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EXAMINE VARIOUS FORECASTING METHODS FOR OUTPATIENT HEALTHCARE SERVICES USING ARTIFICIAL NEURAL NETWORKS.

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ABSTRACT

The artificial neural network approaches have been extensively utilized in various engineering and science aspects because it can incorporate both nonlinear and linear systems without needing to make assumptions as a regulatory in many traditional statistical models. The study examined various forecasting methods in healthcare services demand using artificial neural network model, secondly to develop a model for data mining in order to facilitate forecasting of healthcare demand services. Thirdly to analyse the prediction of demand of outpatient healthcare services using the Artificial Neural Network and lastly to evaluate artificial neural networks model for forecast of healthcare services. Health care managers and planners therefore must make future decisions about healthcare services delivery without knowing what will happen in the future. Forecasts would enable the managers to anticipate the future demand and plan accordingly. The MSE, RMSE, and MAPE were used to measure the expected level of fit of a predictive model.

Key Words: *Forecasting, Predictive, Demand, health sector, Artificial Neural network, Supervised Learning, Machine learning, WEKA, prototype.*

Introduction

Globally, medical resources are reported to be scarce because of the rapidly growing and aging populations, which are characterized by unequal proportions of health resources distribution and medical investments that are generally insufficient. This results in a fabulous gaping between demand and supply of these resources, while also causing the increase in attention on optimizing health resources management. This makes resource availability and heath demand forecasts to become very important. The outpatient department (OD) is concerned with external hospital services. This department is currently experiencing difficulties as the years go by due to the continually increasing patient volumes and the increasing health conditions complexity. Predicting outpatient visits is significant in enabling proper resource allocation and planning, while also enabling efficiency in scheduling of appointments in OD. This helps in crowd reduction and provision of health care services that are of high quality (Walkins, 2015). Furthermore, daily outpatient visit records are the major components to facilitate hospital management since they have a direct relation to the hospitalization services and the medical examinations workload. Information on outpatient types and amount can help to produce proper and reliable forecasts which facilitate allocation of the critical health resources (such as hospital beds, surgical and medical equipment) such forecasts when accurate can help managers in hospitals to come up with the appropriate decisions that can effectively meet the forecasted health care demand (Mouhib & Wael, 2008).

Globally, forecasting is aimed at influencing the supply of health products and medicines. Suppliers, who need to device long term investment decisions are key clients dependent on demand forecasts. In a bid to ensure the optimal drug availability and optimal prices, forecasting seeks sustainable timing and funding of orders. This motivates suppliers to make investments in production capacity (Abdulkader, 2006). Product Development Partnerships (PDPs), national and global health programs are other significant clients. Such clients need to design and size their chains of supply and to implement models that stimulate demand for the existing and new products, hence the need for demand forecasts. International and national technical funders and agencies also utilize demand forecasts to program, market, and budget segmentation decisions and in the production of health products.

Problem Statement

Even though healthcare industry in Kenya today generates large amounts of complex data about patients, hospitals resources, disease diagnosis, electronic patient records, and medical devices, there is lack of an intelligent and sophisticated system that can mine this big data and provide analytical patterns on healthcare services demand forecast in Kenya even though they exist in other developed countries (Neelam, 2006). Forecasts would enable the managers to anticipate future demand and plan accordingly. Lack of accurate and credible information about the future demand for essential healthcare services can costs lives. This is because gaps and weaknesses in demand forecasting result in a mismatch between supply and demand – which in turn leads to both unnecessarily high prices and supply shortages.

Insufficient accurate information concerning the need for crucial health amenities costs lives. When the demand forecast is not carried out properly while there are inherent uncertainties such as newer markets, there cannot be the efficient mobilization of the remaining supply chain in delivering treatment (Neelam, 2006). DM uses procedures and tools set incorporated to the information processed to expose concealed patterns which help health care managers to acquire additional knowledge source for decision making and forecasting (Prasanna, Kuo-Weim & Jaideep, 2011).

