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Using Support Vector Machine "SVM" and Autoregressive Integrated Moving Average "ARIMA" to predict number of males and females who will be have Stroke at European Gaza Hospital

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Abstract

Stroke is among the world leading cause of morbidity and mortality and the principal cause of long-term disability. Stroke patients need to stay for long time at hospitals for treatment and rehabilitation. Hospitals should be prepared for receiving stroke patients. Stroke forecast prediction can contribute to better preparedness of hospitals in treatment of stroke which lead to improving the functional outcome of the patient, thereby decreasing the national expenses in health.

Gaza strip have a special case due to clashes escalation between Palestinian protesters and Israeli troops at the border of Gaza, because of that, the Ministry of Health at Gaza needs to temporary release patients from hospitals on Thursday weekly to receive hundreds of wounded people on Friday.

We used two methods of time series forecast; ARIMA and Support vector machine. Real data of stroke patient from European Gaza Hospital in Khan Younis city from 1/1/2012 to 31/03/2019 were used to

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examine the forecasting accuracy of the models, our sample included all the patient hospitalized at hospital through the study period, which consists of (1141 patients) 521 Males and 620 females.

The main findings are SVM performs better than ARIMA method, therefore we used SVM to predict number of patients who will have stroke next nine months.

Keywords: Stroke, ARIMA, Support Vector Machine (svm), MASE, MPE, RMSE, KPSS,AIC.

1. Introduction

The incidence of stroke varies between developed country and developing countries in Europe countries these numbers equal 41 per 100,000 and at developing countries it varies from 27.5 to 63 per 100,000 but in north of Palestine was reported as 51.4 per 100,000. (Benamer et al.,2009[2]),(Sweileh et al.,2008[26])

There are many methods were used to predict time series data but the main challenge is to choose the accurate one, the emergency state is the main problem which faced the hospitals administrations, in this paper we used two methods in predictions, our data is brain stroke data, we want to use ARIMA method and SVM method to predict number of patients who will be have a brain stroke for next nine months and compare between these two methods to choose the best one, our finding were the SVM is performed better than ARIMA method.

This motivated us to use SVM method for prediction of futures brain stroke cases . Rest of the paper is organized as follows. In this section we gave some related works, in section 2 and section 3 we gave a brief description of ARIMA and SVM . Section 4 results and conclusions were discussed.

In 1960's up to few years ago, prediction models were used by researcher depending on time series analysis, however in this paper we used time series and machine learning methods such support vector machine,

(Shakti et al.,2017[19]) they conduct a study to predict annual automobile sales by using ARIMA models,(Das and Padhy,2012 [6]) they predict of futures prices in Indian stock market by using support vector machine techniques, (Mandle et al.2012 [14]),they predict a protein structure by using support vector machine,(Mandal et al.2014[15]), they study the effectiveness of time series modeling ARIMA in forecasting stock price at India markets, (Adebiyi et al.2014 [1]), they predict stock price by using ARIMA model from two different markets Nokia stock price and Zenith Bank stock price, (Kim,2003 [11]) , he predict a financial time series forecasting using support vector machine, (Yang et al.2017[27]) they predict bus

arrival time by using support vector machine with genetic algorithm, (Samui et al.,2011 [19]), they predict rainfall in Vellore (India) by using support vector machine and relevance vector machine.

Data Source: data sets are collected from European Gaza hospital records in Khanyounis city from 01/01/2012 to 31/03/2019 with 521 males of brain stroke and 620 females of brain stroke.

2. Preliminaries

This section introduces some basic definitions and concepts

2.1 **Autoregressive Integrated Moving Average**(ARIMA) models:

ARIMA models can be divided into three stages as:

a) Identification stage.
b) Estimating and diagnosing stage.
c) Forecasting stage.

