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PREDICTING DEMAND 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 specific objectives of this study first was to examine 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. This study aimed at examining artificial neural network as an approach to health services demand forecast in Nairobi County in Kenya. The model was trained under the WEKA environment and applied to predict the demand for health services in various categories for private health care providers in Nairobi county Kenya. 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 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 generate consistent results in both training and validating data sets. This is confirmed by regression model and artificial neural network model.**

1. INTRODUCTION

Health care is possibly the most important industry in Kenya for the application of process improvement techniques because of its sheer size, its current performance with respect to efficiency, and its central place in our society. Neural Networks (NNs) are flexible non-linear data driven models that have attractive properties for forecasting. Statistical methods are only efficient for data having seasonal or trend patterns, while artificial neural techniques can accommodate the data influenced by the special case, like promotion or extreme crisis demand fluctuation. (Nikolaos & Kourentzes, 2013). Artificial intelligence forecasting techniques have been receiving much attention lately in order to solve problems that are hardly solved using traditional methods. ANNs have the ability to learn like humans, by accumulating knowledge through repetitive learning activities. Animal brain's cognitive learning process is simulated in ANNs. ANNs are proved to be efficient in modeling complex and poorly understood problems for which enough data are collected. ANN is a technology that has been mainly used for prediction, clustering, classification, and alerting of abnormal patterns.

1.1 Problem Statement

Health information and healthcare data analytics have been extensively used to measure health indicators, comparative analysis for planning and administration of quality health services and scientific research across the globe (Tombul et al., 2006). However, the current situation is that healthcare managers and planners must make future decisions about healthcare services delivery without knowing what will happen in the future. 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 the future demand and plan accordingly. Lack of accurate and credible information about the future demand for essential healthcare services can actually 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 key health amenities costs lives. When demand forecast is not carried out properly while there are inherent uncertainties such as newer markets, there cannot be 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 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 approaches like K-means and SOM, which are not able to handle advanced forecasting and data dimensionality. ANN approach formulation is easy, parallel in nature, noise insensitive and can support adoption in real time situations. Wang et al, (2005) suggests 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

1.2 Objectives of the study

The main objective of this study was to predict demand for outpatient healthcare services using artificial neural networks-based model.

i. To examine various forecasting methods in healthcare services demand using artificial neural network model.

ii. To analyse the prediction of demand of outpatient healthcare services using the Artificial Neural Network.

iii. To evaluate artificial neural networks model for forecast of healthcare services.

1.3 Research questions

The study focused on the following questions:

i. What are various forecasting methods in healthcare services demand using artificial neural network model?

ii. What is the prediction of demand of outpatient healthcare services using artificial neural network model?

iii. How to validate artificial neural networks model for forecast of healthcare services?

2. EMPIRICAL ANALYSIS

As indicated by Kesten & Armstrong (2012) demand forecasters can consult various existing forecasting systems and techniques. These strategies can be assembled into 17 classifications. Twelve depend on judgment, specifically unaided judgment, expert surveys, decomposition, 4 organized analogies, judgmental bootstrapping, game theory, intentions and expectations survey, experimentation, expectation markets, simulated interaction and conjoint analysis. The five strategies that remain require quantitative information. They are extrapolation, causal models, and quantitative analogies, govern based estimating and neural nets,

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While it is past the extent of this proposition to present a thorough portrayal of forecasting strategies the section beneath features a couple of methods that require data mining and quantitative data. Judgmental forecasts depend on investigation of such subjective contributions as official suppositions, contracts/insurance/POS organization estimates, client surveys, mental appraisals of the market, instinct, outside (expert) sentiments, and the views of directors and staff. Health care managers may utilize staff to create a judgmental forecast or a few conjectures from which to pick from. Lawrence (2015) inferred that individuals can perform like computers and advanced techniques in extrapolating patterns. These outcomes were gotten even though the general population had no data other than the historical information on the forecasted series. As such, the extrapolation by individual depended on indistinguishable data from the computer extrapolation. Recent outcomes in Lawrence, Edmundson, and O'Connor (2016) bolster Lawrence's initial discoveries. These investigations recommend that further research is required on when and how to utilize judgment for extrapolation, this examination is planned erase such doubts. For additional investigation on extrapolation, trial plans ought to be utilized to survey speculations on every part in particular circumstances (for instance, what is the benefit of lessening the pattern where substantial changes are anticipated?), the evaluation of the best method to utilize specialists, the utilization of consolidated estimates, and the most ideal approach to evaluate vulnerability. This study will endeavor to utilize test designs on anticipating the outpatient request services by joining forecast models to bring out forecasts that are more accurate.