This technology enables the precision of various methodologies that can be utilized for problem-solving, decision making, estimation, innovation, and analysis, detection, planning, forecasting, and teaching (Salim et al., 2013). The Artificial Neural Network (ANN) approach poses more attractions compared to the various present data-driven methods like K-means and SOM, which are not able to handle advanced forecasting and data dimensionality. ANN approach formulation is smooth, parallel in nature, noise insensitive, and can support adoption in real-time situations. Wang et al. (2005) suggest that since the 1990s, ANN, as per the understanding of the brain and nervous system, is gradually used hydrological prediction. Kisi (2005) posits that ANNs have successfully been applied in various diverse fields such as health fields as noted by Tombul et al., (2006) the artificial neural network approaches have been extensively utilized in various engineering and science aspects because it has the ability to incorporate both nonlinear and linear systems without needing to make assumptions as a regulatory in many traditional statistical models. Therefore, this study aims at predicting demand for outpatient healthcare services using artificial neural networks

Objectives of the study

The main objective of this study was to predict the need for outpatient healthcare services using a plastic neural networks-based model.

i. To examine various forecasting methods in healthcare services demand using an artificial neural network model.
ii. To analyse the prediction of demand for outpatient healthcare services using the Artificial Neural Network.
iii. To evaluate artificial neural networks model for the forecast of healthcare services.

Research questions

The study focused on the following issues:

i. What are various forecasting methods in healthcare services demand using an artificial neural network model?
ii. What is the prediction of demand for outpatient healthcare services using an artificial neural network model?
iii. How to validate artificial neural networks model for the forecast of healthcare services?

Literature Review

Kesten & Armstrong (2012) describe the two most common types of neural networks applied in management sciences to be the feed-forward and recurrent neural networks in comparison with feed-forward systems common to medical applications. A feed-forward network can be single-layered (e.g., Perceptron, ADALINE) or multi-layered (e.g., Multilayer Perceptron, Radial Basis Function). Kesten & Armstrong (2012) describe information flow in feed-forward networks to be unidirectional from the input layer, through hidden layers to the output layer, without any feedback. Whereas, a recurrent or feedback network involves dynamic information processing having at least one feedback loop, using outputs as feedback inputs (e.g., Hopfield)

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An Artificial Neural Network (ANN) is an information processing paradigm that is inspired by the brain. ANNs, like people, learn by examples. An ANN is configured for a specific application, such as pattern recognition or data classification, through a learning process. Learning mostly involves adjustments to the synaptic connections that exist between the neurons. The model of Artificial neural network which can be specified by three entities.

Interconnection can be defined as the way processing elements (Neuron) in ANN are connected. Hence, the arrangements of these processing elements and geometry of interconnections are essential in ANN. These arrangements always have two layers, which are common to all network architectures, Input layer, and output layer, where the input layer buffers the input signal, and the output layer generates the output of the network. The third layer is the Hidden layer, in which neurons are neither kept in the input layer nor the output layer (Kesten & Armstrong, 2012). These neurons are hidden from the people who are interfacing with the system and acts as a black box to them. On increasing the hidden layers with neurons, the system’s computational and processing power can be improved, but the training phenomena of the system gets more complicated at the same time. A neural network without an activation function is essentially just a linear regression model. The activation function does the non-linear transformation to the input, making it capable of learning and performing more complex tasks. To put in simple terms, an artificial neuron calculates the ‘weighted sum’ of its inputs and adds a bias, as shown in the figure below by the net information.

