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Knowledge Discovery in Health Domain using Deep Neural Network Algorithms

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ABSTRACT

Knowledge discovery in databases (KDD) primarily depends on finding a strategy for effectively processing data. Data mining is a critical phase in the KDD process for extracting a valuable pattern from a dataset. Pattern extraction and discovery are complex processes that often require a vast dataset. Several applications and systems are used for health care and clinical data to diagnose and record patient records. The installed systems' primary goal is to extract a relevant pattern capable of improving healthcare services. To improve healthcare services, data mining necessitates the right design and execution of data mining algorithms to detect a unique pattern from large amounts of data. As a result, we propose using patient information from the Hewa Hospital in Sulamani, which is in charge of cancer and blood diseases, as a case study for our research. The primary goal of this research is to look at deep neural networks (DNN) and artificial neural networks (ANN) as classification algorithms that can assist us in making better judgments. The results show that the DNN algorithm outperforms the ANN method. When utilizing a 70:30 training and testing dataset, the score can reach 87.84.

KEYWORDS: Knowledge Discovery in Database (KDD) , Healthcare, Deep Neural Network (DNN), Artificial Neural Network (ANN) and classification algorithm

1 INTRODUCTION

The fast expansion of dataset sizes and technology necessitates knowledge discovery for the health domain, which will significantly influence the healthcare system in the future. The world's population has recently increased at an alarming rate. In addition, the expense of health care is skyrocketing. One method to deal with these changes is to use data mining and technology to improve healthcare and medical care processes. Furthermore, there is a great desire to enhance healthcare systems to better serve patients in various ways. One of the most important benefits of employing data mining in health is discovering hidden links within massive amounts of data. It is not easy to extract confidential information related to one another on only one record using a standard and well-known analytical procedure.

For example, if we suppose that a patient has high blood pressure, examining one variable is insufficient because various other factors influence blood pressure in the human body. As a result, the analysis should incorporate multiple factors to get the most accurate results. The analysis of large amounts of data is a complex undertaking that necessitates an extensive understanding of the dataset structure and the techniques used for knowledge discovery. [1] [2]

Many researchers in the information sector have been interested in approaches [3]. The knowledge discovery process comprises multiple procedures such as data cleansing, data integration, data selection, and knowledge display. The primary function of data mining in any data analysis is to uncover patterns in datasets. Furthermore, data mining is regarded as a critical field of research in order to extract relevant information from large data sets [4].

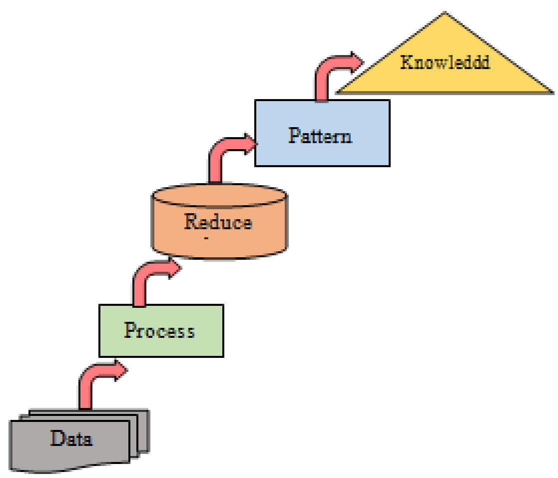


Figure 1 knowledge discovery main steps.

Because of the necessity to establish an effective approach to forecast future outcomes in the health domain area, the use of data mining methods and techniques is becoming increasingly popular in the healthcare profession. [5]. Data mining techniques are used in a variety of sectors, including health fraud detection, illness identification, appropriate medical treatments for patients, and determining the lowest cost for patients.

Furthermore, it aids the community of healthcare researchers in developing policies and medicine recommendation systems for patients. The health-care organization publishes data that is quite detailed. This data comprises incredibly complex information and elements, and identifying a pattern is one of the most difficult tasks in the health care industry. [6].

The primary goal of this research is to create a mechanism for classifying cancer into particular diagnostic categories based on medical records utilizing deep neural networks (DNN). This study aims to improve on the prior method's performance by using a deep neural network on a healthcare dataset. As a result, the goal of this study is to find a pattern in health-care data.

