

Artificial Neural Network-Based Pelvic Inflammatory Disease Diagnosis System

Yahaya Mohammed Sani¹, Dere Boluwatife Adesola², Hussaini Abubakar Zubairu³, and Ilyasu Anda⁴

^{1, 2, 3}Department of Information and Media Technology, Federal University of Technology, Minna, Nigeria

⁴Department of Library and Information Technology, Federal University of Technology, Minna, Nigeria

{¹yahayasani, ³abu.zubairu, ⁴ilyasu.anda} @futminna.edu.ng, ²dereboluwatife20@gmail.com

Abstract—Pelvic Inflammatory Disease (PID) is a reproductive health infective disease of feminine genital tract and high among minority adolescent girls and young adult women. Clinical manifestation of PID differs among patients and decision of medical experts are based on clinician experience instead of hidden data in the knowledge database. The diagnosis of PID based on heuristic lead to errors where ectopic pregnancy could be mistaken for PID. This paper presents an Artificial Neural Network model to diagnose pelvic inflammatory diseases based on a set of clinical data. The ANN model was trained with 259 clinical data as input to the neural network. The system can predict the presence or absence of PID based on the available symptoms. The system recorded an accuracy of 96.1% based on the confusion matrix. The obtain result is promising, an indication that the system can be effective in diagnosis of PID cases.

Keywords-pelvic inflammatory disease; artificial neural network; computer simulation; diagnosis system; confusion matrix

I. INTRODUCTION

Pelvic Inflammatory Disease (PID) is a reproductive health infective and disorder of the female genital tract, such as the uterus, fallopian tubes, and pelvic structures [1]. The rate of the disease remains high among minority adolescent girls and young adult women [1]. About 1 million (1, 000, 000) women experience an acute Pelvic Inflammatory Diseases (PID) annually and the rate is higher in younger generation and first-time mothers. A worrisome figure of about one hundred thousand women are rendered infertile annually because of PID infection, and a good number of ectopic pregnancies cases are cause by PID. Early detection and accurate diagnosis of PID is a key factor in controlling the disease. However, most developing nations face shortages of health workers who can accurately read and interpret diagnostic results of some life-threatening diseases [2], which is the best, easiest and most cost effective way to prevent the disease, therefore, there is need for machinebased diagnosis systems. In this paper, Artificial Neural Network was used to diagnose PID disease based on some collected clinical data. Artificial Neural Network (ANN) is extensively applied in science and technology with applications in various areas of chemistry, physics, and biology [3]. It is a soft computing technique, that had been applied successfully in different fields of science, specifically in pattern recognition, fault diagnosis, forecasting and prediction [3]. ANN has successfully been employed for pattern recognition and survival prediction in several clinical settings [4]. The advantage of ANN lies in its ability to capture nonlinearities and complex interactions between several factors. Trained on a number of predictive factors, neural networks have been considered to improve the accuracy of survival prediction for patients with lung and colorectal cancer [5]. ANN is a computer program that mimics biological neurons and the network becomes conversant at discovering clusters. Computer Aided Decision making in medicine can enhance and improve the consistency of care [6]. The rational of computer aided decision application in medicine is to build systems that can assist human expert in the area of performance, flexibility, reliability, adequate response time, and timely response. It has the potential to cover rare conditions, because it is not possible for clinical expert to possess the compendium of all of the indices of diseases. Furthermore, computerized systems are becoming vital tools for making lives easier and with digitization of patient information that is readily available in electronic form; it is possible to compute with certain degree of accuracy clinical indices, like the possibility of diagnosis or the clinical outcome. [6] reported that computer-assisted diagnoses in medicine outperform specialists. Similarly, [7] asserts that medical diagnosis requires the use of computer programs as they help in supporting clinical decisions. The benefit of using computer aided decision making in medical field has resulted in human support and costs to decrease and as well led to increased diagnostic accuracy [8]. Computer aided decision making in the domain of medicine can assist computer scientists to develop and test hypothesis. Pelvic Inflammatory Disease (PID) is a major health concern for women; it is an infection of the reproductive organs in women. The pelvis is in the lower abdomen and includes the fallopian tubes, the ovaries, the cervix, and the uterus. PID is initiated by infection that ascends from the vagina and cervix into the upper genital tract. Chlamvdia trachomatis is the predominant sexually transmitted organism associated with PID [9]. According to the U.S. Department of Health and Human Services, this condition is common and affects about 1 million women each year in the United States. Different types of bacteria can

