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Trend Analysis of Herbal Medicines in the Treatment of Diabetes a Case Study in the Kumasi Metropolis

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ABSTRACT **Original Research Article**

Diabetes is a chronic disease that arises when the pancreas fails to produce sufficient insulin or when the body is unable to effectively utilize the insulin it produces.

It is one of the major causes of premature illness and non -communicable diseases accounting for 60% of all death worldwide. This research was undertaken to unfold the current pattern of diabetes cases in the Kumasi Metropolis and to come out with an adequate model for forecasting future trends. Therefore, the research questions include; what is the trend and an adequate model for forecasting future diabetes cases in Kumasi Metropolis? A seven year (2006-2013) secondary data was used for this study. .It was sourced from the Amen scientific herbal clinic with which a time series trend analysis was used to perform the trend analysis using Minitab version 16. The model developed from quadratic trend was Y(t)=36.78+0.0275*t-0.00354*t2. Analysis of the data was carried out using the Box – Jenkins ARIMA (ARIMA) approach with the help of Gretl.

The presence of unit root was tested using the ADF test on the time series data from the year 2006 – 2013. The p – values of the ADF showed the stationarity of the data therefore data is good for ARIMA. This research was undertaken with the prior motive to develop an adequate model for forecasting future trends. It evolved that ARIMA (1, 1,1) fits the data well.

We therefore recommend that it should be used in forecasting future cases of this disease.

Keywords: Diabetes, Trend Analysis, Time Series, Forecasting, Stationarity.

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Introduction

The utilization of Alternative Medicine (AM) has increased globally and has drawn significant attention from researchers. This growing interest is largely driven by concerns that, despite being widely perceived as harmless, some alternative therapies may pose potential risks to patients. Alternative Medicine encompasses a broad range of therapeutic practices that fall outside conventional medical systems. These practices may be classified into pharmacological approaches, such as herbal medicine and homeopathy; physical therapies, including acupuncture and chiropractic care; dietary interventions, such as macrobiotic and vegetarian diets; and cognitive or mind–body techniques, including hypnosis. Although AM represents a diverse and heterogeneous field, the present study specifically focuses on examining the application of homeopathy and its effects on diabetes (Al-Rowais, 2002).

Herbal medicine comprises the use of herbs, herbal materials, herbal preparations, and finished herbal products in which the active ingredients are derived from plant sources. Herbs refer to raw plant materials such as leaves, flowers, fruits, seeds, stems, wood, bark, roots, rhizomes, or other plant parts, which may be used in their whole, fragmented, or powdered forms (WHO, 2014).

Historically, medicinal plants have played a central role in the prevention and treatment of various human diseases across different cultures. One such condition for which herbal remedies have been traditionally utilized is diabetes mellitus. Diabetes is primarily characterized by persistent hyperglycaemia, which increases the risk of microvascular complications such as retinopathy, nephropathy, and neuropathy. The disease is also associated with reduced life expectancy, considerable morbidity resulting from diabetes-specific complications, and an elevated risk of macrovascular disorders including ischaemic heart disease, stroke, and peripheral vascular disease. In addition, diabetes significantly impairs overall quality of life. Clinically, diabetes is defined as a chronic metabolic disorder that arises either from insufficient insulin production by the pancreas or from the body's inability to effectively utilize the insulin produced (WHO, 2006).

Diabetes mellitus is broadly classified into three main types. Type 1 diabetes, also referred to as juvenile or insulin-dependent diabetes, occurs when the immune system destroys the pancreatic beta cells responsible for insulin production. Consequently, the pancreas loses its capacity to produce adequate insulin required for proper regulation of blood glucose levels. This form of diabetes is commonly diagnosed during childhood and, although manageable with lifelong insulin therapy, remains incurable. Type 2 diabetes accounts for over 90 percent of all diabetes cases and typically develops during adulthood. It arises when insulin secretion is insufficient or when insulin resistance prevents normal regulation of blood glucose levels. The condition is strongly linked to lifestyle factors such as unhealthy dietary habits, physical inactivity, and obesity, and its prevalence increases with age. The third category, gestational diabetes, is characterized by elevated blood glucose levels that occur during pregnancy in women without a prior history of diabetes. While gestational diabetes often resolves after childbirth, affected women face a higher risk of developing type 2 diabetes later in life (Baker et al., 2011).

Diabetes is a chronic metabolic disorder and may also be associated with genetic syndromes, surgical interventions, drug use, malnutrition, infections, and other underlying illnesses (Kim et al., 2011). The complexity of the disease and its multifactorial nature have made its management a major global health concern.

Although Western medical practice has often questioned or downplayed the efficacy of many traditional herbal remedies, medicinal plants continue to play a vital role in the health care systems of indigenous and rural communities. It is estimated that nearly one-quarter of modern pharmaceutical prescriptions are derived from plant sources or plant-based synthetic compounds, while approximately 80 percent of the world's population—particularly in developing countries—still relies largely on herbal medicines for primary health care. Despite remarkable advances in conventional medicine, herbal medicine remains highly significant within many cultural and social contexts (WHO, 2002).

The global prevalence of diabetes across all age groups was estimated at 2.8 percent in the year 2000 and is projected to rise to 5.4 percent by 2025. Current therapeutic options for diabetes management include insulin therapy and various oral hypoglycaemic agents such as sulfonylureas, biguanides, α-glucosidase inhibitors, and glinides. However, in many developing countries, these treatments are often expensive and not readily accessible. In addition, the side effects associated with some oral antidiabetic drugs have contributed to increasing interest in alternative treatment options, particularly herbal remedies. As a result, traditional plant-based medicines continue to be widely used and play an important role in diabetes management. In recent years, herbal medicines have gained prominence as potential sources of hypoglycaemic agents. Marles and Farnsworth (1995) estimated that more than 1,000 plant species are used worldwide in traditional medicine for the treatment of diabetes. The antidiabetic properties of these plants are largely attributed to their bioactive constituents, including phenolic compounds, flavonoids, terpenoids, coumarins, and other phytochemicals known to reduce blood glucose levels. Due to their perceived effectiveness, relatively low cost, and fewer reported side effects, herbal drugs are commonly prescribed and utilized.

Against this background, the present study seeks to investigate traditional herbal medicine practices among indigenous communities in Ghana. Specifically, the study examines the relevance of herbal medicine in contemporary health care delivery, explores public attitudes toward herbal medicine, and assesses the level of collaboration between traditional healers and orthodox medical practitioners in promoting an effective health care system in Ghana.

According to a World Health Organization (WHO) report, approximately 347 million people worldwide were living with diabetes as of 2012. In 2004, an estimated 3.4 million deaths were attributed to complications arising from high blood glucose levels, with more than 80 percent of these deaths occurring in low- and middle-income countries. Although diabetes was once considered relatively rare in sub-Saharan Africa, its prevalence has increased rapidly in recent decades. By 2010, over 12 million people in the region were living with diabetes, and approximately 330,000 deaths were linked to diabetes-related conditions. Projections indicate that by 2030, about 26.9 million people in sub-Saharan Africa will be affected by diabetes. Prevalence estimates vary widely across countries, ranging from 60 percent in Cameroon, 70 percent in Ghana, 80 percent in Tanzania and South Africa, to nearly 100 percent in Guinea. Of the estimated 7.02 million diabetes-related deaths in Africa in the year 2000, Ghana accounted for approximately 302,000 deaths. By 2030, diabetes-related deaths in Africa are projected to reach 18.2 million, with an estimated 815,000 deaths occurring in Ghana alone (WHO, 2004).

