E- Health Tracking Using Deep Learning and Artificial Neural Network

Sarojini Yarramsetti[1*]

[1]Nehru Institute of Engineering and Technology, Coimbatore, Tamilnadu, India.

Abstract:

The rapid innovation and discovery in healthcare management saved many lives. The shortage of both healthcare experts and individuals able to keep track of patients' medical records is a major impediment in the field of healthcare management. This research proposed a Deep Learning-based artificial neural network (DL-ANN) for use in healthcare management, with the goal of reducing reliance on both human resources and external barriers. In order to manage healthcare data effectively, DL-ANN employs a three-layer network structure that consists of an input layer, a hidden layer, and an output layer. In addition, ANN's hidden layer is responsible for all data analysis processes. Data from each patient's electronic health record (including lab results, medications, and diagnoses) is analyzed using DL-ANN (EHR). Medical professionals can search these EHRs for a specific patient by name or other identifier. DL-ANN has been used to improve healthcare administration by optimizing records management. Both the standard system and the suggested system have been analyzed, and the latter has been found to perform better and have a higher reliability ratio. The suggested research on DL-ANN revealed increased precision, better performance, and a reduced error rate. The results of the experiments show that compared to the state-of-the-art methods, the proposed DL-ANN model has superior accuracy ratios of 95.6%, performances of 97.6%, sensitivity ratio values of 96.3%, efficiencies of 98.1%, error rates of 93.5%, delay time ratio of 33.2%, and specificity ratio of 11.2%.

Keywords: Artificial Neural Network, Deep Learning, Records, layers and Staff management.

1. Introduction of Healthcare Management with Deep Learning Methods

Healthcare management is the control and administration of health data and monitoring of patient [1]. Health care has focused on delivering social benefits to fulfil its contribution increase life satisfaction by enhancing fitness [2]. Private firms focus on generating financial benefits to maintain their investment's sustainability [3]. Health management addresses major challenges such as data distributed in various formats to easily and accurately generate [4]. Health services are now a value-based patient delivery paradigm with emerging challenges leading to structural improvement and healthcare delivery management [5]. Healthcare systems must be constantly proactive in management because of various framework interdependencies such as the emergence of environmental requirements and overlapping interests, which may exacerbate the mechanism of decision-making [6]. Healthcare organizations want to create resources for optimizing patient results and improving system success by protection, quality, efficacy, affordability, usability and suitability [7,8]. Accessibility and efficiency are the two main dimensions that patients consider and respect. The access period shall be the interval between appointment and appointment in effect

[9, 10]. This report's key aim is to identify deficiencies in patients' accessibility planning and the recommendation of measures to increase healthcare services provision [11]. The health record for the documentation and information on the patient's health care is the primary depository. The automated equivalent of a patient paper charts is an electronic health record (EHR) it is provided are patient-centric records and approved users with secure information instantly [12,13].

Deep learning is an unstructured knowledge-based neural network class, and it provides the medical sector with the opportunity to analyses data with unprecedented speeds without losing its accuracy [13,14]. Neural network's well-designed combination uses a layered architecture to screen data at an astounding rate [15]. Health services use deep learning approaches such as artificial neural networks to expand inexpensive treatment availability [16]. Deep learning (DL) has gained unparalleled exposure to analyzing and diagnosing biological and medical issues [17]. The methodology has accomplished various features that have been impossible to overcome by others and by individual professionals to explore meaningful features and tasks [18]. Biological and medical instruments, processing and software, currently produce high data volumes in images, sounds, text, graphs and signals [19]. The increasing availability of medical evidence and exponential development in DL methodology differences have made it possible to document medical care's impressive findings [20].

ANN applications' primary objective is to examine the relationship between preventive or treatment technologies and patient outcomes [21]. Practices like diagnostic processes, treatment protocols, personalized medicine, medication development, and patient monitoring and care are employed with the ANN system [22]. DL approaches can show clinically relevant information which may be used to assess, cure, monitor, and avoid health problems submerged in huge quantities of medical records [23]. ANN and DL can enable physicians to diagnose symptoms and treat disease for a fraction of their time. The recent results of patient treatment and the potential of diagnostic imagery development [24]. Increasingly, ANN is a popular diagnostic method to advise decisions about healthcare management. Giving a comprehensive study on inquiries from the ANN health department [25]. DL-ANN further improves care practitioners' capacity to consider better the people in charge's everyday behaviors. The input is stored instead of in the network database, which ensures no effect on the function.

The main contribution of this paper:

- Designing DL-ANN has been proposed to improve patient health care management and reduce the risk levels for healthcare staff.
- Analyzing the ANN hidden layer to improve the electronic health record to enhance the accessibility of doctor and patients.
- The numerical results have been performed, and the proposed DL-ANN enhances high sensitivity, specificity, efficiency, improved performance, and less delay time compared to other methods.

2. Literature Review

Akkaş, M. A., et al. [26] discussed IoT based healthcare management. IoT were impact the world of media through remote wellness and surveillance, support to the identification and management of chronic conditions, and the provision of personalized medicine. The information gathered is transmitted via IoT technology from the wireless sensor network to the central database. In terms of resilience and accuracy of the information gathered, the system's performance is measured in various network topologies and network consistency and quality.

Ali, F., El-Sappagh, et al. [27] explored the bidirectional long short-term memory (Bi-LSTM). When it comes to smart fitness tracking. A novel method for collecting patient data for efficient healthcare monitoring is made possible by wearable sensors and social media platforms. Data mining, ontologies, and bidirectional long short-term memory are the primary areas of focus for the proposed large-data analytics engine (Bi-LSTM). According to the findings, the proposed model effectively handles heterogeneous data and improves the accuracy of condition descriptors and medication side effect estimations.