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(Box and Jenkins,1976[3], Box and Jenkins 1994[4])
ARIMA model can be denoted by ARIMA(p,d,q) where:
p is the order of autoregressive part
d is the order of differencing part.
q is the order of the moving average processing.
ARIMA model can be written as:

$$W_t = \mu + \frac{\theta(B)}{\phi(B)} a_t \quad \text{.................................... (2.1)}$$

Where:
t It is the time.
W_t It is the response series Y_t or difference of response series.
μ It is the mean.
B It is the backshift operator that is $BX_t=X_{t-1}$.
$\phi(B)$ It is the autoregressive operator where $\phi(B) = 1 - \phi_1 B - .... - \phi_p B^p$
$\theta(B)$ It is the moving average operator where $\theta(B) = 1 - \theta_1 B - .... - \theta_q B^q$
a_t It is the independent random error.

2.2 Support Vector Machine (SVM)
Least Square Support Vector Machine (LS-SVM)

Suppose we have a training data set of N points $\{x_i, y_i\}_{i=1}^{N}$ with input data $x_i \in \Re^n$ and $y_i \in \Re$ then:

$$\underset{w,b,e}{Minimize} J\left(w,e\right) = \frac{1}{2} w^T w + \frac{1}{2}\gamma \sum_{i=1}^{N} e_i^2 \quad (2.2)$$

Subject to $y_i = w^T \varphi(x_i) + b + e_i \forall i = 1,2,.....,N$

Where:
φ It is the non linear mapping to a higher dimension space.
γ It is the regularization parameter.

The primal space model of the optimization of equation (2) is given by:

$$y = w^T \varphi(x) + b \quad (2.3)$$

The lagrangian for equation (2) is given by:

$$L(w,b,e;\alpha) = J(w,e) - \sum_{i=1}^{N} \alpha_i \{w^T \varphi(x_i) + b + e - y_i\} \quad (2.4)$$

Where:
$\alpha = [\alpha_1, \alpha_2, ..., \alpha_N]^T, \alpha_i \geq 0 (\forall i = 1,2,......,N)$ Are the Lagrange multipliers.

The partial derivatives if L with respected to w, b, e_k, α_k equate them to zero finally eliminate w, e_k
Then linear system we can express as:

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$$\begin{bmatrix} 0 & 1 \\ 1^T & \Omega+\gamma^{-1}I \end{bmatrix}_{(N+1)\times(N+1)} \begin{bmatrix} b \\ \alpha \end{bmatrix}_{(N+1)\times 1} = \begin{bmatrix} 0 \\ y \end{bmatrix}_{(N+1)\times 1} \qquad (2.5)$$

Where:

$\gamma > 0$ And it is the regularization parameter.

$y=[y_1, y_2, ..., y_N], 1=[1,1,....,1]$, $\Omega(i, j) = k(x_i, x_j)(\forall i, j = 1,2,.....,N)$

Finally the LS_SVM decision function is given by:

$$y(x) = \sum_{i=1}^{N} \alpha_i k(x, x_i) + b \qquad (2.6)$$

Where:

α, b they are the solution of linear system

2.3 Dynamic Least Square Support Vector Machine (DLS_SVM) (Yugang,2006[28])

Yugang et al.(2006)[28] they create a Dynamic Least Square Support Vector Machine (DLS_SVM) from Least Square Support Vector Machine to used as time series forecasting, the main feature of DLS_SVM is that it can track the dynamics of non-linear time varying systems by deleting one existing data point whenever new observation added.

Suppose:

$$Q_N = \begin{bmatrix} 0 & 1 \\ 1^T & \Omega+\gamma^{-1}I \end{bmatrix}_{(N+1)\times(N+1)} \qquad (2.7)$$

Now to solve equation (5) we need Q_N^{-1} and when new observation added to the existing training sets then Q_N becomes:

$$Q_{N+1} = \begin{bmatrix} Q_N & k_{N+1} \\ k_{N+1}^T & k_{N+1}^* \end{bmatrix}_{(N+2)\times(N+2)} \qquad (2.8)$$

Where:

$k_{N+1}^* = \gamma^{-1} + k(x_{N+1}, x_{N+1}) = \gamma^{-1} + 1, k_{N+1} = [1 + k(x_{N+1}, x_i]^T, i = 1,2,......,N$