Diabetes is increasingly recognized as one of the leading causes of mortality worldwide, reportedly claiming one life every 30 seconds according to the World Health Organization and the International Diabetes Federation. Furthermore, the WHO projects that diabetes will become the seventh leading cause of death globally by the year 2030 (WHO, 2010).

Diabetes constitutes a significant public health challenge in China as well as globally. Epidemiological evidence indicates that approximately 9.7% of Chinese adults aged 20 years and above are living with diabetes, while an additional 15.5% exhibit pre-diabetic conditions (Yang, Lu et al., 2010). Mortality attributable to diabetes has risen sharply, increasing from 5.1 per 100,000 population in 1985 to 15.4 per 100,000 by the year 2000 (Lumpur, 2000). Despite this growing burden, diabetes management in China remains suboptimal. Studies reveal that in 2001, nearly 80% of individuals diagnosed with diabetes neither used antidiabetic medications nor accessed evidence-based interventions, and only about half adhered to recommended treatment guidelines (Pan, 2005; Hu, Fu et al., 2008). However, these studies did not clearly identify specific areas for improving diabetes care. The situation is further complicated by the extensive reliance on Traditional Chinese Medicine (TCM), which emphasizes clinical observation and symptom-based diagnosis rather than laboratory-based assessments. Consequently, individuals with diabetes often alternate between TCM, conventional medical therapies, or a combination of both, depending on personal preference (Donnelly, Wang et al., 2006).

In many developing regions across Africa, Asia, and Latin America, herbal medicine plays a crucial role in addressing primary healthcare needs. In Africa, it is estimated that up to 80% of the population depends on traditional or herbal remedies as a first line of care. In China, traditional herbal medicines account for approximately 30–50% of total medicinal consumption. Similarly, in countries such as Ghana, Mali, Nigeria, and Zambia, herbal treatments are frequently used at home as the initial response for managing fever related to malaria and other common illnesses, particularly among children (WHO, 2003). The United Nations Development Programme (UNDP, 2007) further estimates that about 80% of Ghana's population relies on herbal medicine for basic healthcare services. This widespread utilization is often attributed to factors such as affordability, accessibility, cultural acceptance, and the perceived effectiveness of traditional remedies (VOA News, 2006). Ghana is especially rich in medicinal plant resources, with approximately 1,000 known medicinal plant species, of which about 80% have been identified through baseline scientific studies (Cultural News, 2007).

Reports from the African Conservation Foundation (2007) indicate that Ghana is home to an estimated 45,000 traditional healers, many of whom are formally recognized and licensed through professional bodies operating under the Ghana Federation of Traditional Medicine Practitioners' Association (GHAFTRAM). These practitioners play a vital role in delivering healthcare services, particularly in rural and underserved communities.

A major strategy for incorporating traditional medicine into Ghana's formal healthcare system has been the decentralization of health services. However, available records suggest that decentralization in Ghana, as in many other African countries, has largely been driven by economic constraints, inadequate logistics, and declining public funding for healthcare delivery (ACF, 2007). Although PNDC Law 207 (1988) established the legal framework for decentralizing Ghana's healthcare system, it did not initially provide for the formal integration of traditional medicine, especially at the local government level. While recent efforts have sought to address this gap, full nationwide integration of traditional medicine into the healthcare system remains incomplete.

However, such epidemiological studies from Africa are very scanty and among its majority rely on Western Medicine. In addition, to my knowledge till date, there are few such individual studies conducted in West Africa and even Africa at large on effects of homeopathy in diabetes. Therefore, realizing the need to establish baseline information on herbal treatment on diabetes, this paper is to examine the prevalence use of herbs, analyses the usage effect on the Ghanaian social demographic characteristics and investigate some risk factors associated with the herbal usage in the treatment of diabetes in the Ghanaian economy with view to making future predictions and recommendations for improving health and safety in the country.

Research Questions

In the course of this study, the following research questions will be answer:

1. What trend model can aid reduce diabetes occurrences in Kumasi Metropolis?
2. How best the monthly reported diabetes cases in the Kumasi Metropolis?

Objectives of the Study

Main Objective

The main objective of the study is to assess the pattern of diabetes in Kumasi Metropolis.

Specific Objectives

a) To unfold the current trend of diabetes cases in the Kumasi Metropolis
b) To find a trend model and forecast for diabetes in the near future.

Significance of the Study

The relevance of any academic inquiry is often measured by the extent to which it addresses critical practical or theoretical challenges, informs social policy, or contributes to professional practice (Bacho, 2001). In this context, diabetes has emerged as a major global public health concern, attracting increasing scholarly and policy attention due to its significant contribution to premature morbidity and mortality worldwide. Non-communicable diseases, with diabetes as a key component, are responsible for approximately 60% of all global deaths, underscoring the urgency of research aimed at understanding, preventing, and managing this condition.

However, with regard to its related problems, this study therefore will provide education and awareness of the disease as it examines the trend of diabetes and rate at which people prefer using herbal medicine for treating diabetes.

Limitations

The study will be based on secondary data from registered herbal centers and practioners from a region in the country hence findings from the study cannot be generalized to the rest of the country due to difference in genetic make-up and socio-economic and dietary habit in difference sections across Ghana. Primary data will not be use since it involves one's personal health which is private and confidential; this study is also based on statistical analysis and not on clinical research, and errors are therefore minimized on such track. Constraints such as financial and time within which the study period, restrict researcher to also gather primary data which has to be on an interval timely bases. Regardless of the above limitation, the resultant error is assumed to be insignificant.

Research Methodology

This chapter focuses on the research processes, the kind of research tools and the procedure used in carrying out the study. These chapter takes into account the research design, instruments for collection of data and statistical analysis procedure.

Research Design

A research design provides a systematic structure that guides the process of data collection, analysis, and interpretation, while also determining the suitability of specific research methods for achieving the study objectives. It serves as a conceptual blueprint that enables the researcher to organize the investigation logically, assess the adequacy of the research process, and draw valid and reliable conclusions.

This study utilizes secondary data comprising documented cases of diabetes obtained from Amen Scientific Herbal Clinic, located in Kumasi, the capital city of the Ashanti Region of Ghana. The dataset spans an eight-year period from 2006 to 2013 and is organized on a monthly and annual basis to facilitate temporal analysis.

Data Collection

Information for the buildup of this research work was obtained by making use only of secondary data. The secondary data were sought from Amen scientific herbal clinic from 2006 to 2013

Statistical Analysis Procedure

The use of statistical software package Minitab and Gretel will be used to analyze the data to achieve the objects of the study. The analysis will comprise of both preliminary and further analysis

Preliminary Analysis

This analysis will comprise of finding statistic(s) such as mean, standard deviation, skewness and kurtosis to check the assumptions of normality in the data. It will also deal with plots of time graphs and correlation.

This analysis will entail of accessing the researcher's generated hypothesis using a time series analysis technique. This technique is purely used because the data (secondary) was obtained in a timely equal interval thus, monthly

Time Series Theory

A time series refers to a sequence of quantitative observations recorded at consistent time intervals. Time series analysis involves statistical techniques that identify patterns within such data and facilitate the selection of appropriate models for predicting future outcomes. These forecasts are essential in analytical and decision-making processes, as they support parameter estimation, efficient allocation of limited resources, and the modeling of stochastic behavior over time.

