ARTIFICIAL NEURAL NETWORK-BASED PELVIC INFLAMMATORY DISEASE DIAGNOSIS SYSTEM

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ABSTRACT

Pelvic Inflammatory Disease (PID) is a reproductive health infective disease of feminine genital tract and is commonly affecting the young women and adult female. 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 Artificial Neural Network based 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. An accuracy of 96.1% was recorded based on the confusion matrix. The obtained result is promising, an indication that the system can be effective in diagnosis of PID cases.

Keywords: Pelvic Inflammatory Disease (PID), Artificial Neural Network, Computer Simulation, Diagnosis System, Confusion Matrix.

INTRODUCTION

Pelvic Inflammatory Disease (PID) is a reproductive health infective and disorder of the female genital tract (uterus, fallopian tubes) and pelvic structures (Dayal, Singh, Chaturvedi, Krishna, & Gupta, 2016). The rate of the disease is still high, especially among adolescent girls and not too mature women (Dayal et al., 2016). About 1 million (1,000,000) women experience an acute 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 caused by PID. Early detection and accurate identification of the disease is a key factor in controlling the disease. However, most developing nations face inadequate medical experts who can accurately read and interpret diagnostic results of some life-threatening diseases (Ahmad, 2009), there is a need for machine-based 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 (Amato, López, Méndez, Hampl, & Havel, 2013). It is a soft computing technique that has been applied successfully in different fields of science, specifically in pattern recognition, fault diagnosis, forecasting and prediction (Amato et al., 2013). ANN has successfully been employed for pattern recognition and prediction of survival rate in many clinical settings (Baxt, 1995). The advantage of ANN lies in its capability to identify nonlinearities and complex interactions between several factors. After training on some predictive indicators, ANNs was discovered to have performance improvement on the prediction of survival rate of lung and colorectal cancer patients (Bagdood, AlJuhani, & Alahmari, 2018). 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 (Mahesh & Manjula, 2013). 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 experts 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 accessible in electronic form; it is very feasible to compute with certain degree of accuracy clinical indices, like the possibility of diagnosis or the clinical outcome. Mahesh and Manjula (2013) reported computer-assisted diagnosis in medicine outperform specialists. Similarly, Shanthi, Sahoo, and Saravanan (2009) 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 lead to human support and reduced costs and go a long way to increasing the diagnostic accuracy (Shi, Wang, & Wang, 2013). Computer aided decision making in the domain of medicine can assist computer scientists to develop and test hypothesis. PID is a major health concern for women; it is an infectious disease of female reproductive organs. Pelvic is the lower abdominal region that comprises of fallopian tubes, ovary, cervix, and uterus. The diseases is usually caused by an infectious act that moves through the female sexual organ and cervix to the upper area of the genital tract. Chlamydia trachomatis is the bacterial organism that usually transmit PID (Bugg & Wand 2016). According to the United State (US) division of Health and Human Services, this condition is common and affects about 1 million women each year in the United States. There are several types of disease causing agents that can cause PID, including the same disease causing agents that is responsible for Sexually Transmitted Infections (STIs); gonorrhoea and chlamydia. What commonly occurs is that microbes first go in to the vagina and cause an infection. As time progresses, this infection can make its way into the women genital organs. PID can be very precarious, even fatal, if the infection spreads to the blood stream of the victim (Saba, Al-Zahrani, & Rehman, 2012). 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 (Higuera, 2016). ANN recorded a success story in the examination of blood and urine samples of diabetic patients (Catalogna et al., 2012; de Canete, Gonzalez-Perez, & Ramos-Diaz, 2012), tuberculosis diagnostic process (Elveren & Yumuşak, 2011), classification of leukaemia (Dey, Lamba, Kumari, & Marwaha, 2012), diagnostic and analysis of metastatic carcinoma cytology effusion (Barwad et al., 2012), diagnosis of tumour endoscopy (Barbosa, Roupar, Ramos, Tavares, & Lima 2012), and predicting mortality in patients with intertrochanteric fractures (Schindlbeck, Dziura, & Mylonas, 2014). Nevertheless, not much research on diagnosis PID patients takes advantage of ANN. In this paper, the author propose an ANN based prediction of PID.

