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A CLINICAL DECISION SUPPORT SYSTEM FOR THE DIAGNOSIS OF GYNECOLOGICAL DISEASES

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ABSTRACT

Gynaecological diseases diagnosis is one of the important issues in the medical field globally because gynaecologists have to analyze and diagnose the disease according to various and similar symptoms. They may accidentally miss some symptoms that lead to a misdiagnosis. Hence, this paper aimed for developing a clinical decision support system (CDSS) to assist the gynaecologists in the diagnosis process for eleven types of gynaecological diseases that represent the most important diseases that are frequently diagnosed in gynaecologist's clinics which are: Polyps, Infections, Fibroids, Prolapse, Cancer, Endometrial hyperplasia, Migrants, Amenorrhea, Abortions, Dysmenorrhea and Infertility. In the proposed system, a multilayer perceptron (MLP) feed-forward neural network was used. The input layer of the proposed system included 54 input variables. An iterative process was used to determine the number of neurons and hidden layers. Furthermore, a resilient backpropagation algorithm (Rprop) was used to train the system. In particular, a 10-fold cross-validation scheme was used to access the generalization of the proposed system. We obtained 94.5% classification accuracy from the experiments made on the data that were taken from 550 patients' medical records suffering from eleven gynaecological diseases managed at the gynaecological clinics at Jordan University Hospital (JUH).

Keywords: *Gynecological diseases, Diagnosis, Clinical Decision Support Systems (CDSSs); Multilayer Perceptron (MLP); Neural Network; Resilient Backpropagation Algorithm (Rprop);*

1. INTRODUCTION

There are many diseases that a woman may face, these diseases are multiple and different. Their symptoms are different and similar among themselves [10]. As a result of a large number of these diseases, they cannot be restricted and assembled in one research. Many of these depend on an increase or decrease in the spread of any disease of these diseases and on the place or the environment where patients live [2]. As there are countless gynaecological diseases and variations of the same, one has to understand that gynaecological problems will have multiple and varied symptoms [24, 25]. A gynaecologist has to analyze and diagnose the disease according to many and similar symptoms. The patient may not be in opposition to spell out all her problems or may not know about symptoms of a disease and even the disease itself. The gynaecologist may accidentally miss some of the symptoms [4]. All gynaecologists in the world may not know all types of gynaecological diseases. However, when several symptoms and tests are involved, the ultimate diagnosis may be difficult to obtain, even for a medical expert. Furthermore, similar symptoms for multiple diseases may boost the chance for medical misdiagnosis. Consequently, over the past few decades, this has given rise to computerized diagnostic tools proposed to assist physicians to clarify the confusing data in case of imprecision and uncertainty [8], these computerized tools are called clinical decision support systems (CDSS) which are types of computer programs that can be developed through several kinds of machine

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learning techniques and are used to assist clinicians at the point of care [1]. The implementation of these systems could have several beneficial effects; they improved patient safety by reducing medication errors and adverse events; medical errors imply actions such as the conclusion of the wrong diagnosis, the prescription of incorrect treatment or the inefficient execution of correct treatment. Additionally, CDSS improved clinical documentation and patient satisfaction [18, 9, 26]. Moreover, they supported medical education and training and provided immediate feedback to patients [13]. Initially, the CDSS mainly used statistics, logic, and probability theory to support the diagnosis process, but since the late 1980s, it has been implemented to recommend decision-making from the treatment planning stage [26]. In the gynaecology domain, multiple studies showed the effectiveness of applying neural networks which are one of the most popular soft computing methods in building CDSS for assisting physicians in their decisions. The gynaecology domain has many diseases that have varies and complex symptoms. Hence there are not many types of research in this specific domain, and there is not specific research lie any disease of gynaecological diseases for diagnosis except for cancer. All researches presented only one disease of gynaecology such as ovarian cancer or breast cancer. In [19] research presented a system for treating gynaecological diseases developed a decision-support system which helped a gynaecologist analyze and prescribe medicines for such diseases with fewer errors [20]. This system prescribes medicine for a gynaecological disease based on various symptoms of the disease. That implementation is based on the multi-layered feed-forward neural network structure. This system is almost the only one of its kind which deals with more than one disease in one system. It is dealing with cervix symptoms, uterus symptoms and others. This system deals with gynaecological diseases in terms of description of treatment but does not classify the diagnosis. In [14] proposed two systems to diagnose two types of cancer, they are breast cancer and ovarian cancer, using a group of laboratory tests and the age of the patient. These methods provide an objective approach to backpropagation neural networks. The breast cancer study involved 104 patients (45 malignant and 59 benign subjects) and achieved accuracy 72.9%, meanwhile the ovarian cancer study involved 98 individuals (35 malignant, 36 benign and 27 control subjects). It achieved an accuracy of 85.5%. In [20], he described a neural network-based approach to breast cancer diagnosis; the model developed can determine which women are more likely to suffer from a particular kind of tumour before they undergo mammography. While [12] developed in their study the artificial neural network model, this study included 686 women, 431 (62.8%) had a benign and 255 (37.2%) had a malignant ovarian tumour, and achieved accuracy 97.7%. And other several studies are available for analyzing symptoms of the patient and diagnosing the disease. But very few of these studies analyze and diagnose diseases in specialized fields and more than the disease at the same time, like gynaecology. And these studies cannot diagnose more complex and difficult to analyze several diseases in the same software. There are many and various diseases that spread in the gynaecologist's clinics which are difficult to be identified in one research [2].