cause PID, including the same bacteria that cause the sexually transmitted infections (STIs); gonorrhoea and chlamydia. What commonly occurs is that bacteria first enter the vagina and cause an infection. As time passes, this infection can move into the pelvic organs. PID can become extremely dangerous, even life-threatening, if the infection spreads to the blood stream of the victim [10]. ANN has been found to be useful and widely used in medicine. ANN is used in predicting the Thrombo-embolic stroke disease, predicting and medical diagnostic approaches [11]. ANN recorded a success story in the analysis of blood and urine samples of diabetic patients [12, 13], tuberculosis diagnostic process [14], classification of leukaemia [15], diagnostic and analysis of metastatic carcinoma cytology effusion [16], diagnosis of tumour endoscopy [17] and predicting mortality in patients with intertrochanteric fractures [18]. However, to the best of our knowledge, not much research on diagnosis PID patients takes advantage of ANN. In this paper, we propose an artificial neural network for the prediction of PID.

II. RELATED STUDIES

[19] conducted a review using a comprehensive search of MEDLINE, PubMed, and EMBASE, from January 1985 to February 2017 focusing on methods for prevention of long term sequelae especially infertility. The research result revealed that it is essential to raise the awareness and knowledge of females in general regarding PID and its symptoms, as early detection will significantly decrease the likelihood of severe complications. However, it does not solve the problem of modern diagnostic techniques for PID.

[20] examined the proportion of Pelvic Inflammatory Disease caused by Chlamydia trachomatis considering five (5) separate methods of estimating age-group-specific population excess fractions (PEFs) of PID due to C. trachomatis, using routine data, surveys, case-control studies, and randomized controlled trials. The result of the findings shows PEFs of PID due to C. trachomatis decline steeply with age by a factor of around 5-fold between younger and older women. However, the major limitation of this study was that the etiology of PID in different age groups were not covered and the issue of diagnosis was not considered.

[21] Examined the diagnosis of PID based on physical examination to determine the nature and location of the pain and check for fever, abnormal vaginal or cervical discharge, and for evidence of gonorrhoea or chlamydial infection. If the findings suggest PID, treatment is necessary, then patient undergo treatment. This is because there are no precise tests for PID; a diagnosis is usually based on clinical findings. Regrettably, this method of diagnosis does not provide accurate results based on symptoms observed from patient as a different ailment with relatively close symptoms could be mistaken for PID.

[22] Studied cases of trichomoniasis among females in Western province of Sri Lanka, focusing on the sociodemographic aspects and presenting symptoms and signs at clinical examination. Their findings however revealed that the presence of typical symptoms or type of vaginal discharge on examination cannot be used as the sole criterion for the diagnosis of trichomoniasis. These results indicate that treatment of patients based on symptoms per se can lead to over usage of metronidazole. This also shows the importance of laboratory support to diagnose of vaginal infection. This is the gap that this research set to bridge.

[23] Used randomized controlled trial of screening for Chlamydia trachomatis to determine whether screening and treating women for chlamydial infection reduces the incidence of pelvic inflammatory disease over the subsequent 12 months. Although some evidence suggests that screening for chlamydia reduces rates of pelvic inflammatory disease, especially in women with chlamydial infection at baseline, the effectiveness of a single chlamydia test in preventing pelvic inflammatory disease over 12 months may have been overestimated.

[24] In their study revealed that clinical assessment remains the cornerstone of PID diagnosis. Maintaining a high index of suspicion for infection as the cause of pelvic pain and associated symptoms in women with risk factors supports early treatment. Scheduled follow up provides a safety net to ensure further investigation of persistent symptoms and signs; just as importantly, follow up provides an opportunity to check patient understanding, answer questions and to discuss prevention of further episodes of PID. However, the above technique is manual based, time consuming as it does not give accurate result of diagnosis.