Abdel-Aal et al (2016) fit a univariate ARIMA model to 108 months of monthly patient visit volume data for a primary care clinic using univariate Box-Jenkins methods. This model was utilized to predict visits over the 24-month period that followed. The clinic center served a populace of 13,000 and no specific age range or patient populace subtle elements were talked about. The visits information demonstrated an exceptionally standard rehashing design with expanding pattern in the month to month visits. Visits ran from around 400 to 850 patients over the 11-research period. The investigation found that the ARIMA models had an anticipating precision with a mean total rate blunder of 1.86% and a most extreme outright rate mistake of 4.23% throughout the last two data years. Since the visit design was so normal, this investigation likewise considered a basic impromptu extrapolation strategy for producing forecasts (alluded to as extrapolating the growth curve) which included utilizing past visits estimations multiplied by a factor decided utilizing the proportion of past visits demonstrating foreseen development. In our investigation we will utilize ad-hoc strategy to create more precise forecasts with mean outright rate mistake of 0.55% and a most extreme supreme rate blunder of 1.17% by centering information of two last data years.

3. RESEARCH DESIGN

The neural networks approach is one of the most important fields of Artificial Intelligence (AI), which is a modern science used in a lot of modern and complex 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 brain of human being. 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 effect the methods' forecasting performance. The essential elements that determine the ANN are:

3.1 Architecture structure and learning algorithm.

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

Feed-forward back propagation network is one of the most neural networks 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

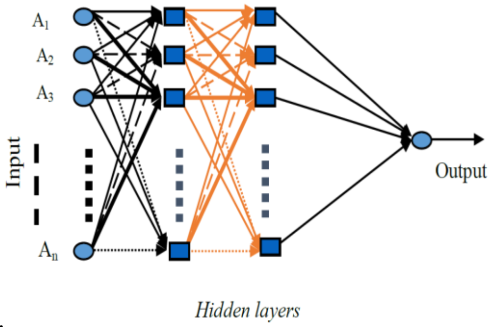

Figure 3.1 Multilayer Back Propagation Neural

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 layers 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:

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

3.2 Selected method

An Artificial Neural Network (ANN) is a system based on the operation of biological neural networks. The model is founded upon the functionality of a biological neuron. Software implementation of a neural network can be made with their advantages and disadvantages. The advantages include: A neural network can perform tasks that a linear program cannot; when an element of the neural network fails, it can continue without any problem by their parallel nature; a neural network learns and does not need to be reprogrammed; can be implemented in any application; and can be implemented without any problem. The disadvantages include neural network needs training to operate; architecture of a neural network is different from the architecture of microprocessors therefore needs to be emulated; requires high processing time for large neural networks. ANN is an adaptive, most often nonlinear system that learns to perform a function from data (Chendroyaperumal, 2009). ANN is built with a systematic step-by-step procedure to optimize a performance criterion or to follow some implicit internal constraint, which is commonly referred to as the learning rule. The input/output training data are fundamental in neural network technology, because they convey the necessary information to "discover" the optimal operating point. The nonlinear nature of the neural network processing elements provides the system with lots of flexibility to achieve practically any desired input/output map.

The key factors that make ANN highly suitable for demand forecasting include it does not require any pre-assumed functional relationship between the factors of demand like Income, Population and Literacy levels (Moturi & Kioko, 2013).

3.3 Training of Artificial Neural Networks

ANN must be configured such that the application of a set of inputs produces the desired set of outputs. Various methods to set the strengths of the connections exist. One way is to set the weights explicitly, using a priori knowledge. Another way is to 'train' the neural network by feeding it teaching patterns and letting it change its weights according to some learning rule. The learning situations can be categorized in two distinct sorts: *Supervised Learning* or Associative Learning in which the network is trained by providing it with input and matching output patterns (Moturi & Kioko, 2013). In this research and model building, we used a supervised ANN model using the actual demand data system.

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3.4 Study Population

The study concentrated on both public and private hospitals within Nairobi County. The hospitals will form study population.

3.5 Data Collection Methods

Data collection instrument was developed to help in collecting monthly outpatient data from the hospital register. The instrument will contain outpatient register data from the year 2012- 2017. This will give six years data which were broken down into monthly data giving 72 data points to be used in this study. To facilitate the analysis of the data was classified the 72 data points into monthly, quarterly, and yearly data values.

