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Classification of Leukemia using Artificial Neural Networks

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تصنيف سرطان الدم باستخدام الشبكة العصبية

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ABSTRACT

Background:

In the United States, cancer is a leading cause of death and a significant cost of healthcare. Improving treatment outcomes and survival rates depends on accurate early cancer prediction and understanding the genetic pathways underlying its formation. Over the past 20 years, efforts have been made to classify cancer types using machine learning and deep learning techniques.

Materials and Methods:

In this study, a data sample of (138) patients was used, where the sample for the first population (myeloid leukemia) was 65 patients who were given (1), and the second population sample (lymphocytic leukemia) was 73 patients who were given (2). The data was divided into 75% for training and 25% for testing.

Results:

Classification results using neural networks were good, showing high prediction accuracy and a classification rate of 91.4%, confirming the high efficiency of the neural network. However, the results could be more robust and generalizable with access to a larger dataset. To address this issue, we plan to conduct future experiments on a larger and more diverse dataset to further validate the performance of our model.

Key words:

Neural Network, Classification, Artificial Intelligence, Leukemia.

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INTRODUCTION

A terrible diverse disease, cancer is characterized by aberrant cell tissue proliferation. Every year, millions of individuals pass away as a result of the disease's late or undetected identification. Therefore, it becomes crucial to accurately detect the presence of cancer cells. Given the prevalence of cancer, we must develop more accurate methods for diagnosis and therapy. Neural networks are a hot topic for research, particularly in the fields of radiology, cardiology, cancer, urology, and other. One of the main reasons for the low survival rate of cancer worldwide is the lack of early diagnosis of cancer, which reduces the possibility of treatment and cure. Early detection can result in a long survival rate, which is crucial in cancer diagnosis. Manually interpreting large medical images takes a lot of time and effort. As a result, neural network-based cancer detection technologies are introduced, which can lead to early diagnosis and treatment [16]. In recent past, technological activity has increased the idea of artificial intelligence has emerged as one of the main research areas. Artificial neural networks (ANNs) are computer systems designed to simulate the information processing methods of the human brain in order to generate, extract, and develop new information. Modeling neurons was the initial use of artificial neural network research in computer systems. The connections between neurons have numerical weights and learning in the neural network is done by modifying these weights. Another way to describe artificial neural networks is as a system that simulates a process that occurs in the human brain. Layers of nerve cells are connected to create artificial neural networks. Basic tasks including categorization, grouping, data aggregation, conceptualization, and prediction can be carried out by artificial neural networks. Applications for artificial neural networks can be found in engineering, the military, industry, finance, entertainment, and health [3].

Layers of artificial neural networks are created by combining different neurons. To receive inputs and transmit outputs, the neurons that make up this structure are in contact with one another [4]. Generally speaking, an ANNs is consist of three layers: the input layer, which sends inputs to the following layer; the hidden layer, which sends information from the input layer to the output layer without going through certain procedures; and the output layer, which generates output in response to input layer information [3].

The input layer is the network's leftmost layer, and the neurons that make up that layer are referred to as input neurons. The output neurons are located in the output layer, which is at the right. Since the neurons in the middle layer are neither inputs nor outputs, it is known as the hidden layer [1]. As shown in Figure 1, which contains only one hidden layer, as for the cells (the number of input cells is three, four hidden cells and two output cells) for each layer.

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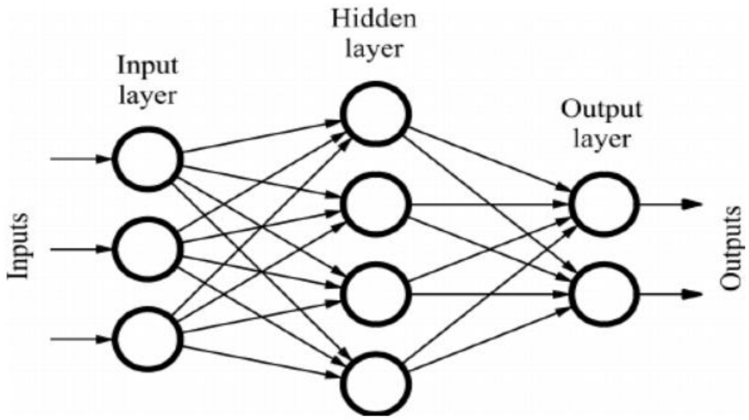