[25] Uses laparoscopy to diagnose Pelvic Inflammatory Disease. The research result shows that the clinical diagnosis of PID is notoriously imprecise, as the use of surgical procedures that allow for greater precision (such as laparoscopy) are no longer considered a part of standard assessment. To complicate matters further, patients often do not present with the classically described PID presentation. An acute presentation with severe lower abdominal pain resulting in a shuffling gait or the "chandelier sign" on clinical examination is rare. The heterogeneity of infectious agents now causing PID is thought to contribute to the varied clinical presentations for which symptoms can range from mild to severe.

[26] Investigated the risk of Pelvic Inflammatory Disease following Chlamydia trachomatis Infection: Analysis of Prospective Studies with a Multistate Model, to estimate the probability that a Chlamydia trachomatis (CT) infection will cause an episode of clinical pelvic inflammatory disease (PID) and the reduction in such episodes among women with CT that could be achieved by annual screening. They reappraised evidence from randomized controlled trials of screening and controlled observational studies that followed untreated CT-infected and -uninfected women to measure the development of PID. The available data were compatible with both the homogenous and piecewise homogenous models. Given a homogenous model, the probability that a CT episode will cause clinical PID was 0.16 (95% credible interval (CrI): 0.06, 0.25), and annual screening would prevent 61% (95% CrI: 55, 67) of CT-related PID in women who became infected with CT.

[27] Analysed two (2) provincial, comprehensive health services administrative databases (encompassing hospitalizations and all physician-delivered services) for pelvic inflammatory disease and ectopic pregnancy trends from 1992 through 2009 in women of reproductive age in British Columbia, Canada. Trends were compared to provincial Chlamydia surveillance data by time-series analysis, using the cross-correlation function method and Granger causality testing. The research result shows that Chlamydia cases substantially increased from 1992 through 2009. Inpatient, outpatient, and total diagnoses of pelvic inflammatory disease and ectopic pregnancy declined from 1992 through 2003. After 2003, pelvic inflammatory disease rates continued to fall, while ectopic pregnancy rates significantly increased. The male Chlamydia urethritis rate increased from 39.4 to 173.6 cases/100 000 from 1996 to 2009. In the context of increasing Chlamydia infection rates, the reproductive complications of Chlamydia infection in women are declining overall. A recent increase in rates of ectopic pregnancies is cause for concern. In view of the foregoing, outcome of the research cannot be considered accurate and efficient to be adopted as a basis for statistics.

III. RESEARCH METHODOLOGY

A. Data Collection

A total of 256 patients record treated for Pelvic Inflammatory Diseases (PID) were collected for this research. The data were obtained from three different hospitals; bay clinic in Minna (93 records), Niger State, optimal scan centre (51 records) also in Minna metropolis and Kwara state Advance Diagnostic Centre (112 records). Nine predictor variables; pelvic pain, lower abdominal pain, vomiting, painful urination, painful sex, waist pain, tiredness, irregular bleeding and vagina discharge were selected to build the Artificial Neural Network model for diagnosis of PID because of their previously established influence on patient outcomes after diagnosis. PID disease was recorded from the medical record as previously known clinical evidence of the disease confirmed by a typical history, positive, negative or acute stage. The output of the network is the patient PID status. This description is illustrated in Figure 1.

B. Data Transformation

The data collected was transformed into a suitable format for the training of the network. The transformation is a matrix of data concerning patients for whom the diagnosis (positive, negative or acute) about PID disease is already known. Each row of the matrix refers to one patient. The first m elements of the row are medical data and the last n elements represent the output (diagnosis). The term "medical condition" represents symptoms and other information provided by the medical specialist. Figure 2, is the transformation of collected data.

Each of the possible symptoms will be used to train the network. This network has one hidden layer as shown in Figure 1 and was trained with a two-layer feed forward and back-propagation algorithm. The network was implemented in MATLAB software using the neural network toolbox component of MATLAB environment. However, the data in Figure 2 is incompatible for direct implementation in

MATLAB; therefore, Figure 3, show the coded that transform the data in Figure 2 into 0's and 1's as a compatible format for the MATLAB. The transformed data is shown in Figure 4. The 'yes' is transformed to 1 and 'No' to 0.