Now we need to save computation time then matrix inversion lemma has been applied to calculate Q_{N+1}^{-1} as:

$$Q_{N+1}^{-1} = \begin{bmatrix} Q_N & k_{N+1} \\ k_{N+1}^T & k_{N+1}^* \end{bmatrix} = \begin{bmatrix} Q_N^{-1} + Q_N^{-1} k_{N+1} k_{N+1}^T Q_N^{-1} \rho^{-1} & -Q_N^{-1} k_{N+1} \rho^{-1} \\ -k_{N+1}^T Q_N^{-1} \rho^{-1} & \rho^{-1} \end{bmatrix} \qquad (2.9)$$

Where:

$\rho = k_{N+1}^* - k_{N+1}^T Q_N^{-1} k_{N+1}$

After we add new data and Q_{N+1}^{-1} has been known then we rearrange the training dataset as $[x_2, x_3, ...x_{N+1}, x_1]$ to get the predicted matrix as:

$$\hat{Q}_{N+1} = \begin{bmatrix} \hat{Q}_N & k_1 \\ k_1^T & k_1^* \end{bmatrix} \qquad (2.10)$$

Where:

$$k_1^* = \gamma^{-1} + k(x_1, x_1) = \gamma^{-1} + 1, k_1 = [1, k(x_1, x_i)]^T, i = 1,2,......., N,$$

$$\hat{Q}_{N+1} = \begin{bmatrix} 0 & 1^T \\ 1 & \Omega + \gamma^{-1} I \end{bmatrix}_{(N+1)\times(N+1)} \quad with(\Omega = k(x_i, x_j), i, j = 1,2,......, N+1$$

Then the inversion of equation (10) is equal to:

$$\hat{Q}_{N+1}^{-1} = \begin{bmatrix} \hat{Q}_N & k_1 \\ k_1^T & k_1^* \end{bmatrix}^T \qquad (2.11)$$

Finally we can compute α, b from equation (5) with $\hat{Q}_N^{-1}$ and repeat again and again until all the data exhausted.

3. Main Forecast Performance Measures

3.1 The Mean Squared Error (MSE)

Zhang(2003)[28] define the mathematical definition of this measure as:

$$MSE = \frac{1}{n}\sum_{t=1}^{n} e_t^2$$

The properties of MSE by Hamzacebi (2008)[9] are (12):

- Its measure the average squared deviation of predicted data.
- MSE gives an idea of the errors occurred during forecasting.
- MSE emphasizes the total forecast error is in fact much affected by large individual errors.
- MSE affected by transformed of data.
- MSE is a good measure of overall forecast errors.
- Good forecasting gives minimum MSE.

3.2 The Mean Absolute Error (MAE) (Hamzacebi (2008)[9]),(Zhang(2003)[30]) ,(Park(1999)[16]),(Cao(2003)[5])

They defined Mean Absolute Error (MAE) mathematically as:

$$MAE = \frac{1}{n}\sum_{t=1}^{n} |e_t| \qquad (3.1)$$

The properties of MAE are :

- MAE measures the average absolute deviation of forecasted value from original one.

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- Its show the magnitude of overall error.
- MAE doesn't give any idea about the direction of errors.
- MAE affected by transformed of data.
- Good forecasting gives minimum MAE.

3.3 The Root Mean Squared Error (RMSE) (Zhang(2007)[29]) ,(Park(1999)[16])

Mathematically Root Mean Squared Error (RMSE) can be defined as:

$$RMSE=\sqrt{MSE}=\sqrt{\frac{1}{n}\sum_{t=1}^{n}e_t^2} \qquad (3.2)$$

The RMSE properties are :

- Its measure the average squared deviation of predicted data.
- RMSE gives an idea of the errors occurred during forecasting.
- RMSE emphasizes the total forecast error is in fact much affected by large individual errors.
- RMSE affected by transformed of data.
- RMSE is a good measure of overall forecast errors.
- Good forecasting gives minimum RMSE.

3.4 The Mean Percentage Error (MPE) (Hamzacebi (2008)[9]), (Cao(2003)[5])

Mean Percentage Error (MPE) can be defined mathematically as:

$$MAPE=\frac{1}{n}\sum_{t=1}^{n}\left|\frac{e_t}{y_t}\right|\times 100 \qquad (3.3)$$

The RMSE properties are:

- It’s a percentage measure of average absolute error.
- It's affected by transformed of data.
- Doesn't show direction of error.