Mangalampalli et al. [27] in their study presented system for treatment gynecological diseases, to develop a decision-support system which can help a gynecologist analyze and prescribe medicines for such diseases with fewer errors. This system prescribes a medicine for a gynecological disease based on various symptoms of the disease. That implemented based on the multi-layered feed forward neural network structure. This system is almost the only one of its kind which deals with more than disease in one system. It is dealing cervix symptoms, uterus symptoms and others, this system deals with gynecological diseases in terms of description of treatment does not classification of the diagnosis. In [28] the authors describe a neural network based approach to breast cancer diagnosis; the model developed is able to determine which women are more likely to suffer from a particular kind of tumor before they undergo a mammography. Also, improving the quality of an **Electronic Health Record** (HER) is believed to play an important role in future medical development, and would be further improved when data utilization functions such as the Clinical Decision Support System (CDSS) are implemented [23].

In Traditional, research on the CDSS has been focused on terminology and diagnosis [26], therefore, in this study, we aimed for developing a clinical decision support system (CDSS) to assist the gynaecologists in the diagnosis process for eleven types of gynaecological diseases that represent the most important diseases that are frequently diagnosed in gynaecologist's clinics while all previous CDSS research's in this area are limited to one or two type of diseases.

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The remainder of this paper is organized as follows: Section 2 presents basic concepts of theoretical background of MLP neural network and the Rprop training algorithms that is related to work in these areas. The proposed System Architecture is presented in Section 3 The experimental results have been presented and discussed in Section4. We conclude the paper Section 6 and future work.

2. THEORETICAL BACKGROUND

The theoretical background of MLP neural network and the Rprop training algorithms that are related to our work are presented in this section.

2.1. Multilayer Perceptron (MLP) Neural Network

Neural networks are a powerful data modelling tool that can capture and represent complex input/output relationships. They are used whenever there are problems of prediction, classification or control in areas as diverse as finance, medicine, engineering, geology and physics. One of the most popular types of neural networks that are widely used in building CDSS is MLP neural networks. In an MLP neural network structure, some signals flow from input units, forwarded through hidden units, eventually reaching the output units [21]. In other words, an MLP neural network is a layered network in which each layer only receives inputs from previous layers [21]. Figure 1 illustrates an MLP neural network structure with one hidden layer.

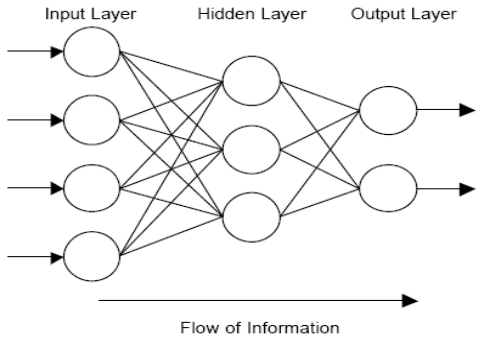

Figure 1. An MLP neural network

The input layer in an MLP contains units that simply serve to introduce the values of the input variables. The hidden and output layers contain units that are called neurons where each neuron is connected to all of the neurons in the preceding layer [23]. When the network is executed (used), the input variable values are placed in the input units, and then the hidden and output layer units are progressively executed. Each neuron in both the hidden layers and the output layer calculates its activation value by taking the weighted sum of the outputs of the units in the preceding layer [22]. The activation value is passed through the activation function to produce the output of the neuron. When the entire network has been executed, the outputs of the output layer act as the output of the entire network [5].