Data Attributes

- Age- Age of the patients
- Gender- gender of the patients
- Type of disease diagnosed
- Frequency of visits

3.6 Model Training and Analysis

Data training was conducted before forecasting can be done. The forecasting ability is compared based on two types of statistical parameters: measures of central tendency and the measures of dispersion. There are several methods used to measure the concept of "central tendency." In this thesis we considered only the mean and medians. The mean gives equal weight to each observation and may be considered the "balance point" of the data (Chendroyaperumal, 2009). The error in the data sometimes influences the mean to an unfair degree. In this situation we would consider median: that is, we arrange the observations in numerical order from the highest to lowest, or vice versa, and then select the midpoint of the arranged data as our average. The measures of central tendency are: MAPE (Mean Absolute Percentage Error), Median APE (Median Absolute Percentage Error), MPE (Mean Percentage Error), MSE (Mean Square Error). The measure of dispersion can be used as the measure of the spread of a distribution. For some distributions (series of data) there is a possibility of having the same mean, but the values may be spread over a wider region. In this case the measure of dispersion helps to find which series is better (Moturi & Kioko, 2013). Definitely, the series that is having lesser dispersion (of observations) is better than the series that disperses more. The measures of dispersion considered are: MD (Mean Deviation), MAD (Mean Absolute Deviation), Variance, Coefficient of Variance, Theil's U Coefficient. The descriptions of these measurements are:

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)

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. 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)

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 measures of dispersion compare the range of performance of a method. The mean deviation is one such measure. The deviation is computed with respect to the mean of a series. In the equation below the dispersion (of forecasted values) is measured with respect to the actual data series

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Mean Deviation (μ): $=(\sum_{i=1}^{n} \frac{(A-F)}{n})$ ……………………(vi)

In computing mean deviation, the positive and negative deviations may cancel out each other. Comparison based on such value may lead to erroneous conclusions. The absolute deviation overcomes this affect and gives the absolute deviation from the actual series.

Mean Absolute Deviation $=(\sum_{i=1}^{n} \frac{I(A-F)I}{n})$ ……… (vii)

Because of the modulus sign which was used in the mean absolute deviation and the consequent awkward algebraic manipulation the mean deviation is not easy to use. A far more useful measure is the variance that uses the square deviation, which are all positive and hence de not cancel out each other

Variance $==(\sum_{i=1}^{n} \frac{[I(A-F)I-\mu]2}{n})$ ………………… (viii)

The coefficient of variance can be used to give some measure of the relative importance of the standard deviation (square root of variance) referred to mean. For example: (a) A standard deviation of one ft in the measurement of the lengths of planks whose average length is hundred ft, (b) the same variation of one ft in the measurement of planks whose average length is five ft. Obviously the spread about the mean of the lengths in case (a) is less important than the spread in case (b). The coefficient of variance is used in such instances to decide the relative precision.

Coefficient of Variance = $\frac{1}{A}\sqrt{\frac{1}{n}\sum_{i=1}^{n}(F-A)2}$ ………… (ix)

The Theil's U-coefficient computes the goodness of the formal method as compared with naive method. The drawback of this measure is that its interpretation is not straightforward. Mathematical expression for Theil's U -coefficient is

Theil's U Coefficient $\sqrt{\frac{\sum_{i=1}^{n-1}\left(\frac{F_{i+1}-A_{i+1}}{A_i}\right)^2}{\sum_{i=1}^{n-1}\left(\frac{F_{i+1}-A_{i+1}}{A_i}\right)^2}}$

4. DATA PREPARATION AND CHARACTERISTICS

The data was collected from 23 hospitals across Nairobi County. The list of hospitals where data was collected is presented in the Table 4.1.

Table 4.1: Name of the Hospitals

	Name of the Hospitals		Name of the Hospitals
1	Westland health centre	13	Unity Maternity &Nursing Home
2	Mama Lucy Hospital	14	Arrow Web Hospital
3	Mbagathi Hospital	15	Ngaira health Centre
4	Ruaraka Hospital	16	Nairobi Remand Prison
5	Mathari Hospital	17	Police Band Dispensary
6	Kayole Hospital	18	Makadara Health Centre
7	Pummwani Hospital	19	Lunga Lunga Health Centre
8	Ngara Health Centre	20	Kasarani Medical Centre
9	Penda Health care	21	Ruai Health Centre
10	Modern Komarocks	22	Shauri Moyo Clinic
11	Oasis Health	23	Eastleigh Health Centre
12	Umoja hospital		

Data Collected was for the year 2017 and 2018 and it was done manually in all the hospitals where records were checked, filled and data collected form was filled. The Characteristics and elements of respondents which were being investigated include, gender, age, marital status, education status, and the number of patients admitted for a given type of disease in one year. The characteristics for Mbangathi hospital are recorded in Table 4.2.

