

Neural Network-Based Health Personnel Monitoring System

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ABSTRACT

Problems of the conventional health personnel management system include poor monitoring and evaluation. The system also suffers inadequate record-keeping, delayed personnel data aggregation and poor talent and file management. In this research, a neural network-based health personnel monitoring and management system is proposed as a solution to these problems. The system is based on a set of services and clients responsible for data management and has application and database servers as major components. The application servers hold and update the administrator's settings as well as provide the interaction media. The database server contains all the system datasets and provides mechanism for standard and secured data access. The simulation model, theoretical framework and user interface were implemented using Java programming language. The adequacy and suitability of the proposed system were investigated based on case study of on-duty data obtained from selected health personnel at the Health Centre, Federal University of Technology, Akure (FUTA), Nigeria. Obtained results presented the new system as a good health personnel monitoring and management platform.

Keywords: Health personnel, monitoring system, neural network, human resource, system administrator

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I. INTRODUCTION

In most working environment, there are several resources of which the most important is the human resource (HR). Effective and efficient management of HR will go a long way in achieving the set goals and objectives. Stakeholders in human resource management including researchers have realized that managing people proactively or reactively was no longer viable and therefore, strategic and effective human resource management is the new focus. Strategic HR management has continued to facilitate encouraging return on investment and sustainable competitive advantage. In view of this, HR professionals' role has changed greatly from administrative to highly strategic. HR strategists are now focused on mechanisms for streamlining various functions for the overall organization's success [1]. The traditional human resource management (HRM) has changed from people-oriented approach to knowledge and technology-based administration. This is necessitated by the competitive demand of the market place for a re-orientation of strategic human resource philosophies and practices. The upsurge of technology-based management systems has led to several and related human resource management systems for core services at global and national levels.

A computerized human resource management and control system consists of a fully integrated, organization-wide network of HR-related data, information, services, databases, tools and transaction [2]. It is good for improved HR administration, transactions and process performance. Other benefits include increased access to HR data, streamlined and standardized processes, consistent and accurate data and a higher internal profile for HR.

In the health sector, adequate monitoring and management of human and material resources is germane for good service delivering. The sector relies on its workforce for effective, efficient and high quality service delivery. Efficient workforce is also required for providing primary health and preventive services, diagnose and treat patients [3]. However, in many health care and delivery systems, human resources systems are limited, inconsistent, out-dated, or unavailable resulting in evidenced-based information for a good understanding on them. Furthermore, there is little consistency on how human resource strategies are effectively managed by most health service providers. Information Technology (IT)-based framework for the management of human resources can be a useful tool for promoting or enhancing evidence-based policy options for the health services. It is also important in ensuring that the recruitment, training and deployment of health workers are conducted in the most efficient ways.

2. REVIEW OF RELATED WORKS

The author in [4] presented a neuro-fuzzy expert system for human resource procurement and performance evaluation. The neuro-fuzzy mechanism carried out the relevant deductions and inductions on both qualitative and qualitative knowledge modeled in the databases, neural network and fuzzy logic. The system is specifically equipped to perform comparative analysis of the performance of peer personnel using hypothetical data while other major tasks of monitoring and controlling of personnel development, productivity and behavior patterns were not handled.

The authors in [5] presented a neural network-based human activity monitoring system as a means of promoting efficiency and optimization of performances. Though the system effectively classified human activity and presented detailed prescriptions, it failed with cases of over-fitting. In [6], a health services monitoring system is presented. The system facilitates the accomplishment of workforce projections, production, utilization and exit processes for enhanced capacity and contribution to meeting the health needs and objectives. The system is suitable for the determination of the sources and uses of information on human resources but its usefulness in real-life monitoring is not ascertained.

The authors in [7] presented a system for online tracking and monitoring of health personnel at their duty post. The system also provides efficient search, update and verification of prospective personnel duty, qualification, assignments, designation and status. It however lacks the mechanism for promoting unique and updated identity management which results in several conflicts, redundancies and record and data duplications. A model for effective human resource management with focus on job satisfaction, professional and organizational commitment as dependent variable is presented by the authors in [8]. The model is suitable for implementation in electronic-based human resource management but requires very complex hardware and software facilities with high human skill and financial demands.