An artificial neuron (illustrated in figure 2) is defined as follows:

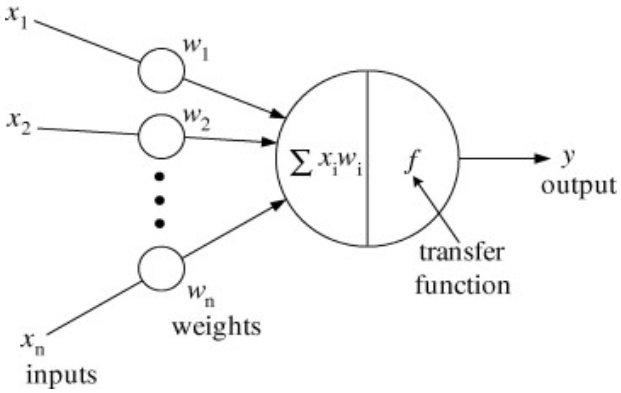

Figure 2. A single artificial neuron

- It receives several inputs (either from original data or from the output of other neurons =in the neural network). Each input comes via a connection that has a strength (or weight).
- The weighted wi sum of the inputs xi is formed to compose the activation of the neuron. Gathering the weighs of the inputs according to Eq.1:

$$Sum = \sum_{i=1}^{n} x_i w_i \quad (1)$$

- The activation signal is passed through an activation function (y) (also known as a transfer function) to produce the output of the neuron as illustrated in Eq.2:

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$$y = f\left(\sum_{i=1}^{n} x_i w_i\right) \quad (2)$$

2.2. Backpropagation and Resilient Backpropagation (Rprop) Algorithms

MLP neural networks have been applied successfully to solve difficult and diverse problems by training them with a highly popular algorithm known as backpropagation which uses the data to adjust the network's weights in a manner that minimizes the error in its predictions on the training set [5]. However, because backpropagation iteratively searches for a set of weights that minimize the error function of overall training pairs. Therefore, MLP networks have an error surface, which is in general complex and believed to have many local and global minima. This occurs because the algorithm always changes the weights in such a way as to cause the error to fall. But the error might briefly have to rise as shown in Figure 3. If this is the case, the algorithm will get stuck (because it can't go uphill) and the error will not decrease further [5]. This requires rerunning the algorithm with new random initial weights and other network parameter hoping to reach the global minima in the new run. As a consequence, backpropagation is never assured to find global minima [5].

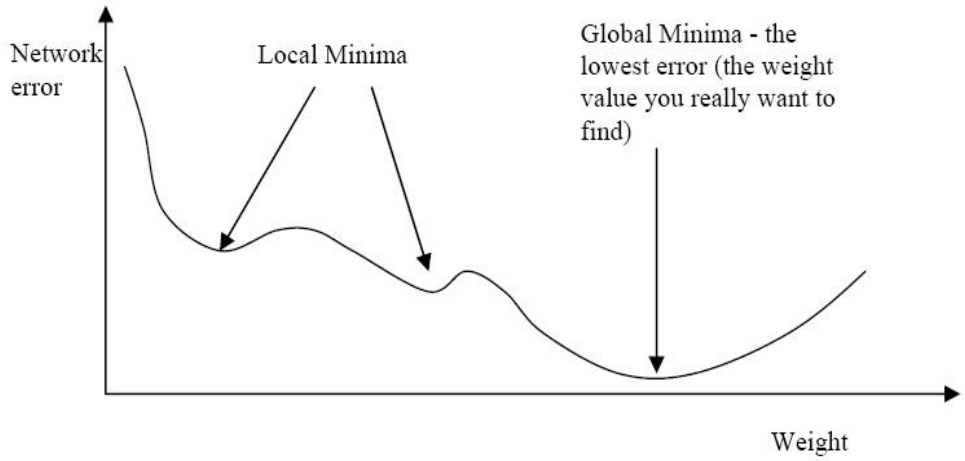

Figure 3. An Error Surface

Therefore, the Resilient Back Propagation (Rprop) was devised [11] to eliminate the harmful influence of the magnitude of the partial derivative. The detailed about the computational equations and the algorithm can be found in [3].

2.3 Gynecological Diseases

Gynecology word comes from the Greek, whereas gynaika (γυναίκα) meaning woman is the medical practice dealing with the health of the female reproductive system (uterus, vagina and ovaries). Literally, outside medicine, it means "the science of women". It is the counterpart to andrology, which deals with medical issues specific to the male reproductive system. The female reproductive tract is a complex and intricate system. It must stay balanced in order to remain healthy [4].

As every woman knows, there could be myriad gynecological conditions. Most of the times, women tend to ignore symptoms of gynecological diseases or any kind of infection [29]. They are typically too embarrassed to discuss gynecological symptoms with their doctors, or are afraid to approach a qualified gynecologist. Just to being with, most gynecological problems relate to different varieties of infections. For instance, vaginal infections are extremely frequent occurrences across the globe. Typically, it is a yeast infection which is rather common place. Such an infection

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is nothing to be ashamed of, as it does not indicate anything conclusive. Almost all women have had to deal with such infections which may result because of organisms which would generally be present, even in a vagina that is perfectly healthy. As there are countless gynecological diseases and variations of the same, one has to understand that gynecological problems will have multiple and varied symptoms [2].

