideas is the conventional approach. The link between ideas is not reflected in the coding system. In order to translate the clinical ideas provided by coding in EHRs into low dimensional space and change them into low dimensional characteristics for representation, researchers proposed representation learning. These low-dimensional characteristics also show the connection between several concepts. After receiving a representation of a clinical concept, researchers can use that concept in subsequent tasks to give doctors valuable information and aid in their decision-making by analysing the relationship between that concept and other clinical concepts, like the connection between diseases or between diseases and clinical activities (Hochreiter and Schmidhuber, 1997). These investigations covered mortality analysis, rehospitalization prediction, illness prediction, etc. As illustrated in Figure 5, the deep learning methodology may convert the EHRs into a patient representation.

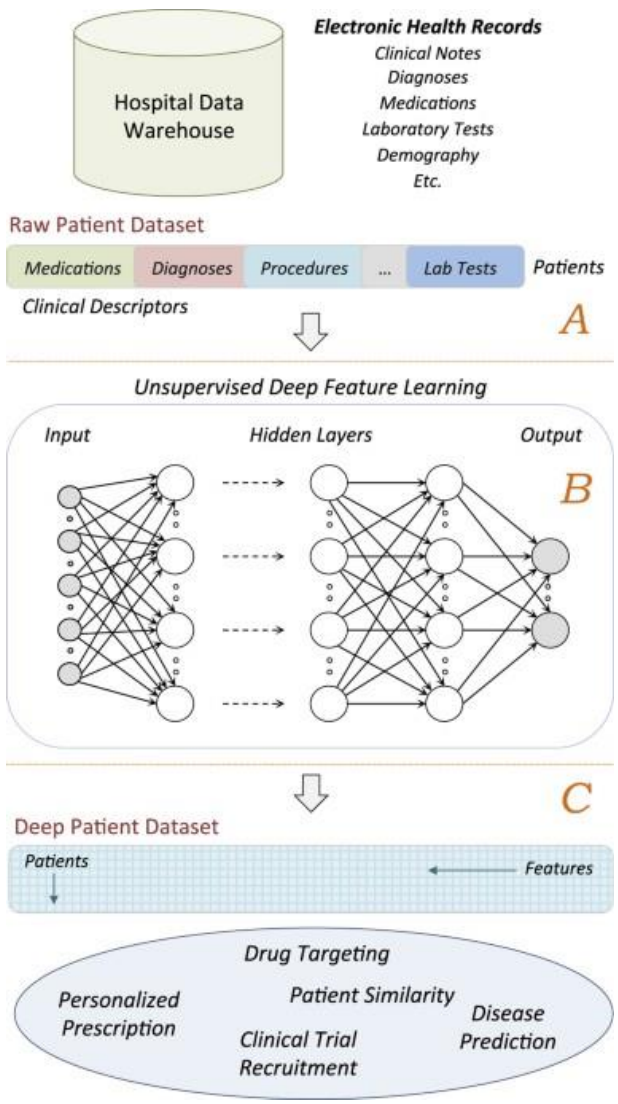

Figure 5: An Unsupervised DL System that Turns Raw EHRs into Patient Representations

3.3 Genomics

The field of study known as genomics investigates the performance, structure, and editing of genes. Many academics have used it to the area of genetics in an effort to uncover deeper patterns because of its great capacity to analyse data and automatically extract features.

Deep learning algorithms are able to extract HD features, better information, and much more complicated structure from biomedical information than classic machine learning approaches. This is due to the fact that biological data is often more complex. Deep learning has seen extensive application in the field of genomics in recent years, being utilised for a variety of tasks including expression of genes, RNA measurement, gene slicing, and others (Hu et al., 2016). In the field of bioinformatics, deep learning introduces new methodologies and contributes to a deeper understanding of the underlying causes of human disorders.