1. Related Studies

Gul et al. (2018) conducted a review using MEDLINE, PubMed, and EMBASE, from January 1985 to February 2017 focusing on methods for prevention of long term infertility due to PID. The research result revealed that it is necessary to increase the wakefulness and awareness of females in general regarding PID and its symptoms, as early detection will significantly decrease the likelihood of severe complications. However, it does not address the issue of modern diagnostic techniques for PID.

Jefferson, Pendleton, Lucas, and Horan (1997) examined the ratio of PID triggered by Chlamydia trachomatis considering five different approaches of measuring Population Excess Fractions (PEFs) of PID related to specific age group caused by Chlamydia trachomatis. The study adopted the use of routine data, survey approach, case studies, and randomized test controlled trials. The result of the findings shows that there is decline in population excess fractions of the disease caused by Chlamydia trachomatis with age by a factor of approximately 5-fold between younger and adult

women. However, the drawback back of this research was the failure of the study to cover etiology of the pelvic inflammatory diseases in different age groups and issue of diagnosis was not considered.

Price et al. (2016) examined the diagnosis of PID based on physical analysis to define the nature and position of the pain and all the symptoms associated with gonorrhoea or chlamydial infection. However, if the result shows PID, therapy is required, then patient undergoes treatment. This is due to the fact that there is no specific examinations for PID; detection of PID usually depends on clinical results. 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.

The American Social Health Association (ASHA) studied cases of trichomoniasis amongst women in Sri Lanka, direct focus on the socio-demographic perspective and giving symptoms and signs at clinical analysis. Their findings however revealed that the presence of symptomatic vaginal discharge alone is not enough for the confirmation of trichomoniasis. Therefore, treatment of patients based on single symptom alone can be misleading in terms of drugs prescription and dosage. This also highlights the role of laboratory experiment in the cause of diagnosis of vaginal infection. This is the gap that this research set to bridge. Pipa et al. (2010) used randomized controlled trial of screening for Chlamydia trachomatis to examine the possibility of reduce the incidence of pelvic inflammatory disease among women treated for chlamydial infection over the period of one year. Although research findings asserts that screening for chlamydia bacteria minimizes rates of PID, mostly in female with the bacteria infection at initial stage, the effectiveness of only chlamydia test in mitigating PID over 12 calendar months may have been exaggerated. Shannon and Sarah (2018), in their study revealed that clinical assessment of PID is a very crucial process in the PID diagnosis. Maintaining a high index of perceive bacterial infection as the causative agents of pelvic pain and related signs in female with evidence of risk factors gives credence to early treatment. There is need however, for a further investigation of continuous symptoms and signs that may provide an opportunity to examine patient understanding, and to discuss preventive measure against new occurrences of the disease.

But, the above technique is manual based, time consuming and it does not give accurate result of diagnosis. To address this shortcoming, Trent, (2013) have used laparoscopy to diagnose Pelvic Inflammatory Disease. The research result shows that clinically diagnosis of PID is usually very confusing and inaccurate because surgical processes that allow for reasonable level of accuracy and precision are no longer considered as state of art form of assessment. In addition, patients hardly present a classical description of PID. Clear and precise presentation with serious lower part of abdominal pain that result in a shuffling gait on clinical examination is not common. The non-homogeneous nature of PID causative agents is a contributing factor to the imprecise clinical findings.

Price et al. (2013) investigated the chance of PID resulting from C. trachomatis, where analysis was done with Multistate Model to measure the chances that C. trachomatis bacterial will cause clinical PID and its mitigation that could be realized through screening. The study further appraised the findings from controlled random trials of screening and studies through observation that followed untreated CT-infected and uninfected women to measure the development of PID. The data were in tandem with that from either homogenous or piecewise homogenous models. With homogenous model, the chances of Chlamydia trachomatis causing a PID was 0.16, while that of prevention of PID through annual screening among women was 0.6.