Time series models are built on the assumption that observed values fluctuate around an underlying time-dependent structure and that these variations follow a defined probability distribution.

Methods of Trend Analysis

- ❖ linear trend analysis
- ❖ Quadratic trend analysis
- ❖ Exponential trend analysis

Linear Trend Analysis

$Y_t=\beta_0+\beta_1 t$

Where β_0 and β_1 are trend parameters respectively. This implies a straight long line growth or decline.

The Quadractic Analysis

$Y_t=\beta_0+\beta_1 t+\beta_2 t^2$

Where β_0 and β_1 are trend parameters

The Exponential Trend Analysis

$Y_t=\beta_0 * \beta_1 t * e$

Where β_0 and β_1 are trend parameters

Measure of Accuracy of Trend Analysis

Mean Absolute Percentage Error (MAPE)

It evaluates how closely the fitted time-series values match the actual observations and reports the level of accuracy in percentage terms.

Mean Absolute Deviation (MAD)

It assesses the accuracy of the fitted time-series values using the same unit of measurement as the original data, thereby making the magnitude of forecasting error easier to interpret and understand.

Mean Square Deviation (MSD)

This measure is closely related to the Mean Squared Error (MSE), which is commonly used to evaluate the accuracy of fitted time-series values. However, it is often preferred to MSE because MSE values are calculated using different degrees of freedom across models, making direct comparisons less reliable.

Stationary and Non-Stationary Series

A time series is said to be strictly stationary if the joint distribution of X_{t1}, X_{t2}, …X_{tn} is the same as the joint distribution of X_{t1+T}, X_{t2+T}, …X_{tn+T} for all t_{1+T} …… t_{tn+T}. Thus, shifting the time position by T periods has no effects on the joint distributions, which therefore depends on the interval between t_1………t_n. If a time series is not stationary then it is said to be non-stationary. A simple non-stationary time series model is given by

$Y_t = \mu_t + e_t$.

Where μ_t denotes a time-varying mean component, and e_t represents a weakly stationary stochastic process. In contrast to stationary processes—where statistical properties such as the mean and variance remain constant over time—non-stationary series exhibit moments that evolve with time. However, non-stationary data can often be transformed into a stationary process through differencing. Once differenced sufficiently, the resulting series is referred to as homogeneous or integrated of a certain order.

Ensuring stationarity is a fundamental requirement in time-series modeling, as it guarantees the stability of autoregressive coefficients and the invertibility of moving-average components. When these conditions are satisfied, the estimated model becomes suitable for forecasting and inference (Hamilton, 1994).

Stationarity is typically assessed by testing for the presence of a unit root, which indicates whether a series contains a stochastic or deterministic trend. A variety of statistical procedures exist for detecting unit roots. For time series exhibiting both seasonal and non-seasonal patterns, unit root tests must be applied to each component accordingly. Commonly used tests for non-seasonal unit roots include the Dickey–Fuller (DF) test, the Augmented Dickey–Fuller (ADF) test, the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test, and the Zivot–Andrews (ZA) test (see Dickey & Fuller, 1979; Kwiatkowski et al., 1992; Zivot & Andrews, 1992).

Unit Root

The Unit Root Test was introduced by Dickey and Fuller in 1979 to examine whether a time-series variable contains a unit root or is stationary. The formulations of the unit root process and the stationary process are presented respectively.

$\rho t = \emptyset_1 \rho_{t-1} + e_t$

$\rho t = \emptyset_0 + \emptyset 1 \rho_{t-1} +$

If $\emptyset_1$=1 then the series is said to have unit root and is not stationary.

H_0: *Series is level or trend stationary*
H_1: *series is level or trend non−stationary*

If the KPSS test's test statistic value is smaller than the critical value, it does not reject the null hypothesis that the data is level or trend stationary.

The Unit Root Test, as put out by Dickey and Fuller (ADF), similarly evaluates the premise below.

H_0: *Series hasunitroot*
H_1: *Series hasnounitroot*

If the ADF test's test statistic is lower than the critical value, it rejects the null hypothesis that the data has a unit root.

Lag

Lag is a difference in time between an observation and a previous observation. Thus Y_{t-k} lags Y_t by k periods.

White Noise

The first time a group of random variables, ωt, with a mean of 0 and a finite variance of $\sigma\omega 2$ was used to simulate noise in engineering was when it was named white noise. This is written as ωt ~ (0, $\sigma\omega 2$). The term "white" comes from the comparison to white light and means that all potential periodic oscillations are present with the same strength. will, at times, necessitate the noise to be iid random variables characterized by a mean of 0 and a variance of $\sigma\omega 2$. I shall differentiate this scenario by referring to it as white independent noise or by denoting ωt ~ (0, $\sigma\omega 2$). Gaussian white noise is a very useful type of white noise series. In this case, the $\omega t(s)$ are independent normal random variables with a mean of 0 and a variation of $\sigma\omega 2$. In other words, ωt ~ iid N (0, $\sigma\omega 2$).

Autocorrelation Function (ACF)

It is usually not possible to get a full picture of a time series process, but the ACF is very helpful for getting a partial picture of the process so that we can build a forecasting model.

The autocorrelation coefficient, also known as the lagged or serial correlation, tells you how closely the values of a time series variable are related to each other. This is defined with lag k as:

$$\rho(k) = \frac{\sum_{t=1}^{N-K}(Yt-\bar{y})(Yt+k-\mu)}{\sum_{t=1}^{N}(Yt-\bar{y})(Yt-\bar{y})} = \frac{Ck}{Co}, \quad \text{for } k = 0,1,2,\ldots$$

Where C_k is covariance of the lag k and C_o is the variance.

The collection of the values of $\rho(k)$ is called the autocorrelation function (ACF) or correlogram for $\rho(k)$= 0, 1, 2…

Properties of Autocorrelation Function (ACF)

(i) The autocorrelation function at lag zero (0) is 1. i.e $\rho(0)= 1$
(ii) The autocorrelation is independent of the scale of measurement of the time series, hence is dimensionless (has no unit).
(iii) The autocorrelation is an even function of the lag. i.e. it is symmetric and 0 and so, it is only necessary to compute the positive or negative half.
(iv) The autocorrelation lies between -1 and 1 i.e. $-1 \leq \rho(k) \leq 1$

ARIMA Models

The term ARIMA refers to the Auto-Regressive Integrated Moving Average framework, a widely used approach for modeling and forecasting time-series data. Within this framework, autoregressive components represent the influence of past values of the differenced series on its current value, while moving average components capture the effect of past forecast errors. The integrated component indicates that the original time series is rendered stationary through successive non-seasonal differencing.

A non-seasonal ARIMA model is conventionally denoted as ARIMA (p, d, q), where *p* specifies the order of the autoregressive structure, *d* represents the degree of non-seasonal differencing required to achieve stationarity, and *q* denotes the order of the moving average component, corresponding to the number of lagged error terms included in the model.

Formally, a stochastic process X_t is said to follow an ARIMA (p, d, q) specification if the differenced series $\nabla^d X_t = (1 - B)^d X_t$ constitutes an ARMA (p, q) process. This definition implies that the original non-seasonal time series must become stationary after being differenced *d* times before autoregressive and moving average dynamics can be appropriately modeled.

