

Original Article

AI-Enhanced Clinical Decision Support Systems with Neural Networking

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Abstract - The health sector has experienced a clear paradigm shift in the past couple of years, especially in using groundbreaking technologies such as machine learning, artificial intelligence, etc. This paper's primary goal is to show how patients diagnose their medical condition based on different parameters, including age, BMI, blood pressure, pulse rate, respiration rate, body temperature, CBC, lipid profile, and blood glucose. The results were used to categorize patients into three levels based on the intensity of their fluctuations: level 1, level 2, and level 3. Medical experts can use such an analysis as a preliminary diagnosis for treatment, depending on whether other methods are required. The research incorporates developing two models, one deployed with LSTM-The model and another with deep learning. While both techniques proved their efficiency, the LSTM model received a higher accuracy score, evaluated by the root mean squared error scores.

Keywords - Artificial Intelligence, Deep Learning, Healthcare, LSTM, Neural Network.

1. Introduction

Healthcare with AI has brought a lot of discoveries in patient care and diagnostic areas, which has changed how healthcare professionals deal with patient problems and treatment. Nevertheless, a sizable problem in the process is that neural networking in clinical decision support systems (CDSS) is not entirely explored. At present, scientists have concentrated on using neural networks for diagnostics and patient engagement while not paying enough attention to these networks' potential for creating one system that will produce equally essential decisions. The apparent drawback of CDSS in overcoming the complicatedness of health data, which would negatively affect patient results and overall health, is their inability to accurately carry out the final tasks. The proposed paper presents a system, denoted as a new neural network framework with parallel LSTM and cutting-edge deep learning techniques to upgrade CDSS functionality. Our approach is beyond the traditional kind as it combines all the vital data for versatile and accurate diagnosis of a person's state of health. With this combination, we can develop a more elaborate analysis of the time series and improve pattern recognition, thereby boosting the predictive accuracy of CDSS. This results from setting a new standard in the AI-powered healthcare industry. The novelty of our study can be found in the implementation/use of the LSTM method for

forecasting trends over time and deep learning networks for the exact pattern discovery in medical datasets. Our research projects aim to take the industry to the next level as an example of achievement and development in this area by developing a better incorporated, improved, and scalable AI-driven healthcare solution.

2. Literature Review

In terms of the impact of AI and ML on the healthcare industry, it is among the most significantly impacted industries. In this twenty-first century, technologies have become new paths to precision, personalized treatment, and operational efficiency. In the early development stages of AI, Davenport, T.H. [2] and Kalakota, R. [3] initiated the spectrum of topics of how people can use AI to significantly change the health service sector by classifying it as diagnostics, engagement of the patients, and the administrative side of healthcare. Nonetheless, these head-start discoveries have just dealt with a scratch on what you can do with them. The ethical limitations of AI in the healthcare industry are brought to light in the text. It was found that developing systems that would include algorithms and software for the automatic processing of high-risk patients during routine office visits would take approximately 3 million hours of work time from the healthcare system [2]. [3]



The doctors are the general spectators of this movie from an accurate image interpretation that can make systems effective; also, it can reduce medical errors, and patients can infer their data, which can help in general health promotion. As AI technologies have matured, ethical considerations have come to the forefront, highlighting concerns around data privacy, algorithmic bias, and the imperative for transparent AI methodologies. These ethical challenges underscore the complexity of integrating AI into a field as sensitive as healthcare, demanding ongoing scholarly attention and industry regulation. Technological innovations, particularly in ML, have expanded AI's healthcare applications beyond initial expectations. The flexibility of LSTM networks can be seen in their ability to give in-depth time series predictions [5], and the capabilities of CNNs to perform image analysis demonstrates AI pervasiveness. The automation pattern is self-regulated with thorough customization, contributing to LSTM's modesty and simplicity compared to other models in the industry. Generally, LSTM has been accepted as a crucial tool in dynamic healthcare data environments.

