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BREAST CANCER SEVERITY PREDICATION USING DEEP LEARNING TECHNIQUES

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ABSTRACT

Breast cancer is one of the most common types of cancer most often affecting women. It is a leading cause of cancer death in less developed countries. Thus, it is important to characterize the severity of the disease as soon as possible. In this paper, we applied deep learning methods to determine the severity degree of patients with breast cancer, using real data. The aim of this research is to characterize the severity of the disorder in a shorter time compared to the traditional methods. Deep learning methods are used because of their ability to detect target class more accurately than other machine learning methods, especially in the healthcare domain. In our research, several experiments were conducted using three different deep learning methods, which are: Deep Neural Network (DNN), Recurrent Neural Network (RNN) and Deep Boltzmann Machine (DBM). Then, we compared the performance of these methods with that of the traditional neural network method. We found that the f-measure of using the neural network was 74.52% compared to DNN which was 88.46 %, RNN which was 96.79% and DBM which was 97.28%.

KEYWORDS

Breast cancer severity, Medical data, Deep learning, Deep neural network, Recurrent neural network, Deep Boltzmann machines.

1. INTRODUCTION

Cancer is considered as the second cause of death worldwide and around 70% of cancer cases occur in low- and middle-income countries [1]. Breast cancer is now the foremost cause of cancer-related deaths in women in both of the developed and less developed world. Moreover, the less developed world is suffering from a rising breast cancer disease with a growing number of younger women who are exposed to cancer [2]. In recent times, many health institutions worldwide are working to spread awareness about breast cancer. That is because discovering and treating the disease early reduce number of patients' death.

In breast cancer, tumors appear when cancer makes a mass of tissue in some part of the patient’s body. Various body parts, such as the digestive system, the nervous system or the circulatory system could be affected by these tumors. However, when tumors invade or destroy tissues other parts of the body, they are called metastasized. When a tumor reaches this phase, it becomes harder to treat. Thus, diagnosis time is the most important issue to treat breast cancer. Therefore, it is important to predict the severity of the disease as early as possible before spreading to other parts of the body [3].

For this reason, there are many studies that suggest the use of intelligent methods to detect breast cancer as early as possible. As a result, treatment will be given in a timely manner, which increases the cure rate of the disease.

Traditionally, measuring the severity of breast cancer is carried out manually. For example, doctors manually analyze and interpret data related to patients, disease ….etc. Without using a data analysis system, the analysis will be slow, because experts spend some time to examine the sample. The analysis will also be very subjective, because it depends on the past experience of the expert. Alternatively, using some methods from data mining, such as decision tree, Support Vector Machine, neural networks and deep learning yields faster and more accurate results.

The main objective of this research paper is to use deep learning techniques on the real data of breast cancer patients in order to predict the severity of the disease in these patients. The real data of cancer patients was collected from Gaza strip hospitals.

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Breast cancer stage is usually expressed as a number on a scale of 0 through 5, with stage 0 describing non-invasive cancers that remain within their original location, while stage 5 describes invasive cancers, that have spread outside the breast to other parts of the body [4]. In this research, we predict which stage the patient reached. We considered patients in stage 4 and stage 5 as highly severe.

We argued that this study supports the diagnosis of the disease by doctors for predicting a patient's severity condition by applying deep learning methods. Deep learning is a machine learning method that utilizes many levels of artificial neural networks to carry out the process training data. Deep learning has been used in a lot of research on the analysis of medical data, such as works [5]-[12]. We used deep learning because of its ability to detect the target class more accurately than other machine learning methods, especially in the healthcare domain [5].

The rest of the paper is structured as follows: the second section discusses the related work, the third section addresses our material and methods, the fourth section is about experiments and results, the fifth section is a discussion, while the sixth section implies the conclusions and suggestions for future work.