The authors in [9] presented a multi-layered perception neural networks-based system for tracking and classification of moving objects and scene understanding. The application scenario consists of an entrance access of a touristic village crossed by vehicles and the main focus was on recognising possible presence of pedestrians in the zone. Though, the system recorded high classification rates, its performance under real-life circumstances were not investigated. In [10], a fuzzy logic-based system for linguistic description of students' behaviour and learning characteristics elicited from teachers is presented. The system also handles the inherent uncertainty associated with teachers' subjective assessments. Neural networks were used to add learning and generalization abilities by encoding teachers' experience through supervised neural-network learning. The system effectively managed the inherent uncertainty associated with human expertise in diagnosing aspects of students' learning style, especially for marginal cases but lacks the platform for real-life monitoring.

A prototype of cloud mobile health monitoring system that uses cloud computing, location data and neural network-based Wireless Body Area Sensor Networks (WBASN) and Smartphone application for patients monitoring is presented in [11]. Though, the prototype is said to have capabilities for monitoring patients' location and health status through the use of some mobile devices, its implementation and practicality were not presented.

A semantic neural classifier-based event detection system is presented in [12]. The system screens continuous video streams and detects relevant events, specifically for video surveillance. Real-time information is automatically collected by the system for the use of security personnel and decision makers. The proposed system is able to detect and classify the movements of mobile objects but required specialized equipment and environment to function. In [13], the design and preliminary performance analyses of a multi-sensor personal navigator prototype are presented. The implementation algorithms integrate the Global Positioning System (GPS), Micro-electro-mechanical inertial measurement unit (MEMS IMU), digital barometer and compass to provide seamless position information facilitating navigation and tracking of the military and rescue ground personnel. The prototype main point is its presentation of an open-ended architecture that incorporates a simplified dynamic model of human locomotion used for navigation in dead reckoning (DR) mode. However, in its present form, it lacks navigation and imaging sensor data that can be used to monitor confined and indoor environments.

3. PROPOSED HEALTH PERSONNEL ON-DUTY MANAGEMENT SYSTEM

The architecture of the proposed neural-network-based system is shown in Figure 1. The system is based on a set of services and clients responsible for data management. The client platform directs the application logic and its interactions with the user. The application servers hold and update the administrator's settings and also provide the interaction media for the clients and administrator. The database server is a repository of all the system datasets and provides mechanism for standard and secured access to the data.