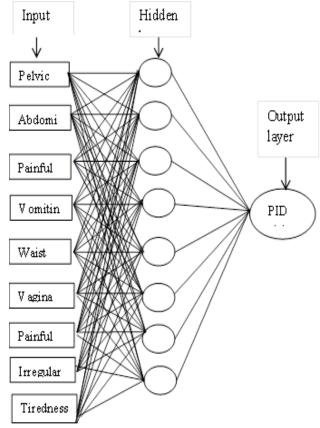


Figure 1. Schematic Diagram of a Typical ANN Model

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Figure 2. Data Transformation Matrix

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8 -	n=c(i,j);	
9 -	n=sum(double(cell2mat(m)));	
10 -	if n==241	
11 -	d=[d,1];	
12 -	else	
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Figure 3. Transformation code

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Figure 4. Transformed Data Set for Training

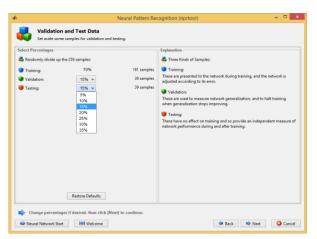


Figure 5. Validation and test selection window

As shown in Figure 4, the format is a form of matrix containing information about health status of patients and their diagnosis in form of 0's and 1's.

C. Artificial Neural Network Training

Artificial Neural Network training is the organization and structuring of the network for the intended application and setting the weight for the beginning of the process. The network was trained using patient's data record obtained from three different hospitals and whose output is already known. The neurons in hidden layer will learn the data pattern in the course of training and map relation between input pairs and output pairs. Training and testing of neural network model for PID disease was carried out in MATLAB programming environment using the neural toolbox.

As shown in Figure 5, 70% of the data was used for training, 15% for validation and 15% for testing.

D. System Architecture

The architecture of the system is shown in Figure 6. It depicts the logical model and structure that defines the organization and behaviour of the system. The user interacts with the system through the user interface to select symptoms. The selected symptoms are send to the ANN inference engine to compute the status of the patients before displaying the result. The result of the processed information can be view by the user through the user interface as an output from the system.

IV. RESULTS AND DISCUSSION

The result obtained from the implementation of the system is discussed in this section. The designed and implementation of the system was performed in MATLAB. Toolbox for Neural network was used for performance evaluation of the networks which consists of a 9 number three-layer feed forward network of inputs and single output. Back propagation approach was adopted for training the network. The trained network is shown in Figure 7.

As shown in Figure 4, the symptoms were converted to 0's and 1's to form set of symptoms for the network. About four to five medical conditions were assigned to each symptom, and the classification was repeatedly performed for better training of the network. The implementation of ANN based approach to recognized PID affected and nonaffected patients based on specified symptoms signifies the ability of the ANN trained network to learn the training patterns corresponding to symptoms of the patients. The interface to the application is shown in Figure 8.

The interface was designed using GUI component of MATLAB R2013a. This is the first page where user can navigate to explore the other part of the system. The interface for the selection of the symptoms at run time is shown in Figure 9.

After the selection of the symptoms as applicable and submit to the system, the ANN inference engine will process it and the status of the user will be displayed on the output channel. A typical example of user's status based on the selected symptoms is shown in Figure 10. Another run of the system was carried out by different user and different symptoms, as shown in Figure 11.

The response from the selection from Figure 10 is as shown in Figure 12.

Furthermore, the system was run (see Figure 13) where no symptoms is selected by the user. The response on clicking the submit button is as shown in Figure 14. This aspect was implemented to ensure that empty fields are not submitted to the application.

The last test that was carried out was and evaluation, where some of the selected were either yes or no, as shown in Figure 15.

The response to selection in Figure 15, is shown in Figure 16.

The selected combination of the symptoms and the output from the system was compared with the database of the medical record and the result is in tandem. This shows the relative accuracy of the system.

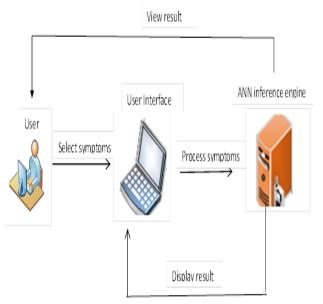


Figure 6. Proposed System Architecture

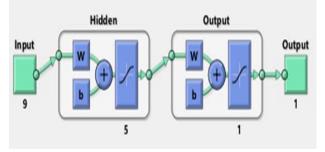


Figure 7. Proposed Neural Network



Figure 8. The System User Interface



Figure 9. Symptoms Selection Interface

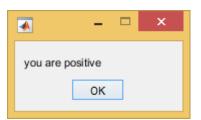


Figure 10. User's PID status based on the selected Symptoms



Figure 11. Symptoms selection page for negative response



Figure 12. Patient's status of symptoms



Figure 13. Interface with no symptoms selected

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Figure 14. No symptoms selected



Figure 15. Symptoms selection with for negative response.