2. RELATED WORK

Due to the large quantity of data in the medical field, many published papers have applied machine language on such data. For example, Danaee, Ghaeini and Hendrix in [6] used a deep learning method called Stacked Denoising Autoencoder (SDAE) to extract functional features from gene expression profiles with high-dimensional data. They used machine learning classification techniques to evaluate the extracted features and found that the new features are very useful in cancer detection. That is because genes, which are highly interactive, could be useful cancer biomarkers for the detection of breast cancer. They concluded that SDAE can be used to extract genes that predict breast cancer and have potential as biomarkers or therapeutic targets.

Fombellida et al. in [7] applied different artificial metaplasticity methods for the diagnosis of breast cancer data. Metaplasticity can be considered as a set of algorithms that have a learning ability based on higher-level properties of biological plasticity. They used neural networks with multilayer perceptrons method at the artificial neuron learning level.

Benzheng et al. in [8] proposed a deep learning method called deep convolutional neural networks in order to classify breast cancer histopathological images. They classified each of the pathological images as one of two breast cancer classes. They found that the model in a prior knowledge that considers class and sub-class labels of breast cancer. That can control the distance of features of different breast cancer histopathological images. They conducted several experiments and the results showed that the model has a classification accuracy of up to 97%, which is a high classification accuracy.

Sekaran, Ramalingam and Mouli in [9] presented a computer-aided diagnosis system to perform automated diagnosis for breast cancer. The system employed deep neural network (DNN) as classifier model and recursive feature elimination (RFE) for feature selection. They used DNN with multiple layers of processing attaining a higher classification rate than SVM. They obtained an accuracy of 98.62%, which is better than other used methods.

Nawaz , Sewissy and Soliman in [10] presented a deep learning approach based on a Convolutional Neural Network (CNN) model for multi-class breast cancer classification. Their method aims to classify breast tumors into benign or malignant, along with predicting the subclass of the tumors, like fibroadenoma, lobular carcinoma …etc. Experimental results using the BreakHis dataset showed that the DenseNet CNN model achieved a high processing performance with 95.4% of accuracy.

Rashed and Abou El Seoud in [11] used a new network architecture inspired by the U-net structure for the early detection of breast cancer using mammograms. The results indicate a high rate of sensitivity and specificity.

Xie et al. in [12] introduced a deep learning method to analyze histopathological images of breast cancer *via* supervised and unsupervised deep convolutional neural networks. They adapted Inception_V3 and Inception_ResNet_V2 architectures to the binary and multi-class issues of breast cancer histopathological image classification by utilizing transfer learning techniques. The

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experimental results demonstrated that Inception_ResNet_V2 network-based deep transfer learning provides a new means of performing analysis of histopathological images of breast cancer.

From the above research, we can conclude that most of the previous studies concentrated on classifying breast tumors as benign or malignant. But, our work considers the severity of the tumor rather than its classification. Also, the other works applied their methods on histopathological images using computer-aided diagnosis systems, where our work used a dataset, because sometimes such a system is not available. Finally, our work used real system from local medical institutes, whereas other systems mostly used public datasets.

3. Materials and Methods

3.1 Dataset Sources and Description

In our experiments, we used four sources to collect information about breast cancer patients. We collected data from: general hospitals, tissue examination laboratories, radiation centres and death certificates. The data was collected from all hospitals and counselling centres in Gaza city, Palestine, over the period of 4 years from 2011 to 2014. We collected about 721 patients' records. The description of the attributes is depicted in Table 1. Our dataset consists of several attributes and the class is the severity of the disease. The attributes contain general features, such as age, marital status, incidence date and whether the patient is a smoker or not. Also, we have some specific attributes, such as which part of the origin is affected, laterality attribute which describes which side of the origin is affected, morphology attribute which describes the form of carcinogenic cells, the stage diagnosis attribute which describes the originally infected cells and the spread of the disease to neighbouring

Table 1. Attributes description.