There are many diseases that woman can be faced, those diseases are multiple and different their symptoms, varies and similar among themselves, as result to the large number of those diseases, cannot be restricted and assembled in one research. And may depend upon an increase or decrease in the spread of any disease of these diseases and on the place or the environment where patient live [2].

In particular, there are varies diseases that spread in Jordan, exhibiting the most important diseases and that are frequently diagnosed in the gynecologist's clinics. And this thesis include these diseases like: Polyps(Cervical, Endometrial), Infections(Cervicitis, Endometritis, Cervical Erosion, Endometrial atrophy), Fibroids, Prolapse, Cancer(Cervical ,Uterine), Endometrial hyperplasia, Migrants(Adenomyosis, Endometriosis), Amenorrhea, Abortion , Dysmenorrhea and Infertility. Each disease of those diseases has many different symptoms that shown in **Table 1** but must remember that not all of the symptoms can exist when being a patient and it depends on extent status of the patient and severity of her disease.

Table 1: All Diseases And Their Symptoms

No	Diseases	Symptoms and signs
1	Polyps	• Intermenstrual bleeding. • Postmenopausal bleeding. • Excessive bleeding during a menstrual period(menorrhagia) • Spotting bleeding after intercourse. • Abnormal Vaginal discharge
2	Infection	Spotting bleeding after/during intercourse • Abnormal Vaginal bleeding • Intermenstrual bleeding. • scanty menstrual blood (spotting) • Dysmenorrheal • Lower abdominal pain • Fever • Abnormal Vaginal discharge which may be : o Non-smelly vaginal discharge o Smelly vaginal discharge o Yellow vaginal discharge o Vaginal discharge containing blood
3	Fibroids	• Painful bleeding during menstruation. • Frequent urination. • Pain during sexual intercourse. • Bleeding between periods (heavy irregular bleeding). • Low back pain, pelvic pain • Painful urination
4	Prolapse	• Urinary frequency • Urinary incontinence • Difficulty stopping urination • Difficulty starting urination • Dragging sensation in lower abdomen • Difficult or painful urination • Feeling of rectal fullness

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		• A feeling of fullness in the lower abdomen • Increased urge to urinate • Painful bowel with cycles of diarrhea and constipation. • Difficulty emptying the bowel • Valur pain
5	Cancer	• Abnormal vaginal bleeding • Difficult or painful urination • Post coital bleeding • Abnormal vaginal bleeding • Vaginal discharge containing blood • Painful sex (Dysparunia) • Vaginal discharge • Pelvic pain • Loin pain • Decrease appetite
6	Endometrial hyperplasia	• Heavy menstruation • Extended menstruation • Menorrhagia • Irregular menstruation
7	Migrants	• Several menstrual cramps. • Painful intercourse. • Painful orgasms. • Painful bowel movements often with cycles of diarrhea and constipation. • low back pain, pelvic pain • Pain before and/or after menstruation. • Heavy or irregular menstrual bleeding. • Intestinal distress such as bloating, vomiting, nausea. • Painful menstruation • Longer periods
8	Amenorrhea	• Increase appetite or decrease appetite. • Lower abdominal pain • Painful intercourse. • Redundant breast • Dry skin. • Abnormal hair growth mainly at face
9	Abortion	• Vaginal bleeding • Uterine bleeding • Menstrual cramps • Lower abdominal pain • Trauma
10	Dysmenorrhea	• Painful menstruation • Menstrual cramping
11	Infertility	• Genital infection • Pelvic infection • Endocrine dysfunction • Sexual dysfunction • Male factor

3. SYSTEM ARCHITECTURE

The following subsections explain how the input variables that were used in the training and testing processes were encoded for building the heart disease CDSS, and how the number of hidden layers and hidden neurons in each layer was chosen.

3.1 Data Preparation and Encoding for the Input Layer

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When a patient report to a physician, a large number of possibly relevant inputs must be considered during the diagnosis. A physician reaches an accurate diagnosis or treatment decision based on observations, the patient's answers to questions and physical examinations [6].

In this paper, the gynaecological disease dataset used for testing and training the system consisted of a total 550 cases (in which each disease has a total of 50 cases) gathered from the gynaecology clinics at JUH, located in Amman, Jordan. Moreover, 54 variables essential to the diagnosis of the gynaecological diseases of interest were interpreted from each patient's medical record. These variables were divided into two categories:

i. Basic information of a patient (including age, marital status and pregnancy).
ii. Symptoms (51 factors in total), were divided into six categories as follows: menstrual problems, vaginal problems, sexual problems, urinary and abdomen problems, pain problems and finally another problem.

