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Prediction Model to Enhance Resource Efficiently For Hospitals

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ABSTRACT

Hospital administrators need to oversee assets/resources successfully, while keeping up a high caliber of consideration. For hospital facilities where admissions from the emergency section and OPD along with inpatient wards required a large extent of admission or affirmations. The capability to estimate these admissions (affirmations) flow and accordingly ward occupancy is particularly valuable for efficient resource planning purposes. Since emergency patient admissions regularly contend with arranged elective admissions, handling emergency demand may bring about enhanced elective planning too. Several algorithms, tools and software are developed by the researchers to achieve effective medical decision support systems. New software and algorithms are continuously emerging and upgraded depending on the real time situations. We analyse some of the existing models for gauging every day emergency inpatient admissions and inhabitance. The models are connected to past years of everyday information. By measuring their mean square error (MSE) in a cross validation system, we find that emergency admission (inflow of patient) are generally irregular, and consequently, unusual, while emergency admission (patient inflow) can be estimated utilizing our proposed prediction model. Confronted with variable emergency patient admission and inhabitance, hospital management centers must set up a resource backup (reserved bed and staff's). Our methodology permits the prediction estimation of the necessity reserve capacity.

Keywords: Forecasting, Health care management, artificial intelligence, Hospital resource management.

1. INTRODUCTION

Increasing attention has been directed recently to better management of health care resources, i.e., by providing good and more efficient patient care while minimizing resource use [1], [2]. Public hospitals in Australia operate under severe and conflicting constraints. They are medically and legally obliged to accept any patient arriving at the emergency department (ED), and to provide them the finest possible care. The point, at which this ability is exhausted, due to lack of ED beds or of other resources, is called "hospital bypass" or "ambulance diversion." Hospital performance is scrutinized both by the government [3] and the public through the media.

Hospitals also operate under strict budgetary limits; hence, they need to allocate resources in a cost-effective way. Our investigations suggest that ED resources are typically exhausted due to back propagation of congestion within hospital wards, i.e., insufficient ward resources to admit patients from the ED (access block [4]). This situation arises from the manner in which the emergency and elective patient streams interact: elective patients are booked days or weeks in advance, whereas emergency patients arrive in an unplanned fashion, beyond the control of the hospital, and driven by factors such as illness patterns, time of day, and sociodemographic effects. If electives are booked assuming a certain percentage of emergency demand, and it turns out to be an underestimate, then the two streams conflict. In such a case, some demand is reduced by canceling planned elective admissions (even on the day of surgery). However, previously admitted elective patients will consume beds for their entire stay, thereby reducing the hospital's ability to admit emergency patients to the overnight wards for several more days. Decisions regarding acceptable rates of elective admissions are made with lead times ranging from several days to several weeks ahead, due to the need to schedule patients and facilities such as surgical suites. Tactical decisions regarding other resources require lead times varying from a few days for staffing rosters to much longer term for construction of new facilities or training new staff.

These constraints highlight the need for a modeling approach that can give decision makers a reliable estimate of future patient levels, based on current known levels. However, there are fundamental limitations to what such models can achieve: the variance inherent in random processes limits how well they can be predicted.