Unit root test

Stationarity tests of series named unit root test and there are many indices for testing unit root test such: (Hyndman & Athanasopoulos(2018)[10]).

3.4.1 Dickey–Fuller tests:

From unit root hypothesis test one can distinguish series that appear to be stationary when it has a unit root. (Fuller,1976[7] ; Said & Dickey,1984[18]).

3.4.2 Augmented Dickey-Fuller test (Fuller ,1976[9])**:**

It is an augmented version of Dickey Fuller test for a larger and more complicated set of time series models.

Augmented Dickey Fuller test computed as:

$$\Delta Y_t = \beta_1 + \beta_2 t + \delta Y_{t-1} + \sum \alpha_i \Delta Y_{t-1} + \varepsilon_t \qquad (3.4)$$

Where:

ε_t is a pure white noise error term.

ΔY_{t-1}=($Y_{t-1} - Y_{t-2}$) and so on.

Then the ADF test whether $\delta = 0$

3.4.3 Phillips Perron(pp) unit root test (Phillips & Perron ,1988[17]):

The Dickey Fuller test assumes that the error terms u_i are iid (independent and identical distribution) also takes care of possible serial correlation in the error terms by adding the lagged difference terms of the regressed. But in PP non parametric statistical methods is used to take care of serial correlation in the error terms without adding lagged difference.

The PP regression is:

$$\Delta Y_t = \beta^{\backslash} D_t + \theta Y_{t-1} + u_t \qquad (3.5)$$

Where:

D_t is the deterministic components (constant or constant plus trend), u_t is $I(0)$ and may be heteroskedastic . **Heteroskedastic** means that the variance of the errors is not constant(Seddighi, Lawler & Katos, 2000[20]). Both in ADF and PP the stationary test tests the null hypothesis that a time series is stationary $I(1)$.

3.4.5 KPSS test:

The most commonly used stationarity test, the KPSS test, is due to (Kwiatkowski et al., 1992[13]). They derived their test by starting with the model

$$Y_t = B_0 + B_1 t + \theta_t + u_t \qquad (3.6)$$

$$\theta_t = \theta_{t-1} + \varepsilon_t, \qquad \varepsilon_t \sim WN(0, \sigma^2_{\varepsilon})$$

where u_t is stationary time series and is said to be integrated of order zero, $I(0)$ and may be heteroskedastic. The null hypothesis that Y_t is $I(0)$ is formulated as $H_0: \sigma^2_{\varepsilon} = 0$, which implies that θ_t is a constant.

Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test: null hypothesis is that the data are stationary and non-

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seasonal.

Definition: The KPSS test statistic is the Lagrange Multiplier (LM) or score statistic for testing

$H_0: \sigma^2_z = 0$ versus $H_a: \sigma^2_z > 0$ and is given by

$$\text{KPSS} = T^{-2} \sum_{t=1}^{T} \hat{S}^2{}_t / \hat{B}^2 \qquad (3.7)$$

Where $\hat{S}^2{}_t = \sum_{t=1}^{T} \hat{u}_t$, $\hat{u}_t$ is the residual of a regression Y_t on t and $\hat{B}^2$ is a consistent estimate of the long-run variance of u_t using $\hat{u}_t$.

3.6 Definition: Akaike's Information Criterion(AIC)(Shumway & Stoffer,2018[23]).

$$\text{AIC}= \log\hat{\sigma}^2_k + \frac{n+2k}{n} \qquad (3.8)$$

Where $\hat{\sigma}^2_k = \frac{SSE(K)}{n}$

And SSE(k) denotes the residual sum of squares under the model with k regression coefficients.

k is the number of parameters in the model. The value of k yielding the minimum AIC specifies the best model, and n is the sample size.

3.6.1 Definition: AIC, Bias Corrected (AICc)

$$\text{AICc}= \log\hat{\sigma}^2_k + \frac{n+k}{n-K-2} \qquad (3.9)$$

As with the AIC, the AICc should be minimized.

4. Results and discussion

From Fig. (1), Fig. (2) and Fig. (3) we illustrate that there is a trend in male and female data sets therefore we should remove this trend by differencing before start our analysis of data sets.