This paper is structured as follows: Section 2 describes the associated efforts to the suggested model. The approach for this article is presented in Section 3. Section 4 depicts the experimental conditions and discussion of this study, and Section 5 concludes.

2 RELATED WORK

There have been several efforts to apply various categorization algorithms in previous research. for example,

a) Naive Bayes classifier: the Naive Bayes method has been utilized in several categorization healthcare systems to predict the performance of the dataset. The Nave Bayes has the capacity to compute the patient type probability depending on how their diseases or illnesses are classified into distinct classifications [7, 17] . The fundamental significance of the Nave Bayes algorithm is that it is renowned for being simple to implement for classification and achieving a very strong and high accuracy [8]. The data is often divided into classes, and the naive Bayes algorithm is mostly used to categorize instances based on their classes. Let's look at an example: Given a patient P, there will be a collection of characteristics that belong to the patient (d@i)f=a,b,....(p) and P c denotes the patient. Every patient will be assigned to a separate set. Furthermore, the Naive Bayes (NB) is known as conditional probability X of for a patient P the formula may be represented as:

X(c,f)= X (P: a, b,...., and so on)= X (P)X (P I)

Where P c is the number of matching classes for each patient in the dataset [9, 10].

b) K-nearest neighbor classification.

One of the most frequent classifiers that relies on the patient's categorization is the K-nearest neighbor (KNN). Every patient will be classified according to a separate class label. The KNN classifier's learning process is influenced by the labels supplied in the training dataset. The KNN maintains all patient records using a distance function based on similarity. This distance function calculates a pattern from the dataset concerning the patient's medical record and other system features [11].

The objective function, given a medical record R, aims to discover the similarity K nearest neighbors for each patient using their medical history record. The similarity score assessment for each patient depends on the testing data sets and the number of class labels for the patients. In KNN, the measuring formula that calculates the score is as follows Eq1:

$$\mathrm{score}(r, f_i) = \sum_{r_j = KNN(r)} sim(r, r_j)\, \delta(r_j, r_i) \quad \dots\dots\dots\dots\dots\dots\dots\dots..Eq1$$

The KNN(r) reflects the total number of nearest neighbors to which each patient belongs in R. Where r j is a class of f i, (r j,f i) has two basic values: (1 or 0). R will be matched to the class that scored the best result from the training set in the testing data [12].

d) Support Vector Machine classifier

Support Vector Machines (SVM) are supervised algorithms that are commonly used for classification and regression analysis. Support vector machines are the most successful algorithms for categorizing training data into classes in order to identify the best answer in the search space [13]. SVM models the answer using a probabilistic classification setup, which primarily classifies the classes' problem in the hyperplane of data into numerous points.

Assume that Y is a collection of features represented by points (y1, z1), (yn, zn), and that the training point yi RN is labeled zi 1, +1, where I = 1,...,n.

The following equation is used to compute the measure procedure of identifying hyperplane using training data as shows is Eq2:

$$\mathrm{w} \cdot \mathrm{y} + \mathrm{b} = 0 \text{ and} \begin{cases} \mathrm{w} \cdot \mathrm{x_i} + \mathrm{b} \geq +1 \text{ if } \mathrm{z_i} = +1 \\ \mathrm{w} \cdot \mathrm{x_i} + \mathrm{b} \leq -1 \text{ if } \mathrm{z_i} = -1 \end{cases} \quad \dots\dots\dots..Eq2$$

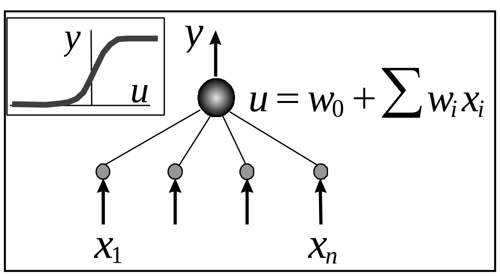
In the following equation, I denote the number of feature points N, and the dot (.) represents the w·y=∑_i 〖w_i·y〗_i, which is utilized for each feature vector w and y. The SVM aims to expand exploration in the search space throughout the learning phase in order to find the best separation hyper-plane (OSH). The OSH has a maximum margin on both sides, which may be calculated using the following equation Eq3.

$$\text{Minimize}(\mathrm{w}) = \frac{1}{2}||\mathrm{w}||^2 \qquad \dots\dots\dots Eq3$$

d) Neural Network Artificial (ANN)