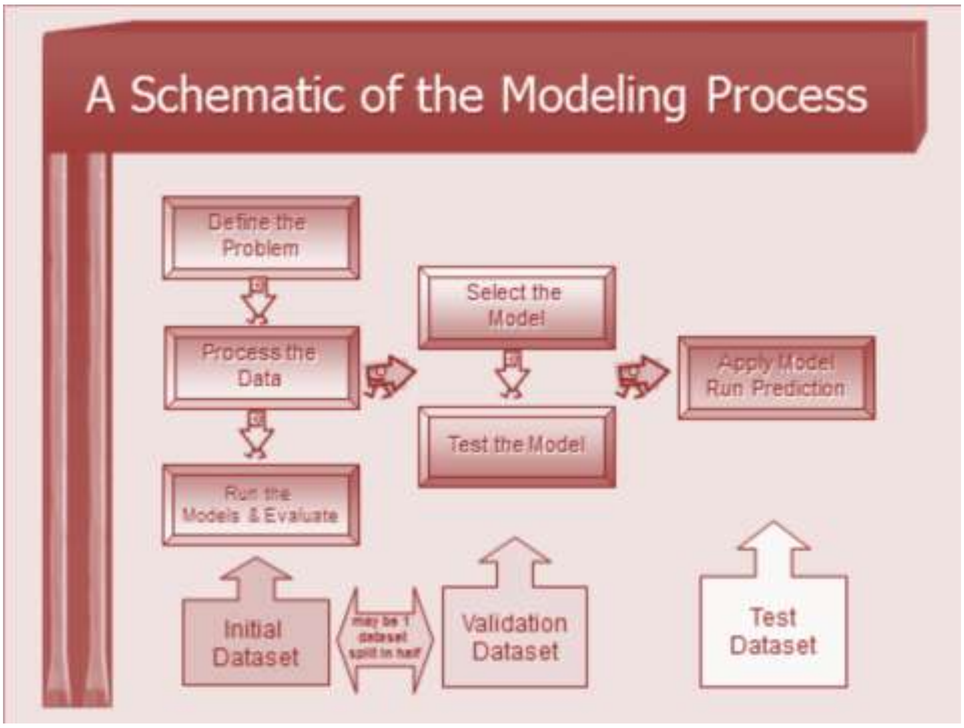

Figure 1: Prediction model architecture

Each and every year, the field of computer science becomes more sophisticated as new types of technologies hit the market. Despite that, the problem of developing intelligent agents that will precisely simulate human brain activity is still unsolved. One of the most prominent models of intelligent agents built in computer memory is represented by neural networks (NN). Thus here in this research, we will be introduced to the basics of NN, alongside with the prediction pattern that can be successfully used in different types of "smart" applications. Specifically, a hospital resource management predictor based upon neural networks will be explored. During my intellectual analysis into the world of artificial intelligence, I was fascinated how "magically" a correctly constructed artificial neural network (specifically feed-forward network) can predict values, according to those specified at the input. This "forecasting" capability makes them a perfect tool for several types of applications:

Function interpolation and approximation, Prediction of trends in numerical data, Prediction of patient inflow in hospital, Prediction of movements in financial markets and so on. All the examples are actually very similar, because in mathematical terms, you are trying to define a prediction function F(X1, X2 … Xn), which according to the input data (vector [X1, X2... Xn]) is going to "guess" (interpolate) the output Y. The most exciting domain of prediction lies in the field of hospital management. A patient inflow prediction strategy based on computer intelligence sounds like a very prominent and interesting field of study.

2. LITERATURE SURVEY

The objective of prediction model is to estimate number of emergency patient that will be admitted in next several weak. The underlying problem applies to a wide variety of environments, such as general practice, diagnostic center, surgical center etc... Here we analyse some of the existing model and its pros and cons. many existing technique, such as queueing models [7] and Markov model [5, 7], has also been applied in estimating patient flow. We consider both a structured model in which we endeavored to predict tenancy from patient arrival and patient discharge processes, and a “blackbox” approach where we modeled occupancy directly. An Intelligent Heart Disease Prediction System (IHDPS) on data mining techniques is proposed by Sellappan Palaniappan et al. [8]. The techniques used are decision trees, Naïve Bayes and Neural Network. It is developed on .Net platform.

The dataset has several attributes like age, sex, blood pressure and blood sugar which are used to predict the risk of patients getting a heart disease. Shantakumar B. Patil et al. as in [9] applied a methodology for the extraction of significant patterns from the heart disease warehouses for heart attack prediction. As a first step the data ware house is preprocessed in order to make it suitable for the mining process. K-means clustering algorithm has been applied to the data warehouse and the patterns are mined using MAFIA algorithm. Then neural network is trained with the selected patterns to predict heart disease efficiently. Dilip Roy Chowdhury et al. [10] applied a back propagation neural network in predicting neonatal disease diagnosis. The authors applied back propagation algorithm to train a neural network on different categories of neonatal diseases. The accuracy is 75% with higher stability. Milan Kumari et al. [11] has solved Cardiovascular Disease dataset using different data mining algorithms such as Support Vector Machine, Decision Tree, Artificial Neural Networks, and Ripper Classifier.