In general, it will write the model as

$\emptyset(B)(1 - B)^d Xt = \theta(B)\omega_t$

If $(\nabla^d X_t) = \mu$ this is written write the model as

$\emptyset(B)(1 - B)^d Xt = \propto + \theta(B)\omega_t$

Where $\alpha = (1 - \emptyset_1 - \cdots - \emptyset_p)$

The Box – Jenkins Arima Model

The Box-Jenkins methodology is the collection of steps for finding, fitting, and verifying ARIMA models using time series data. The shape of the fitted model directly affects the forecasts. By Box-Jenkins, a p^{th} order autoregressive model (AR (p)) has this basic shape:

$X_t = \alpha + \emptyset_1 X_{t-1} + \emptyset_2 X_{t-2} + \cdots + \emptyset_p X_{t-p} + \omega_t$

Where X_t = Response (dependent) variable at time t, X_{t-1}, X_{t-2}, $\ldots_{t-p}$ = Response variable at time lags t − 1, t − 2, . . . , t − p, respectively.

$\emptyset_1, \emptyset_2, \ldots \emptyset_p$ = Coefficients to be estimated, and ω_t = Error term at time t.

Also, a q_{th}- order moving average model: MA (q), has the general form $X_t = \mu + \omega_t + \theta_1\omega_{t-1} + \theta_2\omega_{t-2} + \cdots + \theta_q\omega_{t-q}$

Where X_t = Response (dependent) variable at time t, μ = Constant mean of the process, $\emptyset_1, \emptyset_2, \ldots \emptyset_p$ = Coefficients to be estimated, ω_t = Error term at time t, and ω_{t-1}, ω_{t-2} ,… ,ω_{t-p}= Errors in previous time periods that are incorporated in the response X_t. Autoregressive Moving Average Model: ARMA (p,q), which has the general form $X_t = \alpha + \emptyset_1 X_{t-1} + \emptyset_2 X_{t-2} + \cdots + \emptyset_p X_{t-p} + \omega_t + \theta_1\omega_{t-1} + \theta_2\omega_{t-2} + \cdots + \theta_q\omega_{t-q}$

AIC, AICc, BIC

The selection of an optimal statistical model is commonly guided by penalized information criteria, including the Akaike Information Criterion (AIC), its corrected form AICc, and the Bayesian Information Criterion (BIC), as originally developed by Akaike, Schwarz, and later discussed by Sakamoto. These criteria provide a systematic means of evaluating the relative quality of competing models estimated from the same dataset. Candidate models are compared based on their respective criterion values, with preference given to the model that yields the minimum information criterion, indicating a superior balance between goodness of fit and model simplicity.

Rather than serving as absolute measures of predictive accuracy, information criteria are intended solely for ranking alternative models. Each criterion evaluates how closely a model's fitted values are expected to approximate the true underlying process, while simultaneously incorporating a penalty term that increases with the number of estimated parameters to discourage overfitting. The AICc, introduced by Hurvich and Tsai, represents a refinement of the AIC that includes a second-order correction for small sample sizes, making it particularly suitable when the number of observations is limited relative to the complexity of the model.

Forecasting

After the appropriate model has been identified and estimated, diagnostic checks are conducted to ensure that the residuals exhibit white-noise characteristics. The estimated coefficients are then tested for statistical significance, and the validated model is re-estimated prior to forecasting. Predictions are obtained as expected values evaluated at specified future time points.

Preliminary Analysis and Further Analysis

This chapter presents the results of the analyzed data by the use of time series trend analysis. It comprises of preliminary and further analysis.

Preliminary Analysis

Preliminary analysis will comprise of finding statistic(s) such as mean, skewness and kurtosis to check the assumptions of normality in the data.

Table 1: Year Distribution of Diabetes Attendance (2006-2013)-Morbidity

YEAR	NUMBER OF ATTENDANCE	PERCENTAGES
2006	454	12.14
2007	438	11.69
2008	557	14.86
2009	526	14.03
2010	483	12.89
2011	453	12.09
2012	425	11.34
2013	412	10.99
TOTAL	3748	100

From Table above, it can be seen that years 2008, 2009 and 2010 recorded the highest number of attendance with almost 12.88-14.81% with year 2013 recording the lowest number of about 10.99%.

Table 2: Descriptive Statistics: Diabetes Cases

VARIABLE	MEAN	COEF VAR	MINIMUM	MAXIMUM	SKEWNESS	KURTOSIS
ATTENDANCE	39.06	39.89	13.00	79.00	0.17	-0.73

The table above shows the descriptive statistics of Diabetes Attendance. Table 2, tells us the Mean, Coefficient of variation, Minimum, Maximum, Skewness and Kurtosis in each Attendance. Mean of the attendance is 39.06, Coefficient of variation is 39.89, Minimum is 13.00, Maximum is 79.00, Skewness is 0.17 and Kurtosis is -0.73. The distribution of the data is positively Skewed and Platykurtic in nature.