In Table 2 the datasheet that was used in gathering the patient's variables is illustrated; whereas we can notice from the table that most of the attributes were assigned to have a yes or no value to indicate the presence or absence of an attribute.

Table 2. Patient's Data Record

i. Patient's Basic Information			
- Age: -----			
- Marital Status: Single/Married		- Pregnancy: No/ Yes	
ii. Symptoms			
A. Menstrual Problems:			
- Menopause:	No/ Yes	- Painful menstruation:	No/ Yes
- Cramps menstruation:	No/ Yes	- Pain before and/or after menstruation:	No/ Yes
- Intermenstrual bleeding:	No/ Yes	- Extended menstruation:	No/Yes
- Regular menstruation : Absent/ regular / irregular		- Postmenopausal bleeding :	No/Yes
-Amount of bleed: Absent/ Spotting / Normal / Heavy			
B. Vaginal Problems			
- Something protruding out of vaginal :	No/ Yes	- Abnormal vaginal discharge :	No/ Yes
- Yellow non-smelling vaginal discharge :	No/ Yes	- Abnormal vaginal bleeding :	No/ Yes
- Reduction in symptoms when lying down :	No/ Yes	- Yellow smelling vaginal discharge:	No/ Yes
- Pressure symptoms with long-standing :	No/ Yes	- Vaginal discharge containing blood	No/ Yes
C. Sexual Problems:			
- Bleeding after sexual intercourse :	No/Yes	- Sexual dysfunction :	No/Yes
- Bleeding during sexual intercourse :	No/Yes	Pain during sexual intercourse :	No/Yes

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D. Urinary and Abdomen Problem

- Urinary frequency:	No/Yes	- Difficulty starting urination:	No/Yes
- Difficulty stopping urination:	No/Yes	- Urinary incontinence:	No/Yes
- Dragging sensation in the lower abdomen:	No/Yes	- Increased urge to urinate:	No/Yes
- A feeling of fullness in the lower abdomen:	No/Yes	- Difficult or painful urination:	No/Yes
- Painful bowel with cycles:	No/Yes	- intestinal distress:	No/Yes
- Difficulty emptying the bowel:	No/Yes	- Feeling of rectal fullness:	No/Yes

E. Pain Problems :

- Bladder pain:	No/Yes	- Low back pain	No/Yes
- Valur pain :	No/Yes	- Lower abdominal pain:	No/Yes
- Pelvic pain :	No/Yes	- Loin pain:	No/Yes
- Painful orgasms:	No/Yes		

F. Another Problem:

- Redundant Breast:	No/Yes	- Abnormal Hair Growth Mainly at the Face :	No/Yes
- Male Factor :	No/Yes	- Appetite : Decrease/ Normal/Increase	
- Fever:	No/Yes	- Endocrine Dysfunction:	No/Yes
- Fatigue:	No/Yes	- Thyroid Deficiency:	No/Yes
- Trauma :	No/Yes	- Dry Skin :	No/Yes

We notice from Table 2 that we encoded the non-numerical variables by giving some of them two values (No or Yes) and for other variables are three values. The meaning for these encoding values is illustrated in Table 3.

Table 3. Encoding Meaning

Category	Variable/s	Meaning: our encoding
Patient's Basic Information		
	Age	Numerical Value
	Marital Status	Single: 0
		Married: 1

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	Pregnant	No: 0 Yes: 1
Symptoms		
Menstrual Problems	Regular Menstruation	Absent : 0 Irregular : 0.5 regular : 1
	Amount of Bleed	Absent : 0 Spotting : 0.25 Normal : 0.5 Heavy: 1
Another Problem	Appetite	Decrease: 0 Normal: 0.5 Increase: 1
Remaining Symptoms	Remaining Variables	No: 0 Yes: 1

The collected data was then partitioned into subsets using the cross-validation technique which is: an estimation of accuracy for a predictive model. It is determined by the overall number of correct classifications divided by the total number of instances in the dataset. One round of cross-validation involves partitioning a sample of data into subsets, performing the analysis on one subset (called the training set), and testing the analysis on the other subset (called the testing set). ANN goes through overfitting. Therefore, a third subset called the validation set is used to avoid overfitting. Moreover, to reduce variability and to avoid bad splits that may produce overfitting, multiple rounds of cross-validation are performed using different partitions, and the tested results are averaged over the rounds [23].

In this paper, ten-fold cross-validation was used to access the generalization of the network model that was built. A percentage of 80%, 10% and 10% data split of the complete data samples were applied to represent the train, validation and test subsets respectively [24]. This provides for each fold a total of 440, 55 and 55 sample cases for the train, validation and test subsets respectively. Each disease in the training set will be represented by 50 samples of the total samples of the training set. Also, each disease in the validation set will be represented with 5 samples and 5 samples for the test set. To find the classification accuracy for a model, we must calculate the classification accuracy for each fold as the first step, and after that averaging the result over the ten folds.