Mosaffaie J et al. [28] explored the Driving force-Pressure-State-Impact-Response (DPSIR) framework to evaluate health data. An evaluation of the status and dynamic of watershed health is critical in integrated watershed management to recognize effective management reactions. This analysis focused on examining Gorganroud's water shift health's key environmental problems using the DPSIR system. The priority of watershed issues using the Friedman test was the watershed's main challenge: the lack of groundwater, flood capacity, and soil erosion rate. Except for the S-index, the findings showed that all others had an upward trend during the study period.
Khan, M. A. et al. [29] expressed the modified deep convolutional neural network (MDCNN) forheart disease prediction. The IoT technology was recently implemented to collect the sensor valuesto diagnose cardiovascular disease in health systems. Many researchers focused on cardiovasculardiagnosis, but the findings of the diagnostic are not accurate. An IoT system is proposed for the more precise evaluation of heart diseases with a modified deep convolutional neural network (MDCNN) to deal with this problem. The findings show that the MDCNN-based prediction framework for heart disease is stronger than other approaches.

Angola, N et al [30] described the secure healthcare management system using blockchain (SHEMB). Ethereum-based blockchain enables privacy to be protected from cryptographic data hidden and access control in decentralized databases. An Ethereum architecture is proposed to address the demands of different stakeholders, providers, and others involved in the generation and access of patient information records in the context of decentralized and transactional privacy protection. The results show the realistic and safe essence of SHEMB.

Based on these surveys, there are many existing Bi-LSTM, DPSIR, MDCNN, SHEMB, such as less sensitivity, specificity, low efficiency, less delay time. Therefore this paper overcome these issues by DL-ANN has been proposed to reduce the healthcare risks and improve the high accessibility. Medical application of ANN includes clinical diagnosis, cancer prediction, speech recognition, stay forecast, the study of images and interpretation and medicine development. ANN is used in decision-making support for primary services providers and the health sector to have timeframe utilisation solutions.

3. Deep Learning-Based Artificial Neural Network (DL-ANN)

This paper discussed the improved electronic health records management and authentication process based on the DL-ANN model. Electronic health records are secured with encrypted systems and strong password to login systems, making unwanted patient information changes much easier for anyone. The ANN consists of three layers (input, output, hidden). In this network, the data is moved from input nodes to output nodes through hidden nodes. Each neuron in one layer has direct neuronal connections in the following layers. Physicians and healthcare workers can access the keyword for the identification of patients. DL-ANN for reliable hospital administration has been configured record management. A comparative study has been conducted for the traditional and proposed scheme, showing higher efficiency and better reliability. The outcome of the proposed DL-ANN analysis has been improved with a low error rate and high efficiency.

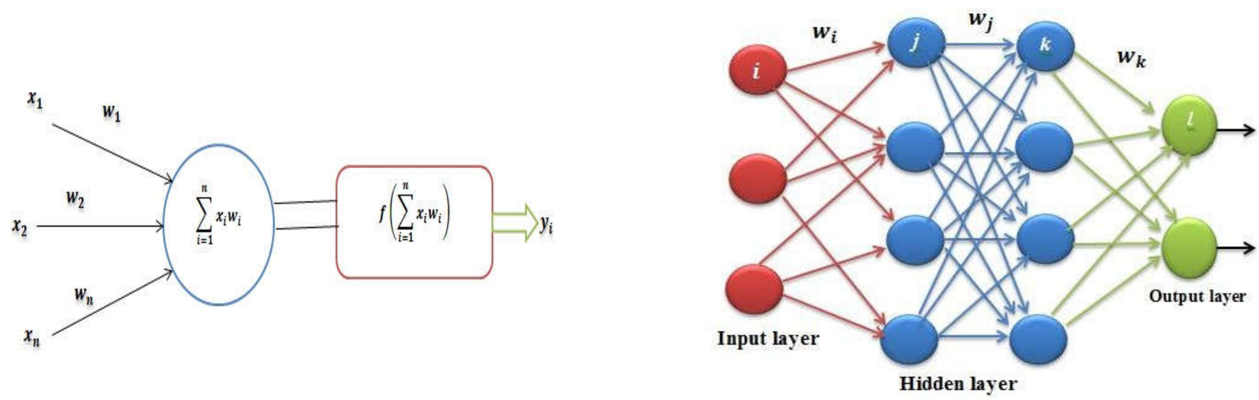


Figure 1: Deep Neural Network.

Figure 1 shows the Deep Neural Network**.** Each input data x_i has a corresponding weight w_i. All the weighted inputs $x_i * w_i$ are then transmitted through a non-linear activation function F, to convert the neuron's preactivation level to a production Y_i. The conditions of discrimination were omitted for convenience. The Y_i Output is then used as a node in the following layer. Several activation functions are available that differ in how the pre-activation level is mapped to the output level. The most common activation function is to rectify the neurons that use the rectifying linear unit. Different layers may change their input in various ways, and signals from the first layer (input layer) pass through the final layer (output layer) and likely several times after crossing the layers in equation (1):

$$Y_j = f(\sum x_i w_i) \quad (1)$$

As shown in equation (1) output of the neural network has been determined. Equation 1 represents a multi-layered feedback neural network with two groups in which all neurons in the next layer of nodes in one layer are a fully connected network. A nonlinear function shall be added to the weighted sum of the inputs for each neuron j in the first hidden layer. For a second hidden layer, the product of transformation Y_k acts as an input in equation (2),

$$Y_k = f(\sum x_j w_j) \quad (2):$$

As deliberated in equation (2), the hidden layer product has been computed. The data is distributed through the network to the output level, where the softmax function gives the likelihood of a particular observation belonging to each class in equation (3):

$$Y_i = f(\sum x_k w_k) \quad (3)$$

Equation (3) shows the output of the hidden layer node. The first layer is the input where the data are entered and data can be viewed in neuroimaging as a one-dimensional vector, each with the same value as a voxel. w_k is a weight of the node, x_k is an input of the hidden node, F is an activation function, Y_i is an output of the hidden node.