To ensure our previous results we run the diagnostic tests, our findings are in table (1), from this table the null hypothesis from ADF, PP, and DF is data for male and female are not stationary and from p.value we cannot reject null hypothesis so that both data sets are not stationary at their levels, these results met with Fig. (1), Fig. (2) and Fig.(3), but the null hypothesis for KPSS test is data does 'not need differences, from p.value of KPSS at table (1), we can reject null hypothesis for both data sets, therefore both data sets (Males and Females) need differences.

We run the first difference on both data sets our findings are in table (2), from this table our both data sets become stationary respected to KPSS, ADF, PP, and AD tests.

We run the criterion for selected the optimal ARIMA models for both data sets our findings are on table (3) and from this table we conclude that the optimal model for male data sets is ARIMA(0,1,1) because all the criterion are minimum but the optimal model for female data sets is ARIMA(1,1,1) because all the criterion are minimum.

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To ensure our results we run auto arima model selection the results are met in both data sets our findings are in table (4)

The results of ARIMA predicted values for both data sets are in table (5) and Fig. (4).

We run SVM to predict value for both data sets and our findings are on Fig. (5)

From table(6) we illustrate that SVM performed better than ARIMA method which gets the minimum error measures in both data sets, then we used SVM to predict the number of patients (males and females) who will have brain stroke from 1/4/2019 to 31/12/2019 at European Gaza Hospital in Khan Younis and our findings are maximum prediction of stroke patients was in next November and December (2019),where the numbers of patients are 33 for each month distributed as 24 males and 9 females, table (7).

5. Recommendations

Our recommendations are to use SVM instead of ARIMA method for prediction because it performs better than ARIMA method and our recommendation for administrative of European Gaza Hospital in Khan Younis to prepare themselves for these numbers of patient who will have a brain stroke for next nine months.

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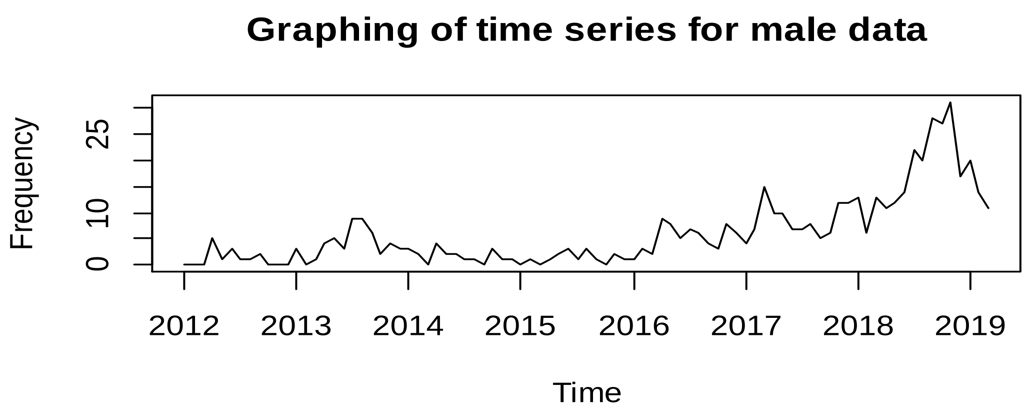