An Artificial Neural Network (ANN) is a computational model based on biological nerve systems. ANNs have been employed in a variety of real-world applications, including prediction systems, finance, and industry. Because the neural network learns and evolves dependent on the amount of input information, the information supplied to the ANN network has a large influence on the structure. One of the benefits of ANN is that the neural network may learn from observed datasets by employing the random function. The input layer, hidden layer, and output layer are the three layers that make up the fundamental structure of an ANN. These layers process the data and help to identify patterns that can be used. The system's synaptic connections, which link the neurons, need to be adjusted because of learning [13].

Additionally, the ANN model depends on the weights of the neurons, whereas the weighting schema impacts the input data in the neurons and enhances and speeds up the learning process in the ANN model [14].



$$y = f\left(\sum_{j=1}^{d} w_j x_j + w_0\right) \equiv f\left(\sum_{j=0}^{d} w_j x_j\right)$$

Threshold is incredibly effective and efficient since the neurons' calculations can be altered dependent on the input weights.

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3.1 Methods and Materials

The main objective of this part is to describe the major actions conducted throughout the investigation. Data pre-processing, classification, and evaluation are the processes used to classify health-related data.

Pre-processing is the initial step that is necessary to prepare the data by removing any extraneous characteristics and missing information. This step must be taken in order to increase performance.

Second, algorithms for classification are used in the training and testing of the health care dataset. In the evaluation process, the performance will be evaluated using different data sizes.

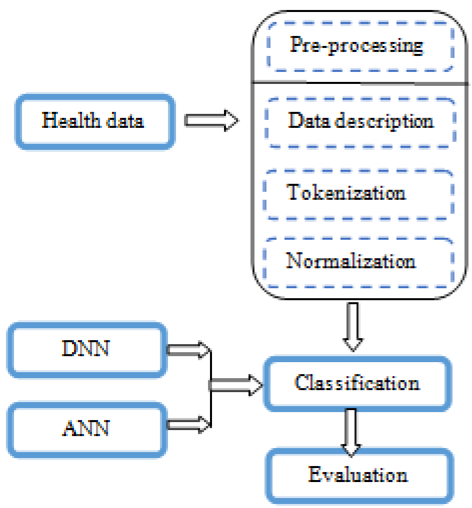

Figure 2 Health care System Architecture

3.2 Dataset Description

The methods vast majority of the patient-related data in this huge data set was gathered from an Iraqi hospital. An overview of the dataset can be seen in Table 1. An effective data preparation relies heavily on having a comprehensive picture of the data. When used to identify your data type and separate noise or outliers, descriptive data summarization techniques are helpful.

If your data collection is large and you have a lot of data, you can use a data reduction approach to shrink it. Due to the magnitude of the data set in this dataset, data reduction techniques are utilized to shrink the dataset.

Table 1 Dataset description

NAME OF DATA SET	DETAILS
Description	This data set contains patient's information.
Data set characteristics	Categorical
Attribute characteristics	Categorical, Integer
Associated tasks	Classification, association rules
Number of instances	26199
Number of attributes	9
Missing values	0
Area	Health care

Table 2 Lists the variables that are considered in analysis by Deep Neural Network (DNN)

Variable name	P1	P2	P3	P4
Diagnosis Sub-Type	1	2	2	3
Diagnosis Type	1	4	1	1
Department	19	6	2	2
government	5	5	1	6
patient jobs	1	1	2	2
blood group	1	2	2	2
gender	2	1	2	1
department name	1	2	2	3
Type	In	out	out	In

P denotes how many patient records there are, where. We start by counting the separate category for each attribute. Data classification primarily aims to convert the representation into a numerical value according to the category to which it belongs.