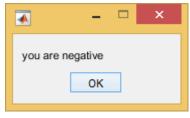


Figure 16. Negative status

V. PERFORMANCE EVALUATION

In this paragraph, the performance evaluation methods adopted is discussed. The performance evaluation approaches adopted for PID diagnosis are sensitivity and specificity and confusion matrix. Explanation of these methods are provided in this section.

A. Sensitivity and Specificity Analysis

The equation for sensitivity and specificity analysis are shown in equation (1) and (2).

Sensitivity =
$$\frac{TP}{TP + TN} * (\%)$$
 equation 1
Specificity = $\frac{RP + TN}{RP + TN} * (\%)$ equation 2

The meaning of each acronyms is shown in Table 1.

Acronyms	Meaning
TP	True positives
TN	True negatives
FP	False positives
FN	False negatives

SENSITIVITY AND SPECIFICITY ACRONYMS AND MEANING

The implications are as follows:

TABLE I.

- **TP:** Input symptoms is identified as a patient with PID diagnosed by the expert clinicians.
- **TN**: Input symptoms is identified as normal that is labelled as non-PID infected person by the medical experts.
- **FP:** Input symptoms is identified as PID infected patient that is classified as a healthy by the medical experts.
- **FN**: Input symptoms is identified as non PID infected that is classified as PID infected by the medical experts.

B. Confusion Matrix

Confusion matrix reveals information about actual and predicted classifications done by any classification system [28]. Performance of such a system is therefore evaluated using the data in the matrix [29]. Figure 17 shows the confusion matrix for the system.



Figure 17. Confusion Matrix

The explanation for the colour coded confusion matrix is; Green colour is the number of correctly predicted that a case is negative, red colour is the number of incorrectly predicted that a case is positive, blue colour is the number of incorrectly predicted that a case is negative and ashe colour is the number of correctly predicted that a case is positive. The accuracy of the system was 96.1%, which is relative high in terms of correct prediction. As revealed in Figure 15, 48 samples where correctly classified, 2 was misclassified as zero, 5 samples were misclassified as one, while 126 samples were classified correctly as one. In terms of validation, 8 samples where correctly classified as zero, 0 sample was misclassified as zero, 1 sample was misclassified as one, while 30 samples were classified correctly as one and the total matrix for the validation was 97.4%. For the testing, 7 samples were correctly classified as zero,1 sample were misclassified as zero, 1 sample were misclassified as one, while 30 samples were classified correctly as one and the total matrix for the testing was 94.9%. From Figure 4.8, 63 samples were correctly classified as zero, 3 samples were misclassified as zero, 7 samples were misclassified as one, 186 samples were classified correctly as one and the total accuracy of the system was 96.1%. This shows relative high accuracy of the system.

VI. SUMMARY AND CONCLUSION

Pelvic Inflammatory Disease (PID) is a reproductive health infective disease among minority adolescent girls and young adult women. Diagnosis of PID patient is complex and it requires good acumen because PID exhibits symptoms that could be mistaken for ectopic pregnancy. Thus, this paper designed, developed and implemented an ANN based diagnostic system to diagnose PID based on set of available symptoms for effective and accurate diagnosis of PID status. Evaluation of the performance and accuracy of the system was performed using Sensitivity and specificity analysis and confusion matrix. The system was designed with the capability to receive user's symptoms and notify or show the PID status, based on the assessment or evaluation of the inputted symptoms. The system is user friendly, easy to navigate and highly interactive. The test and evaluation of the system reveals that the system is able to accurately predict the patients' status based on the input symptoms. The system was evaluated by clinicians and medical personnel and the performance was adjudged satisfactory. However, the implementation was based on the case of common symptoms. Since, medical expressions of PID differ among individual, with some show little or no symptoms, future research of similar system should consider the case of absence or few symptoms.

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