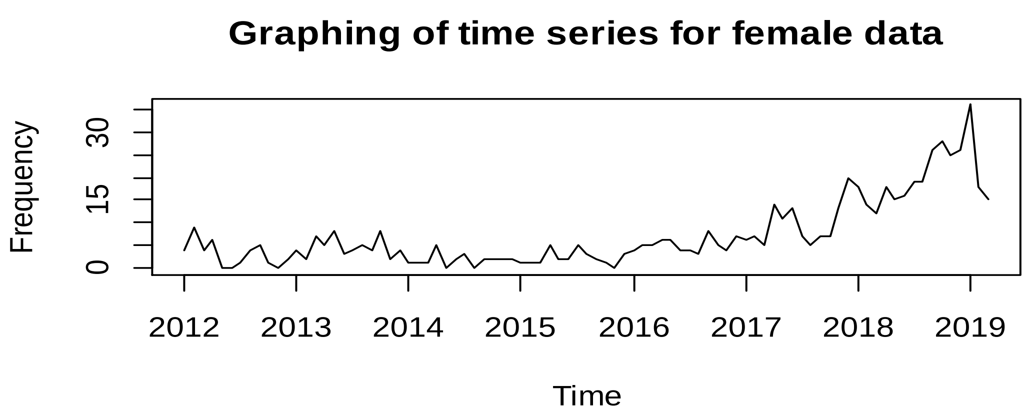

Fig.(1): Time series plot of stroke patients at European Gaza hospital from 1/1/2012 to 1/03/2019

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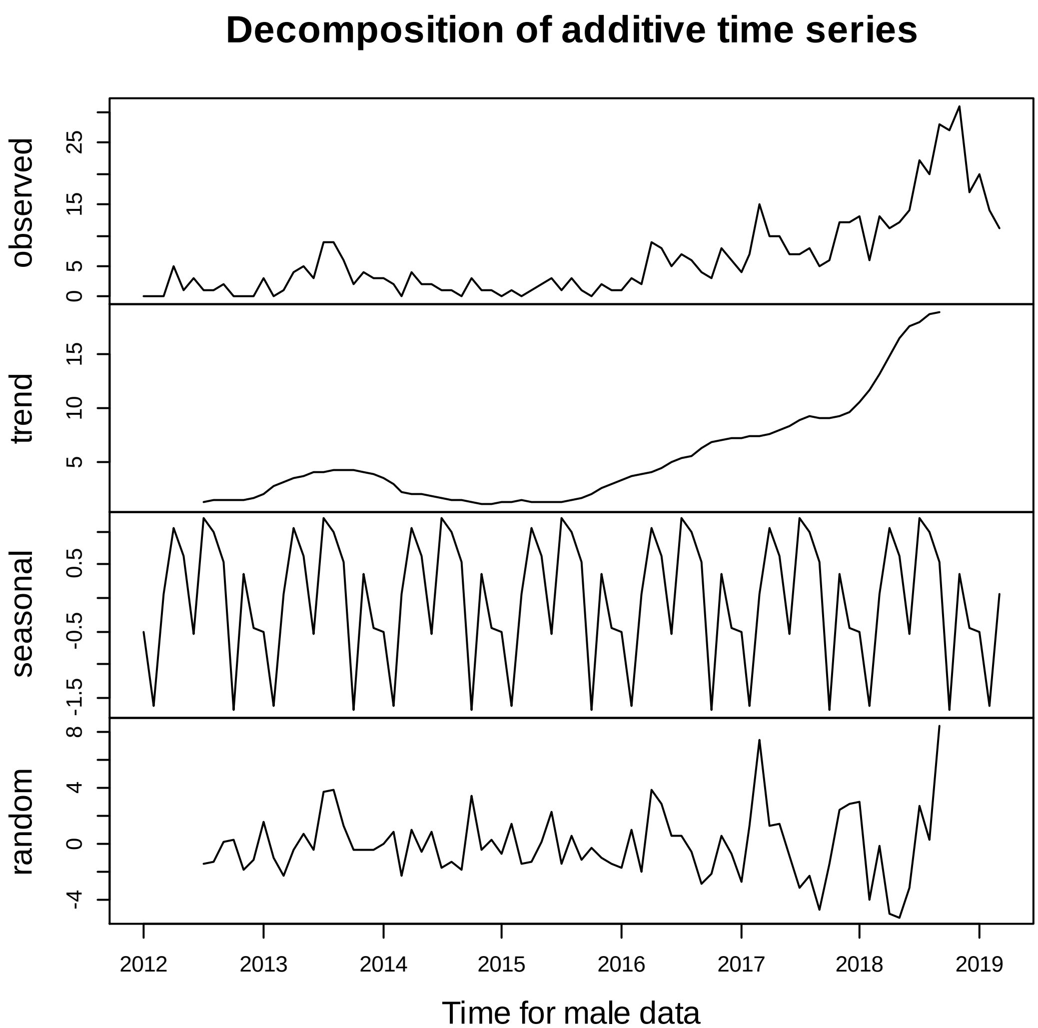

Fig(2): Time series components plot of stroke patients"Male" from 1/1/2012 to 01/03/2019.