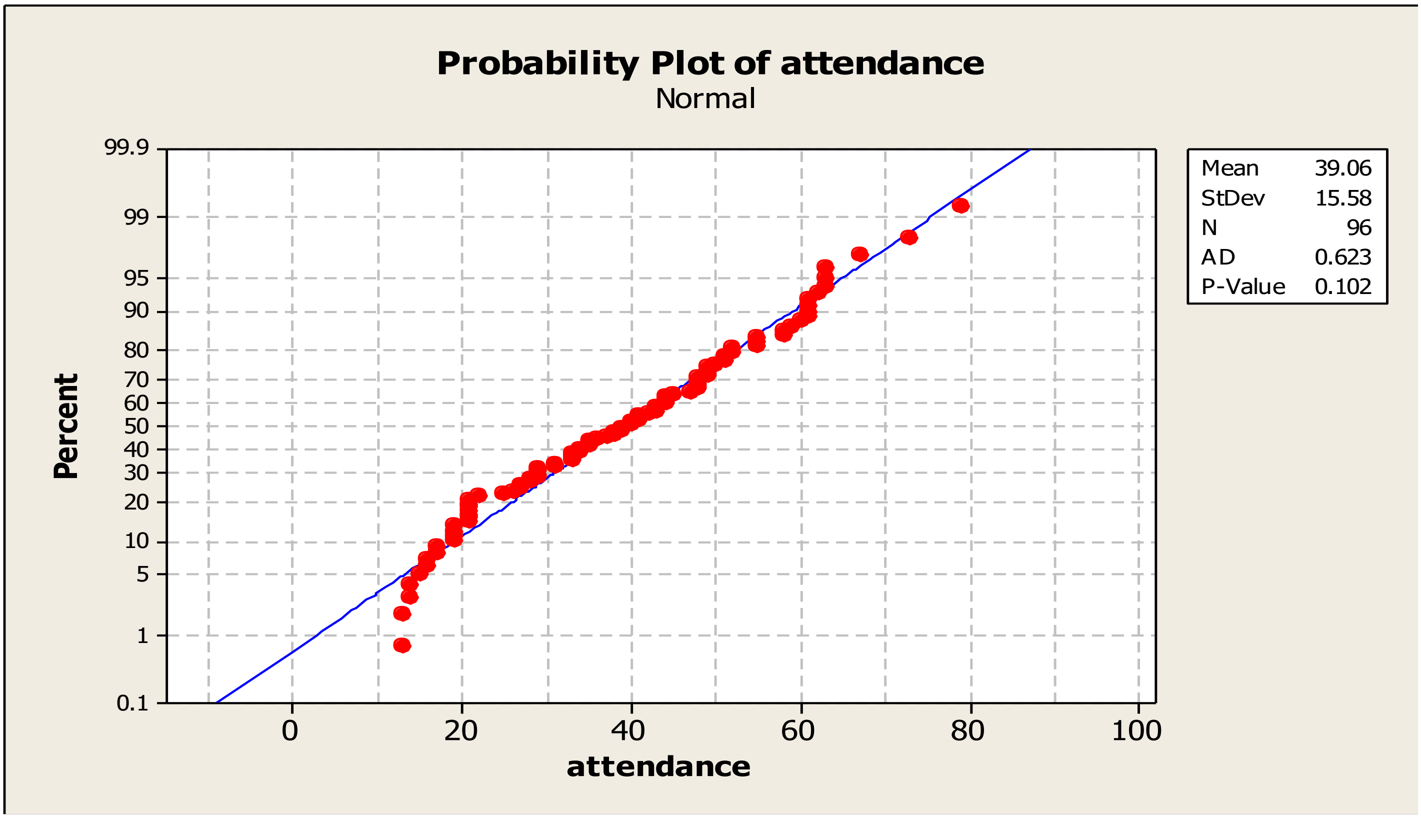


Figure 1

Figure 1 presents the probability plot of the reported diabetes cases used to assess the normality assumption. The normality assessment is conducted using the Anderson–Darling test, where the null hypothesis assumes no significant departure between the observed data and a theoretical normal distribution. Since the obtained p-value (0.102) exceeds the chosen significance level of 0.05, the null hypothesis is not rejected, indicating that the data follow a normal distribution. The reference straight line displayed in the plot represents the theoretical normal distribution, and the close alignment of the observed data points with this line supports the normality assumption. Similarly, Figure 2 shows that the plotted values lie close to the reference line, further confirming that the data are approximately normally distributed.

Graphs of the Trend Analysis

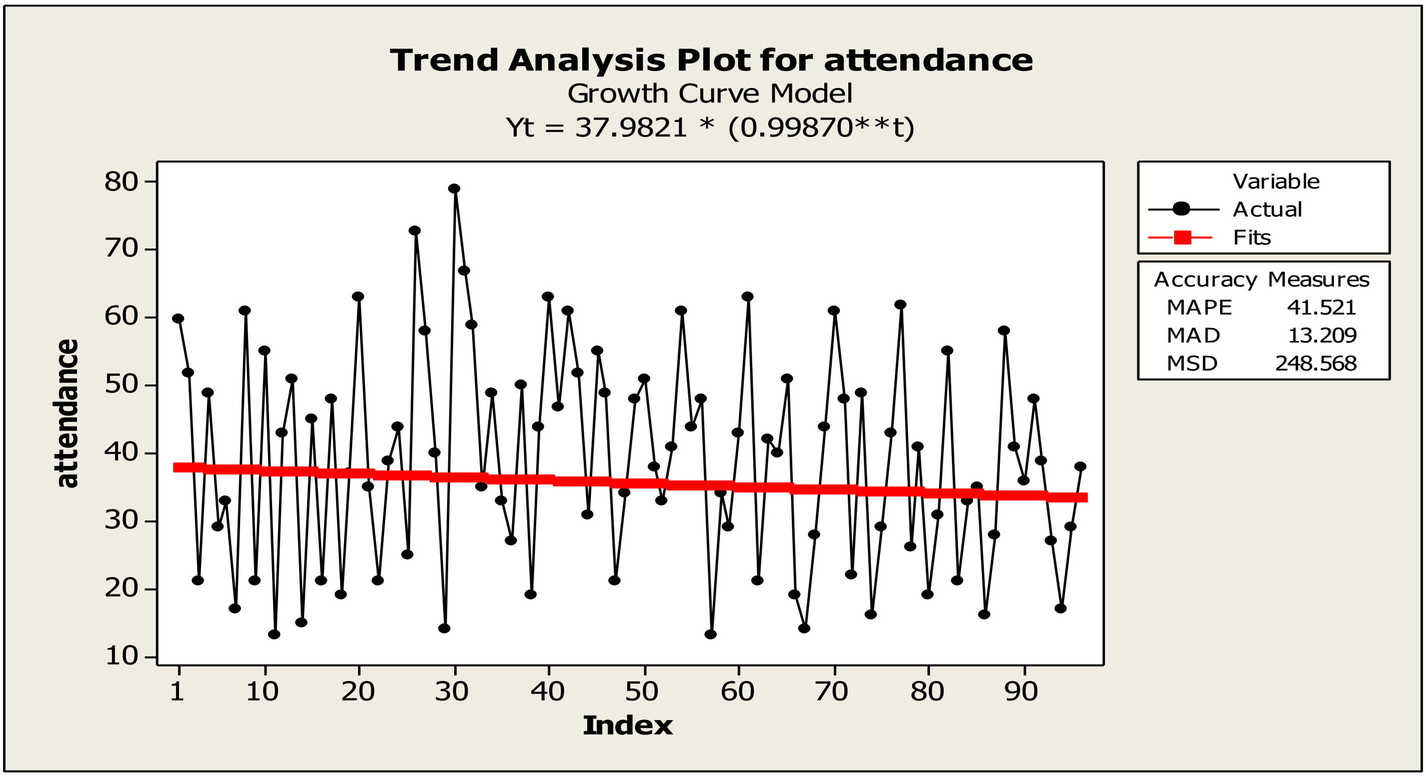


Figure 2

Fitted Trend equation for figure 2
Y_t=37.9821*(0.9987**t)