Figure1: General structure of artificial neural network [3]

However, some networks contain more than one hidden layer. For instance, the network in Figure 2 has four layers one input layer, one output layer, and two hidden layers: these multilayer networks are sometimes called multilayer networks or (MLPs) [1].

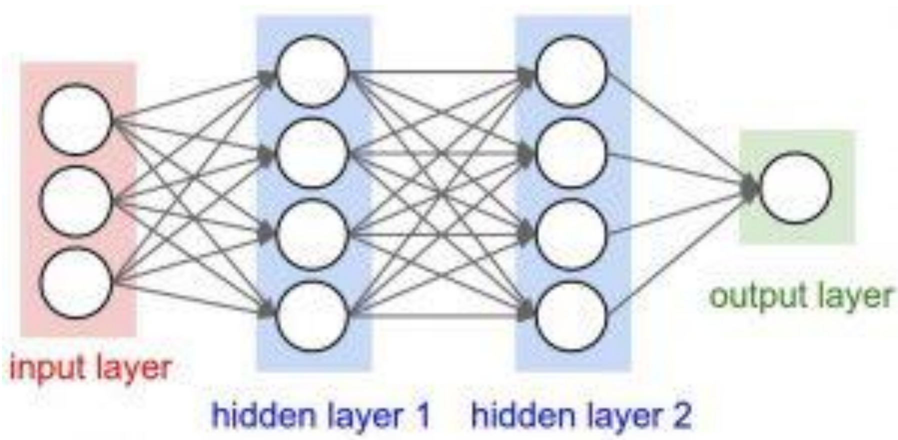

Figure2: Network with multiple hidden layers [3]

Each neuron has a threshold value and an activation function, and each connection contains a connection weight [5]. It determines whether each input has a positive or negative weight based on the sign of its weight. The signal strength at the connection is affected by the weight and the activation value is the weighted sum of the summation unit, and the output is generated based on the signal from this activation value. The relation between weight of each element and input and output of the ANN system is shown in the figure 3.

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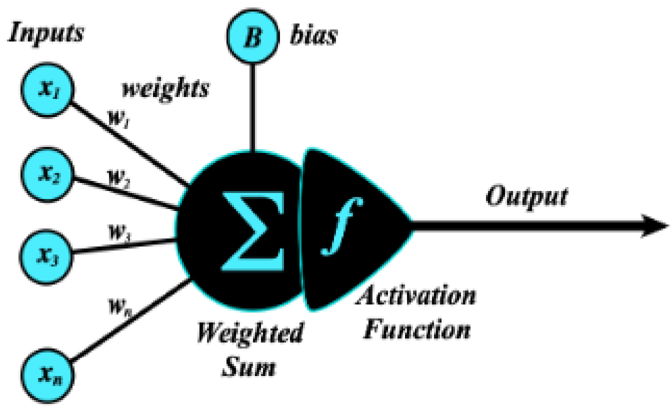

Figure 3: Weight of each element of the ANN system [4]

1. Types of Artificial Neural Networks[2]

- Feed forward Neural Network.
- Recurrent Neural Network (RNN).
- Convolutional Neural Network (CNN).
- Modular Neural Network (MNN).
- Radial basis function Neural Network (RBFNN).
- Multilayer perceptron

Feed forward Neural Network

Artificial NNs known as feed forward NNs are those in which there is no cycle in the connections between units. The first artificial neural network type to be created was feed forward NNs. They are also less complicated than their RNN counterpart. It is called feed forward because information flows only forward in the network (without loops) as it first passes via the input nodes, then via the hidden nodes, and finally via the output nodes [6].