The expression of AI and ML effect is enhanced in real-world applications, producing concrete cases that make productive outcomes. These technologies go beyond just improving diagnostic capability to some extent; they play a vital role in enabling remote patient monitoring, too, and are firmly on the way to setting new standards of care delivery. In both cases, though, AI application is shown to have practical challenges of health care systems integration, the need for data infrastructures, and clinicians' training. The results show that a foundation is laid for further research, and AI has massive potential to predict health conditions and personalized medicine. Despite the progress, significant gaps remain in fully leveraging AI's potential, pointing to a prosperous future with opportunities for innovation and improvement in healthcare outcomes.

3. Materials and Methods

3.1. Neural Network Models

Thinking about a neural network will resemble a train of machine learning algorithms that work the same as the nail neurons. The neural networks can comprehend those hidden patterns and correlations by learning from the data, which finally yields decision-making. The neural network methodology is based on learning, modeling, or making generalizations about the network's relationship to the inputs and outputs regardless of the network's nonlinearity and complexity of the system. It also builds or unmasks the chaotic or unpredictable data pattern. The neural network is a got-up of several neurons that are interlinked. The brain may be compared to a neural network by fulfilling a similar role. It comprises an input layer, several hidden layers, and an output layer.

The units, which are nodes within these layers, are allocated with weight and a threshold value. The node gets

activated and relaxes its output according to the given threshold value when its output exceeds that stated value. The subsequent neural network will not receive data from the previous stage on the next layer unless the stipulated condition is met. Obviously, the node pattern comprises input data, weights, thresholds, and output layers. The weightings are set to the importance grades of the variables towards the production and are collected after exploring the input layer. The output of one neuron is the following signal to the succeeding neuron. Thus, the data is passed from one layer to the next layer. Then, that neural network can be defined as a feedforward network. The ones that move in the opposite direction from the output to the input are the backpropagation networks. The neural network learns and improves with the training data.

The neural network approach also exhibits a similarity to statistical techniques such as curve fitting, regression, etc. The input data and the algorithm influence the efficiency of a neural network. Neural networks are widely used for classification, pattern recognition, prediction, etc., irrespective of the discipline. The potentiality of a neural network with high accuracy, processing speed, performance, latency, error tolerance, scalability, and volume made it more convenient than the traditional methodology [6].

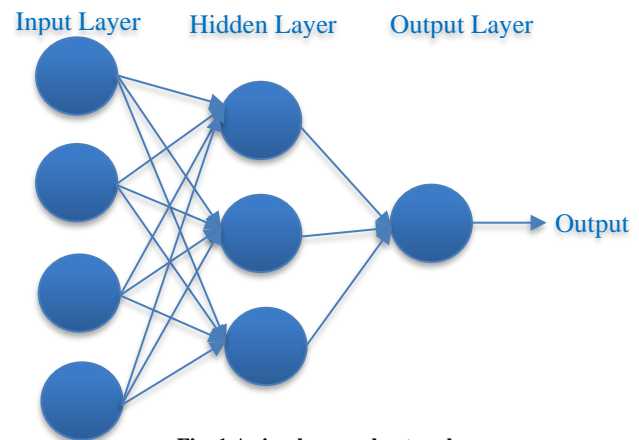


Fig. 1 A simple neural network

A simple feedforward neural network with one hidden layer is represented in FIG 1. This network has an input layer, a hidden layer, and an output layer. Since there is no feedback connection or loops in the network, it is a directed acyclic graph. The hidden layer in this network consists of 3 neurons. The number of hidden layers determines the depth of a neural network. A better model is developed by minimizing the error. So, the output obtained from passing the training data into the network is compared with the actual production, and the error expressed in it is minimized gradually by altering the weight of the neurons. It is done using the backpropagation algorithm, and this method of decreasing the error based on the change in the weight of the neuron by iteratively passing the data through the network is known as the stochastic gradient descent method.

3.2. Long Short-Term Memory

Recent advances in the Long Short-Term Memory (LSTM) network are considered a more sophisticated Recurrent Neural Networks (RNN) version. This makes it possible for the network to store information in the sequential layers and access it in different recursive steps. RNNs, for simplicity's sake, are forward networks with irreversible memory inside them. According to its name, RNN is a recurrent function that is repetitive and performed equally, equivalent to every input. The inputs are chosen by the given (latest) output and the results from the previous input. Despite this, if the input results in production, input depends only on the calculation before the next time. For instance, it cannot process long sequences, so it is not the best model. Another problem of RNN is the vanishing and exploding gradient, which decreases or increases due to the learning process. The LSTMs are built to deal with the long-term dependency and vanishing gradient problems by implementing these features. Hence, LSTM plays essential roles, including classifying, processing, and predicting time series data—usually characterized by the indeterminacy of the duration of time lags.