The final layer is the output layer which gives the likelihood of a particular subject belonging to one category or the other within the classification context. The layers between the input layers and the output layers are referred to as the hidden layers, the number reflecting the network's depth. Each layer contains artificial neurons or "knots," whereby any neuron in the previous layer is completely connected to the neurons.

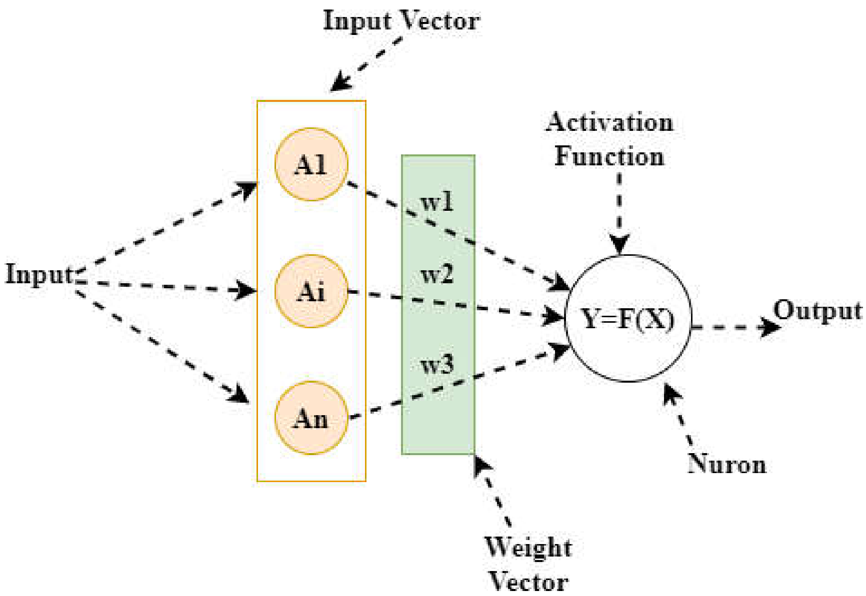


Figure 2: Single Neuron Model

Figure 2 shows the records obtained with a single element can be seen as an input vector $A = (A_1, A_2, \dots, A_n)$any pair of connected neurons is weight-related. The jth neurons are thus expressed as the weights $w_j$where the relation weight $w_{1j}, w_{2j}, \dots w_{nj}$ between the element processing A_i and the element processing A_j Is represented. The threshold value of a neuron controls your actionability. Although the neuron's action potential depends on the weights associated with the neuron's input, a limit modulates the neuronal reaction to a special stimulus, limiting the reaction to a predetermined set of values. Equation 2 determines the y output of the neuron as a weighted $n + 1$ input activation function f.

The $n + 1$ is the same as the n inputs. The threshold of the neuron input is included in equation (4):

$$\text{Extra input } sum = \sum_{i=1}^{n} x_i w_i \tag{4}$$

$$y = f(\sum_{i=0}^{n} x_i w_i) \tag{5}$$

$$f(x) = \{ 1 \; if(\sum_{i=0}^{n} x_i w_i > 0) \\ 0 \; if(\sum_{i=0}^{n} x_i w_i \leq 0)\} \tag{6}$$

Threshold input is declared in equation (4), (5), (6). Module the neuron's reaction to a specific stimulus that limits this reaction to a predetermined set of values. Equation 4 determines the neuron

y output as a weighted sum activation function $f()$ with inputs $of\ n+1$. This $n+1$ is the n signalinput. The threshold saturation function and sigmoid function in equation (7) and (8):

$$\text{Saturation function,} \quad f(x) = \frac{1}{1+e^{-x}} \tag{7}$$

$$\text{Sigmoid function} \quad f(x) = \frac{e^{x}-e^{-x}}{e^{x}-e^{-x}} \tag{8}$$

As discussed in equation (7) and (8), threshold saturation function and sigmoid function has been described. The first layer is the input where the data are entered and data can be viewed in neuroimaging as a one-dimensional vector, each with the same value as a voxel. The final layer is the output layer which gives the likelihood of a particular subject belonging to one category or the other within the classification context. The layers between the input layers and the output layers are mentioned as the hidden layers, the number reflecting the network's depth. Each layer contains artificial neurons whereby any neuron in the previous layer is completely connected to the neurons.

The importance of neural networks over traditional programming overcome issues with no algorithmic solution or the solution available. Neural networks are useful for dealing with issues like forecasting and pattern recognition that people solve. In clinical diagnosis, imaging and interpretation, signal analysis and interpretation, and pharmaceutical growth, neural networks have been applied since healthcare systems are transformed into a value-driven patient-centric treatment model in developing countries with new complications in improving healthcare structure and management.

Neural networks have been used to predict possible diseases like the recurrence of different forms of cancer, cardiology and help doctors in prognosis and decision-making. For instance, the EEG data is trained in a neural network model epilepsy prediction. Epilepsy prediction EEG data sources for detecting spikes in epilepsy. The study shows that ANNs provide a realistic solution for automatically detecting unmedicated waste from low-cost computers in real-time. ANN's have proved to be a valuable tool in myocardial infarction clinical diagnosis. The distinguished network patients with a significantly higher sensitivity from patients with no acute myocardial infarction than doctors with their diagnoses.

An ANN model is more effective as a predictor of treatment outcomes in another study of patients in the intensive care unit. The ANN model has used in the systematic clinical environment hemodynamic shock and inflammatory reaction syndrome patients. The results measured were death probability during admission to the hospital.

In addition, ANN can be used to predict patient prognostic variables result over time. ANN models may create a specific series of forecasts on recurrence possibilities monitoring hours to ensure doctors' survival available curves of probability for patients. Complication usually seen in patients stay with the hospital. In figure 3 illustrates Medical Sensor Network for Assessment of Patients Monitoring.