The two primary forms of feed forward neural networks are as follows:

1- Single-Layer Feed forward NN (SLFFNN)

2- Multilayer Feed forward NN (MLFFNN)

Recurrent Neural Network (RNN)

Neural models that take context into account in their decision-making process are known as recurrent neural networks. Since it includes at least one feedback loop, a recurrent neural network differs from a feed forward neural network in that it contains four layers: input, hidden, delay and output. The hidden layer provides inputs to the delay cell neural network, while the output layer provides inputs to the delay cell neural network [6].

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Radial basis function Neural Network (RBFNN)

The RBF network is an ANN that uses radial basis functions as activation functions. The output of the network is a linear mixture of the radial basis functions of the inputs and neural parameters [6]. RBF networks are useful for the following reasons:

1. Approximation of a function.
2. Predicting time series.
3. Classification.
4. Control of the system.

Convolutional Neural Network (CNN)

In the realm of deep learning, the CNN algorithm is the most popular and used. The main benefit that CNN has over its predecessors is its ability to recognize pertinent elements automatically and without supervision by humans. CNNs have been widely used in a variety of domains, including as voice processing, computer vision, face recognition, etc. CNNs were modeled after neurons found in both human and animal brains. Specifically, in the brain of a cat. CNN uses local connections and shared weights to fully use 2D input-data structures, such as picture signals, in contrast to traditional fully connected (FC) networks [7].

Modular Neural Network (MNN)

Modular Neural Networks draw further from the biological inspiration of neural networks and emulate the modularization of the brain. Similar to how regions of the brain have different tasks, neural networks can be designed to break down a single large task into numerous smaller ones [8]. The "divide and conquer" strategy, which is composed of multiple sub modules with independent functions, is adopted by MNN. Because there is no connection between sub modules and each sub module corresponds to a sub task, MNN is capable of efficiently resolving dynamic and complicated modeling issues [9]. Numerous autonomous sub neural networks are created to address the lesser tasks. After that, an intermediary receives the findings from the sub-neural networks and aggregates them into a single result. Although there are alternative middlemen, another neural network might be the most biologically plausible. A gating network is one of those additional intermediates. The Mixture 0f Experts (MOE) approach makes use of a gating network. The experts are trained to solve the particular problem space they have been allocated after first being defined to split the problem space. These experts may be neural networks, but they may also be other learners, such as Bayesian networks, decision trees, and support vector machines. The gating network, which acts as an intermediate, is then trained to determine which expert to apply to which input [8].

Multilayer Perceptron

MLP is a particular FFNN model that can resolve regression and non-linear classification issues. In MLP, neurons are regarded as the processing elements. When the layers are layered on top of one another, the neurons are dispersed each layer in parallel fashion. Additionally, every

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layer's neurons are completely coupled to all other neurons in the following layer. Input and output are the names of the first and last layers, respectively. The hidden layers are those that lie between the input and output. The network receives input variables from the first layer. Neurons are arranged in a one-directional form via MLP. Neurons except for the first layer receive input from the outputs of neurons in the previous layers, Neurons in the first layer, however, get input from the outside. . To control the impact of related input on neurons, weights are assigned to the connections between the layers. Each neuron in MLP uses summation and activation functions consecutively to produce the output [10].

2. RELATED WORK

In 2021, It has been suggested an artificial intelligence algorithm that is stable and dependable. In order to extract the gait characteristic parameters of patients with varying ages, disease types, and disease courses, this approach learned the existing clinical gait data. It then repeatedly iterated the data and simulated the relevant gait parameters of patients. Experiments showed that the trained ANN scored the same as the human for most of the data (82.2%, Cohen's kappa = 0.743). ANN and enhanced Ashworth scores as adjudicated by human raters were strongly correlated ($r = 0.825$, $P < 0.01$). Since ANN is a dependable and robust artificial intelligence algorithm, it can offer fresh concepts and approaches for clinical rehabilitation assessment [11].