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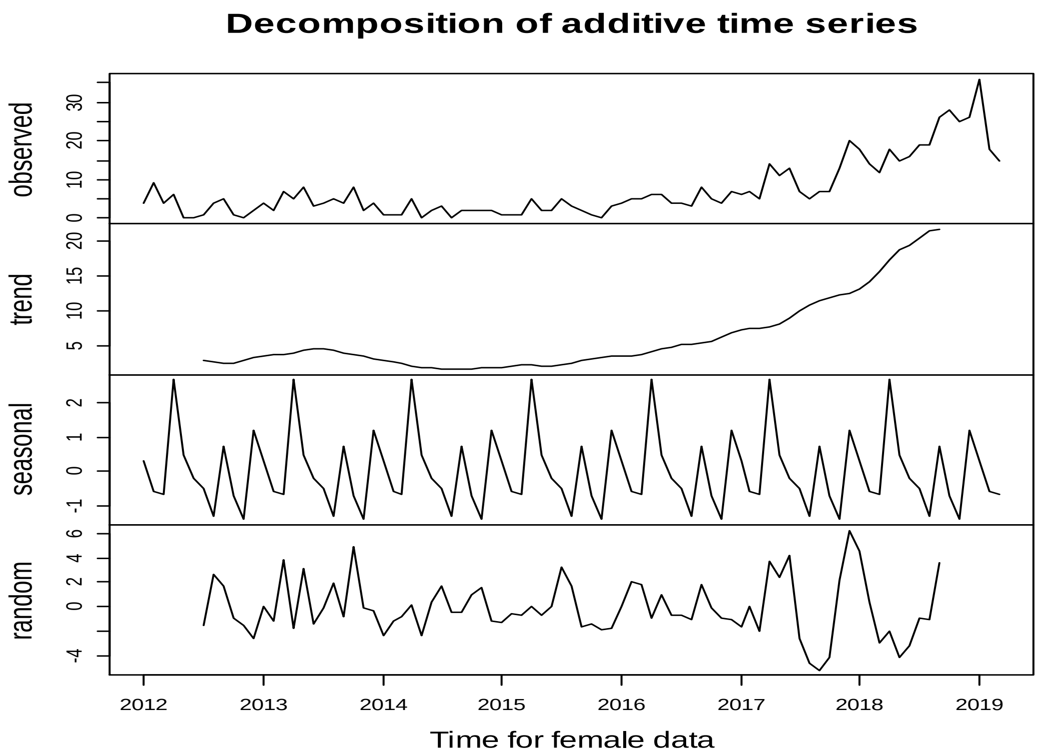

Fig(3): Time series components plot of stroke patients "Female" from 1/1/2012 to 01/03/2019.

Table (1) Diagnostic Time series results

Diagnostic Time series results			
Male data		Female data	
Test	P.value	Test	P.value
KPPS	0.01	KPPS	0.01
ADF	0.4265	ADF	0.4843
PP	0.2331	PP	0.2567
DF	0.2038	DF	0.1348

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Table(2) Diagnostic Time series results after differencing

Unit root tests after differences			
Male data		Female data	
Test	P.value	Test	P.value
KPPS	0.1	KPPS	0.1
ADF	0.01	ADF	0.01
PP	0.01	PP	0.01
DF	0.01	DF	0.01

Table(3) Optimal ARIMA model

Criteria of selecting ARIMA model						
	Male			Female		
Model	AIC	AICc	BIC	AIC	AICc	BIC
ARIMA(0,1,1)	**358.07**	**358.23**	**362.73**	377.66	377.83	382.32
ARIMA(0,1,0)	372.39	372.45	374.73	388.67	388.73	391
ARIMA(1,1,1)	358.87	359.21	365.86	**377.21**	**377.55**	**384.21**
ARIMA(0,1,2)	359.06	359.39	366.05	378.07	378.4	385.06
ARIMA(1,1,2)	360.8	361.36	370.12	381.51	382.07	390.83