Attribute	**Description**
Marital status	married :1, single: 2, divorced: 3, widowed: 4
Incidence date	Date
Affected part	diagnostic codes
Morphology	NOS =1, Infiltrating duct carcinoma= 2, Juvenile carcinoma of breast= 3, not given=4
Surgery	Given: 1, not given=0
Smoker	yes: 1, No: 0
Laterality	left: 1, right: 2, not paired: 3
Stage	Localized=1, Regional by both direct extension and lymph nodes=2, Regional by direct extension=3, Regional by lymph nodes=4
Radio therapy	Given: 1, not given: 0
Chemical therapy	Given: 1, not given: 0
Immuneotherapy	Given: 1, not given: 0
Hormonal therapy	Given: 1, not given: 0
Clump thickness	Number between 1 and 10
Severity (class)	True = disease dangerous level, False = disease at the beginning

cells. Also, the table describes the radiotherapy attribute which shows whether the patient had radiotherapy or not, the surgery attribute which shows whether the patient had surgery or not, immunotherapy attribute which shows whether the patient had immunotherapy or not, the chemical therapy attribute which gives whether the patient had chemical therapy or not and the hormonal therapy attribute which gives whether the patient had hormonal therapy or not. The last attribute is clump thickness. The class label contains two types of severity, which are high and low.

3.2 Preprocessing

After we integrated data into one dataset, some preprocessing steps have been applied, such as removing repeated patients' records, removing patients with little information and removing some private data columns, such as names and telephone numbers.

After that, data cleaning has been carried out. We used the missing values method in order to replace the missing values, then we set the role (class) of the dataset. In our case, the class attribute is severity, noting that we renamed the class from grade to severity. We used particular features which were selected from the real dataset, so that the classification model used only useful and relevant information.

3.3 Backpropagation Neural Network (BNN)

We used the traditional neural network as the baseline for our experiments. Backpropagation (BP) is a common method for neural networks. Figure 1 gives the architecture of the neural network with backpropagation. BNN is a set of connected nodes called neurons. Neurons are connected by edges. Neurons and edges have weights which are adjusted during the training process. BNN uses loss function to calculates the difference between the predicated output of the neural network and the actual output. Therefore, the goal of using the BNN is to update weights in the network to be as close as possible to the target output, by making the values of the predicated output closer to the values of the network output.

From research, it is found that BNN works only for a small number of hidden layers. From there, we came to the idea of deep learning using more hidden layers [13].

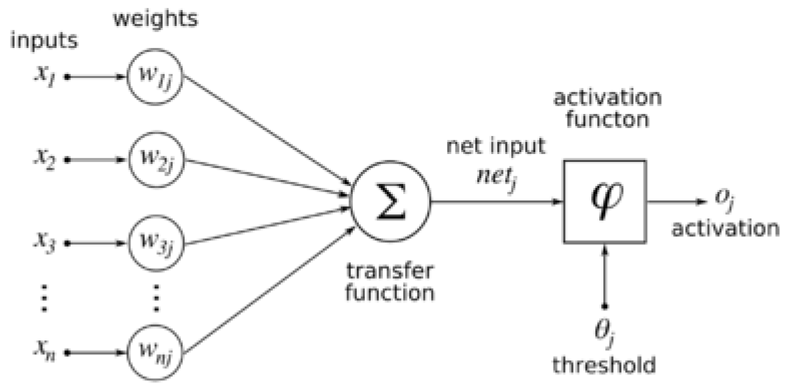

Figure 1. Backpropagation neural network [13].

3.4 Deep Learning Methods

Deep learning is an advanced method that has a collection of algorithms used for building and training neural networks. We used deep learning to improve the performance of traditional neural networks. In deep learning, input data is passed through a set of nonlinear transformation layers to reach the output. We input a set of features and use learning to predict the complex dependencies among these features.

Unlike traditional neural network which builds analysis with data in a linear way, deep learning uses multi-level layers to model high-level abstractions in data, which are composed of multiple nonlinear transformations. In each layer of the deep learning model, nodes train on a separate set of features based on the preceding layer's output [14].

In this paper, we used three common deep learning architectures which are: deep neural network (DNN), recurrent neural network (RNN) and Deep Boltzmann Machine (DBM).

1. ***Deep Neural Network (DNN)***: It is also called multilayer perceptron, which is a multilevel complex neural network. It contains many hidden layers. It uses sophisticated mathematical forms to model data in complex ways.