Table 4.2: July 2017-June 2018 Data Mbagathi Hospital

Characteristics	N	Percentage
Sex		
Male	2632	28.73
Female	6527	71.26
Age		
< 20 years	586	6.4
20- 39 years	2604	28.43
40 -59 years	4181	45.64
≥ 60 years	1739	18.98
Marital status		
Single	1343	14.66
Married	6601	72.06
Divorced	809	8.83
Widowed	214	2.34
Unknown	169	1.84
Educational status		
No schooling	142	1.55
Primary level	6263	68.37
Secondary level	1646	17.97
Occupational level	292	3.19
Higher education level	684	7.47
Unknown	133	1.45

From Table 4.2, the study found that female was 71% while male was 28.73 showing that many females were visiting Mbagathi hospitals between the year 2017-2018. Majority were aged between 4-59 years giving 45%. In terms of marital status majority are married giving72% while most of the outpatient are having primary level of education at 68.37%.

4.2 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 4.3: 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
2017-2018	Umoja hospital	26038	22472.5
2017-2018	UnityMaternity &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)

Table 4. 4: 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%

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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 PERCENTAGE ERROR (MPE)				**2.15%**

The result shows that MPE is 2.15% indicating validity of forecasting.

4.2 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 4.5: 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%
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%**

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.

5. SUMMARY

In Kenya today, the healthcare managers and planners must make future decisions about healthcare services delivery without knowing what will happen in the future. This is because there does not exist an intelligent and sophisticated system that can mine this big data and provide analytical patterns on healthcare services demand forecast in Kenya. Forecasts would enable the managers to anticipate the future demand and plan accordingly make the necessary adjustments. The main objective of this project was to examine data mining as an approach to public health services demand forecast in Nairobi County. Specifically, we set out to explore the various forecasting methods in healthcare services demand, identify the most suitable healthcare services demand forecasting methods for Nairobi County and finally develop and validate a data mining model for forecast of public and private healthcare services demand for Nairobi County. 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 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 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.

Conclusion and Recommendation

Estimating future capacity and demand in a medicinal service setting and advanced the notion that when underlying demand issues are analyzed, it can be valuable in building up a more vigorous forecast. Therefore, there is need to concentrate on estimating the demand of hospital space for budgeting and planning. For this data to function accurately, it largely depends on central availability of accurate data from all hospitals in the county for all medical cases attended to. My recommendations to the county government and the implementers of Kenya Health Information System in the Ministry of health is to get all data from all hospitals and in the country to enhance the functioning of forecasting models built from such data.

REFERENCES

[1] Abdel-Aal et al.(2016) "Recruitment and Selection Practices in Manufacturing SMEs in Japan: An analysis of the link with business performance". Ruhuna Journal of Management and Finance, Volume 1 Number 1, ISSN 2235-9222.

[2] Computers in Biology and Medicine.

[3] Abernethy, M. (2010). Data mining with WEKA, Part 1: Introduction and regression. Retrieved March 12, 2014, from http://www.ibm.com/developerworks/library/os-weka1

[4] Balaji, D. (2011). Forecasting the Demand of Pharmaceutical Product Based on Its Sales Record. National Conference on Emerging Research and Advances in Mechanical Sciences (pp. 13-18). Chennai: Dept. of Mechanical Engineering College of engineering, Guindy Anna University.

[5] Beech (2001). Application of Data Mining Techniques to Healthcare Data. STATISTICS FOR HOSPITAL EPIDEMIOLOGY, 25(8).

International Journal of Novel Research in Computer Science and Software Engineering
Vol. 6, Issue 3, pp: (1-11), Month: September - December 2019, Available at: www.noveltyjournals.com

[6] Cote and Tucker (2001) Choice of models for the analysis and forecasting of hospital beds. Health Care Management Science 8: 221–230

[7] Chendroyaperumal, C. (2009). DEMAND FORECASTING TECHNIQUES: AN EVALUATION. National Institute of Management Studies. Retrieved March 8, 2018, from www.researchgate.net

[8] Cones et al. (2008)Shortterm patient census forecasting models. Hospital Financial Management 34 (11): 38.

[9] Mackay, M and M. Lee. 2005. Choice of models for the analysis and forecasting of hospital beds. Health Care Management Science 8: 221–230

[10] Mostafa (2010) Forecasting: Methods and Applications. Hoboken, NJ: John Wiley and Sons.

[11] Diaz et al. (2015). Principles of forecasting: a handbook for researchers and practitioners. Norwell, MA: Kluwer Academic Publishers.

[12] Hans, L. (2013). Predictive Analytics for Demand Forecasting and Planning Managers – A Big Data Challenge. (S. K. KAIST College of Business, Ed.) Delphus Inc, .

[13] Harleen, K., & Siri, K. W. (2006). Empirical Study on Applications of Data Mining Techniques in Healthcare. Journal of Computer Science, 2(2), 194-200.