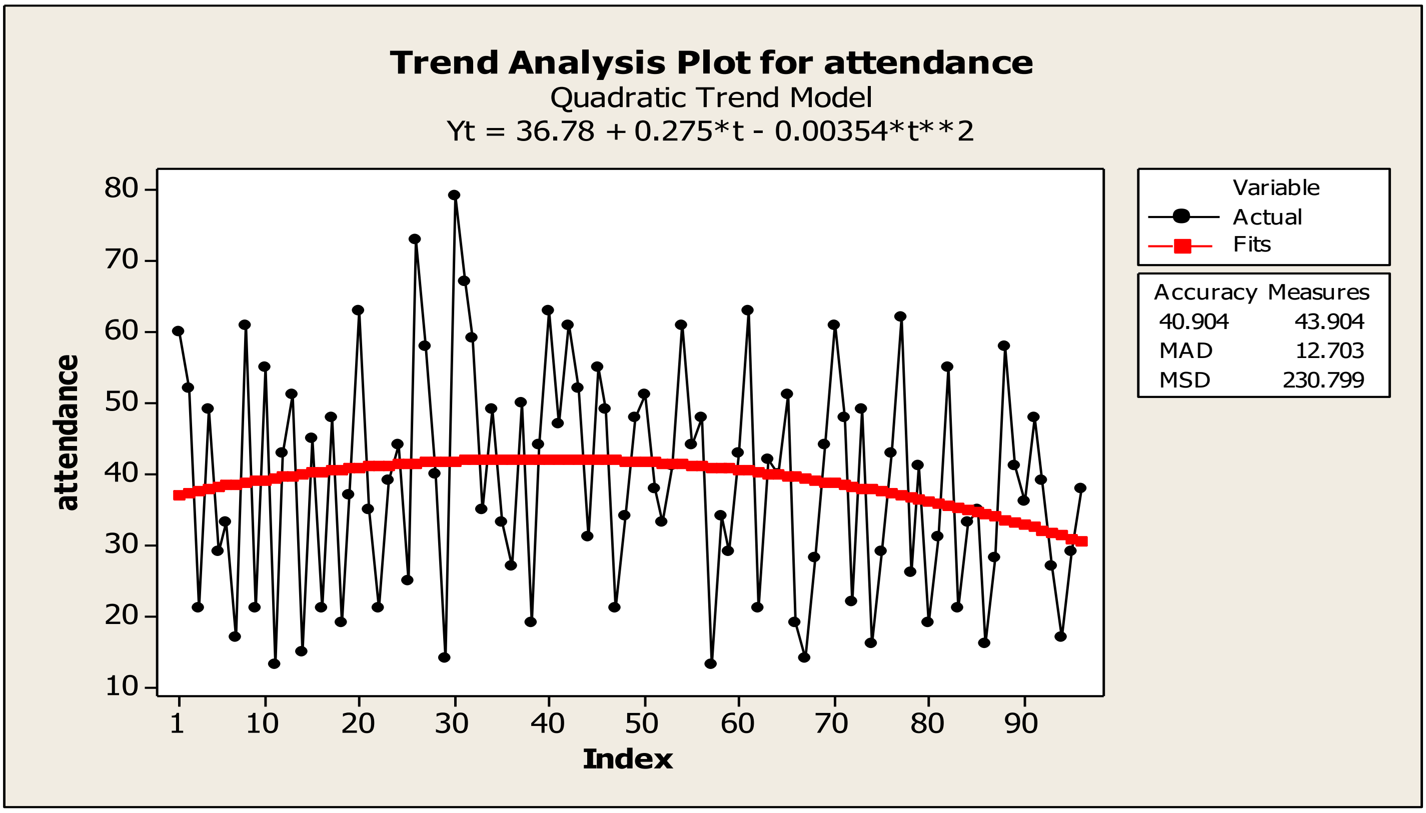


Figure 3

Fitted Trend equation for figure 3
Yt=36.78+0.275*t-0.00345*t**2

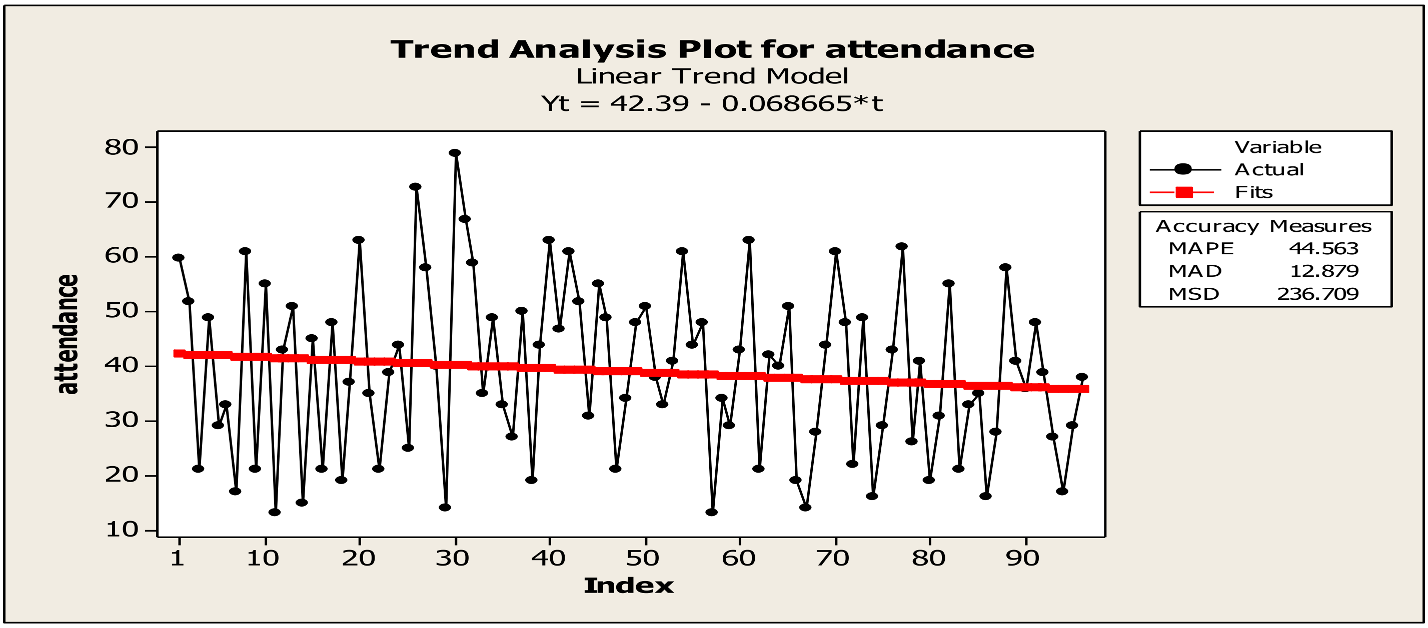


Figure 4

Fitted Trend equation for figure 4
Yt=42.39-0.068665*t

Table 3: Trend Analysis for the Data

MODEL	MAPE	MAD	MSD
LINEAR	44.563	12.879	236.709
QUADRATIC	40.904*	12.703*	230.799*
EXPONENTIAL	41.521	13.209	248.568

Comparing the measure of the accuracy of the trend analysis (Linear, Quadratic and Exponential), Quadratic trend analysis had the least measures of MAPE, MAD and MSD. Hence Quadratic trend model is the best model to fit the trend for the incident of Diabetes in Kumasi Metropolis.