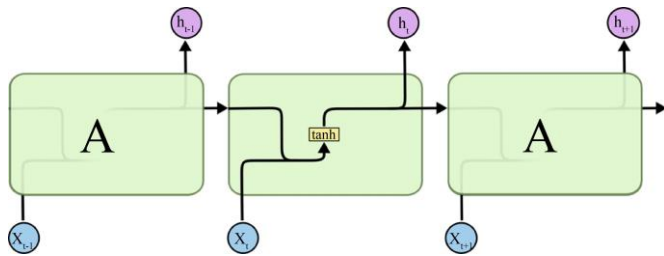


Fig. 2 Structure of repeating module of RNN [7]

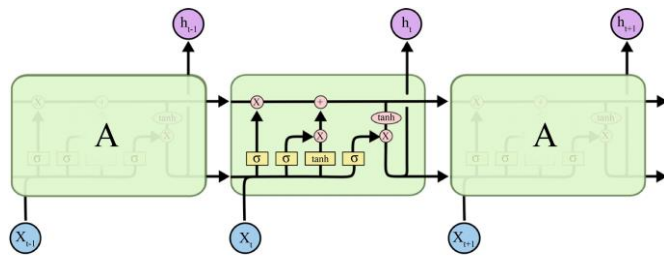


Fig. 3 Structure of repeating module of LSTM [7]

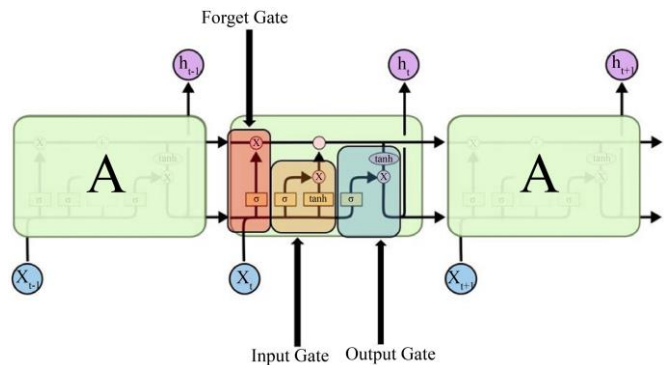


Fig. 4 LSTM Gates [8]

RNNs are represented as a chain of neural network layers that set the framework, for example, the tanh layer. LSTMs, unlike RNNs, have a newly modified chaining module structure with four distinct layers.

LSTM, which was produced, solves the vanishing gradient problem in the normal RNN through a more effective gradient flow within the network by embedding the LSTM cell on a hidden layer. The LSTM unit is a particular type of cell state: a forget gate, an input gate, a t gate, and an output gate.

The forget gate of the LSTM is the initial gate, and it chooses to keep or discard data received in the previous time steps. The SK is obtained by transferring the last hidden layer and the current input information to the sigmoid function. Output can be set to fall between 0 and 1. The final result becomes zero when the value is close to 0 and remains the same if the value is close to 1.

The input gate is gate number two. This decides which feedback is suitable to revise or update the memory, but only with the information of the current time step. Meanwhile, the arguments for the hidden states before and the current one are mapped over the sigmoid function for the sake of finding out importance—furthermore, the information pulled from the secret state and the present unverständlich wird. -1 to 1 value is the output of the tanh function. Then, the eligibility of the data is decided through a multiplication of the production from decrease and increase by element with element.

Upon clicking, the cell state becomes active after the input gate has been activated. Cell state is a state of single units in the network, so only they propagate the information from start to end.