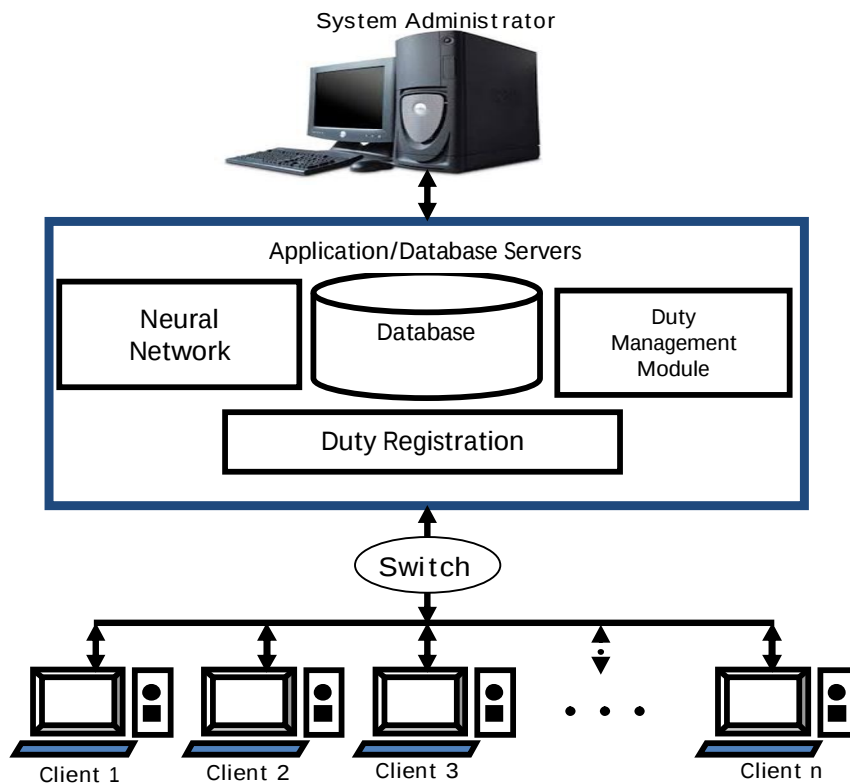


Figure 1: Architecture of Health Personnel Management System

The duty registration module (DRM) enables all authenticated personnel to register assigned duties in each working day while the duty management module (DMM) keeps daily records of all duties carried out by each registered personnel. DMM also provides to the administrator, the work schedule for a specified personnel in a given period. The neural networks (NN) module interprets data from sensors, extracts relevant information and grants or restricts access to the system based on pre-established rules. Its operation is based on back-propagation supervised learning algorithm which is widely used in training Multi-layer Perceptron (MLP) which refers to the network consisting of a set of sensory units (source nodes) that constitute one or more hidden layers of computational nodes. The input signal propagates through the network in a forward direction, from left to right and on a layer-by-layer basis. The back-propagation neural network (BPNN) provides a computationally efficient method for changing the weights in feed forward network, with differentiable activation function units, to learn a training set of input-output data.

a. Image Value by Singular Value Decomposition (SVD)

The NN component of the system uses SVD to convert digital image into an array of integer values by using the system's Application Programming Interface (API). The array is used for the computation of the image value representation. The input into the network is the extracted feature values which reflect the intrinsic property of the face and lie in a certain range. Suppose M is an $m \times n$ matrix with entries from the field K , which represents the field of real or complex numbers, singular value decomposition of M is performed as follows:

$$M = U\Sigma V^* \quad (1)$$

U is an $m \times m$ unitary matrix over K , Σ is an $m \times n$ diagonal matrix with non-negative real numbers on the diagonal and V^* is an $n \times n$ unitary matrix which denotes the conjugate transpose of the $n \times n$ unitary matrix V . The diagonal entries of Σ are the singular values of M which are listed in descending order. The diagonal matrix Σ is uniquely determined by M . The single value matrix A is computed from:

$$f_{A^T A}(\lambda) = \det(A^T A - \lambda I) \quad (2)$$

is the eigenvalue and I is the matrix of the input face image.

b. Network Input Data Normalization

The input data is normalized mainly for standardizing and transforming the values of all variables from dynamic into specific range by using the following formula:

$$X_{new} = \frac{(X_{old} - X_{min})}{X_{max} - X_{min}} \quad (3)$$

X_{old} and X_{new} represent the raw and transformed data respectively while X_{max} and X_{min} are the maximum and minimum values of the dataset respectively.

c. Training and Test Data

The neural network contains two distinctive modes: training and testing. The first 80% data are taken as the training set while the remaining are taken as the test or validation set. The training cases are used to adjust the weights while the test cases are used for the validation of the network. The training datasets consist of input-output patterns which are presented to the network.

The weights are found through an iterative process, in which the back propagation learning algorithm is used to find the weights such that the difference (error) between the given and network computed outputs is sufficiently small. The statistics of the training data represent the analyses of data encountered during operation. The network is said to be bias if it results in classifiers with lower classification rates and estimators with lower prediction accuracies. Samples or feature vectors that do not have major dominant features,

unrelated to the problem and common to the specific condition are selected.

In several data sets, the unrelated dominant features are not determined until a neural network is trained and checked against a validation data set. A large number of representative training samples or feature vectors are also necessary for training a neural network to ensure its smooth operation over the expected range of the input-feature space without memorizing the training data. This gives the network a better representation of the desired problem and increases the likelihood of the neural network producing the desired outputs.

d. Neural Network Architecture

The proposed system uses a feed-forward neural network model with four input neurons, two hidden layers and one output layer as shown in Figure 2. The model consists of input vectors to the first input layer of neurons, followed by inter-connected layers of neurons, the hidden layer, and finally to the final or output layer of neurons. Each layer directly supplies input to the next layer and feeds the inputs forward through the network. The management of health personnel on duty post is modeled with input layer of neurons for date, time, face, duty position, username and password. Each output indicates the final classification showing whether the input data for a personnel corresponds with the existing information.