As seen in Figure 2, DNN is a multilayer perceptron neural network. It contains a number of hidden layers. It is fully connected and each connection has a weight. Each layer contains a number of nodes which is a set of neurons. In DNN, neurons uses nonlinear activation functions except the input neurons [15].

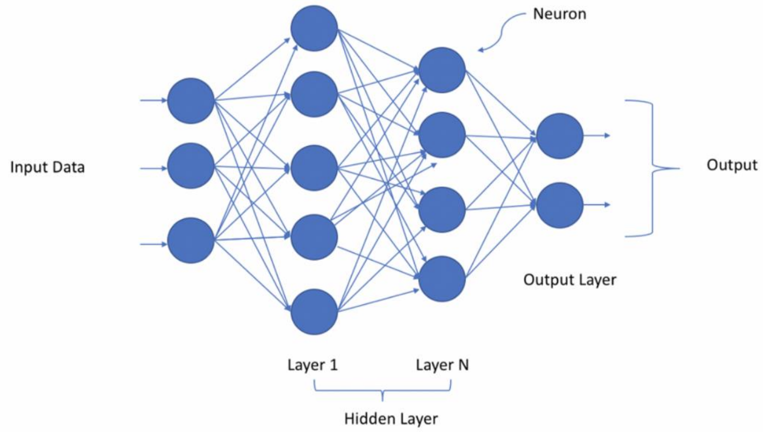

Figure 2. Deep neural network (DNN) [15].

2. ***Recurrent Neural Network (RNN)***: It is another type of deep learning architecture. It connects nodes as a sequence of directed graph. The sequence makes the network have a temporal behavior for a time sequence. As seen in Figure 3, we can use an internal state of RNN nodes as a memory to process a series of inputs. This property differentiates RNN from DNN. Input in RNN not only takes the current input example, but also the examples that appeared previously in time. So, the situation in RNN is unlike in DNN, where inputs and outputs are independent. In RNN, node decisions reached at time step *t-1* affect the decisions reached one moment later at time step *t*. As a result, nodes in RNN have two sources of input; the present and the recent past [16].

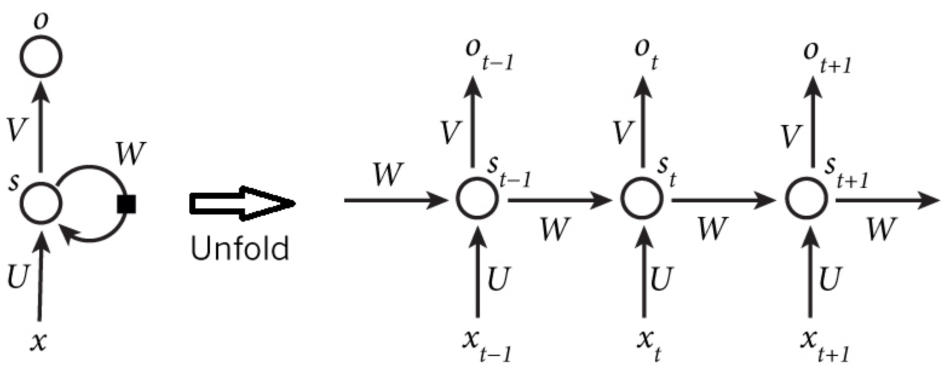

Figure 3. Recurrent neural network (RNN) [17].

3. ***Deep Boltzmann Machine (DBM):*** It is deep multilayer architecture based on Restricted Boltzmann Machine (RBM). The Boltzmann machine is a network of symmetrically coupled stochastic binary units. In DBM, we have a set of units $v \in \{0, 1\}$ as well as a set of hidden units $h \in \{0, 1\}$. As seen in Figure 4, DBM can be considered as an undirected probabilistic graphical model which contains a layer of observable features and a multilayer of hidden features. We often use DBM as a building block for constructing DNN and deep generative models which have recently gained popularity to learn complex and large probabilistic models [18].