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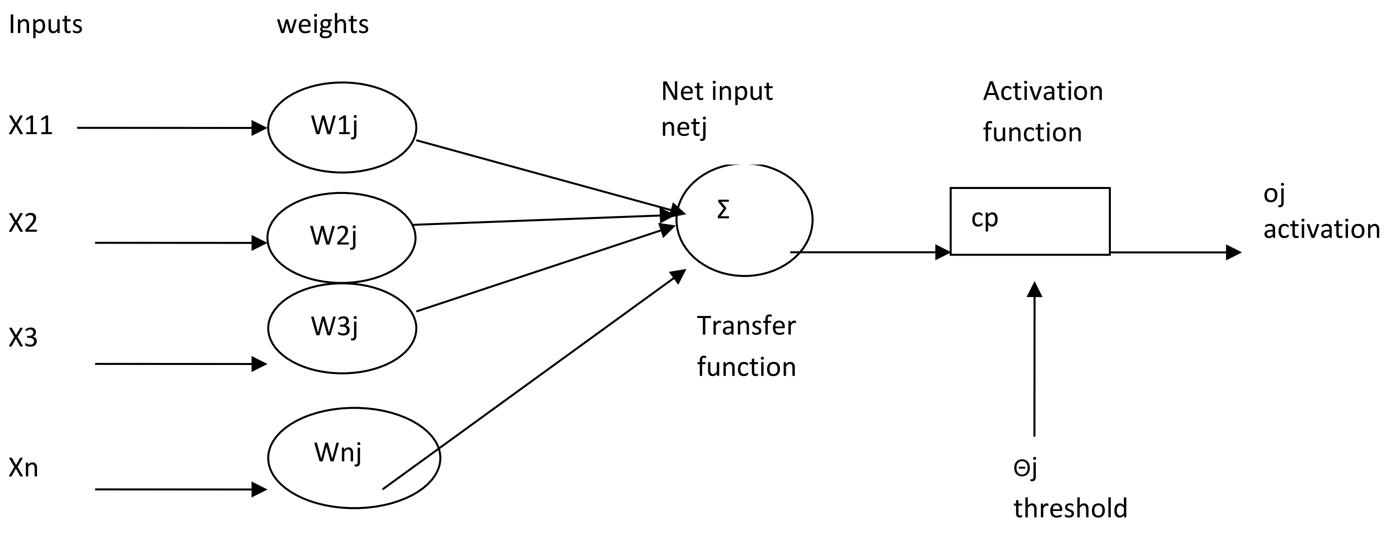

Figure 2. 1: Activation Architecture

There are many forecasting strategies that health care managers utilize for estimating future demands, planning, or solving other issues. Despite this, all forecasting methods have to adhere to a step by step process to be successful. This process consists of five main steps. Time horizon, forecast goal, and resource identification, forecast accuracy monitoring, conduction, and completion of the forecast and forecast techniques/ strategy selection.

Mostafa (2010) suggested a neural system-based method for foreseeing stock market developments in Kuwait. Kimoto et al. (1990) exhibited a way of utilizing a neural network system given historical accounting information and different macroeconomic parameters to predict varieties in stock returns. Leigh et al. (2005) exhibited techniques for utilizing direct relapse and straightforward neural system models for anticipating securities exchange records in the New York Stock Exchange utilizing stock trade information for the period 1981-1999. Hammad et al. (2009) showed an *artificial neural network* (ANN) models could be prepared with the goal that it unites and creates exceptionally exact aftereffects of determining stock costs. Dutta et al. (2006) utilized ANN models for accomplishing profoundly precise aftereffects of anticipating of Bombay Stock Exchange (BSE's) SENSEX week by week;

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shutting esteems for the time of January 2002 - December 2003. Leigh et al. (2005) utilized Bayesian Network (BN) – based way to deal with figure stock costs of 28 organizations recorded in DJIA (Dow Jones Industrial Average) amid 1988-1998. Tsai and Wang (2009) exhibited that BN-based methodologies, for the most part, create higher exactness in forecasting than common relapse and neural system-based methods. Tseng et al. (2012) displayed a work in which the creators connected customary *time series decomposition* (TSD), HoltWinters (H/W) models, Box-Jenkins (B/J) strategy and neural system-based ways to deal with 50 haphazardly chose stocks amid the period September 1, 1998 till December 31, 2010 at determining future stock costs. The creators saw that anticipating blunders are brought down for B/J, H/W; subsequently, this investigation will enhance B/J, H/W by utilizing standardized neural system show and limiting the mistakes by a mix of time arrangement deterioration and non-standardized neural system model to accomplish more exact outcomes. The main reason for all forecasting methods is to 'gauge' or measure or dole out esteem spoken to by a number to the interest variable at a future point in time. That is, these strategies gathered allocate the genuine estimation of the interest in the item, say x, at the next date. This again alludes to allocating esteems to the three parts of interest, in particular, the need, the readiness to purchase, and the capacity to acquire, i.e. buying power (Chendroyaperumal, 2009).