Rekart et al. (2012) have analysed health services administrative databases for PID and the cases of ectopic pregnancy in the span of approximately nineteen years (1992 - 2009), among female reproductive age in Canadian region. The trends was evaluated in relative to the provincial Chlamydia bacteria surveillance data obtained through time-series analysis, based on cross-correlation function and Granger causality testing. The

research result shows that Chlamydia bacterial infection drastically rises from the year 1992 through 2009. Patients, both in and out of the hospital and the cases of PID and ectopic substantially decreased from the year 1992 through 2003. Thereafter, PID cases decline, but the cases of ectopic pregnancy was observed to have significantly increased. Unlike the cases of women, the men Chlamydia bacterium was observed to have increased from 39.4 in 1996 to 173.6 in the year 2009. The research found that in overall, there is decrement in Chlamydia reproductive infection in adult females. The research maintained that progressive increase of ectopic pregnancies cases is a source of worry. Given this review, outcome of the research cannot be considered accurate and efficient to be adopted as a basis for statistics.

2. Research Methodology

2.1 Data Collection

A total of 256 patients record treated for the cases of PIDs 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 ANN model for diagnosis of PID given their previously established impact on patient outcomes after diagnosis. PID disease was recorded from the medical record as previously known clinical evidence of the disease established 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.

2.2 Data Transformation

The data collected was transformed into a suitable format for the training of the network. The transformation is a matrix of data regarding patients for whom the diagnosis is either (positive, negative, or acute) about PID disease is certain. In the matrix, one row correspond to single patient. The first m entities of each row corresponds

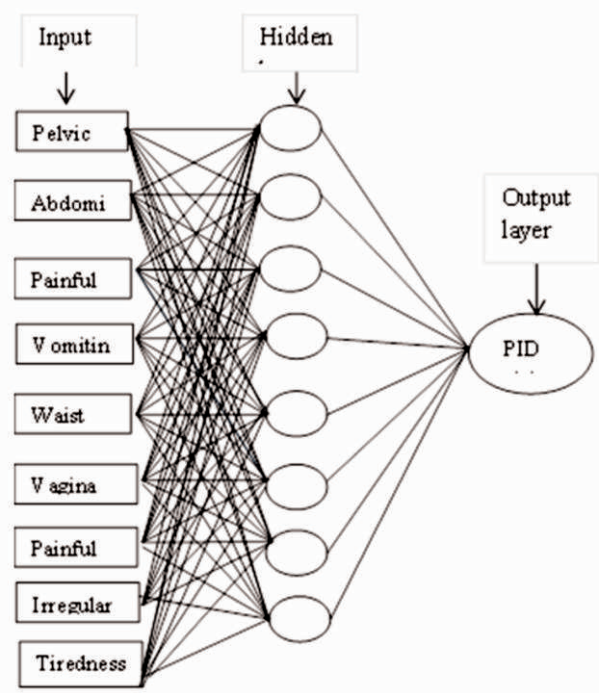

Figure 1. Schematic Diagram of a Typical ANN Model

to medical data, while the last n entities denotes the results (diagnosis). The term "medical condition" represents disease symptoms and related data provided by the specialist (medical personnel). Figure 2 is the transformation of collected data.

Each of the possible symptoms was used for the training of the network. This network has one hidden layer and was trained with a two-layer feed forward and back-propagation algorithm. The network was implemented in MATLAB software using an inbuilt component of MATLAB environment. However, the data in Figure 2 is incompatible for direct implementation in MATLAB; therefore, Figure 3 shows the code that transforms the data in Figure 2 into 0s and 1s as a compatible format for

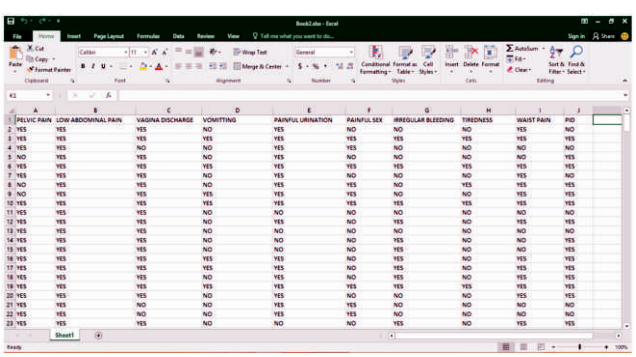

Figure 2. Data Transformation Matrix

the MATLAB. The transformed data is shown in Figure 4. The 'yes' is transformed to 1 and 'No' to 0.