3.3 *Data Normalization*

The practice of reducing data to its standard forms is known as normalization. Using a process called data normalization, attributes are reduced to a limited, distinguishable range by measuring their values. To normalize the class attribute, use the formula below Eq4:

$$v = \frac{v - min_A}{max_A - min_A}(new.max_A - new.min_A) + new.min_A \text{ .... } Eq4$$

Table 3 Data Normalization

Variable name	P1	P2	P3	P4
Diagnosis Sub-Type	0.013	0.027	0.033	0.013
Diagnosis Type	0.028	0.034	0.040	0.017
Department	0.666	0.333	1	0.666
government	0.125	0.041	0.041	0.166
patient jobs	0.15	0.05	0.125	0.05
blood group	0.222	0.222	0.222	0.22
gender	0.333	0.666	0.333	0.66
department name	0.2	0.4	0.4	0.6
Type	In	out	out	In

4. Results and Discussions

The performance and efficacy of the suggested approach to extract knowledge discovery in healthcare dataset have been evaluated through a number of tests. The training and testing data sets, as well as various feature sizes, have been the subject of several investigations. The investigation looks at the efficacy of using deep neural networks (DNN) to assign malignancies to particular diagnostic groups based on their medical records. These malignancies fall into two different diagnostic classifications (Inpatient and Outpatient) and frequently provide diagnostic challenges in clinical settings. As a result, the purpose of this study is to analyze the performance of DNN utilizing the Hiwa cancer hospital Sulaymaniyah data set in Iraq. In order to assess how well the suggested approach performs and meets the study's goals, the DNN algorithm is contrasted with the cutting-edge ANN algorithm.

The dataset includes two labels that divide the patient types into two categories: inpatient and outpatient. Different training and testing datasets are used to compare the performance of the deep neural network (DNN) and artificial neural network (ANN). The chain of DNN and ANN classifiers' chain's training set serves as the input values for the classification model. The classification rate and root mean square error (RMSE) of training and test sets of data with various feature sizes are the evaluation metrics that are used.

4.1 Experiment results for DNN against ANN algorithms

DNN and ANN algorithms have been implemented in the experiment for the purposes of comparison with one another on various training and test sets using70:30, 80:20, and60:40, respectively. The training and testing datasets utilized in each experimental run are shown in Table 4 along with their respective classification accuracy. The experimental results demonstrate that the DNN method outperforms the ANN model in terms of performance. Due to the amount of data that enables the classifier to speed up the learning process and obtain a high accuracy, the best performance was scored while employing 70:30 training and testing data sizes, with the scored values being 73.97% and 66.6% for DNN and ANN, respectively.

Table 4 Results for DNN with respect to different size of each set of data

M	Size of individual sets of data learning: testing)	DNN Classification Accuracy	ANN Classification Accuracy
1	80:20	73.63	63.1
2	70:30	73.97	66.6
3	60:40	71.73	65.4

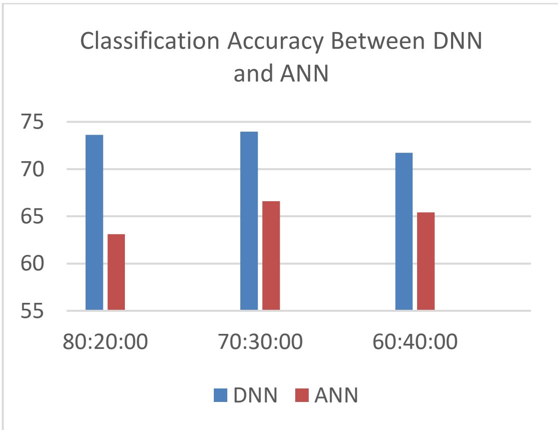

Figure 3 shows the experimental results for DNN and ANN algorithms

4.2 Results for Deep Neural Network (DNN):

A separate sample of input data is used to train the neural network, together with a sample data structure containing values for the desired features. Enhancing the network's capacity to classify data is the training process's most important goal. These training data are very dependent on the experiment's training size. Additionally, the data must have a significant amount of information to enable the network to learn by uncovering the dataset's underlying structure and then apply this "knowledge" to derive a rule for novel circumstances.