The output gate is the third and last, determining the current time step output value. These functions are used in the first layer, where values from the previous hidden state summed with the current input are first passed to a sigmoid function. Now, the cell state's updated state becomes the input of tanh functions. A follow-up to that must be a decision of whether to keep the hidden state's information by a simple participation of multiplication of tanh and sigmoid output. Consequently, this result is the latest hidden layer. Hence, the cells at this level, which separate from their metastatic clones and obtain a new cell state, are considered a transition point.

So, LSTM overcomes the vanishing gradient issue since the long-term dependencies are captured automatically through the succeeding layers.

3.3. Deep Learning

Deep learning refers to the depth of neural networks in that they get more hidden layers than conventional neural networks. Deep learning patterns of complexity are used in that scenario to gain precise and better results. The number of

nodes in the hidden layer of DLNN is the reason behind people with low incomes compared to simple NN—consequently, the number of layers of the neural network and their depth deep neural networks. So, a neural network having more than three

hidden layers will be called a deep neural network. This keyword centers around transforming the available data using specialized functional algorithms to produce abstract representations perceived at higher data marks.

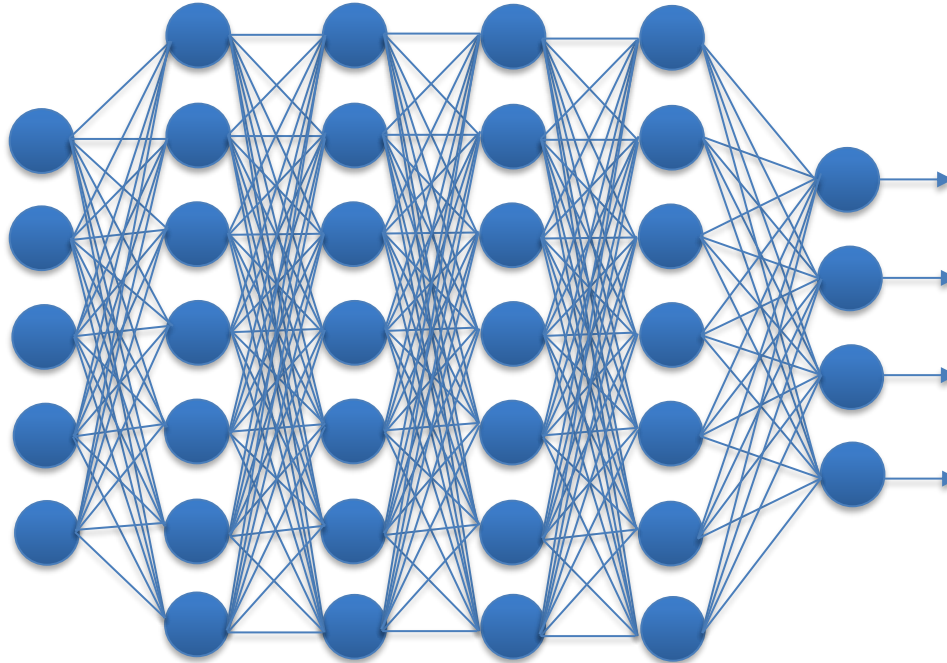


Fig. 5 A deep neural network

The deep neural network is constructed as a hierarchical or layered organization of the connection of neurons to one another. These neurons communicate with one another through signals based on the input that they receive. The neurons in the input layer provide an output to the neuron in the next layer, and so on. Moreover, the neurons process it based on the activation function. The output from a neuron in a layer is passed on to or accepted by another neuron only if it satisfies the condition of value more significant than a threshold; otherwise, the output will be rejected. The associated weight between the neurons of successive layers influences the input and output flow between the neurons in consecutive layers and eventually interprets a final production. Initially, these weights were assigned to neurons randomly. But later, during the model training, these weights are updated iteratively to learn to predict a comparatively accurate and better output. The backpropagation edits the weight.