A Decision Support System for diagnosis of congenital Heart Disease has been proposed by Vanisree K et al. [12]. This again based on Back Propagation Neural network. The proposed system achieved an accuracy of 90%. Niti Guru et al. [13] applied a neural network for prediction of Heart disease, blood pressure and blood glucose level. The author used a supervised network for diagnosis of heart disease and trained using back propagation algorithm. If suppose unknown data is entered by doctor the system will find the unknown data from the training data and generate list of possible disease from which the patient can suffer. Ming Chui et al. [14] applied Fuzzy Neural Networks (FNNS) algorithm to attain knowledge and categorize features in the cardiovascular diseases. Designing an Artificial Neural Network model for the prediction of Thrombo-embolic Stroke was implemented by D. Shanth et al. [15] Using Back-propagation algorithm that had a predictive accuracy of 89%. A. Khemphila et al. [16] has proposed a model for Heart Disease Classification using Neural Network and Feature selection implemented with Back- Propagation algorithm. The output of this has attained an accuracy of training data set as 89.56% and validation data set as 80.99%.

Time-series (TS) analysis has been applied previously to health care and particularly to patient flow. Lin [17] used autoregressive integrated moving average (ARIMA), vector autoregressive moving average (VARMA), and Holt–Winters exponential smoothing models to forecast the monthly discharges and differences in occupancy across several hospitals. He found that in most cases, ARIMA performed as fine as or slightly superior as either VARMA or the Holt–Winters method. Jones et al. [18] described several ARIMA models of daily hospital occupancy resulting from emergency admissions. They found that whereas external covariates such as weather were significantly correlated with the number of admissions, they added little to the model's forecasting ability. Champion et al. [19] fitted ARIMA and seasonal exponential smoothing models to monthly emergency presentations (patient arrivals to the ED), and found that the latter performed slightly better.

Earnest et al. [20] used ARIMA models to forecast ward occupancy due to severe acute respiratory syndrome (SARS) infections, for up to three days ahead. Channouf et al. [21] applied ARIMA models to forecast calls to emergency medical services. They report that for forecast horizons of up to about a week, the analysis show that the best performing model was a mixed-effects regression model with an autoregressive model of the residuals. Beyond that time, no model had any forecasting benefit. Neural Networks has been widely used in the medical field for forecasting disease. NN has been established of their potentials in many domains related with medical forecasting and diagnosis disease. NNs can never substitute the human experts but can help them in decision (judgement) making, classifying, screening and to cross-verify their treatments (diagnosis). To address the above problem face by some of existing model we propose a prediction model based on back propagation neural network which could lead to better prediction model for hospital resource management.

3. PROPOSED METHOD

Here we demonstrate a multi-layer neural network with back propagation learning algorithm, but applied to a different task – patient inflow prediction. The problem of patient inflow prediction is very important and a very popular problem and many researchers work in the area trying many different algorithms and methods for the task. It is easy to explain the popularity of the problem by taking a look at areas where it can be applied. One of the popular areas is hospital emergency patient inflow management - if you can predict future values of patient inflow of admissions, then ... if you can do it really well, then you may achieve a good resource planning. But, let's return to neural networks.

During the training phase, certain amount of previous values of the time series of patient data are presented to the network and the network is trained to predict the next value of the time series data of patient. The more training samples you have, the better prediction models you may get. Also, a very important parameter is window size - how many values from the history are used to predict the future one. The larger the window size you have, the better model you may get, but may not - depending on the time series of patient data, and require experiments. But, a larger window size will decrease the amount of training samples you need, so it is a tradeoff value.