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 0s and 1s.

2.3 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, 0.7 percent of the data was utilized for training, 0.15 and 0.15 percent was utilized for validation and testing respectively.

2.4 System Architecture

The architecture of the system is presented in Figure 6. It

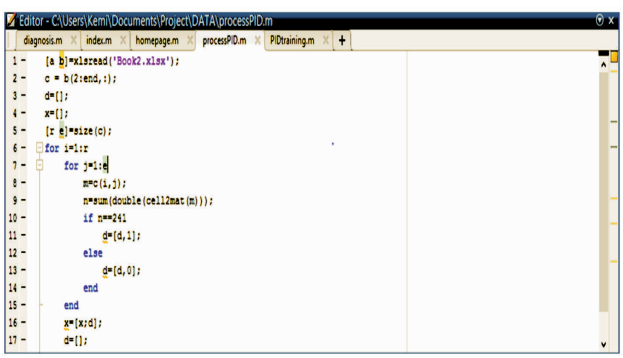

Figure 3. Transformation Code

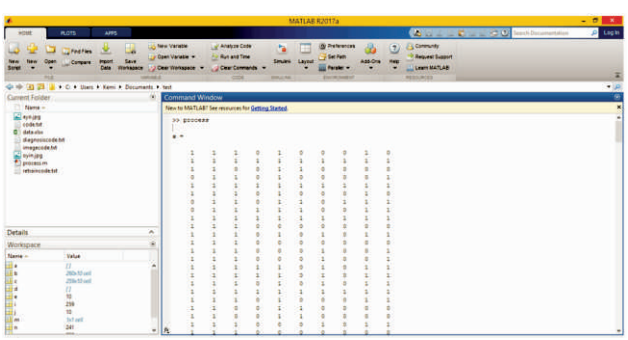

Figure 4. Transformed Dataset for Training

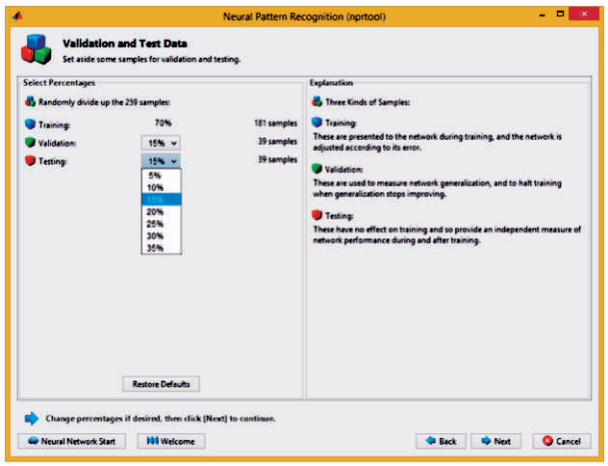

Figure 5. Validation and Test Selection Window

depicts the logical model and structure that defines the organization and behaviour of the system. The user can interact with the system via the user interface to select symptoms. The selected symptoms are sent to the ANN inference engine to compute the status of the patients before displaying the result. The result of the processed information can be viewed by the user through the user interface as an output from the system. The proposed neural network has nine (9) inputs and one (1) output as shown in Figure 7.

3. Results and Discussion

The result obtained from the system implementation is discussed in this section. The design and implementation of the system was performed in MATLAB. An inbuilt Toolbox in the MATLAB environment was utilized for the performance analysis and evaluation of the networks that has nine three-layer of inputs and single output (see Figure 1). Back propagation approach was adopted for training the network.