Research Design

The neural network's approach is one of the most important fields of Artificial Intelligence (AI), which is a modern science used in a lot of current and sophisticated applications, such as robotics industry systems, decision support systems, automated control systems, and identification and prediction systems. ANN approach is an efficient forecasting tool. This method consists of algorithms that mimic the features of the brain of human beings. These features are generating and exploring new knowledge by learning (Rudiger & Jochen, 2000). ANN consists of some elements that should be determined carefully because they affect the methods' forecasting performance. The essential factors that determine the ANN.

The architecture is determined by deciding the number of layers and number of neurons nodes in each segment and there is no general rule for determining the best architecture. The links

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that connect the neurons of a layer to the neurons of another layer are called weights. These weights are determined by a learning algorithm that updates their values (Moturi & Kioko, 2013).

The feed-forward backpropagation network is one of the most neural network architectures that is used widely for forecasting due to its simple usage and success. The multilayer feed-forward ANN consists of three parts: input, hidden, and output layers, as shown in Fig. 3.1 Each layer consists of neurons and stating the neurons number in each layer determines the architecture structure. Back Propagation algorithm is one of the most used learning algorithms which updates the weights based on the difference between the output value of the ANN and the desired real value (Mwangi, 2017). In the forecasting, the inputs are the past observations, and the output is the predicted value.

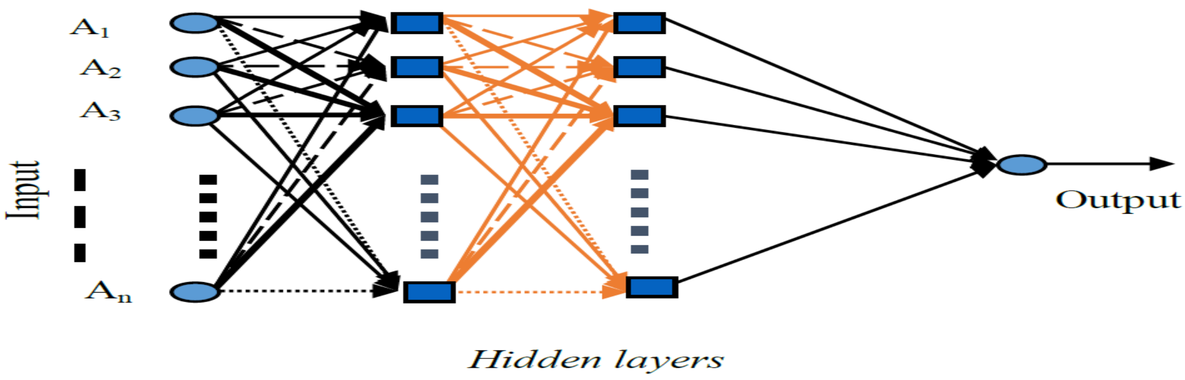

Figure 3. 1 *Multilayer Back Propagation Neural Network (BPNN* with One Output Neuron

The three-layer feed-forward Back Propagation Network (BPN) is the most popular neural network structure, which consists of an input layer, a hidden layer, and an output layer. The sheets are connected through the neurons of each adjacent layer. Due to the transfer process known as the activation function of the hidden layers, the network captures nonlinear phenomena. Information passes only from the forward layer, which is a designated synaptic weight, and then to the next connecting layers (Kesten & Armstrong, 2012). Each neuron j receives input signals from neuron i in the previous layer. This is obtained by:

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$y_j^n = f(net_j^n)$………………………………………………………….. (i)

Where y_j^n is the output of the layer; f is the activation function, widely employed by the logistic sigmoid, hyperbolic tangent sigmoid and squared functions, and net_j^n is the sum of the weight of the previous layer, which is calculated by:

$net_j^n = \sum_{n-1}^{n} w_{ij}^n y_i^{n-1} + b_j^n$ ……………………………….. (ii)

Model Training

During training, forecasting was carried out using 2 interval moving average. A moving average is a technique to get an overall idea of the trends in a data set; it is an average of any subset of numbers. The moving average is extremely useful for forecasting long-term trends. You can calculate it for any period. This is shown in the table below:-

Table 4. 1: Actual moving average forecast

YEAR	Hospitals	OP Actual Cases	OP Forecasted Cases
2017-2018	Westland health centre	27645	0
2017-2018	Mama Lucy Hospital	27274	27459.5
2017-2018	Mbagathi Hospital	26257	26765.5
2017-2018	Ruaraka Hospital	28043	27150
2017-2018	Mathari Hospital	17551	22797
2017-2018	Kayole Hospital	18148	17849.5
2017-2018	Pummwani Hospital	35274	26711
2017-2018	Ngara Health Centre	34897	35085.5
2017-2018	Penda Health care	26354	30625.5
2017-2018	Modern Komarocks	36880	31617
2017-2018	Oasis Health	18907	27893.5

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2017-2018	Umoja hospital	26038	22472.5
2017-2018	Unity Maternity &Nursing Home	30544	28291
2017-2018	Arrow Web Hospital	33714	32129
2017-2018	Ngaira health Centre	35485	34599.5
2017-2018	Nairobi Remand Prison	36751	36118
2017-2018	Police Band Dispensary	37809	37280
2017-2018	Makadara Health Centre	27975	32892
2017-2018	Lunga Lunga Health Center	32486	30230.5
2017-2018	Kasarani Medical Centre	23221	27853.5
2017-2018	Ruai Health Centre	20868	22044.5
2017-2018	Shauri Moyo Clinic	23320	22094
2017-2018	Eastleigh Health Centre	25111	24215.5

4.2.1 Mean Percentage Error

The mean percentage error (MPE) is the computed average of percentage errors by which forecasts of a model differ from actual values of the quantity being forecast. The mean absolute percentage error (MAPE), also known as mean absolute percentage deviation (MAPD), is a measure of prediction accuracy of a forecasting method in statistics, for example in trend estimation, also used as a Loss function for regression problems in Machine Learning. The mean percentage error is relative error expressed as a percentage. Thus, to obtain the percentage error we multiply the relative error by hundred.

MPE =$(\sum_{i=1}^{n} \frac{A-F}{A})/n$ ……………………….(iii)

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Table 4. 2: Mean Percentage error

YEAR	Hospitals	OP Actual Cases	OP Forecasted Cases	%Error
2017-2018	Westland health centre	27645	0	
2017-2018	Mama Lucy Hospital	27274	27459.5	0.68%
2017-2018	Mbagathi Hospital	26257	26765.5	1.94%
2017-2018	Ruaraka Hospital	28043	27150	-3.18%
2017-2018	Mathari Hospital	17551	22797	29.89%
2017-2018	Kayole Hospital	18148	17849.5	-1.64%
2017-2018	Pummwani Hospital	35274	26711	-24.28%
2017-2018	Ngara Health Centre	34897	35085.5	0.54%
2017-2018	Penda Health care	26354	30625.5	16.21%
2017-2018	Modern Komarocks	36880	31617	-14.27%
2017-2018	Oasis Health	18907	27893.5	47.53%
2017-2018	Umoja hospital	26038	22472.5	-13.69%
2017-2018	Unity Maternity &Nursing Home	30544	28291	-7.38%
2017-2018	Arrow Web Hospital	33714	32129	-4.70%
2017-2018	Ngaira health Centre	35485	34599.5	-2.50%
2017-2018	Nairobi Remand Prison	36751	36118	-1.72%
2017-2018	Police Band Dispensary	37809	37280	-1.40%
2017-2018	Makadara Health Centre	27975	32892	17.58%
2017-2018	Lunga Lunga Health Center	32486	30230.5	-6.94%