The final step in preparing the data was: to standardize the training datasets in each fold to have zero mean and unit standard deviation. After that, based on the information that was collected from the training dataset from each fold during the standardizing; the validation and test datasets for that fold were also standardized to have a zero mean and a unit standard deviation.

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3.2. Number of Hidden Layers and Hidden Neurons

Optimizing the number of hidden layer and neurons in each hidden layer for a feed-forward neural network remains one of the unsolved tasks in this research area. Thus several researchers have proposed some general rules for determining an optimal number of hidden neurons for any application the number of training cases and the complexity of the classification problem to be learned [6]. One of the rules is: one hidden layer is enough, and to find the number of neurons for the first hidden layer; add the number of neurons in the input layer to the number of neurons in the output layer and divide the result by two. Another known rule is: if more than one hidden layer must be used to achieve a less generalization error; then the number of neurons in each hidden layer except the first one will be the number of neurons in the previous layer divided by two [7]. Moreover, Kavzoglu, as cited in [15], has shown that in most situations, there is no way to determine the best number of hidden layers without training several networks and estimating the generalization error of each, because the best number of hidden layers and units depends mainly in a complex way on the number of input and output units, the number of training cases and the complexity of the classification problem to be learned [23].

Based on this, we used an iterative process to determine the best number of hidden layers and neurons in each hidden layer. In the iterative process, a ten-fold cross-validation technique is used to choose the best neural model that will provide the highest classification accuracy, the whole process works as follows:

Step1. Start testing the network architecture with only one hidden layer; the formula as shown in equation (3) applied to find the number of neurons in the first hidden layer.

$$n_f = (n_i + n_o)/2 \quad (3)$$

Where n_f is the number of neurons in the first hidden layer, n_i is the number of neurons in the input layer and n_o is the number of the neurons in the output layer. If n_f was not a fixed number then apply the ceil and the floor operations, so you will get two values, and for more precise results take another number which is floor(n_f)-1, so you will have three numbers of neurons in the first layer to start with.

Step2. Add another layer; the number of neurons in this layer will be half the number of neurons in the previous layer.

Step3. Repeat step two until the number of the neurons in the layer is one.

4. EXPERIMENTAL RESULTS AND EVALUATION

To investigate the best system architecture for building the CDSSs for the diagnosis of the gynaecological disease; multiple system architectures were built using the iterative process [16]. Different architectures were compared based on the classification accuracy of each architecture. The model with the highest classification accuracy (less fixed error) was chosen as the final model for building the CDSSs.

In this paper for all models:

- A Feedforward Backpropagation neural network is used for building all models.
- The number of neurons in the input layer is 54 (representing the number of features for each sample).
- The number of neurons in the output layer is 1 (representing one class of the diseases the neural will generate) [17].
- The training algorithm that was used for training the models is the Rprop algorithm.
- Linear Function (LF) and TANH are the activation function that was used in the output layer for each architecture, and the results obtained using both functions were compared.
- The activation function that is used for all the hidden neurons in all the hidden layers is TANH.
- The following values were used 0.07, 0.001 and 48 for the delta initial of the Rprop algorithm, the performance goal error and the number of validation checks to avoid the overfitting of the network respectively.

To find the classification accuracy for a model, we must first calculate the classification accuracy for each fold and after that averaging the results over the ten folds as follows:

- Compute the classification accuracy for each fold; the classification accuracy A_{fi} of an

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individual fold f_i depends on the number of samples correctly classified and is evaluated by the formula:

$A_{fi} = (t/n)* 100\%$ (3)

Where t is the number of sample cases correctly classified, and n is the total number of sample cases.

- Find the average classification accuracy for the ten folds as follows:

$$\text{Average classification accuracy} = \frac{1}{10}\sum_{i=1}^{10} A_{f_i} \quad (4)$$

4.1 Models' Building using One Hidden Layer

Since the input layer contains 54 neurons and the output layer contains 1 neuron, the number of neurons in the first hidden layer will be 27.5 based on the equation in step 1 from the iterative process. Because the result is not a fixed number, applying the ceil operation will produce 28, applying the floor operation will produce 27, therefore the network can be trained with two different numbers of neurons. To make the testing more precise another number is used, which is 28. Accordingly, the network will be tested with three numbers of neurons; 26, 27 and 28.

Each number will be tested twice, once with an LF and another with a TANH as an activation function for the output layer. **Table 4** illustrates the results of 6 different architectures. The best architecture that produced the highest classification accuracy is (54-26-1) with an LF activation function in the output layer. This architecture represents 54 input variables, one hidden layer of 26 neurons and one output layer. The classification accuracy for this architecture is 70.7%. All the remaining architectures produced low classification accuracy varying in an interval [69.6%- 50.3%].