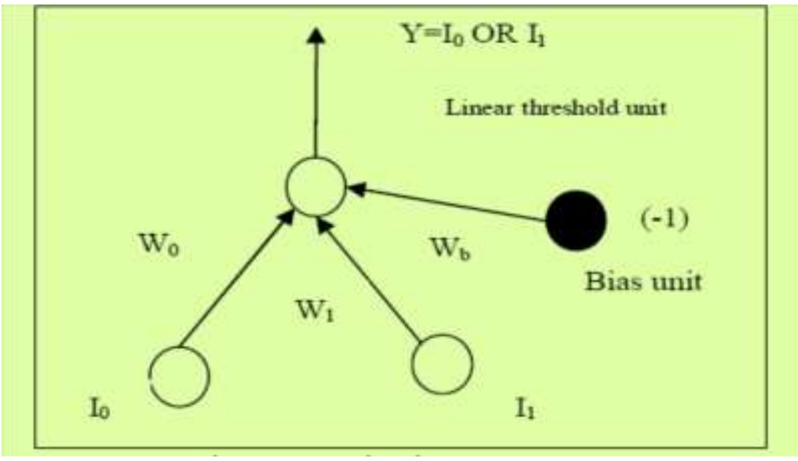

Figure 2: A simple Perceptron

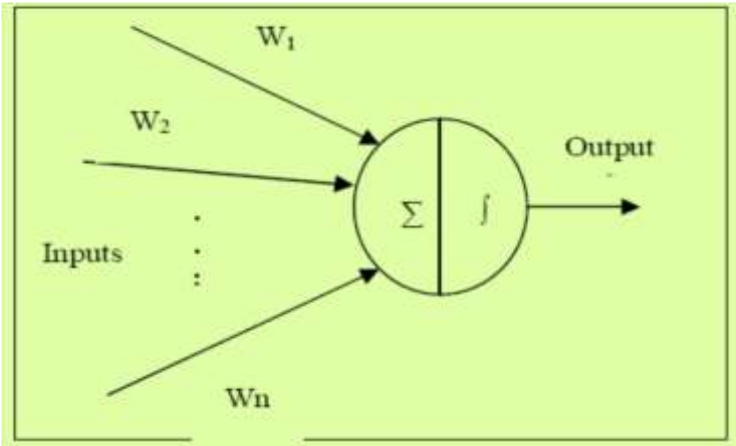

Figure 3: A typical neuron with Activation Function

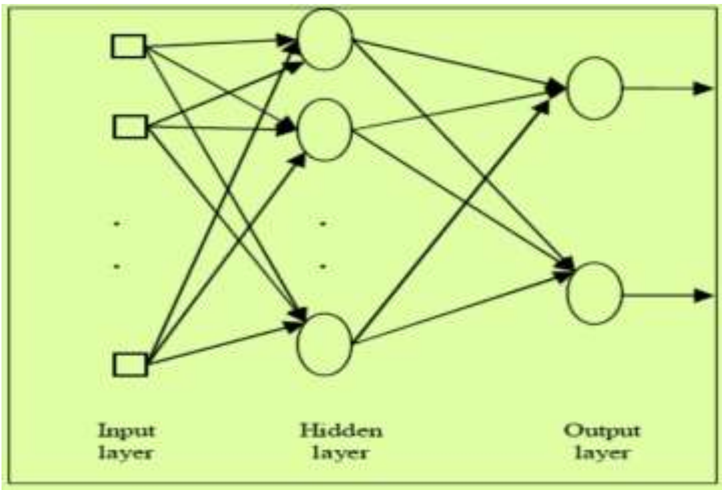

Figure 4: Multilayer Perceptron

It is very important to find the suitable algorithm for modeling of hospital resources management into different levels of patient inflow in hospital management systems. The following Neural Network algorithms are used:

Back propagation Algorithm:

There are many variations of the back propagation algorithm, several of which are described in the literature. The simplest implementation of back propagation learning updates the network weights and biases in the direction in which the performance function decreases most rapidly, the negative of the gradient. Here a one iteration of this algorithm can be written as:

$x_{k+1} = x_k - \alpha_k g_k$	(1)

Where, x_k is a vector of current weights and biases, g_k is the current gradient, and α_k is the learning rate. There are two different ways in which this gradient descent algorithm can be implemented: incremental mode and batch mode. In incremental mode, the gradient is computed and the weights are updated after each input is applied to the network. In batch mode, all the inputs are applied to the network before the weights are updated. In batch mode the weights and biases of the network are updated only after the entire training set has been applied to the network. The gradients calculated at each training example are added together to determine the change in the weights and biases. In batch steepest descent algorithm weights and biases are updated in the direction of the negative gradient of the performance function. Hence, Batch Gradient Descent without momentum Training Algorithm can train any network as long as its weight, net input, and transfer functions have derivative functions. Backpropagation is used to calculate derivatives of performance DPERF with respect to the weight and bias variables X. Each variable is adjusted according to gradient descent:

$\delta X = l_r \times \frac{\delta DPERF}{\delta X}$	(2)

Where, l_r is the learning rate.
Training stops when any of these conditions occurs:
1) The maximum number of Epochs (repetitions) is reached.
2) The maximum amount of Time to train has been exceeded.
3) Performance has been minimized to the Performance Goal.
4) The performance gradient falls below Minimum Performance Gradient value.
5) Validation performance has increased more than Maximum number of validation Failures value

Gradient descent with momentum backpropagation is a network training function that updates weight and bias values according to gradient descent with momentum. It can train any network as long as its weight, net input, and transfer functions have derivative functions.
Backpropagation is used to calculate derivatives of performance PERF with respect to the weight and bias variables X. Each variable is adjusted according to gradient descent with momentum:

$\delta X = m_c \times \delta XDPERF - l_r \times (1 - m_c \times \frac{\delta DPERF}{\delta X})$	(3)

Where $\delta XDPERF$ previous change to the weight or bias is, l_r is the learning rate and m_c is the momentum constant. Training stops when any of these conditions mentioned Batch Gradient Descent without momentum Training occurs.