Deep learning may be used efficiently in genomics to comprehend the causes as well as development processes of illnesses from the molecular level, as well as the connection between genes and the ecology, and it can grasp the variables that contribute to disease. Using the high-throughput biological information, the deep learning approach is able to determine the association that exists between illness and gene. The condition may be understood in a more comprehensive manner, choices can be made more accurately, and patients can be provided with a diagnosis and therapy that are more suitable. The use of deep learning techniques in the field of genomics has been a major driving force behind the advancement of customised treatment and precision medicine (Hu et al., 2019a). Figure 6 presents a model that predicts the interactions that take place between enhancers and promoters.

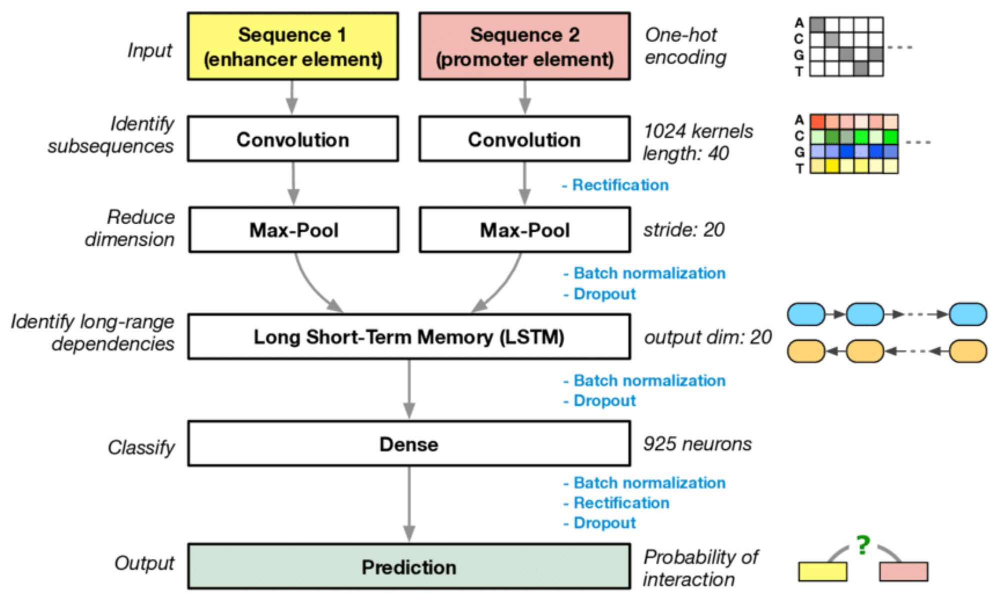

Figure 6: Model for Predicting Enhancer–promoter Interactions

3.4 Drug Development

Deep learning technique has emerged as an innovative approach to the process of developing novel drugs in recent years, coinciding with the increase of biological data. Researchers will be able to conduct out drug development and illness clinical research more efficiently if they use the deep learning technique in the area of drug development. This will also substantially enhance the development of precision medicine.

The procedure of developing new medicines is a difficult and complex procedure. The process of developing a new medicine and bringing it to market often takes at least ten years, making it an extremely drawn-out endeavour that requires a significant investment of resources. Both the experimental approach and the computational technique are used in conventional drug development. The method not only wastes time and resources but also results in significant financial loss. On the other hand, the computational technique may help save time and cut down on losses.

In the process of developing new drugs and designing new drugs, one of the most crucial steps is figuring out how the medication interacts with its target. This process has the potential to reduce costs and shorten the amount of time needed to bring a medicine to market. In recent years, there has been a considerable growth in the amount of biological data, which has provided a data foundation for the use of DL in the field of drug development (Hu et al., 219b). A growing number of researchers have started to use DL in order to investigate the connection between medications and targets. A schematic of a DL model that predicts the “binding affinity scores of drug targets” is shown in Figure 7.