Table 4. Classification Accuracy with one hidden layer

Network Architecture	Activation Function	Classification Accuracy
54-26-1	TANH	50.3%
54-26-1	LF	70.7%
54-27- 1	TANH	55.2%
54-27- 1	LF	69.6%
54-28-1	TANH	53.2%
54-28-1	LF	64.3%

4.2. Models' Building using Two Hidden Layers

For the first hidden layer, we obtained three different numbers of neurons; 26, 27 and 28. So, by applying step 2 from the iterative process, the number of neurons in the second layer will be as follows:

i. When the number of neurons in the first hidden layer was 26, the number of neurons in the second hidden layer will be 26/2 which is 13 neurons. The network architecture will be 54-26-13-1.

ii. When the number of neurons in the first hidden layer was 27, the number of neurons will be 27/2 which is 13.5. As this is not a fixed number, applying the floor operation will produce 13, applying the ceil operation will produce 14. Therefore, this will produce two architectures as follows: 54-27-13-1, and 54-27-14-1.

iii. When the number of neurons in the first hidden layer was 28, the number of neurons in the second hidden layer will be 28/2 which is 14 neurons. The network architecture will be 54-28-14-1.

Consequently, five different architectures will be tested when the number of hidden layers is two. As noticed from **Table 5**, the best classification accuracy is 87% when the network architecture is

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54-26-13-1 with LF. The results for the other architectures vary in an interval [54.5%- 86.9%].

Table 5: Classification Accuracy with two hidden layers

Network Architecture	Activation Function	Classification Accuracy
54-26-13-1	TANH	54.5%
54-26-13-1	LF	87%
54-27-13-1	TANH	58.5%
54-27-13-1	LF	78.7%
54-27-14-1	TANH	60%
54-27-14-1	LF	85%
54-28-14-1	TANH	58.1%
54-28-14-1	LF	86.9%

4.3 Summary of the Results

We started building the models with one hidden layer and ended with 6 hidden layers. We can notice that the best architecture was obtained by using four hidden layers; the architecture is 54-27-14-7-3-1 and obtained 94.5% classification accuracy. Using one hidden layer did not achieve good results, but when another hidden layer has been added, the best classification accuracy has risen from 70.7% to 87% and after that rise to 91.8% when adding three hidden layers. By adding a fourth layer the highest accuracy has been obtained with a percentage of 94.5%. Adding five and six hidden layers lowered the accuracy and did not improve the results. These results can be explained as follows: If you have too few hidden layers, you will get high training error and high generalization error due to under fitting. This was noticed in the low accuracy we obtained when the network was built with one, two and three hidden layers. If you have too many hidden layers, you may also get low training error, but still have high generalization error due to overfitting, as was noticed when we built the networks with 5 and 6 hidden layers.

Based on this, we can conclude that; experiments are the only way to determine the best neural network architecture that is suitable for solving a specific problem.

Table 6 illustrates the summary of the best results we obtained using different hidden layers for building the neural network that will be used as the final model for the clinical decision support system.

Table 6. Summary of Results Regarding Multiple Hidden Layers

Number of hidden layers	Best Network Architecture	Activation Function	Best Classification Accuracy %
1	54-26-1	LF	70.7%
2	54-26-13-1	LF	87%
3	54-28-14-7-1	LF	91.8%
4	54-27-14-7-3-1	LF	**94.5%**
5	54-27-14-7-3-1-1	LF	91.8%
6	54-27-13-7-4-2-1-1	LF	89%

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The effectiveness of the chosen neural network architecture was evaluated on the gynaecological disease test set for each fold independently. After that, the average accuracy is computed to determine how well the chosen architecture will generalize for new samples that were never seen before [9]. The following subsection will introduce the results for each test set of the 10 folds (runs). The experimental results of the ten test sets have also been presented as a confusion matrix. A confusion matrix contains information about actual and predicted classifications done by a classification system. Performance of such a system is commonly evaluated using the data in the matrix. In a confusion matrix, columns represent the predicted data, while rows represent the actual data [25].

To summarize the results of the testing results of the ten folds, **Table 7** illustrates the classification accuracy for all results. As noticed, the highest classification accuracy obtained in fold 9 with an accuracy of 100% and the lowest accuracy obtained was in fold 7 with an accuracy of 82%. The total classification accuracy was also 94.5%. These results were affected by the nature of the data splits for each fold. The one fold that obtained 100% accuracy may have had examples in the training sets that were very similar to the data pattern that was in the test set, therefore it produced high classification accuracy. But in the other fold that obtained 82% accuracy, the examples that the network was trained with were not close to the data pattern in the test set, according to the produced classification accuracy was low.