In 2019, It is described in detail how the machine works learning algorithms based on artificial neural networks (ANNs) can be used to address a range of wireless networking issues. A thorough review of several important ANN types relevant to wireless networking applications like deep neural networks, recurrent neural networks, and spiking neural networks, was first provided. Present the fundamental architecture of each type of ANN along with special examples that are crucial for wireless network design. Long short-term memory, liquid state machines, and echo state networks are a few examples. A comprehensive summary of the range of wireless communication problems that artificial neural networks can address is then presented, ranging from virtual reality applications over wireless networks to edge computing and caching to communications via unmanned aerial vehicles. It was discussed the primary justification for ANN use and the related difficulties for each specific application and gave a thorough example of a use case scenario and listed potential future research areas that ANNs could be used for [12].

In 2020, Presented, a thorough review of supervised learning techniques for spiking neural networks, assessing them both quantitatively and qualitatively. Spiking neural networks and conventional artificial neural networks are compared. The general framework and some related theories of supervised learning for spiking neural networks are then introduced. Additionally, the latest supervised learning algorithms are reviewed from the standpoints of their fundamental mechanisms and their suitability for spiking neural network architecture. And a comparison of the spike train learning performance of some representative algorithms is conducted. Finally, five qualitative performance evaluation criteria for supervised learning algorithms for spiking neural networks were given, as well as a novel taxonomy for supervised learning algorithms based on five performance assessment criteria [13].

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In 2020, a summary of artificial neural networks is presented, their main types are discussed, as well as the advantages and disadvantages of each. According to the discussions that were given, the MLFFNN is a reliable NN that has a wide range of uses. It can produce great outcomes and is simple to program and apply. The MLFFNN is a general model for surfaces without regular peaks and valleys that is preferred for function approximation problems. . Compared to RBF networks, the MLFFNN can provide superior classification results with far more efficient networks for classification applications [6].

In 2022, a new method for identifying high-quality answers to classification problems is proposed. A population-based metaheuristic, the Material Generation Algorithm (MGA) is a bio inspired algorithm that draws inspiration from material chemistry. Consequently, MGA can optimize the PNN's weight values. The enhanced exploitation and exploration capabilities of the MGA enable it to outperform FA and BBO when a large search space is being explored. The PNN's weight was adjusted using the MGA. The outcomes of this PNN-based approach were compared to the classification accuracy of the original PNN, FA-PNN, and BBO-PNN using MGA. By optimizing the PNN weights, the MGA improved the initial solutions, which were produced at random using the PNN. According to experimental results using 11 benchmark datasets, the suggested MGA with PNN outperformed the original PNN, FA-PNN, and BBO-PNN on 9 of the 11 benchmark datasets. This leads us to the conclusion that MGA can be used to investigate how high-dimensional and more actual datasets behave in different situations with respect to trait numbers [14].

3. THE ADVANTAGES AND DISADVANTAGES:

The table below shows the disadvantages and advantages of each model.

Tabel1: Advantages and disadvantages of each model.

Model	Advantages	Disadvantages
ANN [4]	• The ability to process data in parallel. • Data storage across the network. • The ability to function with incomp1ete knowledge. • Having tolerance for faults and a memory distribution.	• Guarantee of appropriate network architecture. • Unacknowledged network behavior. • Hardware reliance.
Perceptron [17]	• The AND, OR, and NAND logic gates can be implemented. • It offers more dependability. • Enhances the ability to	• Choose either the value 0 and 1. • Sort collections of vectors into groups that can be divided linearly.