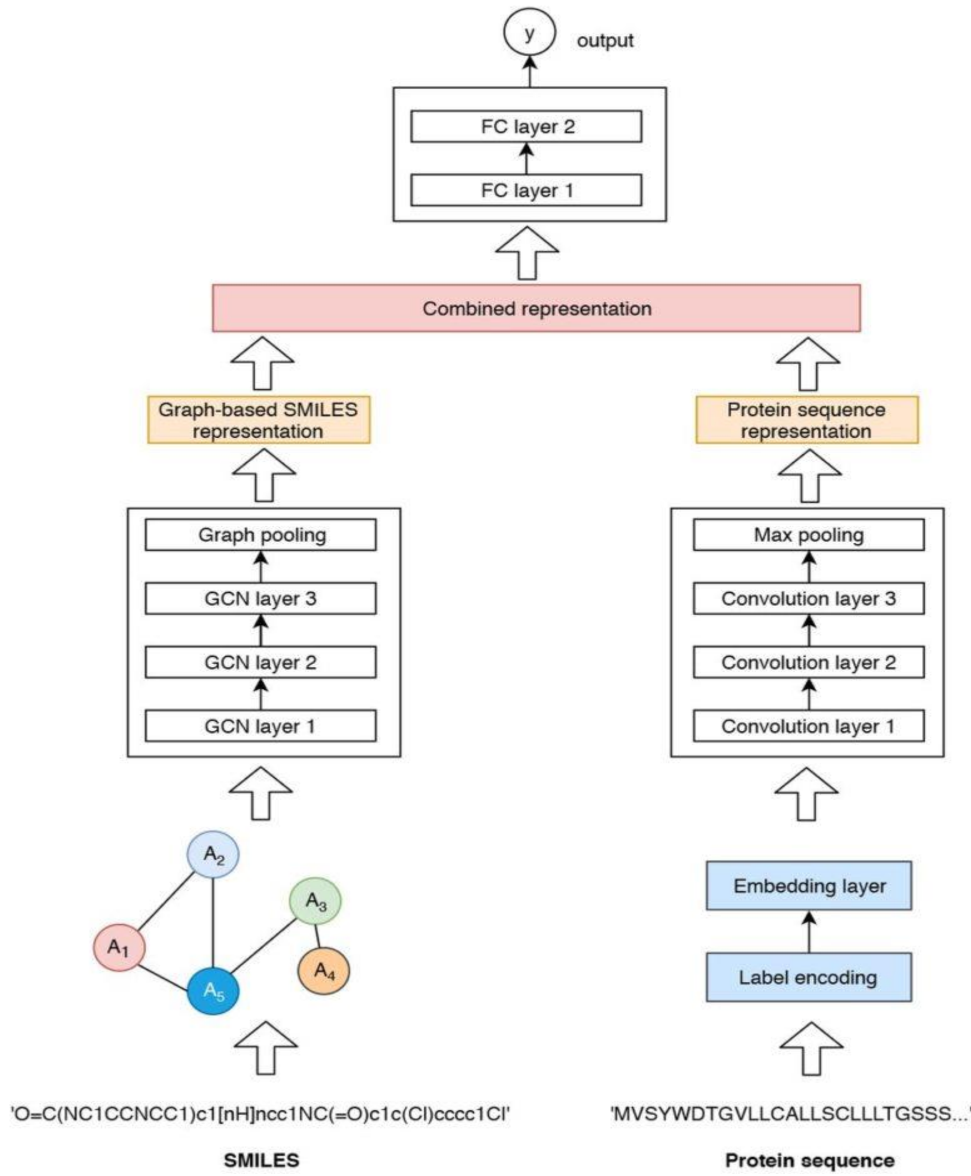

Figure 7: DL Model for Predicting the Scores for Drug-target Binding Affinities

4 Conclusion

According to the findings of our work, artificial neural networks may be used in the decision-making processes of healthcare organisations at all levels. In order to better customise solutions to specific issues, decision-makers are increasingly turning to hybrid models of neural networks. These models are being influenced by recent developments in the relevant area. Researchers identified ANN-based solutions applicable on the macro and micro levels of decision-making, which suggests the potential of its use in settings requiring complicated, unstructured, or restricted information. A better awareness of the ethical, sociological, and economic consequences of utilising ANN in health care organisational decision-making may be required for successful implementation and acceptance.

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Data Availability Statement

The database generated and /or analysed during the current study are not publicly available due to privacy, but are available from the corresponding author on reasonable request.

Declarations

Author declares that all works are original and this manuscript has not been published in any other journal.

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