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2017-2018	Kasarani Medical Centre	23221	27853.5	19.95%
2017-2018	Ruai Health Centre	20868	22044.5	5.64%
2017-2018	Shauri Moyo Clinic	23320	22094	-5.26%
2017-2018	Eastleigh Health Centre	25111	24215.5	-3.57%
MEAN PERCENTAGE ERROR (MPE)				**2.15%**

The result shows that MPE is **2.15** indicating validity of forecasting. In mean percentage error calculation, the negative and positive values cancel out each other and the net error will be reduced to a greater extent. The comparison based on such values may lead to erroneous conclusions.

Mean Absolute Percentage Error

The comparison based on such values may lead to erroneous conclusions. The absolute percentage error overcomes this effect by taking the absolutes to calculate the mean. Thus, the Mean Absolute Percentage Error is considered a more robust measure.

Mean APE: $=(\sum_{i=1}^{n}\frac{IA-FI}{A})/n$ ……………………… (iv)

Table 4. 3: Mean Absolute Percentage Error

YEAR	Hospitals	OP Actual Cases	OP Forecasted Cases	%Error
2017-2018	Westland health centre	27645	0	
2017-2018	Mama Lucy Hospital	27274	27459.5	0.68%
2017-2018	Mbagathi Hospital	26257	26765.5	1.94%
2017-2018	Ruaraka Hospital	28043	27150	3.18%

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2017-2018	Mathari Hospital	17551	22797	29.89%
2017-2018	Kayole Hospital	18148	17849.5	1.64%
2017-2018	Pummwani Hospital	35274	26711	24.28%
2017-2018	Ngara Health Centre	34897	35085.5	0.54%
2017-2018	Penda Health care	26354	30625.5	16.21%
2017-2018	Modern Komarocks	36880	31617	14.27%
2017-2018	Oasis Health	18907	27893.5	47.53%
2017-2018	Umoja hospital	26038	22472.5	13.69%
2017-2018	Unity Maternity &Nursing Home	30544	28291	7.38%
2017-2018	Arrow Web Hospital	33714	32129	4.70%
2017-2018	Ngaira health Centre	35485	34599.5	2.50%
2017-2018	Nairobi Remand Prison	36751	36118	1.72%
2017-2018	Police Band Dispensary	37809	37280	1.40%
2017-2018	Makadara Health Centre	27975	32892	17.58%
2017-2018	Lunga Lunga Health Center	32486	30230.5	6.94%
2017-2018	Kasarani Medical Centre	23221	27853.5	19.95%
2017-2018	Ruai Health Centre	20868	22044.5	5.64%
2017-2018	Shauri Moyo Clinic	23320	22094	5.26%
2017-2018	Eastleigh Health Centre	25111	24215.5	3.57%
Mean Absolute Percentage Error				**10.02%**

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The mean absolute percentage error (MAPE) is the mean or average of the absolute percentage errors of forecasts. Error is defined as actual or observed value minus the forecasted value. Percentage errors are summed without regard to sign to compute MAPE. This measure is easy to understand because it provides the error in terms of percentages. Also, because absolute percentage errors are used, the problem of positive and negative errors canceling each other out is avoided. Consequently, MAPE has managerial appeal and is a measure commonly used in forecasting. The smaller the MAPE the better the forecast. The result shows that MAPE is **10.02** indicating validity of forecasting. Therefore, this is a good MAPE in the forecasting.