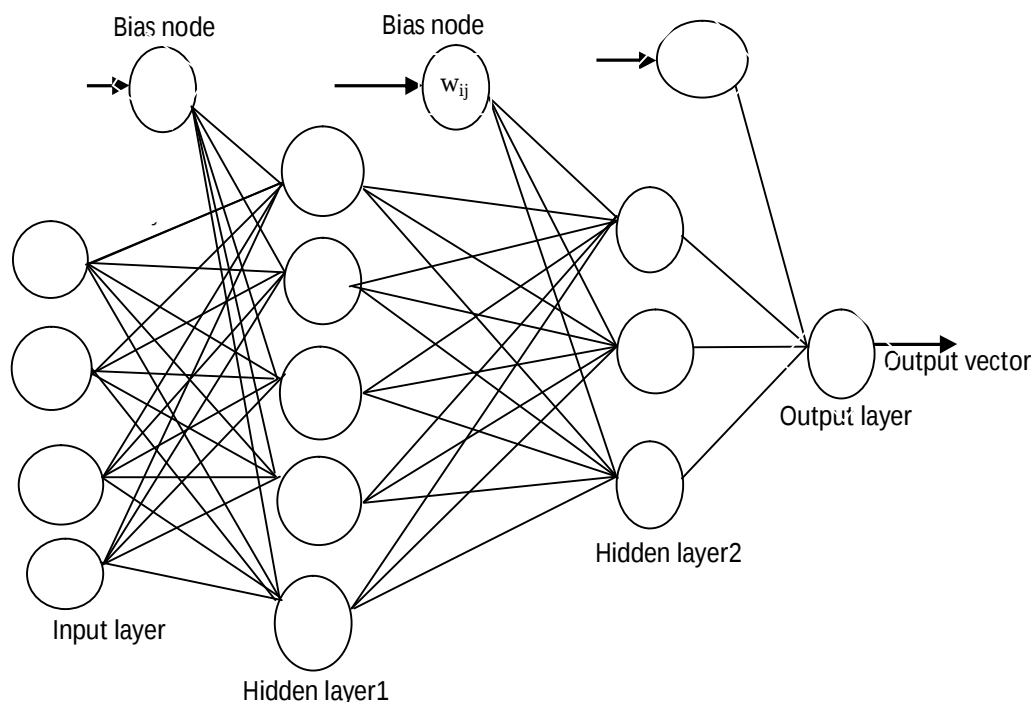


Figure 2 Architecture of a feed-forward neural network with corresponding nodes

The input quantities are fed into the input layer neurons, which in turn, pass them on to the hidden layer neurons, z_i after multiplication by connection weights, w_{ij} . A hidden layer neuron adds up the weighted input received from each input neuron, x_{it} ($x_{it} w_{ij}$) and associates it with a bias (β_h) based on the formula:

$$Z_i = \sum_{x=1, w=1}^{t,j} (x_{it} w_{ij}) + w_h \beta_h \quad (4)$$

The same operation is performed on the neurons leading to the output layer given as:

$$Z_t = \sum_{z=1, w=1}^{n,k} (Z_i w_{jk}) + w_o \beta_o \quad (5)$$

x_{it} are the input quantities such as date and time (x_{1t}), face (x_{2t}), duty position (x_{3t}) for a set of given input t ; w_{ij} is the weights between the input neuron i to the hidden neuron j , and w_{jk} is the weights between hidden neuron j and output neuron k . β_h and β_o are the biases for the hidden and output layers respectively and they are set to a value of 1. w_h and w_o are the weights for the bias hidden and output neurons respectively.

e. Learning Algorithm

Back-propagation supervised learning algorithm was selected for the proposed system. Basically, the back-propagation learning involves a set of inputs presented to the network, and a set of the network's outputs obtained by propagating these inputs through the layers of the network.