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	predict different results.	
MLP [10]	• Nonlinear models can be learned by them. • It can process large amounts of input data and trains models in real time.	• Rather difficult to organize and administer • Comparatively slow.
FFNN [19]	• A number of feed forward networks can function independently with a small middleman to guarantee moderation.	• More variables need to be tuned. • Not appropriate for DL.
RBF [6]	• Designing flexible control systems is a brilliant idea. • The most recently techniques build tiny RBF networks and executes efficient training processes.	• The gradient problem makes training difficult. • The neural network is impacted by the problem of disappearing gradients.
CNN [7]	• Less parameters for learning than a layer that is fully connected.	• It's challenging to design and maintain. • Comparatively slow.
RNN [2]	• Used to boost pixel efficiency when paired with convolution layers. • Capable of modeling sequential data, where each sample can be assumed to depend on earlier ones.	• Issues with the gradient popping and disappearing. • • Training recurrent neural nets may be difficult.

4. DATASET:

Cancer is one of the most common and widespread diseases in Iraq, and blood cancer is a disease characterized by a very high mortality rate compared to other diseases. In this study, real data were taken from the Babylon Center for Oncology Treatment at Marjan Hospital, and this disease was chosen to represent the dependent variable (response variable). The data included a sample of (138) patients, where the sample was for the first community (myeloid leukemia (ML)) with a size of 65 patients who were given (1), and the second community sample

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(lymphocytic leukemia (LL)) with a size of 73 patients who were given (2). As for the explanatory variables, they are (9) variables:

1- Age
2- Gender
3- Weight
4- Job
5- Red blood cell Rate (P.C.V)
6- Blood hemoglobin (H.B)
7- White blood cell Rate (W.B.C)
8- Erythrocyte sedimentation rate (E.S.R)
9- red platelet count (P.C)

5. DISCUSSION AND RESULTS:

Neural networks were used to distinguish between two types of leukemia. By observing Table (2), it is clear that the data was used at a rate of 100% without data loss, as its total number was 138, and the number of training data was 103 at a rate of 75%, while the number of test data was 35 at a rate of 25%. Data preprocessing was performed to improve prediction, as normalization was performed to data, as shown in Figure (5).

Table(2): Case Processing Summary

		N	Percent
Sample	Training	103	75%
	Testing	35	25%
Valid		138	100.0%
Excluded		0	
Total		138	

To clarify the number of layers (components) of the neural network used in our work, they are shown in Table (3) as follows:

- The first part (input layer): consists of nine independent variables.
- The second part (hidden layer): consists of two processing units (neurons).

The third part (output layer): consists of two units and an activation function (softmax).

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Table(3): Information about Networks

Input Layer	Covariates	1	Age
		2	Gender
		3	Weight
		4	Job
		5	(P.C.V)%
		6	H.b
		7	W.B.C
		8	E.S.R
		9	P.C
	No. Unitsa		9
	Rescaling Method for Covariates		Standardized
Hidden Layer(s)	No. the Hidden Layers		1
	No. the Units in Hidden Layer 1a		6
	Activation Function		Hyperbolic tangent
Output Layer	Dependence variables	1	Disease
	No. of Units		2
	Activati0n Function		Softmax
	Error Function		Cross entropy

To clearly and in detail explain the model network, see Figure (4).