$Y = 36.78 + 0.275 * t - 0.00354 * t^2$

Where
Y is the attendance, t is the trend period

Further Analysis

Patterns of Diabetes Cases

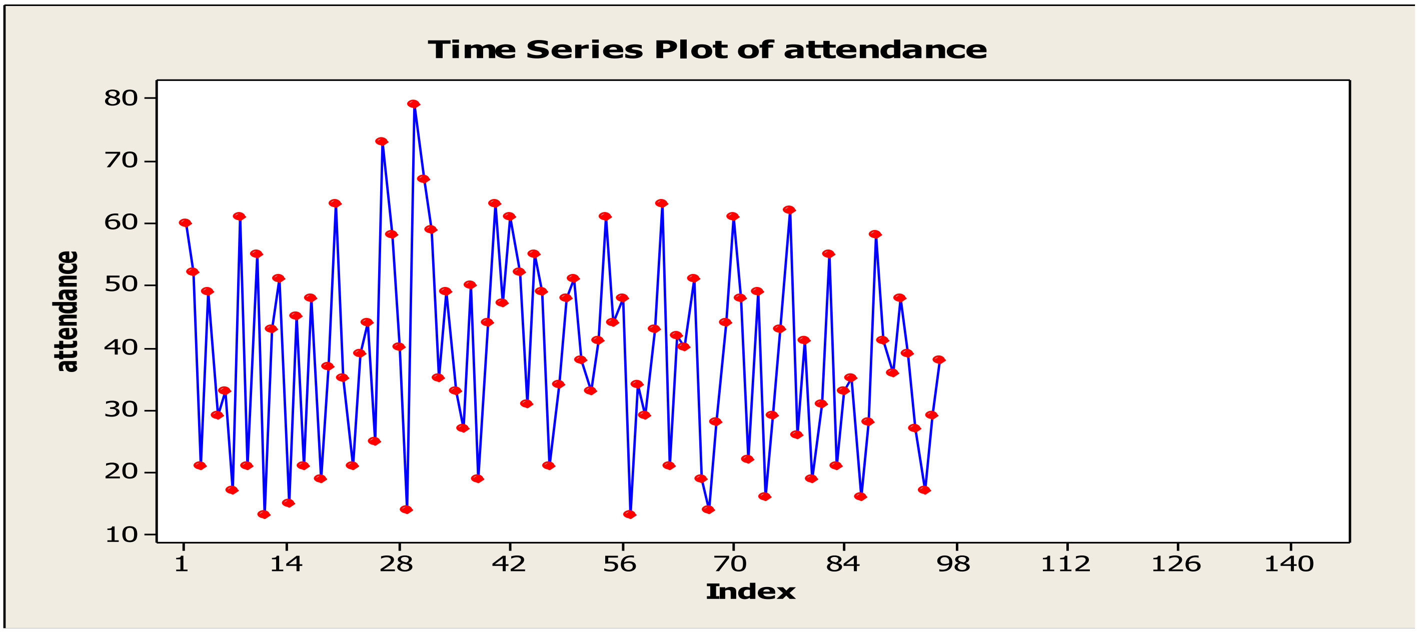


Figure 5

Test for Non-Seasonal and Seasonal Stationarity

A stationary series has a mean, variance, and autocorrelation structure that don't change. Figure 5 above shows the time series plot of the monthly reported cases from January 2006 to December 2013. The plot looks like it's illustrating that the time series doesn't change. The values changed regularly, therefore they were always changing. But the fact that the plot changed regularly didn't mean that the series wasn't stationary. We utilized ACF and PACF to see if the series was stationary. The ACF indicates that the series is non-seasonally stationary and seasonally non-stationary due to the gradual decay of seasonal delays, necessitating seasonal differencing. We did an Augmented Dickey Fuller (ADF) test to see if the series is not stationary.

The ADF test's p value is 0.49340, which is higher than the significance level (5%). This means that we rejected the null hypothesis and decided that the data is not stationary. The p-value of 7.401e-008 after differencing the data suggests that the time series can be considered stationary. The p-value of the ADF test is lower than the p-value, thus we can't reject the null hypothesis and may say that the data is stationary. Based on the aforementioned conclusion, we can see that the series is stationary.

Table 4: ADF Test for Stationarity

TEST TYPE	TEST STATISTICS	P-VALUE
ADF	-1.57895	0.4934

Table 5: Showing the Non Stationarity

TEST TYPE	TEST STATISTICS	P-VALUE
ADF	-6.08644	-7.401e-008

Table 5 showing the stationarity of the data after differencing

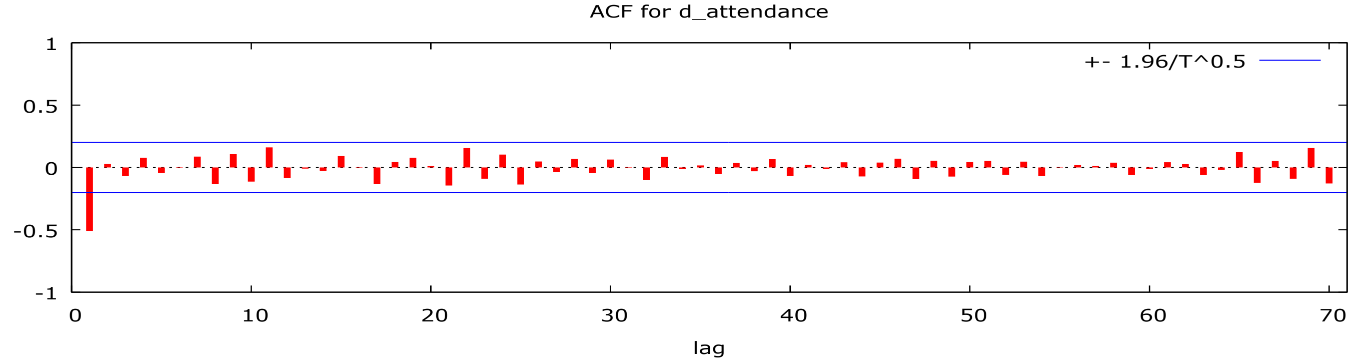
Table 6: Estimates of Autocorrelation Value

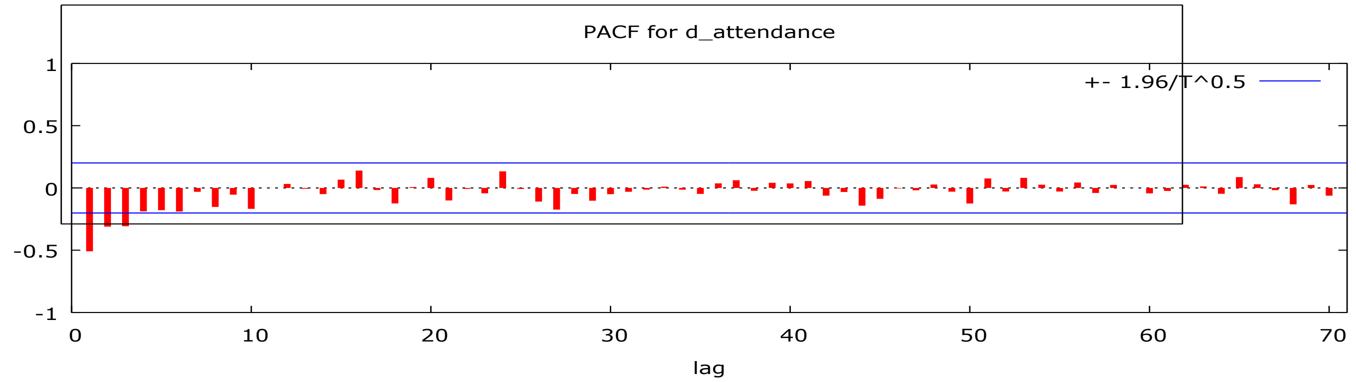
LAGS	ACF	T
1	-0.057999	-0.57
2	-0.043254	-0.42
3	-0.06031	-0.59
4	0.037207	0.36
5	-0.010628	-0.1
6	0.03229	0.31
7	0.099794	0.97
8	-0.055137	-0.53
9	0.101899	0.97
10	0.003566	0.03
11	0.180794	1.71
12	-0.006189	-0.06
13	-0.022557	-0.21
14	0.012437	0.11
15	0.078812	0.72
16	-0.025846	-0.24
17	-0.14416	-0.132
18	0.039133	0.35
19	0.11347	1.02
20	0.001901	0.02
21	-0.107324	-0.95
22	0.099434	0.87
23	-0.036076	-0.31
24	0.014459	0.13

Table 7: Estimates of Partial Autocorrelation Values

LAGS	PACF	T
1	-0.057999	-0.57
2	-0.046775	-0.46
3	-0.066015	-0.65
4	0.027606	0.27
5	-0.012613	-0.12
6	-0.012613	0.3
7	0.107837	1.06
8	-0.042547	-0.42
9	0.113243	1.11
10	0.022477	0.22
11	0.187338	1.84
12	0.037933	0.37
13	-0.011741	-0.12
14	0.032721	0.32
15	0.076596	0.75
16	-0.038616	-0.38
17	-0.153734	-1.51
18	-0.029889	-0.29
19	0.106972	1.05
20	-0.040565	-0.4
21	-0.131893	-1.29
22	0.0577	0.57
23	-0.023301	-0.23
24	0.024693	0.24

Figure 6 and 7 are ACF and PACF plot of the attendance





This section applies the Box–Jenkins methodology for the systematic identification and modeling of the time-series data, implemented using the statistical software gretl and Minitab. The initial stage of model identification involved an examination of the autocorrelation function (ACF) and partial autocorrelation function (PACF) computed from the original series. The estimated autocorrelations and partial autocorrelations are reported in Tables 6 and 7, respectively.