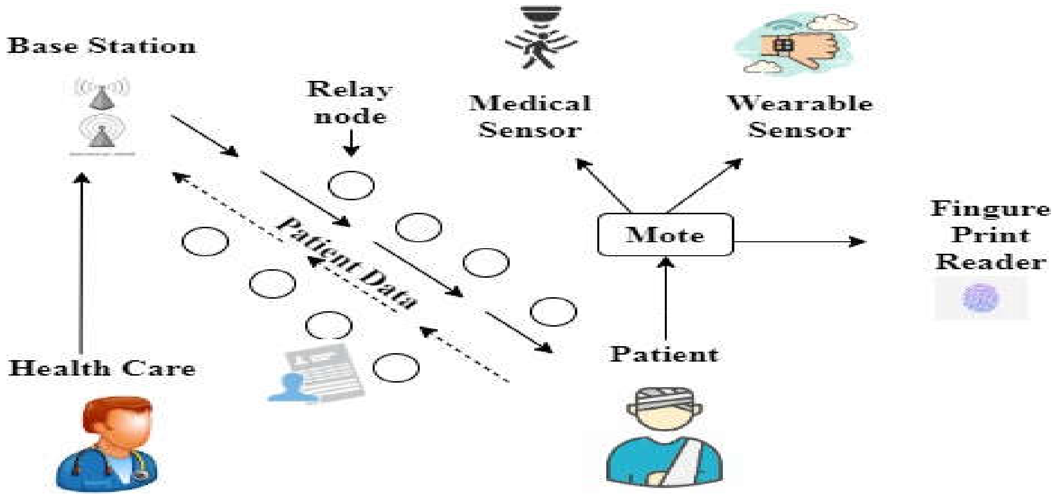


Figure 3: Medical Sensor Network for Assessment of Patients Monitoring

Training a feedback neural network

An input neural network with pairs of input-output examples is trained in supervised education. The network generates an output for each input. The exactness of the response is determined by error E, which is the Difference from current O_{pj} and predicted results of T_{pj}.

$$E = \frac{1}{2}\sum (T_{pj} - O_{pj})^2 \tag{9}$$

As inferred in equation (9) error function has been computed. The inaccuracy of the performance assessed with Equation (9) is reduced to a minimum. Inaccuracy E is distributed to the input sheet that is output. Modifying the weight of the network slightly changes the ratio d of total error E. After weights have been updated, examples are given again. Error calculations, weights adjustments etc., may further increase performance before the current output or network. The following is a description of the derived history algorithm mathematical summary.

1. Present pair p for input-output and generate op for current output.

2. Computing network performance.

3. Calculate δ_{pj} Error for that particular pair p for each output unit J. The mistake is to differentiate the desired $f(net_{pj})$ activating function from the opj current time of the output in equation (10):

$$\delta_{pj} = (t_{pj} - o_{pj})f(net_{pj}) \tag{10}$$

As calculated in equation (10), the current time output has been derived. For every of the hidden unit j of the current paper, calculate the error by recurrent δ calculation. When w_{kj} is k-weighted at j performance, δ_{pk} is a K-layer mistake and f_j is a derivative function for triggering the j hidden unit. Disseminate the error signal back to all cached layers before reaching the input layer in equation (11)

$$\delta_{pj} = \sum_k \delta_{pk} w_{kj} f_j(net_{pj}) \quad (11)$$

As determined in equation (11) backwards, the error signal via all the hidden layers until the input layer. Repeat steps 1 to 4 to an acceptable low error.

Electronic Health Record (EHR)

EHRs are patient-oriented data that easily and securely inform authorized users. Although an EHR has a patient medical health history, it is organised outside of a typical EHR scheme. A representative office collects clinical statistics and offers a wider perspective on the care of patients. In both hospital and outpatient settings in the past decade, electronic health records were widely embraced.

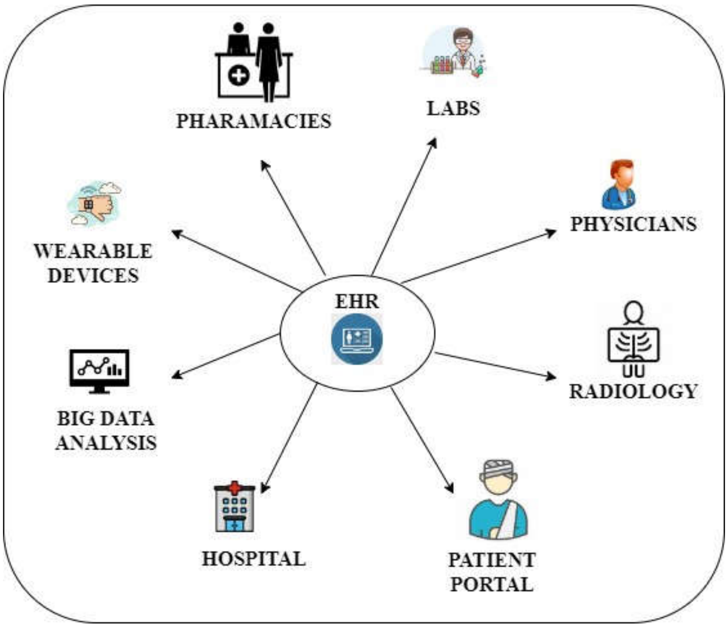


Figure 4: Architecture of Electronic Health Record

Figure 4 Shows the EHR systems consist of the map of electronic patients, which generally include computerized supplier order entry (CPOE), imagery monitoring and healthcare interfaces. Access to electronic patient health reports in pharmaceutical form is an opportunity to access information necessary for providing pharmacy care to patients. Most EHR offers medical analytics on the healthcare provider's side that detects trends, forecast diagnosis, and suggest future treatment alternatives. Integrated patient portal infrastructure typically contains an EMR system for practice management. Patient websites are primarily used to obtain results from the laboratory update patient profiles and suppliers of insurance. Healthcare is one of the most remarkable fields for big data analytics. Health analytics can decrease care rates, prevent infectious outbreaks, prevent illness, and generally improve life quality. EHR and radiology have provided a meaningful workflow that enables us to transform data into higher knowledge volumes, direct our patients through effective treatments. The best applicants for wearable EHR-interfacing are the patients with chronic illnesses, including diabetes, or those focusing on weight loss. Data such as blood sugar levels, daily actions and weight will more accurately connect patient behaviour to health outcomes. Hospital Information Software not only monitors care plans, patient history, accounts and reviews, allowing other divisions, such as an employee and management. However, with the change to this modern system of medical information recording and communication, new error opportunities and other unforeseen safety risks were also developed