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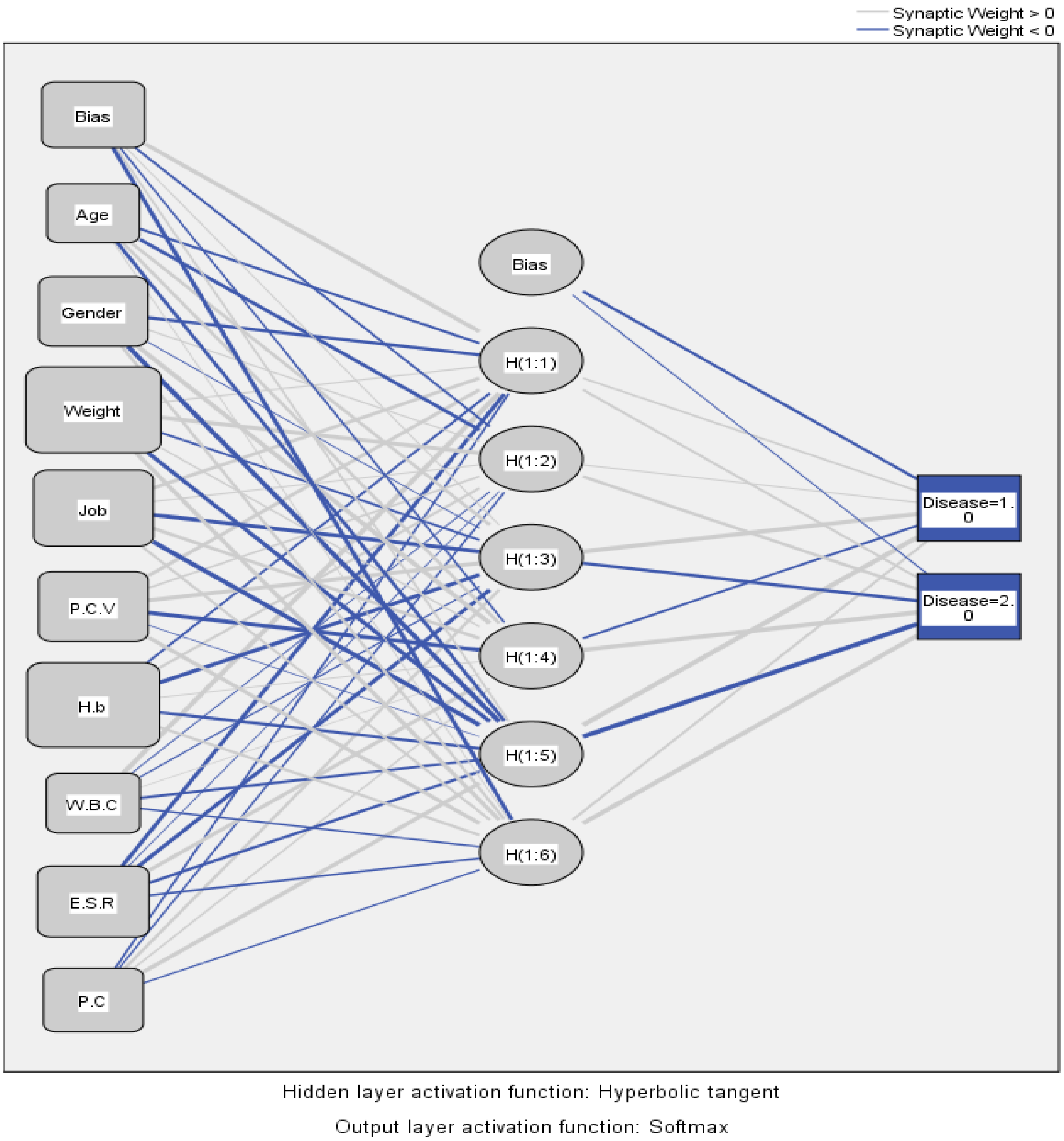

Figure (4): in the current study Neural network model

To ensure that the network is well trained for classification, we note from Table 4 that the percentage of incorrect classification in the training process reached 19.4%, while the percentage of incorrect classification in the testing process reached 8.6%, which indicates that the network classified the data well, as the percentage of incorrect classification was much lower than the percentage of correct classification. The estimation of the parameters for the neural network for the model is shown in Table (5).

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Table(4): Synopsis of the Model

Training	Cr0ss Entropy Error	41.903
	The percentage of incorrect forecasts	19.4%
	St0pping Rule Used	1 consecutive step(s) without reduction in error
	Time Spent Training	0:00:00.06
Testing	Cr0ss Entropy Err0r	8.530
	The percentage of incorrect forecasts	8.6%