The ACF and PACF plots provide essential guidance for determining the appropriate orders of the autoregressive (p) and moving average (q) components of the model. By analyzing the behavior and cutoff patterns of these functions, the Box–Jenkins framework was employed to propose candidate ARIMA (p,d,q)specifications. Multiple tentative models were then estimated and evaluated using the Akaike Information Criterion (AIC), the corrected Akaike Information Criterion (AICc), and the Bayesian Information Criterion (BIC). The model yielding the lowest information criterion value was selected as the most suitable representation of the data.

AIC, AICc and BIC values.

Model Estimation and Evaluation

The model selection process was based on identifying the specification that minimized the values of the corrected Akaike Information Criterion (AICc) and the Bayesian Information Criterion (BIC). The competing ARIMA models and their corresponding AICc and BIC values are summarized in Table 9 Among the candidate specifications considered, the ARIMA (1, 1, 1) model was selected as the most appropriate representation of the data, as it produced the lowest AICc and BIC values relative to the alternative models.

Table 9: Tentative Arima Models

MODEL	AIC	AICc	BIC	Log-likelihood
ARIMA(1)	806.0836**	816.3416**	810.2298	-399.0418**
ARIMA(1)	807.9975	820.8192	813.1802	-398.9987
ARIMA(1)	809.6595	825.0456	815.8788	-398.2970

Table 10: Estimate of Parameters for Arima (1, 1, 1) Model

VARIABLES	COEFFICIENT	S.E	P-VALUE
CONSTANT	39.0486	1.3774	8.50e-177**
AR(1)	0.4287	0.5365	0.4243
MA(1)	-0.5025	0.5083	0.3223

Table 10 gave us estimates, S.E, and P–value of the ARIMA (1, 1, 1) model. The estimate of the Constant is -0.0680701, AR (1) is -0.0619160 and MA (1) is-1.0000 The S.E of the constant is 0.0536020, AR (1) 0.103049 and MA (1) is 0.0496227. The p-value of the constant is 0.2041 and The p-value of AR (1) is 0.5479 indicating that the constant of the models are not significant. The p-value of MA (1) is 2.58e-090indicating MA (1) is significant.

Goodness of Fit

In time-series analysis, the adequacy of a fitted model is largely determined by the quality of its residual diagnostics. A fundamental requirement of a well-specified model is that the residuals behave as a white-noise process, characterized by a zero mean, constant variance, and absence of serial correlation. The Ljung–Box test results, presented in the third panel, yield p-values that consistently exceed the 5% significance level across all examined lag orders, providing no evidence against the white-noise assumption.

These diagnostic outcomes indicate that the residuals do not exhibit systematic patterns or autocorrelation, thereby confirming that the underlying model assumptions are satisfied. Consequently, the selected ARIMA (1, 1, 1) model can be regarded as an appropriate and reliable representation of the observed data, suitable for inference and forecasting purposes.

Table 11: Modified Box-Pierce (Ljung-Box) Chi-Square Statistic

Lags	**12**	**24**	**36**	**48**
Chi-Square	5.1	11.1	21.4	25.0
DF	7	19	31	43

Forecasting

A suitable that a suitable model that fits the data well has been identified and has passed the necessary model adequacy test; hence the model is good for forecasting. Below is the forecasted result for the next two (2) years.

Table 12: Forecasted Diabetes Cases for 2014–2015

PERIOD	**FORECAST**	**UPPER**	**LOWER**
2014	40.00	70.29	9.72
2014	39.46	69.82	9.09
2014	39.22	69.61	8.84
2014	39.12	69.51	8.74
2014	39.08	69.47	8.7
2014	39.06	69.45	8.68
2014	39.05	69.44	8.67
2014	39.05	69.44	8.67
2014	39.05	69.43	8.67
2014	39.05	69.43	8.66
2014	39.05	69.43	8.66
2014	39.05	69.43	8.66
2015	39.05	69.43	8.66
2015	39.05	69.43	8.66
2015	39.05	69.43	8.66
2015	39.05	69.43	8.66
2015	39.05	69.43	8.66
2015	39.05	69.43	8.66
2015	39.05	69.43	8.66
2015	39.05	69.43	8.66
2015	39.05	69.43	8.66
2015	39.05	69.43	8.66
2015	39.05	69.43	8.66
2015	39.05	69.43	8.66

Results and Discussion

This chapter presents the discussion of findings of the project as in chapter four.

In the preliminary analysis, we observed from the overall data that, the reported cases of diabetes is high on months of January at end of the period. Also, the year 2008 recorded the highest number of cases reported with 559 representing almost 15% and the year 2013 recorded the least number of reported cases with 412 corresponding to about 11%. In the nut shell, the total case reported across the period is different from each other.

The initial analysis indicated that the mean number of diabetes patients was 39.06, characterized by a slightly flat tail on the right side (positively skewed), and a kurtosis of less than 3, indicating a non-normal distribution (Platykurtic), which signifies that the variables display broad peaks or high kurtosis. Furthermore we sought to statistically analyze the trend of diabetes cases in Metropolis. By using trend analysis with MAPE, MAD, MSD values 43.904, 12.703, and 230.799 respectively of the model that had the least measure of accuracy. This give evidence that quadratic model is the best model to fit the trend of diabetes in the Metropolis. The model developed from the quadratic analysis is;

Fitted Trend equation

$$Y = 36.78 + 0.275 * t - 0.00354 * t^2$$

Where
Y = number of diabetic cases, t=the trend period (months)

In the further analysis, The p – values of the ADF tests declared the data to be stationary and therefore eligible to fit ARIMA (1, 1, 1) model.

Also, the ACF and PACF graphs let us fit speculative models to the data. It was found that ARIMA (1, 1, 1) fit the data effectively. A further sufficiency test on the model further validated the chosen model.

The model was used to predict how many people would get diabetes each month for the next two years.

Summary, Conclusions and Recommendations

In this work, the researcher reviews the central idea of the study and outlines the steps in the presentation of the study. The study further summarizes the research findings, draws conclusions and makes recommendations on the basis of the findings.

Summary and Conclusion

A quadratic trend model was formulated to fit the trend of the diabetes cases in the Metropolis. In this research, we observed from the descriptive statistics that, the data is skewed to the right indicating that the data is not normally distributed. The presence of unit root was tested using the ADF and on the time series data from the year 2006– 2013. The p – values of the ADF tested the data stationary, therefore data is good for ARIMA.

This research was undertaken with the prior motive to develop an adequate model for forecasting future trends It evolved that ARIMA (1, 1, 1) fits the data well. Therefore the ARIMA (1, 1, 1) model was used in forecasting the future trends of diabetes cases in the Metropolis.

The findings revealed that quadractic model is the model to fit the trend of diabetes in the Metropolis. Also ARIMA (1, 1, 1) model is the model to forecast future trend of diabetes cases in the Metropolis.

Recommendation

Based the findings of the study the following recommendations were made:

- Health services should carry out more educational programs in the Metropolis to create awareness and consequences of diabetes.
- All stakeholders especially the National Diabetes Association (NAD) running programs on diabetes should intensify and expand their services in certain areas in the Metropolis
- Health services as well as National Diabetes Association (NAD) should organize periodic pre.-diabetes program to enhance early treatment and prevention of diabetes

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