The algorithm includes following two passes:
In forward pass an activity pattern is applied to the input nodes and it propagates through the network layer by layer. As a result a set of outputs is produced as the actual response of the network. The weights at the functional points of the network are fixed in the forward pass.

During the backward pass, the synaptic weights are all adjusted in accordance with an error correction rule. The actual response is subtracted from the desired output to produce an error signal. The error signal is propagated backward through the network. The synaptic weights are adjusted to have actual output nearer to the desired output. The weight adjustment is done according to the generalized delta rule to minimize the error.

$\Delta w_{ji} = \alpha(t_j - y_j) g^{|}(h_j) x_i$	(4)

Where, α Is a small constant called learning rate, g(x), is the neuron's activation function, t_j is the target output, h_j is the weighted sum of the neuron's inputs, y_j is the actual output and x_i is the i^{th} input.

4. SIMULTION RESULT AND ANALYSIS:

The system environment used is windows 7 enterprises 64-bit operating system. We have used C# programing and used dot net framework 4.0 visual studios 2010 to develop our prediction model. We have conducted simulation sturdy on following parameter for actual vs predicted result, MSE and RMSE prediction error for per day, per weak, per month.

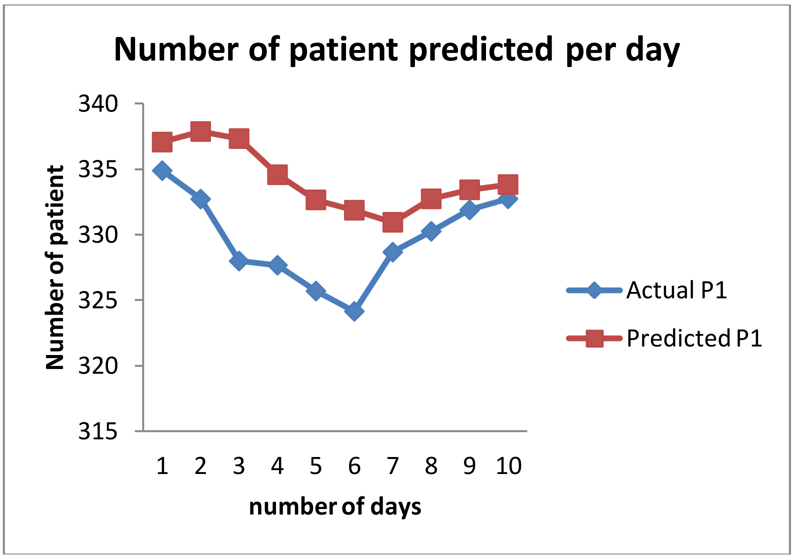

Figure 5: Number of patient predicted per day

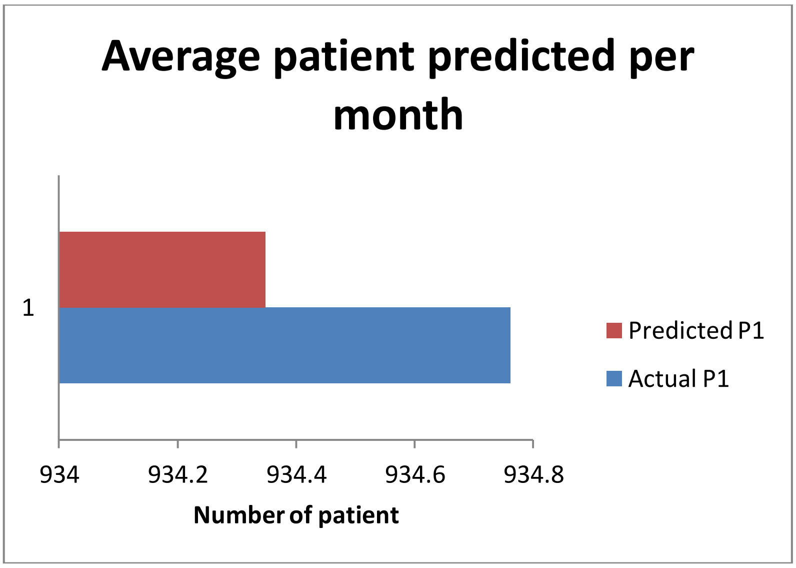

Figure 6: Average patient predicted per month

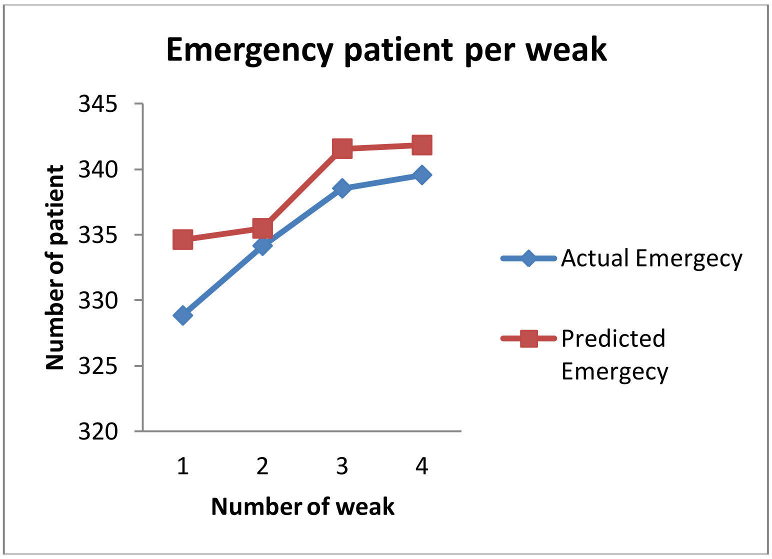

Figure 7: Emergency patient per weak

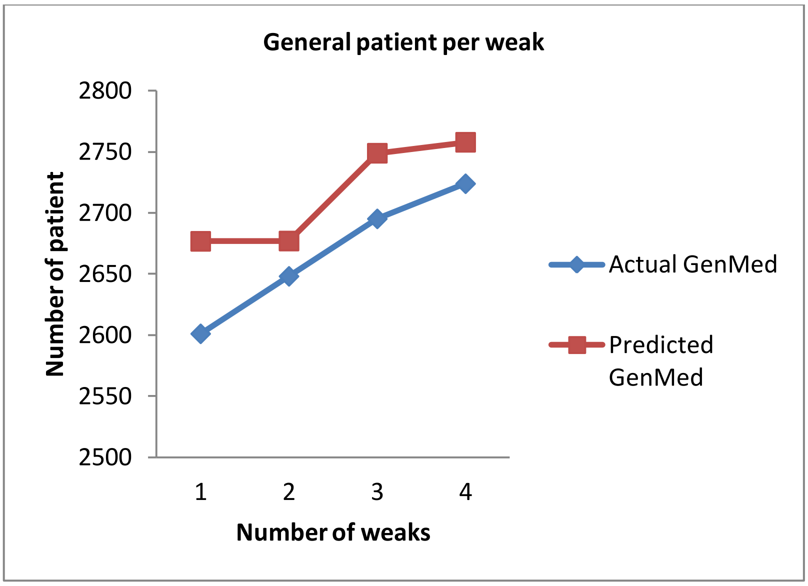

Figure 8: General patient per weak

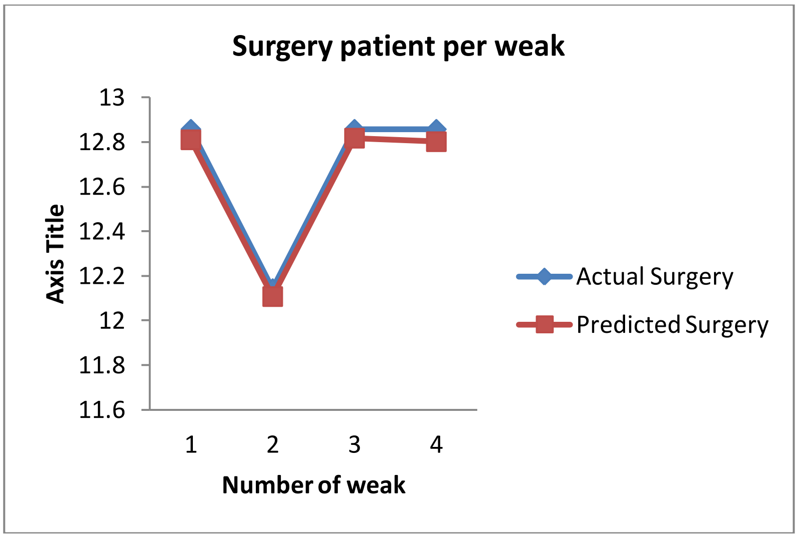

Figure 9: Surgery patient per weak

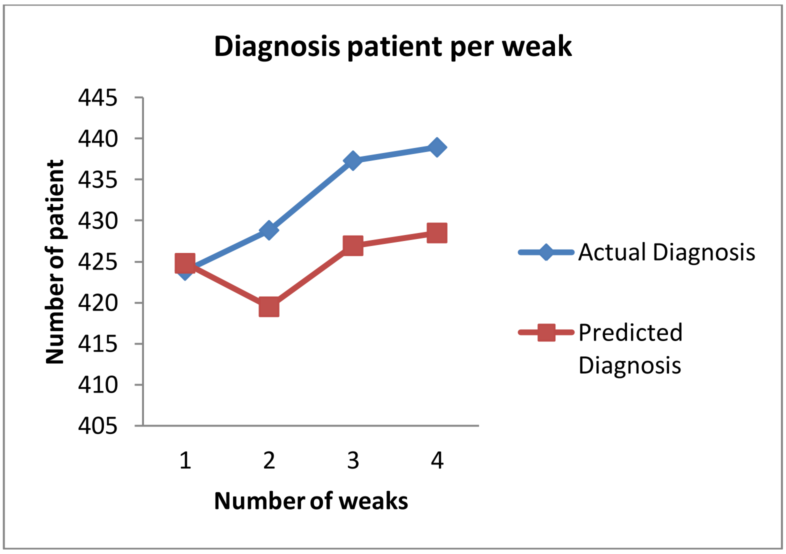

Figure 10: Diagnostic patient per weak

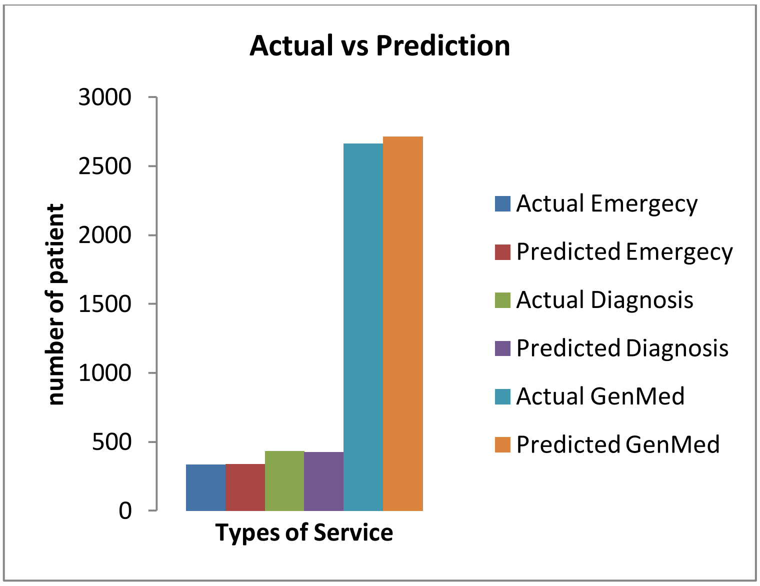

Figure 11: Actual vs prediction of varied services

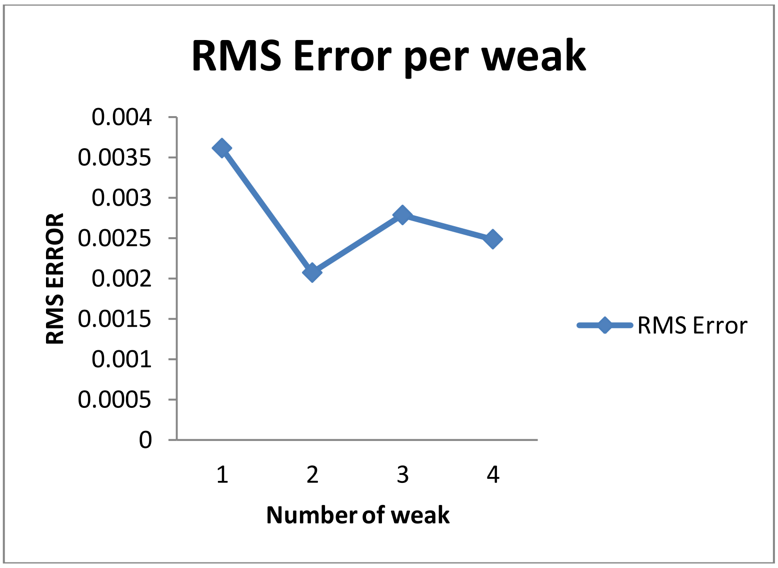

Figure 12: Root mean square error per weak

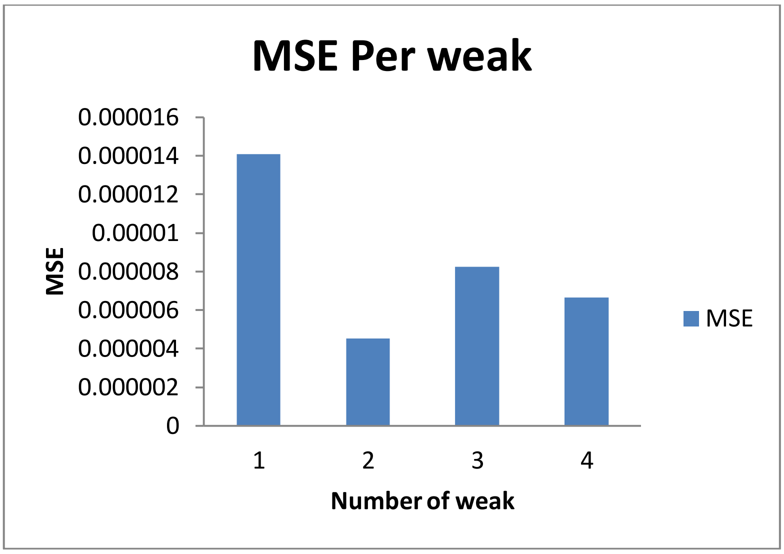

Figure 13: Mean square error per weak