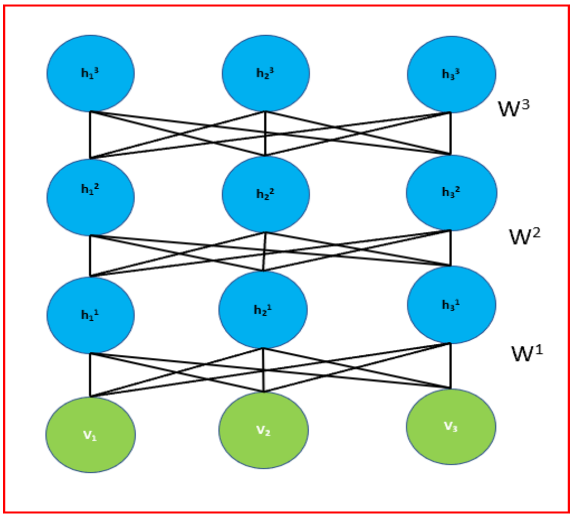

Figure 4: Deep Boltzmann machine (DBM) [18].

3.5 Evaluation

To evaluate our experiment, we used the most common metrics in this area, which are: accuracy, precision, recall and f-measure. In our experiment, we used 10-cross-validation testing. Then, we computed accuracy, which measures the percentage of the test sets that the classifier has labeled correctly. Also, we computed precision, which is the percentage of positive identifications that are actually correct. Then, we computed recall, which is the percentage of actual positives that are correctly identified. Finally, we computed the f-measure, which is a combined metric that takes both precision and recall into consideration.

4. Experimental Results

To experiment the proposed methods, we performed a two-class classification task to discriminate breast cancer severity as severe or not. In our experiments, we used a real breast cancer dataset which contains 721 data points of each class. We used four neural network methods which are:

4.1 Backpropagation Neural Network

To experiment this method, we modelled the network with a sigmoid activation function on all neurons of the network. We trained the model for 500 epochs, with a learning rate of 0.5. Table 2 gives the results of applying NNB. The accuracy was 75.37% and f-measure was 74.54%. This is a particularly weak result in the medical field which needs a highly confident result.

Table 2. Neural network backpropagation (NNB) performance.

Accuracy	75.37%
Recall	70.88%
Precision	78.55%
f-measure	74.52%

4.2 Deep Neural Network (DNN)

To test our data set on DNN, we used three hidden layers with 10, 20 and 10 nodes, as well as 5000 epochs. The evaluation function used was sigmoid function with a dropout of 0.2. Also, we used

Table 3. Deep neural network (DNN) performance.

Accuracy	87.83%
Recall	88.09%
Precision	88.84
f-measure	88.46%

Adam optimizer. As seen in Table 3, using the DNN with this configuration, we obtained an accuracy of 87.8% and an f-measure of 88.46%. These results are better than those obtained using BNN but are still not sufficient for the medical domain.

4.3 Recurrent Neural Network (RNN)

We conducted the third set of experiments using RNN. We used two hidden layers with 5 units for each hidden layer. We, also, used 1000 as maximum iteration to learn. The learning function was standard backpropagation for partial recurrent networks. We set the activation function of the output units to logistic function. We got an accuracy of 96.56% and an f-measure of 96.79%. These results are better than those obtained using BNN and DNN, as shown in Table 4.

Table 4. Recurrent neural network (RNN) performance.

Accuracy	96.56%
Recall	96.96%
Precision	96.63%
f-measure	96.79%

4.4 Deep Boltzmann Machines (DBM)

The fourth method that we used was DBM. In this experiment, we used three hidden layers and 10 nodes for each hidden layer. The learning rate was 0.8 and we used a sigmoid function as the activation function. The number of epochs was 3 and the batch size was 100. Table 5 gives the results of using this method with an accuracy of 97.52% and f-measure of 97.28%.

Table 5. Deep Boltzmann machines (DBM) performance.

Accuracy	97.52%
Recall	97.03%
Precision	97.54%
f-measure	97.28%

5. Discussion

As seen in Figure 5, the worst result came from using Neural Network Backpropagation with an accuracy of 75.37%. Compared to deep learning methods, BNN is too low, mainly because deep learning methods have many nonlinear transformation layers which make them able to detect the complexity of data in complex domains such as the breast cancer domain.