Mean Square error

The Mean Square error enhances the error that is appearing in absolute percentage error. As this is a squared error the outliers are given more weight. The comparison based on this measurement is better and accurate

Mean Square Error: $=(\sum_{i=1}^{n}\frac{(A-F)2}{A})/n$ ……………….. (v)

The smaller the means squared error, the closer you are to finding the line of best fit. Depending on your data, it may be impossible to get a very small value for the mean squared error. For example, the above data is scattered wildly around the regression line, so 6.08 or below is as good as it gets (and is in fact, the line of best fit).

Table 4. 4: Mean Square Error

YEAR	Hospitals	OP Cases	Actual	OP Forecasted Cases	%Error
2017-2018	Westland health centre	27645		0	
2017-2018	Mama Lucy Hospital	27274		27459.5	0.00%
2017-2018	Mbagathi Hospital	26257		26765.5	0.04%
2017-2018	Ruaraka Hospital	28043		27150	0.10%
2017-2018	Mathari Hospital	17551		22797	8.93%

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2017-2018	Kayole Hospital	18148	17849.5	0.03%
2017-2018	Pummwani Hospital	35274	26711	5.89%
2017-2018	Ngara Health Centre	34897	35085.5	0.00%
2017-2018	Penda Health care	26354	30625.5	2.63%
2017-2018	Modern Komarocks	36880	31617	2.04%
2017-2018	Oasis Health	18907	27893.5	22.59%
2017-2018	Umoja hospital	26038	22472.5	1.88%
2017-2018	Unity Maternity &Nursing Home	30544	28291	0.54%
2017-2018	Arrow Web Hospital	33714	32129	0.22%
2017-2018	Ngaira health Centre	35485	34599.5	0.06%
2017-2018	Nairobi Remand Prison	36751	36118	0.03%
2017-2018	Police Band Dispensary	37809	37280	0.02%
2017-2018	Makadara Health Centre	27975	32892	3.09%
2017-2018	Lunga Lunga Health Center	32486	30230.5	0.48%
2017-2018	Kasarani Medical Centre	23221	27853.5	3.98%
2017-2018	Ruai Health Centre	20868	22044.5	0.32%
2017-2018	Shauri Moyo Clinic	23320	22094	0.28%
2017-2018	Eastleigh Health Centre	25111	24215.5	0.13%
Mean Square Error				**2.32%**

The result shows that MSE is **2.32%**indicating validity of forecasting

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Root Mean Squared Errors (RMSE) Analysis

Table 4.3 report the RMSEs of Group 3 data where the minimum error statistics are shown in bold. As shown in Table 4.2, the combined model has the lowest median RMSE as well as the lowest statistics for all other percentiles. The superiority of the combined method over the other two methods is obvious. Despite their volatility, at times these forecasts are the most accurate for a specific hospital. By generating and reporting all three forecasts, individual hospitals managers might be able to develop heuristics to better incorporate the information of a preferred method for his or her department. Because of heteroscedasticity between hospitals, few (if any) valid statistical significance tests can be performed on the results of Table 4.4.

Root Mean Squared Errors (RMSE) for Out-of-Sample Forecasts

The term root mean square error (RMSE) is the square root of mean squared error (MSE). RMSE measures the differences between values predicted by a hypothetical model and the observed values. In other words, it measures the quality of the fit between the actual data and the predicted model.

Univariate analysis is the simplest form of data analysis where the data being analyzed contains only one variable. Since it's a single variable it doesn't deal with causes or relationships. The main purpose of univariate analysis is to describe the data and find patterns that exist within it.

Table 4. 5: Root Mean Squared Error

Elements	Univariate	Multivariate	Combined
Mean	76.8	75.2	**66.8**
5 Percentile	22.9	25.6	**21.9**
25 Percentile	40.7	45.3	**38.9**

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Median	74.0	68.9	**66.3**
75 Percentile	101.6	87.1	**86.1**
95 Percentile	132.9	142.1	**118.0**
Hospitals	**23**	**23**	**23**

Multivariate analysis on the other hand is the analysis of three or more variables. There are many ways to perform multivariate analysis depending on your goals. The two combined will also give different results as shown in Table 4.5.