As shown in Figure 4, the symptoms were converted to 0s

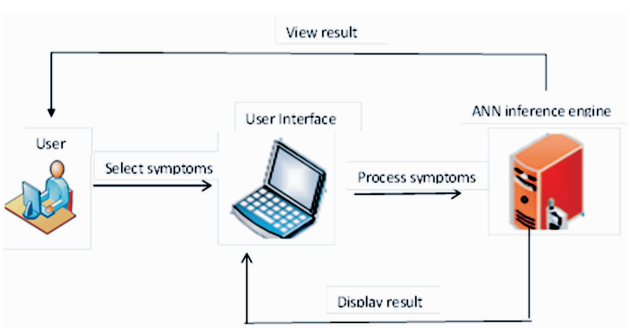

Figure 6. Proposed System Architecture

and 1s 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 non-affected 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 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 as shown in Figure 8. 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 symptom 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 evaluation, where

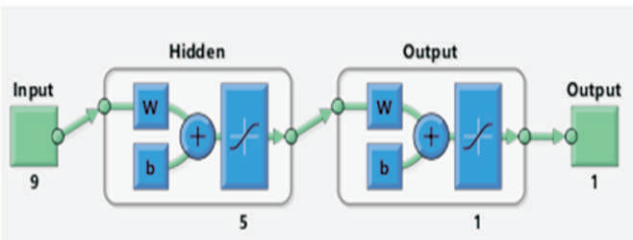

Figure 7. Proposed Neural Network

Figure 8. The System User Interface

Figure 9. Symptoms Selection Interface

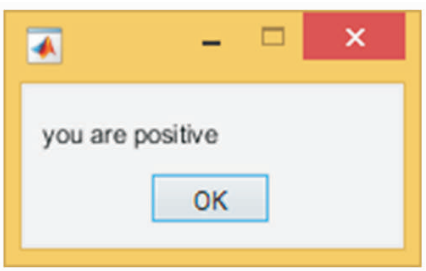

Figure 10. User's PID Status based on the Selected Symptoms

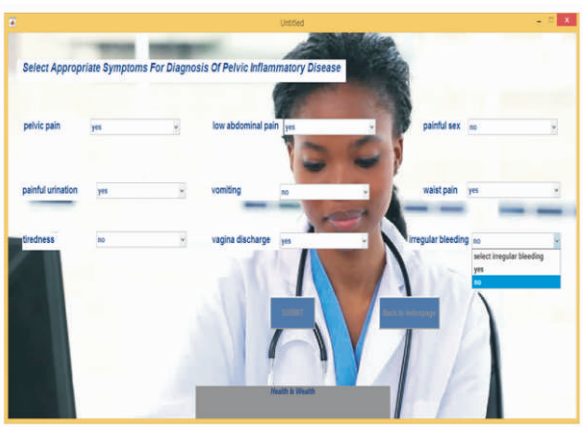

Figure 11. Symptoms Selection Page for Negative Response

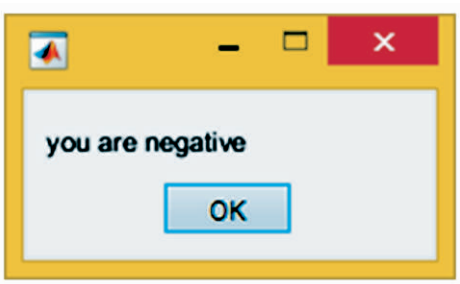

Figure 12. Patient's Status of Symptoms

Figure 13. Interface with no Symptoms Selected

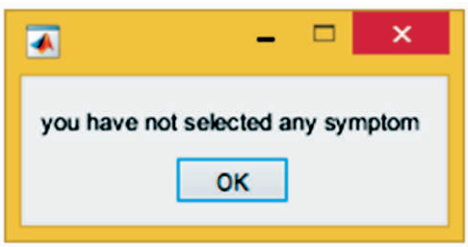

Figure 14. No Symptoms Selected

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.