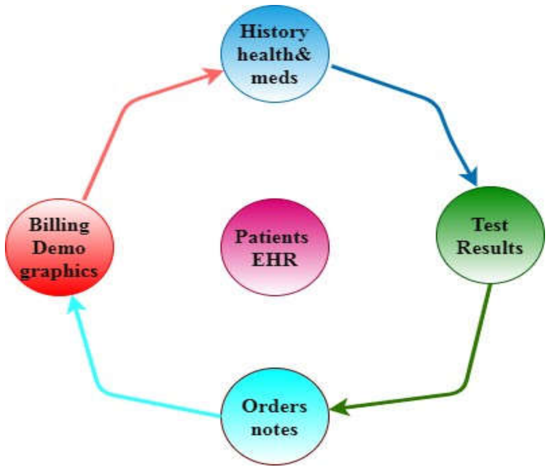


Figure 5: Electronic health record components

Figure 5 shows that electronic health records (EHRs) provide a more inclusive patient health information source. The hospital organization wanted all health reports to be forwarded to the EHRs for various reasons, including eliminating mistakes and harm, reducing costs, increasing the decision-making process and making access to medical information simpler for doctors and quality workers. EHRs are real-time records that quickly and safely supply the approved user to access the clinical information. EHR offers a patient with medical treatment history experience and expands traditional clinical records from the clinical office.

EHRs can include:

- EHR access to evidence-based tools which clinicians can utilize to create decisions about patient care
- The clinical and managerial workflow is easier if the billing process is combined with an EHR. Health billing is an essential mechanism for the continuous operation of every medical office.
- Hospital insurance requires the planning and filing of billing reports to insurers, which means that the right cost for the care they offer is reimbursed to the hospital or the medical office.
- Order sets reflect one computerised provider order entry system clinical decision support (CDS) method to facilitate secure, effective, proof-based patient care.
- Alert physicians outside the usual range of laboratory values and enable the company to handle incoming laboratory findings better.

Improved management of medical practices integrated planning frameworks which directly connect progress notices appointments, coding and automation manage claims. Automatic controls on the health coverage sort testing and receiving laboratory images links to public health resources such as transmissible disease records and databases. Figure 6 demonstrate the Overall architecture for remote patient monitoring.

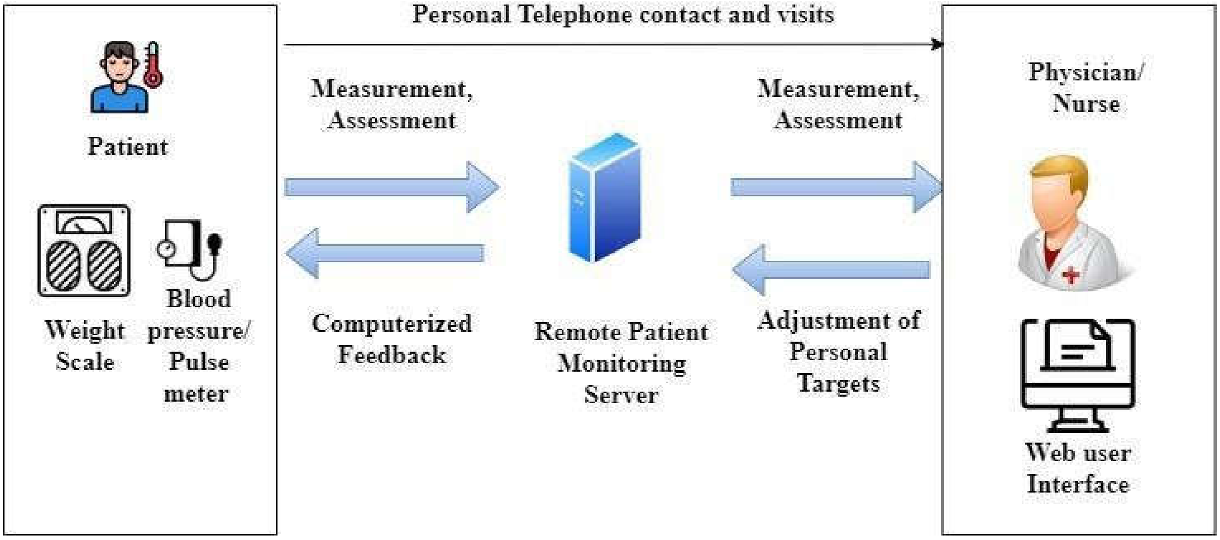


Figure 6: Overall architecture for remote patient monitoring.