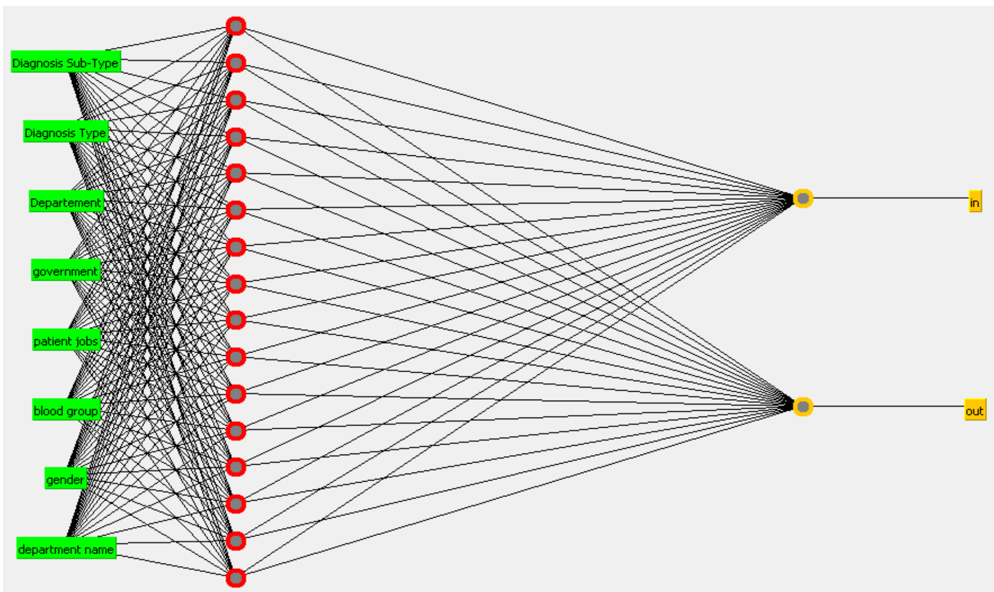

Figure 4 Architecture of deep neural network used in predictions of Iraq hospital dataset.

There are 1 neuron in the output layer of DNN, 8 neurons in the hidden layer, and 8 neurons in the input layer. The patient variables under analysis were split into a learning set and a testing set in order to better comprehend the DNN architecture.

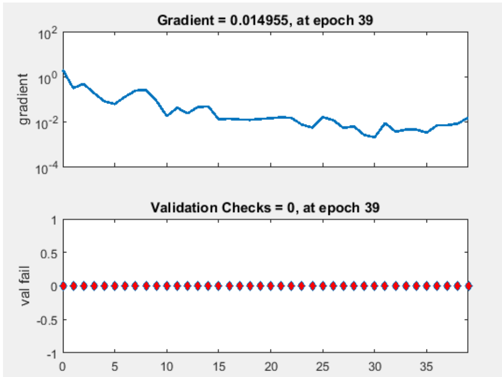

Figure 5 shows the training dataset

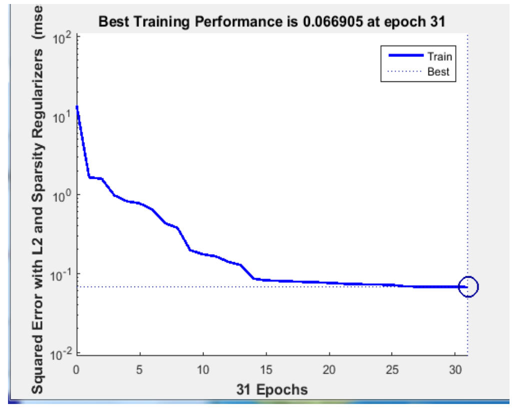

Figure 6 shows the training dataset

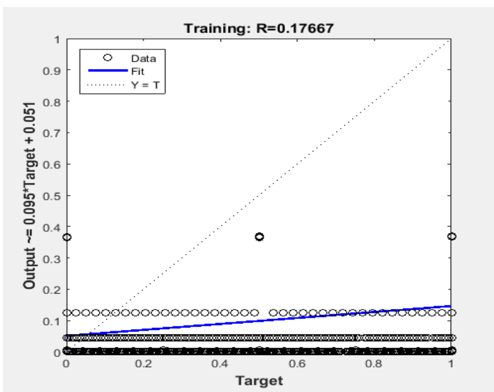

Figure 7 shows the best training

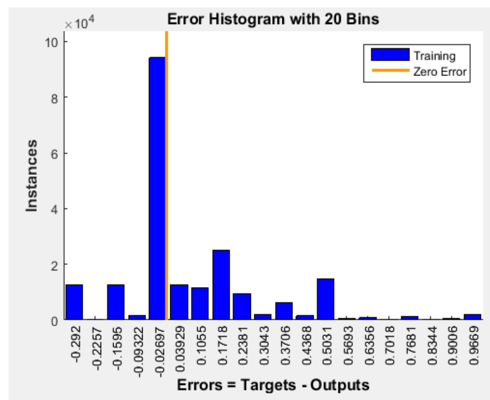

Figure 8 Histogram error with different bin

Table 5 Results for DNN with respect to different size of each set of data.