Table(5): Estimates of Parameters

Predictor		**Predicted**							
		Hidden Layer 1						**Output Layer**	
		H(1:1)	**H(1:2)**	**H(1:3)**	**H(1:4)**	**H(1:5)**	**H(1:6)**	**Disease=1.0**	**Disease=2.0**
Input Layer	**(Bias)**	.460	-.180	.078	-.125	.135	-.385		
	Age	-.251	-.350	.321	.317	-.321	.047		
	Gender	-.325	.087	-.035	.474	-.484	.274		
	Weight	.101	.471	-.202	.110	-.420	.440		
	Job	.367	.078	-.463	.340	-.521	.249		
	P.C.V	.367	.148	.468	-.465	-.009	.433		
	H.b	-.185	.263	-.449	.065	-.313	.290		
	W.B.C	.522	-.061	-.085	.028	-.268	-.133		
	E.S.R	-.372	-.031	-.401	.408	-.307	-.180		
	P.C	-.133	-.118	.301	.119	.459	-.105		
Hidden Layer 1	**(Bias)**							-.279	-.075
	H(1:1)							.169	.225
	H(1:2)							.084	.323
	H(1:3)							.575	-.335
	H(1:4)							-.215	.604
	H(1:5)							.845	.604
	H(1:6)							.244	.529

The prediction was made using the three layers (input, hidden and output) as follows:

H(1:1) $=.460 -.251x_1 -.325\,x_2 +.101\,x_3 +.367\,x_4 +.367\,x_5 -.185\,x_6 +.522\,x_7 -.372\,x_8 -.133\,x_9$
Thus for each of **H(1:2), H(1:3), ...**
H(1:6) $= -.385+.047x_1 +.274\,x_2 +.440\,x_3 +.249\,x_4 +.433\,x_5 +.290\,x_6 -.133\,x_7 -.180\,x_8 -.105\,x_9$

y(1) = -.279+.169 H(1:1) +.084 H(1:2) +.575 H(1:3) -.215H(1:4) +.845 H(1:5) +.244 H(1:6)
y(2) = -.075+.225H(1:1) +.323H(1:2) -.335H(1:3) +.604H(1:4) +.604H(1:5) +.529H(1:6)

When applying the neural model, the correct classification rates for the two cases were as shown in Table 6. The correct classification rate for cases (1), which represent myeloid leukemia, was 83% in the training sample, while it was 94.4% in the test sample. The correct classification rate for cases (2), which represent lymphocytic leukemia, was 78.6% in the training sample, while it was 88.2% in the test sample. Thus, the correct classification rate for the network was 91.4%, which is a good rate for prediction and classification, confirming the high efficiency of the neural network.

Table(6): Classification

Sample	Observed	Predicted		
		1.0	**2.0**	**Percent Correct**
Training	**1.0**	39	8	83.0%
	2.0	12	44	78.6%
	Overall Percent	49.5%	50.5%	80.6%
Testing	**1.0**	17	1	94.4%
	2.0	2	15	88.2%
	Overall Percent	54.3%	45.7%	91.4%

The independent variables affecting the disease were identified, and the most important variable was weight, which was 100%, followed by H.B, which represents 95.7%, ... and finally age (Age), which represents 33.5% and is considered the least influential variable on the disease. The importance of the variables was explained in Table (7).

Table(7): Variables ratios according to the importance of the effect

Ver.	Importance	Normalized Importance
Age	.059	33.5%
Gender	.105	59.8%
Weight	.176	100.0%
Job	.133	75.6%
(P.C.V)%	.106	60.4%
H.b	.168	95.7%
W.B.C	.062	35.3%
E.S.R	.112	63.8%
P.C	.079	44.9%