The clinical outcome discussions have concentrated on lower morbidity, death or biometric marks like diabetes waist circumference. This requires the patient's adherence to the medication and the execution of all therapeutic approaches recommended. To guarantee appropriate supervision and improvement of health conditions, compliance must be recognised as a crucial criterion in the application of patient surveillance. Over the last decade, remote control systems like m health applications have improved accuracy, making it one of the most important software and utilities over recent decades. Repair facilities to promote compliance are all from SMS-based reminders to device monitoring with integrated medical support sensors. Patients' active participation is a significant factor for maintaining a high degree of users retention and increased clinical adherence. These control systems have to be developed to gain greater acceptance by concentrating on the end-user's experience to ensure that they receive the value. Any product needs to be embraced and adopted in the healthcare sector. The proposed DL-ANN has been proposed to enhances an accuracy ratio, better performance, high sensitivity, efficiency, less error rate, delay time and specificity

4. Result & Discussion

The findings confirmed, and medicinal input strengths are clarified through controlled experiments additional clinical input variables are especially recommended. This method has resulted in improved patients' treatment, and higher performance based on these parameters enhances an accuracy ratio, high sensitivity, less error rate, delay time and specificity ratio.

i) Performance ratio and Error rate (%)

The ANN enabled decision-making support systems to improve patient safety by improved error identification, streamlining and medication control. The future study must validate these technologies robustly in future clinical scenarios and in real-life environments to learn how effectively ANN can forecast safety results in health care settings. Diagnosis, electronic signal analysis, medical picture analysis and radiology have been widely used with ANN. Several scholars used the ANNs for modelling in medicine and clinical science. DL algorithms can be implemented easily to deploy intelligent services to improve health care systems' overall efficiency. The purpose of this article is to produce a predictive model based on a detailed study of EHR data gathered by medical organisations to derive valuable information from the patients, medical personnel and related health care systems. Deep Learning (DL) technique predicts patient access shortly in one or more fixed medical facilities. Temporary habits are extracted from a patient's records. The experiment demonstrates the consistency of the technique developed.

(a)

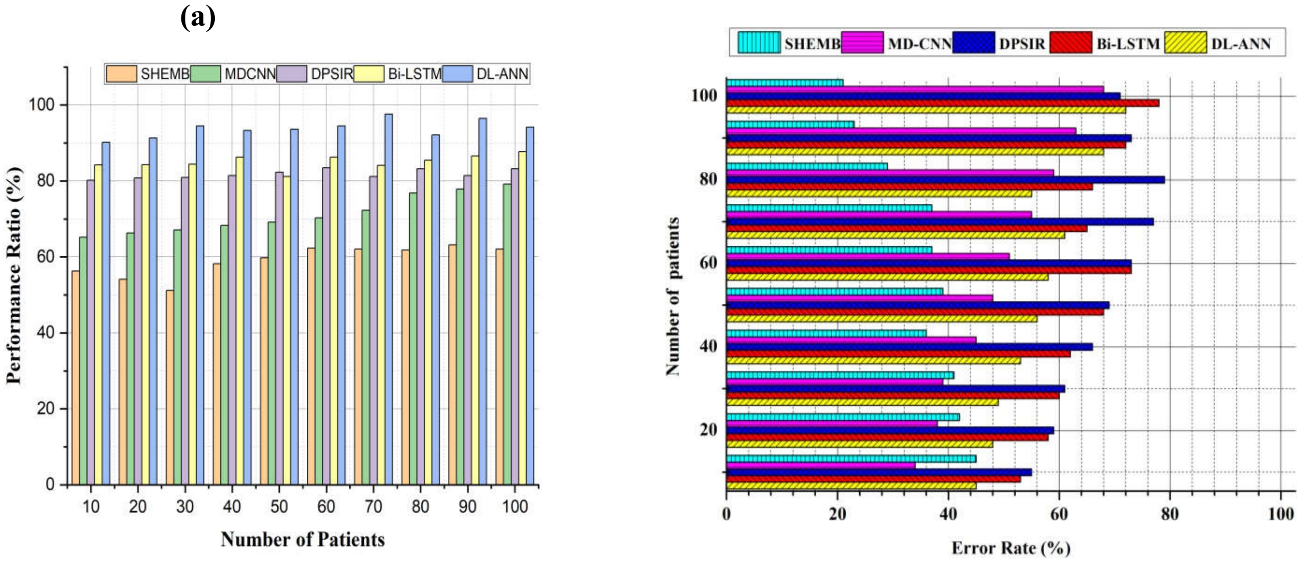
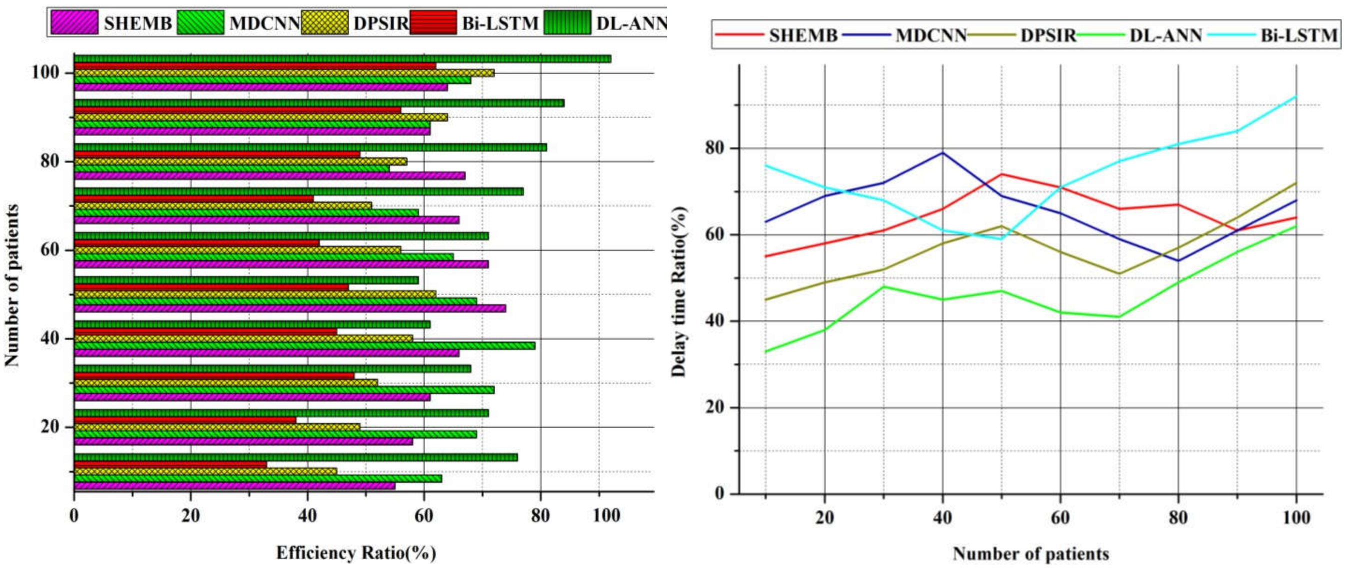