To better judge model accuracy, the symmetric median absolute percentage error (SAPE) has become a statistic often used when judging the accuracy of different methods across different time series. Table 4.6 illustrates the accuracy of the three methods based on the SAPE.

Table 4. 6: Symmetric Absolute Percent Error for 23 hospitals

Elements	**Univariate**	**Multivariate**	**Combined**
Mean	8.0	8.8	**7.3**
5 Percentile	3.4	3.2	**2.7**
25 Percentile	5.1	5.0	**4.7**
Median	7.6	7.8	**6.8**
75 Percentile	9.6	11.4	**8.6**
90 Percentile	13.1	13.9	**10.6**
95 Percentile	16.0	19.4	**17.0**
Hospitals	**23**	**23**	**23**

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Forecasting methods Comparison

For the Linear Regression, Weighted Moving Average, and SVR the same inputs as the ones described for the Neural Network were used (except for the bias). Results obtained using these four methods for the validation sets of all hospitals are displayed in Table 4.8.

Table 4.8: Forecasting Comparison MAPE

	Linear Regression	**Weighted Moving Average**	**Neural Network**	**SVR**	**Average**
	MAPE	**MAPE**	**MAPE**	**MAPE**	**MAPE**
Outpatient Demand	12.67%	**10.02%**	**3.30%**	**5.30%**	7.8%
Lab test Demand	6.54%	7.36%	4.99%	**5.09%**	6.0%
Medical Demand	15.91%	16.50%	3.70%	**6.86%**	10.7%
Antenatal Demand	8.55%	8.96%	5.30%	**5.88%**	7.2%
Radiology Demand	8.41%	8.60%	5.12%	**0.36%**	5.6%
Obstetric Demand	8.27%	11.83%	6.90%	**6.97%**	8.5%
Maternity Demand	10.54%	6.98%	6.60%	**3.24%**	6.8%

As shown in Table 4.8, in four out of seven cases best results are obtained with neural network, when using MAPE as criterion to compare the performance of the different models. When using MAPE as criterion for comparison, neural network appears as the best option for demand forecasting in all cases. These results were obtained using the Neural Network library from WEKA. These results show that WEKA Forecasts using neural network algorithm gives a more accurate forecast results than the Moving Averages and Linear Regression and hence gives a more reliable results for the demand forecast. Testing of accuracy considered multiple variables – Since several factors affect the demand of the health services in Public hospitals as outlined above, this was also put into test. The results showed that if these factors were left out, the results were different from when included, and indeed lesser values of prediction. When we combine Neural network and SRV, the results are as shown in the table below:-

Table 4. 91: The Average of two best methods

Neural Network MAPE	**SVR MAPE**	**Average MAPE**
3.30%	**5.30%**	4.3%
4.99%	**5.09%**	5.0%
3.70%	**6.86%**	5.3%
5.30%	**5.88%**	5.6%
5.12%	**0.36%**	2.7%
6.90%	**6.97%**	6.9%
6.60%	**3.24%**	4.9%

The Table 4.9 indicates that Neural network and SVR method gives the best overall method in terms of data validity in predicting the demand forecast of hospital. Therefore, this study suggests use of combination of Neural network and Support vector

Conclusion

The results show that WEKA Forecasts using neural network algorithm gives a more accurate forecast results than the Moving Averages and Linear Regression and hence gives a more reliable results for the demand forecast. Testing of accuracy considered multiple variables – Since several factors affect the demand of the health services in Public hospitals as outlined above, this was also put into test. The MSE, RMSE, and MAPE can be used to measure the expected level of fit of a predictive model. If a model fits the training data set very well but does not fit the validation data, it is called overfitting. A good predictive model is supposed to

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generate consistent results in both training and validating data sets. This is confirmed by regression model and artificial neural network model. These four tests were used to confirm the accuracy of the forecast results from the model. The results of the model show a trend where the patients visiting the medical facilities is increasing steadily in all forecasts done.

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