An error signal is obtained by comparing the network's outputs with the actual marked or targeted outputs that corresponds with the set of inputs, and this error signal is used to change the network's weights. The errors for each input-output are accumulated and the weights updated after each complete presentation of the training data set to the neural network. To avoid over-fitting of the training data, at frequent intervals during the training session, the network's weights were frozen and the mean square error, on a separate testing data set are calculated. Training is stopped when it is determined that the network's prediction accuracy deteriorates. In the back-propagation algorithm, the optimal weights generate an output vector $Y = (y_1, y_2, \dots, y_p)$ as close as possible to the target values of the output vector $T = (t_1, t_2, \dots, t_p)$ with a selected accuracy. The algorithm adjusts the weights based on the minimization of the squared error.

The network error is defined as:

$$E = \frac{1}{2} \sum_{j=1}^m (d_j - y_j)^2 \quad (6)$$

$$W_{ij}^{new} = W_{ij}^{old} + \delta \frac{\partial E}{\partial w_{ij}} \quad (7)$$

d_j is the output of the neural network j , y_j is the actual output and $j=1, 2, \dots, m$; where m is the number of neuron in the output layer. W_{ij} is the weight from i th neuron in the previous layer to the j th neuron in the current layer. δ equals the learning rate, ∂E and ∂W_{ij} are the error and weight gradients respectively.

f. Learning Rate

Learning rate determines the magnitude of the changes in the weights for every iteration. At each training step or iteration, the network computes the direction in which each bias and link value (weight) can be changed to obtain a better output. The rate of improvement at that solution state is also known. The higher the learning rate (max. of 1.0), the faster the network is trained. If the selected learning rate is too large, then the local minimum may be overstepped constantly, resulting in oscillations and low convergence to the lower error state. Too low learning rate results in large number of iterations, resulting in low performance. The upward and downward adjustments of the learning rate are presented in Equation 8 and 9 respectively.

$$\partial = \partial + (\partial_i \times Mg) \quad (8)$$

$$\partial = \partial - (\partial_i \times Mg) \quad (9)$$

Some biases which are associated with some trainable weights are applied to the neurons. The biases are realized in terms of an input with some constant, say +1 or +B input, and the exact bias b_i (at the i th neuron) is then given, to avoid the neuron from having 0.0 values. For this system, the bias is set at a constant value of 1.

g. Modeling Health Worker's Duty Position

Health workers deliver health care services to members of the community depending on their employer and precise job title. The monitoring of health workers on duty post is modeled as follows:

$$P_t = W \left[\frac{T_t P_i}{D_m} \right] \quad (10)$$

$$W_s = D_p \begin{cases} Od & P_d = d_t \\ Nd & P_d \neq d_t \end{cases} \quad (11)$$

$$O_d = \sum_{k=1, t=1}^{n, N} C_{k=1, t=1}^{n, N} \quad (12)$$

P_i is the duty positions of health workers in a health care and delivery center, T_t is the total time a health worker W is expected to work in a month. $i=1, 2, 3, \dots, n$, $t=1, 2, m$. D_p is the duty position assigned to W . W_s is the duty status and O_d and N_d indicate on and off duty status respectively. P_d represents the required time duration for a health worker to be on duty for any particular day, and d_t is the precise time of the day the health worker is expected to be on duty. A health worker is said to be on duty when the time duration

on duty is the same as the time of the day the worker is on duty, otherwise the worker is said not to be on duty.

h. Arrival and Departure Times Production Rule-Based Modeling

Forward chaining mechanism is applied to duty position, arrival/departure time and activities of health personnel based on the production rule defined as follows:

```

If { } then
    Normal arrival
Else if { } then
    Late arrival
Else if { } then
    Absent
End

```

T_i is the sign in time and d_i is the precise time of the day the health worker is expected to arrive for duty. The production rule for managing the time of departure of health personnel is given as:

```

If {  $T_o = d_i + P_i$  } then
    Normal Departure
Else if {  $T_o \geq (d_i + P_i)$  } then
    Late Departure
Else if {  $T_o \leq (d_i + P_i)$  } then
    Early Departure
End

```

T_o is the sign out time and P_i is the length of time on duty in a particular day.

i. Modeling Health Personnel Activities

The on-duty activity of personnel is modeled for a period of time N as:

$$L = \sum_{j=1}^N [kt(\hat{y})] \quad (13)$$

j is the number of hours spent on the activities, k is the number of days on duty for a month, t is the number of weeks worked in a month C . $\hat{y}$ indicates that the report L is generated for the employee whose details have been obtained earlier and processed successfully based on the established data processing standard.