M	Size of individual sets of data (learning: testing)	DNN model type	Classification rate of training data	Classification rate of Testing data
1	80:20 20958:5240	DNN 8:8-16-8-1: 1	62.84	73.63
2		DNN 8:8-8-8-1: 1	62.60	72.84

3		DNN 8:8-12-4-1: 1	61.60	68.36
4	70:30 18338:6312	**DNN 8:8-16-8-1: 1**	**63.41**	**73.97**
5		DNN 8:8-8-8-1: 1	61.38	73.45
6		DNN 8:8-12-4-1: 1	61.51	73.11
7	60:40 15718:10480	DNN 8:8-16-8-1: 1	62.46	71.73
8		DNN 8:8-8-8-1: 1	60.60	71.59
9		DNN 8:8-12-4-1: 1	60.66	73.05

The most crucial hyper-parameter to modify, according to [15, 16] , is the learning rate. If the training rate is too high, the training algorithm may have convergence issues, and if it is too low, the algorithm may become stuck in a local minimum with poor generalization. In order to locate good minima and achieve the optimum at those minima, this study used an adaptive learning rate that was large in the beginning and smaller at the conclusion. As soon as the deep neural network's RMS error was as low as possible, learning was declared to be complete. Learning was finished using the DNN approach for the network in question in 500 epochs.

In this step, all experiments were conducted using a deep neural network with two hidden layers, momentum of 0, and learning rate of 3. During the learning process, data from the learning set were randomly presented.

Table 6 Classification results for six DNN models with different number of hidden neurons.

Model	Type of DNN	Classification rate of training data	Classification rate of testing data
1	DNN 8:8-6-3-1: 1	**84.56**	**87.84**
2	DNN 8:8-9-10-1: 1	62.84	73.63
3	DNN 8:8-15-1: 1	77.18	78.85
4	DNN 8:8-16-1: 1	82.92	81.47
5	DNN 8:8-4-1: 1	73.76	82.90
6	DNN 8:8-5-5-1: 1	67.97	76.91

The categorization rate scored was 87.84, 81.47, and 82.90, respectively, according to the data in Table 6. This is the accuracy level that was best. The best model 1 scored an 8:8:6-3:1 utilizing DNN, using 8 nodes as inputs, 2 hidden layers (6 and 3), and 1 value as the output. Additionally, when compared to the best models, the performance of models 2, 3, and 6 was below 78.58, resulting in worse results. The outcomes illustrated how a large number of features might affect the performance of a classifier. As a result of the abundance of feature sizes, the results performance appears to be identical.

Table 7 Classification results for DNN model using 70:30 training and testing dataset.

Model	Type of DNN	Learning set		Testing set	
		In Patient	Out patient	In Patient	Out patient
1	Total	7083	11255	2087	5773
2	Correct	5448	9395	1862	4450
3	Wrong	1635	1860	225	1323

In light of the data, we should discuss the outcomes of utilizing a 70:30 split for training and testing. The size of the 70:30 dataset is displayed in Table 4.4. When using DNN, the size of the datasets determines how many are used for learning and how many are used for testing.

The total number of in-patients and out-patients for the learning set was 7083 and 11255, respectively. A total of 5448 instances and 9395 total instances were correctly classified, while 1635 instances and 1860 total instances were incorrectly classified. For in-patient and out-patient testing, respectively, there were 2087 and 5773 instances of testing set overall. 1862 cases were accurately classified overall, accounting for 4450 different occurrences, while 225 instances were incorrectly classified, totalling 1323.