4. Performance Evaluation

In this paragraph, the performance evaluation methods

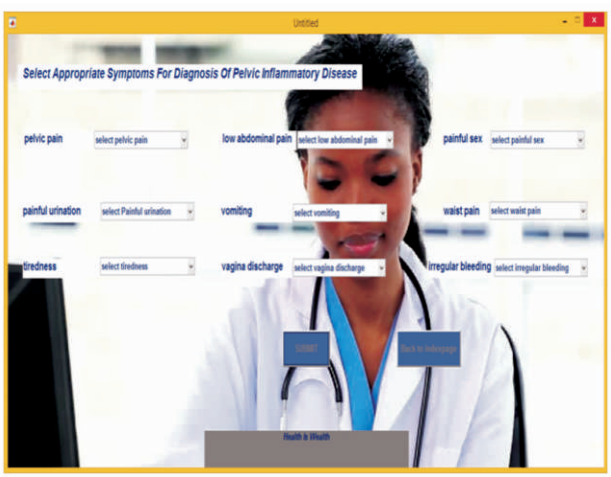

Figure 15. Symptoms Selection with for Negative Response

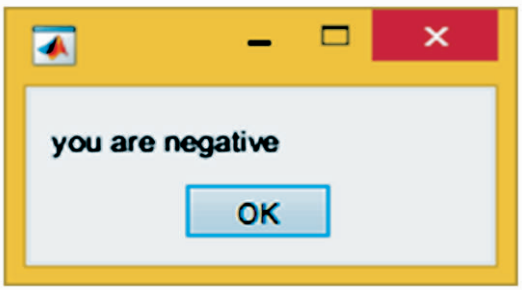

Figure 16. Negative Status

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.

4.1 Sensitivity and Specificity Analysis

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

$$\text{Sensitivity} = \frac{TP}{TP+FN} * (\%) \qquad (1)$$

$$\text{Specificity} = \frac{TN}{FP+TN} * (\%) \qquad (2)$$

The meaning of each acronyms is given in Table 1.

The implications are as follows;

- *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 healthy by the medical experts.
- *FN:* Input symptoms is identified as non- PID infected that is classified as PID infected by the medical experts.

4.2 Confusion Matrix

Confusion matrix reveals information about the predicted

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

Table 1. Sensitivity and Specificity Acronyms and Meaning

and actual classifications done by any classification scheme (Visa, Ramsay, Ralescu, & Van Der Knaap, 2011). Therefore, evaluation of performance is done using the data in the matrix (Polat, & Güneş, 2007). See the matrix in Figure 17.

The explanation for the colour coded confusion matrix is; Green colour represents the correctly predicted that a case is negative, red colour connotes incorrectly predicted that a case is positive, blue colour stands for incorrectly predicted that a case is negative, and ashes colour represents the case of correctly predicted that a case is positive. The system recorded an accuracy of 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 of the samples were accurately classissified 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 17, 63

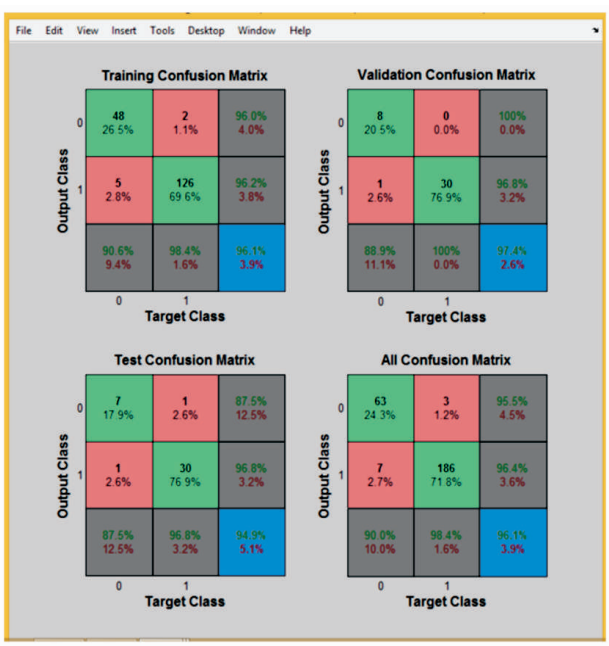

Figure 17. Confusion Matrix

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.

Summary and Conclusion

Pelvic Inflammatory Disease (PID) is a reproductive health infective disease that is prevalent among young females and 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. Performance evaluation and accuracy of the system was carried out 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 easy to use and very interactive. Testing and performance 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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