4. IMPLEMENTATION

The simulation model, theoretical framework and user interface were implemented using Java programming language. Java is a high level language that supports object oriented, portable, distributed, high performance, multithreaded, dynamic and very secure programming. The simulation was on a computer system that executed both the client and server (admin) applications on 2GB RAM and 350 HDD with intel dual core T4200 2.0GHz processor and windows vista operating system. The design tools include NetBeans IDE 7.2 on JDK1.7.0 (Java Development Kit) and MySQL relational database management system (RDBMS).

a. Data Collection

Relevant data for the research were collected based on closed circuit television (CCTV) image of some selected health personnel on duty at the Health Centre, Federal University of Technology, Akure, Nigeria. Some of the services at this centre are listed below.

- First aid
- Surgery and its assistance
- Operating room technician and equipment sterilization
- Treatment of minor and major illnesses
- Dispensing drugs
- Pre and postnatal advices
- Delivering babies
- Child care advice
- Nutrition education, monitoring and feeding
- Education, monitoring and dispensing of immunization
- Family planning services
- Sanitation and hygiene promotion and education
- Screening, monitoring, follow-up and treatment of communicable diseases
- Health care referrals
- Conducting seminars and workshops on school health
- Collection of vital health statistics
- Developing, maintaining and reporting health records
- Home visits
- Community meetings

The collected data were on times, activities, face, duties and schedule of different personnel and their corresponding units and functions which cover the range of inputs for which the network was designed. The collection prioritized neural network expectations and requirements for training, types and sources as well as envisaged output in response to the used data.

b. Simulation Results

The neural network is considered as a pre-processing block between the input and the first layer of the network and a post processing block between the last layer of the network and the output. The input data are date, time, face, duty position, username and password which were pre-processed before presentation to the network. The username and password for each personnel were converted into its ASCII (American Standard Code for Information Interchange) equivalent and added up to represent the data value. In the first layer of the network, the net input is a product of the input times the weight plus the bias. If the input is very large, then the weight must be very small in order to prevent the transfer function from becoming saturated. Normalization of the data was also carried out as a way of constraining them into an investigated and approved range. The network output is reversed and transformed into the units of its original data when the network is put to use. The extraction from the raw data for some selected personnel is presented in Table 1 while a sample of the normalize values of the raw data is presented in Table 2.

Table 1: Raw values obtained from processing personnel data

ID	EMAIL+ PASSWORD	DEPT	SIGN IN TIME	FACE PICTURE
1	2585	376	1189632239034	111985
2	2359	328	966288239285	134207
3	2281	432	1009232639329	200513
4	2578	207	1228688639359	104195
5	2193	207	1231194239388	111195
6	2193	455	1005431039426	273628
7	2137	207	1322951039452	190512
8	2794	328	1191533039523	172329
9	2389	376	1182288239577	216211
10	2578	214	1048976639611	112914

Figure 3 shows the result of the prediction error values at different learning rates for the neural network. The learning rate of 0.6025 has the lowest prediction error of 3.33% and was consequently used for the authentication of personnel's interaction with the system.

Table 2: Normalize values for input into neural network

ID	EMAIL/ PASS-WORD	DEPARTMENT	SIGN IN TIME	FACE PICTURE
1	0.68	0.68	0.62	0.05
2	0.34	0.49	0.00	0.18
3	0.23	0.91	0.12	0.57
4	0.67	0.00	0.74	0.00
5	0.09	0.00	0.74	0.04
6	0.09	1.00	0.11	1.00
7	0.00	0.0	1.0	0.51
8	1.00	0.49	0.63	0.40
9	0.38	0.68	0.61	0.66
10	0.67	0.03	0.23	0.05