Table 8 Sensitivity analysis results for the variables considered in Deep neural networks DNN analysis

Model	Type of DNN	RMSE Train-ing	RMSE Testing data
1.	DNN 8:8-6-3-1: 1	0.4008	0.3975
2.	DNN 8:8-15-1: 1	0.4539	0.4411
3.	DNN 8:8-16-1: 1	0.4712	0.4759
4.	DNN 8:8-4-1: 1	0.4066	0.3524
5.	DNN 8:8-5-5-1: 1	0.42245	0.3884
6.	DNN 8:8-16-8-1: 1	0.6096	0.5136
7.	DNN 8:8-8-8-1: 1	0.4733	0.4492
8.	DNN 8:8-12-4-1: 1	0.4596	0.4367
9.	DNN 8:8-16-8-1: 1	0.60	0.51
10.	DNN 8:8-8-8-1: 1	0.6215	0.5153
11.	DNN 8:8-12-4-1: 1	0.6215	0.5153
12.	DNN 8:8-16-8-1: 1	0.4661	0.4487
13.	DNN 8:8-8-8-1: 1	0.6277	0.5330
14.	DNN 8:8-12-4-1: 1	0.4890	0.4565

After choosing the optimum training and testing set, Table 8 displays the DNN's findings of the sensitivity analysis. To assess the RMSE for training and testing datasets, several model sizes were used in the evaluation. The acquired outcomes show that the model number 4 and DNN 8:8-4-1:1 produced the best performance. The training and testing datasets were used to get the RMSE value, which was 0.4066 for each. In addition, model 13's performance received the weakest scores, with training and testing scores of 0.6277 and 0.5330, respectively.

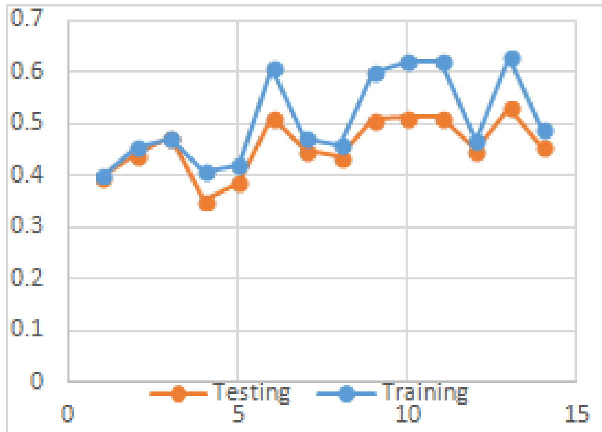

Figure 9 shows RMSE for the training and testing using different DNN model.

The Root Mean Square Error for the training and testing datasets using various DNN models is shown in Figure 9. It is evident from the above-depicted chart that the error percentage is lower than it was for the training data set, which suggests that the DNN in the training dataset was successful in identifying a pattern that reduced the mistake percentage in the testing data. On a platform for computer simulation, deep neural networks (DNN) have been used. First, an experiment was carried out to find the optimal size of each data set (learning: testing), employing three distinct data sizes for training and testing that are (80:20, 70:30 and 60:40). Table 8 listed the data sizes and the training and testing results for each data size. The best model is also chosen after testing many DNN models.

Based on the results, it can be concluded that the 70:30 dataset performed more accurately than the other DNN models, with the DNN 8:8-16-8-1: 1 model producing the best results. The top categorization rates for training and testing were 63.41 and 73.97, respectively. Utilizing the DNN 8:8-16-8-1:1 model. For additional research, a deep neural network built on six DNN models with various numbers of hidden neurons was employed. We evaluated the performance using the training and testing dataset 70:30. The DNN 8:8-6-3-1: 1 model produced the highest Classification rate of training and testing data. The outcome is 84.56 or 87.84, depending on the case.

5. Conclusion

In this study, we proposed a deep learning method to categorize malignancies into certain diagnosis or categories based on their medical records (DNN).In this work, we explore the DNN algorithm's performance and evaluate it against the most advanced ANN algorithm, which aims to identify patterns in health care data. The classification of the performance of the health patient dataset is the primary goal of this work, to sum up. Implementing a deep neural network (DNN) and comparing the findings with those of an artificial neural network (ANN) are two related concepts. Analysis of the data reveals that the methodology is appropriate and successful for KDD in health care datasets. In order to categorize cancer according to their categories for future works, the research community needs to explore a number of concerns and look into healthcare data. Using the findings from section 4 as a guide, these issues—which are detailed in the following points—were discovered.

6. Future Work

Feature selection algorithms, such as ant colony algorithms or specific swarm algorithms, must be used to improve the performance of the characteristics that have been chosen. Suggest a novel method with the capacity to automatically assign the appropriate parameters to improve classification accuracy.

7. Acknowledgements.

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