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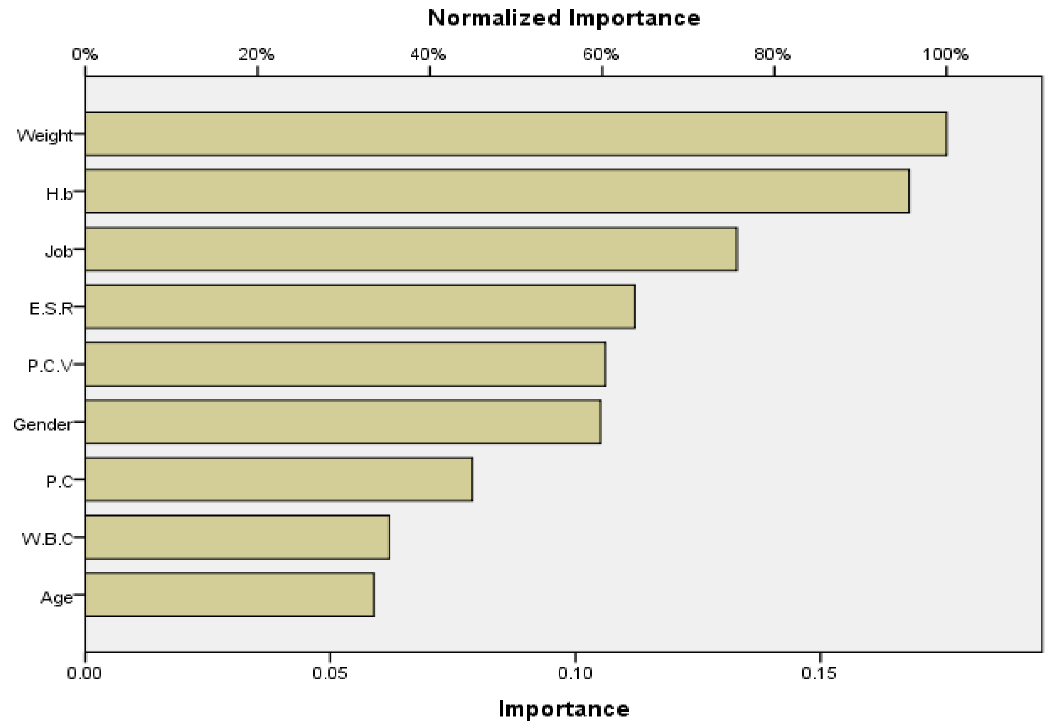

Figure (5): in the current study Normalized importance

6. CONCLUSION

This study demonstrates the potential of neural networks as an effective tool for classifying cancer types based on different biological and clinical features. The results show that neural networks, especially deep learning models, outperform traditional machine learning methods in terms of classification accuracy and robustness. The use of neural networks and other advanced architectures has significantly improved the accuracy of cancer detection.

Conflict of interests:

There are non-conflicts of interest.

8.References

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الخلاصة

مقدمة:

في الولايات المتحدة، يُعدّ السرطان سببًا رئيسيًا للوفاة وتكلفة باهظة للرعاية الطبية. ويعتمد تحسين نتائج العلاج ومعدلات البقاء على قيد الحياة، على دقة التنبؤ المبكر بالسرطان ومعرفة المسارات الجينية الكامنة وراء تكوّنه. وعلى مدار العشرين عامًا الماضية، بُذلت جهود لتصنيف أنواع السرطان باستخدام تقنيات التعلم الآلي وأساليب التعلم العميق.

طرق العمل:

في هذه الدراسة، تم استخدام عينة بيانات من (138) مريضًا، حيث كانت العينة للمجتمع الأول (سرطان الدم النقوي) بحجم 65 مريضًا أعطوا (1)، والعينة المجتمعية الثانية (سرطان الدم الليمفاوي) بحجم 73 مريضًا أعطوا (2). وقُسِّمت البيانات إلى 75% للتدريب و25% للاختبار.

النتائج:

كانت نتائج التصنيف باستخدام الشبكات العصبية جيدة، حيث أظهرت دقة تنبؤ عالية ومعدل تصنيف بلغ 91.4%، مما يؤكد الكفاءة العالية للشبكة العصبية. ومع ذلك، يمكن أن تكون النتائج أكثر متانة وقابلية للتعميم مع إمكانية الوصول إلى مجموعة بيانات أكبر. ولمعالجة هذه المشكلة، نخطط لإجراء تجارب مستقبلية على مجموعة بيانات أكبر وأكثر تنوعًا للتحقق بشكل أكبر من أداء نموذجنا.