Table 7: Summary of All Classification Accuracy for All Folds

Test Sets	Classification Accuracy %
Fold 1	98%
Fold 2	91%
Fold 3	87%
Fold 4	98%
Fold 5	98%
Fold 6	98%
Fold 7	82%
Fold 8	96%
Fold 9	100%
Fold 10	98%
Average Accuracy	**94.5%**

Table 8 Illustrated The Experimental Results Of The 10 Test Sets And Has Also Been Presented As A Confusion Matrix.

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Table 8: The Confusion Matrix of the diagnostic result of the gynaecological diseases: 10- fold cross-validation

Disease Type	Pol	Inc	Fib	Pro	Cancer	Hyper	Mg	Amen	Abor	Dys	Inf	Row sum
Pol	44	2	0	1	2	1	0	0	0	0	0	50
Inc	0	44	1	0	0	3	2	0	0	0	0	50
Fib	2	1	45	1	1	0	0	0	0	0	0	50
Pro	0	0	0	47	3	0	0	0	0	0	0	50
Cancer	0	0	0	0	49	1	0	0	0	0	0	50
Hyper	0	0	1	0	0	49	0	0	0	0	0	50
Mg	0	0	0	0	0	1	49	0	0	0	0	50
Amen	0	0	0	0	0	0	0	50	0	0	0	50
Abor	0	0	0	0	0	0	2	2	45	1	0	50
Dys	0	0	0	0	0	0	0	0	1	49	0	50
Inf	0	0	0	0	0	0	0	0	0	1	49	50
column sum	46	47	47	49	55	55	53	52	46	51	49	550

From the confusion matrix shown in **Table 8,** the accuracy for each class can be calculated as presented in **Table 9**, where the proportion of the disease type in the test dataset that has been correctly recognized by ANN. We notice that the Polyps and Infection diseases got the lowest classification accuracy with a percentage of 88%. The highest classification accuracy was for the Amenorrhea disease with a percentage of 100%.

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Table 9: Proportion Of Correctly Classified Diseases

Disease Type	Accuracy
Polyps	88%
Infection	88%
Fibroids	90%
Prolapse	94%
Cancer	98%
Hyperplasia	98%
Migrants	98%
Amenorrhea	100%
Abortion	90%
Dysmenorrhea	98%
Infertility	98%
The average	**94.5%**

5. CONCLUSION AND FUTURE WORK

In this work, we devloped a CDSS for gynaecological disease diagnosis. The gynaecological diseases were Polyps, Infection, Fibroids, Prolapse, Cancer, Endometrial hyperplasia, Migrants, Amenorrhea, Abortion, Dysmenorrhea and Infertility. The proposed system was developed using one of the most widespread machines learning techniques; an MLP feed-forward neural network and trained using the Rprop training algorithm. It consisted of: an input layer with 54 neurons (representing the input variables of each patient such as age, marital status, pregnant, etc.), 4 hidden layers (where the number of neurons in the first, second, third and fourth hidden layer was 27, 14, 7 and 3 respectively) and an output layer (that produced the type of the disease the patient suffered from). Moreover, ten-fold cross-validation was used to access the generalization of the proposed system using 550 patients' medical recodes collected from the gynaecology clinics at JUH. An accuracy of 88%, 88%, 90%, 94%, 98%, 98%, 98%, 100%, 90%, 98% and 98% were obtained for the Polyps, Infection, Fibroids, Prolapse, Cancer, Endometrial hyperplasia, Migrants, Amenorrhea, Abortion, Dysmenorrhea and Infertility respectively, giving an average of 94.4% classification accuracy.

From these results, we concluded that: the proposed system proved its usefulness in the support of clinic diagnosis decision of gynaecological diseases. Also, if more dataset was used for training the proposed system, that would give more robust results. Moreover, some limitations were noticed in this paper such as some medical records contained missing values because they were filled by resident doctors, which made it impossible to use these records in the gynaecological disease dataset.

In future, this work can be extended by using other types of ANNs such as GRNN, PNN and RBF to compare the results obtained with the ones obtained by using the MLP. We can also apply one of the feature selection algorithms on the gynaecological diseases dataset to choose the medical variables that play a major role in the diagnosis process which may give more accurate results. Moreover, applying other machine learning methods such as Artificial Immune Systems, Neuro-Fuzzy and Decision Trees and comparing the results obtained with the ones obtained using the ANN. Finally, since this system was built by using the medical records that were collected from JUH which is a training hospital, we can apply the system on the medical records that can be collected from other types of hospitals such as, military

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hospitals, public hospitals and private hospitals to compare the results obtained with the ones obtained by using the JUH's medical records.

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