We have trained our prediction algorithm for 10 day of hospital patient data based on those training set we have predicted the future patient inflow. In figure 5 we have predicted for the patient inflow for the next 10 day and found the RMS error around 0.003 and MSE error around .054. In figure 6 we have calculated the average inflow of patient per month and found the RMS error around 0.008 and MSE error around .029. In figure 7 to 10 we have predicted patient inflow per weak for max of four weeks. In figure 11 we have taken the cumulative prediction in flow of patient for varied services such as surgery, diagnosis, general medicine, emergency. In figure 12 we have calculated cumulative RMS error for varied services per weak as follows 0.003, 002071, 0.002, 0.0027, 0.0024 respectively. In figure 13 we have calculated cumulative MSE error for varied services per weak as follows 0.06, 0.05, 0.04, 0.3 respectively.

CONCLUSION

Here we have proposed an approach which is based on back propagation neural network to predict the inflow of patient in hospital. In this paper, the prediction of patient inflow is developed using neural network. The experiment conducted shows that proposed prediction model perform better compared to similar approaches of the state of the art. Our prediction model achieves an overall RMS error around .003 and MSE error around 0.054 for a period of one month considering varied services in hospital industry which is better than most of existing prediction model.

In future we would integrating the proposed prediction model for better scheduling of patient which in turn will improve QoS of HRM and we also address some of the issue faced by our prediction model which is as follows (One of the issues with the Back Propagation NN training algorithm is the degree to which the weights are changed) Back Propagation algorithm had a problem in handle well scenarios when the error surface contains local minims. There is a high probability that the path chosen will lead the error decrease in the direction of local minima. Once it will achieve the point where it cannot decrease anymore (getting stuck into the deepening), it will stop looking for new paths (simply speaking it won't be able to "jump" out from the local minima "hole"). To overcome this issue we use a "smarter" way of searching the global minimum by using the Resilient Propagation algorithm which might give a better and accurate prediction model.

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