Figure 7 (a) Higher performance and 7 (b): and Error Rate

The greatest feasible performance of the proposed DL-ANN is displayed in Figure 7(a). Figure 7(b) displays the DL-error ANN's rate. It demonstrates that the error rate is lowered withacceptable quality when compared to the other approaches including DL-ANN. In the optimizationtasks, our proposed solution performed well. As a result, progress is being made toward better patient identification by healthcare providers utilizing the keyword. Improve healthcare management with DL-ANN-optimized recording.

ii) Efficiency Ratio and delay time ratio (%)

The efficiency of the DL-ANN is shown in Figure 8(a). To help phytosanitary workers take better decisions, efficiently handle patient information, build a customized medical plan from complex data sets and discover new medicines based on ANN in the medical field relies on the processing and interpretation of huge volumes of data sets. Neural networks can learn by themselves and generate output that is not limited to their input. The input is stored in its networks rather than a database data loss. It perturbs the neural network model's input to a limited degree and calculates the resulting output changes. Sensitivity analysis is conducted by ranking the output produced by the same disturbance and input parameter for each response. Figure 8 (A) and 8 (B) shows the Efficiency Ratio and Delay Time.



(a) **(b)**

Figure 8 (a) and 8 (b): Efficiency Ratio and Delay Time

In modern medicine, the likely expansion of ANN aimed at reducing physical employment and reducing the doctor's time, increasing skills and productivity.

iii) Accuracy Ratio:

Deep neural networks use various layers within a multi-layer network to extract various features. The data in an ANN is transmitted through a network layer by layer until the final layer is reached, and the predictions of the network are made when the information enters the final layer activations. These data are processed by several layers of non-linear input data transformations to determine a target output. Each record inspires the customer, the doctor, consultation, and recommendation.

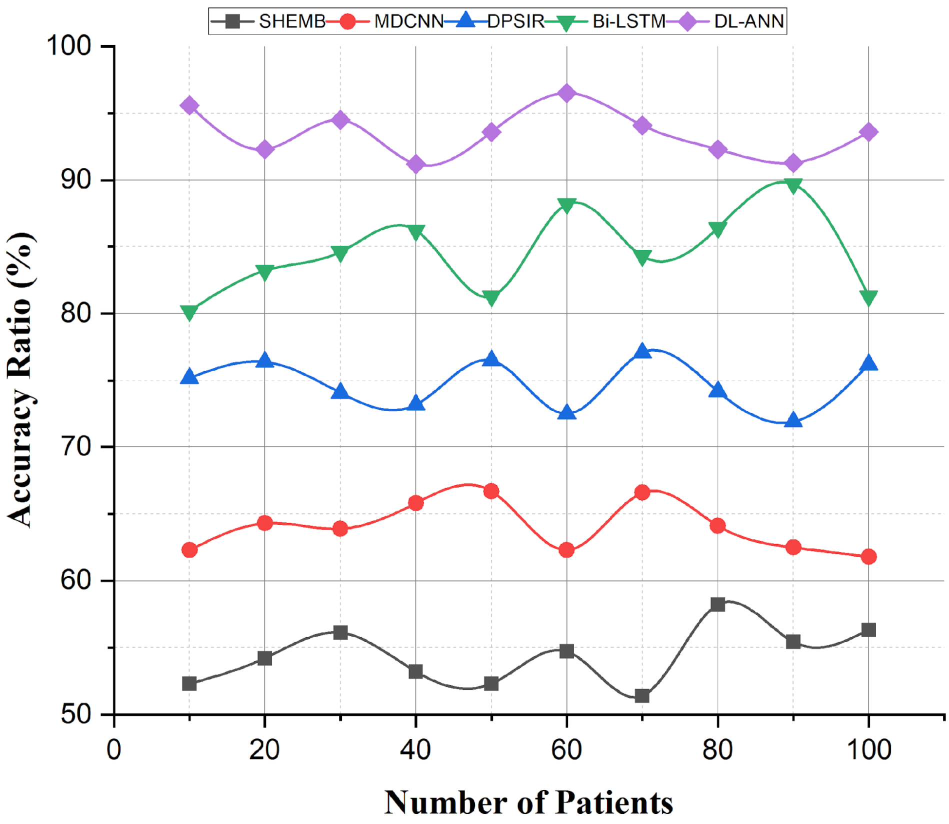


Figure 9: Accuracy Ratio

Personalized predictive medicine requires patient disease modelling and treatment systems, which inherently rely on the long term. Episodic and time irregular patient observations contained in electronic medical records. The DL-ANN suggested, which scans medical reports and stores past disease history, contains existing disease conditions and forecasts potential health outcomes. Figure 9 elaborates the Accuracy Ratio.

iv) Sensitivity Ratio

The characteristic of a test is the capacity for an individual who does not have a negative disease. Human affability in the healthcare area improves the efficacy in targeting several different populations and offers a non-biased approach to treatment that can support better services and increase awareness. Neural networks are structures that operate like neurons with interconnected node. DL-ANN can identify and interpret hidden patterns and associations in raw data using algorithms while constantly learning and improving. It shows that the impact measurement is useful for four construction tasks of models: identifying possible outliers, evaluating device design sensitivity, comparing network sensitivity between training sets and test data and finding vulnerable areas. A highly sensitive examination can indeed help exclude a disease if a person has negative results. Figure 10 elaborates the Sensitivity Ratio