3.3. Methodology

This approach collected and evaluated a sample dataset of patient health history recorded periodically. The database contains as many as Age, BMI, Blood pressure, Heart rate (pulse), Respiratory rate, Body temperature, CBC, Lipid profile, and blood sugar level, among others. Body mass index (BMI) indicates the degree of fat accumulation in the body calculated as the ratio of the body’s weight to the square of its

height. Systolic blood pressure is the amount of force applied to the walls of arteries while the heart is pumping. It measures the heartbeats per second, called Heart Rate (Pulse). The number of breaths per second is the quantity of the Respiratory Rate, and the measurement of the body’s internal temperature is the value of the Body Temperature. CBC (Complete Blood Count) tests these cells’ number, shape, and function. Sampled cells include red blood cells, white blood cells, and platelets. The lipid Profile lists cholesterol levels, triglycerides, and other lipids in the blood. Glucose Levels in Blood Glucose Monitoring blood sugar levels is vital for glucose levels as the assessment of diabetes risk and diabetic management. Pandas is used to upload varied feature datasets, and the exploration and normalization of the data are commenced for crafting the LSTM model. The component MinMaxScalar contains a normalization routine. The data set is divided into 80% for model training and the remaining 20% for model testing and validation.

Once the normalization of the dataset is achieved, building and training the LSTM model using a different set of libraries in Keras is attempted. Next comes the fitting process, followed by calculating the loss using the mean squared error metric. The pLSTM model displays a prognostic future horizon model. The test set is employed for the examination process. The similarity between the features’ essence and quantity to the data set value is obvious.

Besides, an option is set out focusing on the Deep Learning technique. A series of preprocessing is done for the dataset by loading it. Finally, they are importing some of the Python libraries used for forecasting. Panda, NumPy, Keras, Tensorflow, and time series generating tools are imported. The dataset is awakened for training and testing the system by splitting it so that 20% of the data goes for testing the model while the remaining 80% is used for training the model. Considering that the network is intended as a supervised model, the data will go through a conversion process from sequence to data arranged in a way that looks back. In this function, a prediction of values of features in a look back is also provided, the same as the values of features in the last 10. To be more precise, this generator is called the TimeseriesGenerator module in Keras.

The acquired data is then passed through the LSTM structure that has been trained using the Adam optimizer and various epochs, and the mean squared loss function is used for 25 epochs. The next stage in the algorithm is the creation of a generator for data, which is done by `model.fit_generator()`. The trained model is the one that the data was processed for. Therefore, The model is tested against the test dataset, and the network performance is cross-checked. These observations from both models were utilized in the categorization of the patient to level 1, level 2, and level 3 with standardized metrics. The categorization is based on the intensity of the average rate/estimate fluctuations. If the fluctuation is higher, the patient is categorized to level 1, then to level 2, and fluctuation of the lower level is ranked to level 3.

4. Results and Discussion

Although these innovative technologies are up-and-coming, we should confront the challenges of data privacy regulations, ethical and moral aspects, and the extent to which AI technologies are available to all people from different segments of society. In addition to big data's (AI) role in medicine, combining the expertise of technologists, medical

practitioners, and policy-makers would become critical as we delve deeper into what AI can achieve in medicine.

To sum up, technologization in the healthcare sector indicates an era where more people can get high-quality healthcare. These innovations are not only buyers of HIV care but also much needed to balance global health care systems. The advent of this phenomenal field calls for responsible innovations. We must pay attention to the ethical questions and collectively work to ensure that these discoveries positively impact everyone in our society.

As a research goal here, it was focused on building models that connect artificial intelligence and machine learning algorithms to classify the patients' health conditions. This is followed by comparing the two models to ensure sufficient reliability evaluation. The LSTM and deep learning model reflection indicated success in predicting solar PV power generation. The validity of these data was assessed with the statistical aspect of mean squared error. In mean squared error, the loss function of a model with deep learning was explained to have a more significant value than the model with LSTM. According to the statistical concept of mean squared error, the model with a comparatively lesser loss value is considered good. So, by viewing this methodology, it was concluded that the LSTM model performed relatively better than the deep learning model in this project. Currently, these models can be considered for further studies with different datasets with distinguishing features and integration of biochemical markers, physical fitness, mental and emotional health, behavioral and lifestyle factors, and psychosocial well-being for modifying and developing more efficient and innovative models—an in-depth exploration of the challenges associated with the widespread adoption of AI-enhanced clinical decision support systems. Ethical considerations related to patient privacy, bias in algorithms, and transparency in decision-making must be examined along the way.

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