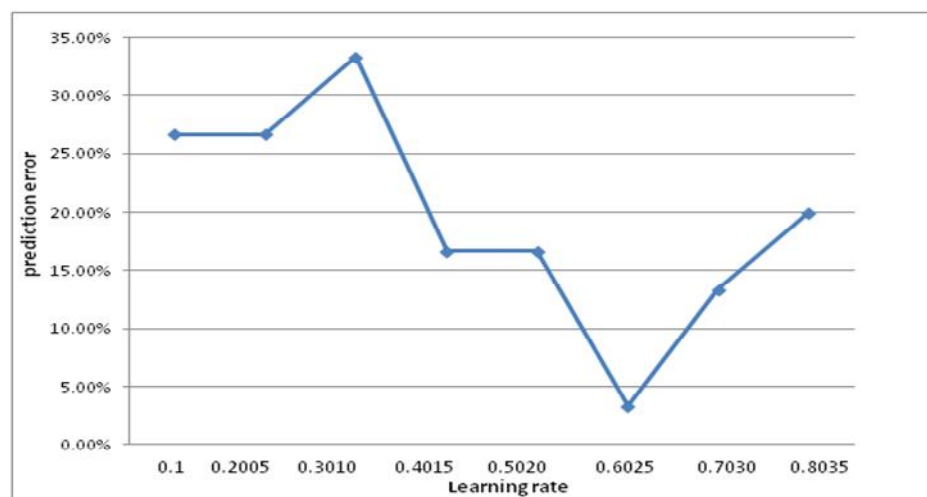
**Figure 3: Prediction error and learning rate**

Table 3: The Artificial neural network for the classification of unregistered data (record)

S/N	Learning rate	Total records (unclassified records)	Correctly classified records	Prediction Error (PE)
1	0.1	5	0	100.00%
2	0.2005	5	0	100.00%
3	0.3010	5	0	100.00%
4	0.4015	5	0	100.00%
5	0.5020	5	0	100.00%
6	0.6025	5	0	100.00%
7	0.7030	5	0	100.00%
8	0.8035	5	0	100.00%

Table 3 shows the result of the classification and prediction error for 8 unregistered data. The value of zero recorded in all cases for “correctly classified records” is due to the non-training of the system and consequently, non-classifications with prediction error of 100%.

The system was appraised with the computation of F-score for Table 3 and obtained results are presented in Table 4. F-score is a measure of accuracy based on the precision p and the recall r . p denotes the quotient of the number of the correct and the returned results while r stands for the quotient of the number of correct and expected results. The score is interpreted as a weighted average of the precision and recall and reaches its best value at 1 and worst score at 0. Precision, recall and F-score are obtained as follows:

$$Precision = \frac{TP}{TP + FP} \quad (14)$$

$$Recall = \frac{TP}{TP + FN} \quad (15)$$

$$F - score = \frac{2 \times recall \times Precision}{Recall + Precision} \quad (16)$$

TP, FN and FP are the true positive, false negative and false positive respectively.

5. CONCLUSION

A neural network-based health personnel monitoring system that offers solution to the data association problem using feed-forward neural networks has been presented. The proposed system has advantages over the conventional personnel management, monitoring and classification schemes in its speed and simplicity. The system is suitable as a tool for effective and efficient evaluation of health personnel. It is also a good platform for providing solutions to the problem of poor record-keeping, delayed personal data aggregation and poor talent and file management in every organisation that provides health services. Area of future researches includes the integration of Radio Frequency Identification (RFID) and fuzzy logic into the system's architecture for greater and improved personnel monitoring and evaluation. Focus will also be on the use of other biometrics data such as fingerprint as part of the input neurons.

Table 4: Obtained F-score Values

S/N	Total Rec.	TP	FP	FN	Precision	Recall	F-score
1	30	22	8	0	0.733	1	0.846
2	30	22	8	0	0.733	1	0.846
3	30	20	10	0	0.667	1	0.798
4	30	25	5	0	0.833	1	0.909
5	30	25	5	0	0.833	1	0.909
6	30	29	1	0	0.967	1	0.983
7	30	26	4	0	0.867	1	0.928
8	30	24	6	0	0.800	1	0.889

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