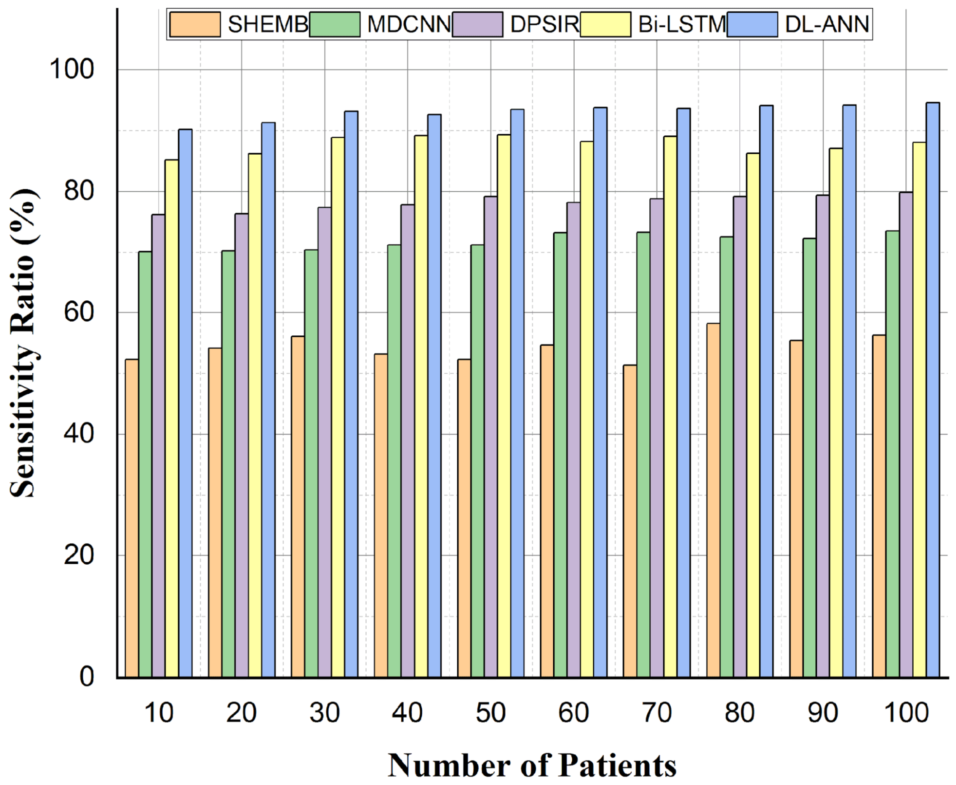


Figure 10: Sensitivity Ratio

Sensitivity refers to the ability of a test to label a person with a disease as positive. A highly sensitive test results in few false-negative outcomes and fewer diseases. The main principles of a test are the capability to recognize a person with no disease.

v) **Specificity ratio (%)**

ANN would maximize healthcare costs for healthcare providers and reduce patients' medical costs. DL-ANN analyzes, automates and predicts processes around the health system. It has been used to predict ICU transfers, optimize clinical workflows and even identify the risk of infections in a hospital. ANN provides significant benefits for advancing precision healthcare based on forecasting current patients results, and it analyses the likelihood of disease of future patients. Table 1 shows the Specificity Ratio.

Table 1: Specificity Ratio

Number of Patients	SHEMB	MD-CNN	DPSIR	Bi-LSTM	DL-ANN

20	28.6	28.5	38.8	37.8	77.5
40	34.9	34.7	25.8	45.9	65.9
60	45.5	49.8	43.8	50.5	75.8
80	54.4	55.3	50.6	59.9	81.9
100	58.8	69.7	59.5	65.8	90.7

vi) Prediction Ratio

Health care administrators are aware of the advantages such as predictive analytics attempts to alert physicians and caregivers to the possibility of incidents and consequences before occurrence and avoid as many health problems as possible. In addition, the use of neural networks to anticipate the likelihood of no-show contributes to the choice of exact designations. Table 2 shows the Prediction Ratio.

Table 2 shows the Prediction Ratio

Number of Patients	SHEMB	MDCNN	DPSIR	Bi-LSTM	DL-ANN
20	28.6	38.8	37.8	35.8	77.5
40	34.9	25.8	45.9	49.7	65.9
60	45.5	43.8	50.5	55.8	75.8
80	54.4	50.6	59.9	60.8	81.9
100	58.8	59.5	65.8	65.7	90.7

Predicting that patients may miss their appointment will lead the facility to better guidance and attention. The ANN-based disease prediction analysis refers to a test's capacity to identify a diseased person as positive. A highly sensitive test results in few false-negative outcomes and fewer illnesses. The basic characteristics of a trial are the ability to identify a person with no illness. This analysis aims to include estimates of potential patient appointments for any hospital beginning with the previous medical history.

5. Conclusion:

This paper demonstrated the artificial neural networks could be implemented at all stages of decision-making in healthcare management. Electronic health records are secured by encryption and strong login and password systems, making unauthorised changes to the patient chart and other information far more difficult for anyone. The DL-ANN's primary objective is to include a patient-driven healthcare advisor to meet such challenges; 1) proposed for healthcare management to reduce staff risks 2) DL-ANN analysis the patient data saved in individual 3) EHR can be accessed by doctors and Staff at healthcare using the keyword for patients identification. A greater understanding of the ethnic, social and economic effects of ANN in strategic decisions in health care organizations will be needed if effective implementation and adoption are implemented.

Declarations

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Code availability: Not applicable.

Authors' Contributions: All author is contributed to the design and methodology of this study, the assessment of the outcomes and the writing of the manuscript.

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