On the other hand, DBM is the best method that we can use to predict severity from breast cancer medical data. That is because of its ability to learn complex and large probabilistic models.

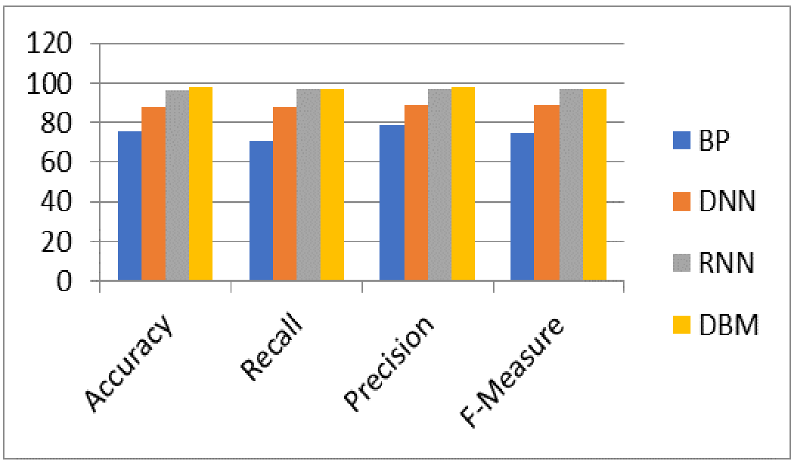

Figure 5. Comparing the performances of the four neural networks methods.

6. CONCLUSIONS

In this paper, different neural network models have been investigated and applied to find the model that best predicts breast cancer severity. The main concern of this paper is to classify patterns of breast cancer dataset into two categories: low severity and high severity of breast cancer grade. We applied four models of neural networks and deep learning: Backpropagation Neural Network (BNN) as baseline, Deep Neural Network (DNN), Recurrent Neural Network (RNN) and Deep Boltzmann Machine (DBM). We found that in general, performance of deep learning methods is much better than that of the traditional neural network. Also, we found that Deep Boltzmann Machine can produce the best results with an accuracy of 97.52% and an f-measure of 97.28%.

In the future, more patients' data will be collected to make a bigger training dataset for further testing and evaluation in order to increase the severity detection hit rate and improve model accuracy. Also, we may integrate histopathological images with our dataset as input to the system for more generalizable results.

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ملخص البحث:

يُعدّ سرطان الثدي واحداً من أكثر أنواع مرض السرطان شيوعاً، علماً بأنه يصيب النساء في معظم الحالات. وسرطان الثدي يأتي في مقدمة الأسباب التي تؤدي الى حالات الوفاة بمرض السرطان في الدول الأقل نمواً. لذا، فإن من المهم الوقوف على شدة الإصابة بهذا المرض في أسرع وقت ممكن.

في هذه الورقة، طبقنا عدداً من طرق التعلُّم العميق لتحديد شدة إصابة المرضى بهذا المرض باستخدام بيانات حقيقية. ويهدف هذا البحث الى تحديد شدة الإصابة بسرطان الثدي في وقت أقصر مقارنة بالطرق التقليدية. وتستخدم طرق التعلُّم العميق نظراً لما تتمتع به من قدرة على الكشف عن الصنف المستهدف على نحو أدق مقارنة بسواها من طرق تعلُّم الآلة، وبخاصة في ميدان الرعاية الصحية.

يتضمن هذا البحث إجراء عدة تجارب باستخدام ثلاثٍ من طرق التعلُّم العميق المختلفة، هي: الشبكة العصبية العميقة، والشبكة العصبية المتكررة، وآلة بولتزمان العميقة. بعد ذلك، تمت مقارنة أداء هذه الطرق بأداء طريقة الشبكة العصبية التقليدية. وقد تبين أنّ مقياس (ف) لاستخدام الشبكة العصبية بلغ 74.5%، مقارنة بِـ 88.46% لطريقة الشبكة العصبية العميقة، و 96.79% لطريقة الشبكة العصبية المتكررة، و 97.28% لطريقة آلة بولتزمان العميقة.