Table(4) Optimal ARIMA model by auto.arima

Optimal Auto.Arima							
Male				Female			
Model	AIC	AICc	BIC	Model	AIC	AICc	BIC
ARIMA(0,1,1)	**358.07**	**358.23**	**362.73**	ARIMA(1,1,1)	**377.21**	**377.55**	**384.21**

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Table(5) ARIMA forecast from 1/6/2018 to 31/3/2019

ARIMA Forecast results from 01/06/2018 to 31/03/2019				
Males		Females		
Date	Forecast	Date	Forecast	Total
1/6/2018	19	1/6/2018	19	38
1/7/2018	19	1/7/2018	21	40
1/8/2018	22	1/8/2018	23	45
1/9/2018	19	1/9/2018	21	40
1/10/2018	20	1/10/2018	26	46
1/11/2018	23	1/11/2018	24	47
1/12/2018	24	1/12/2018	27	51
1/1/2019	22	1/1/2019	22	44
1/2/2019	28	1/2/2019	23	51
1/3/2019	28	1/3/2019	24	52

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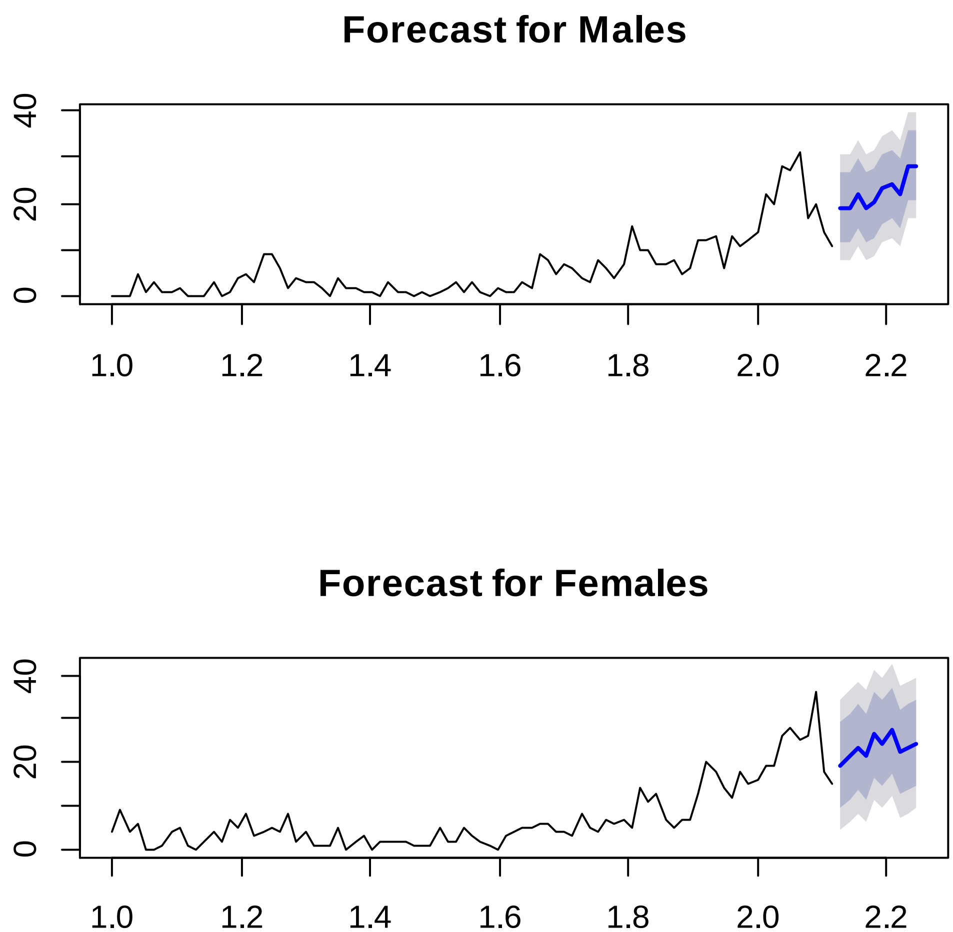

Fig(4): Arima forecast from 1/6/2018 to 31/3/2019.

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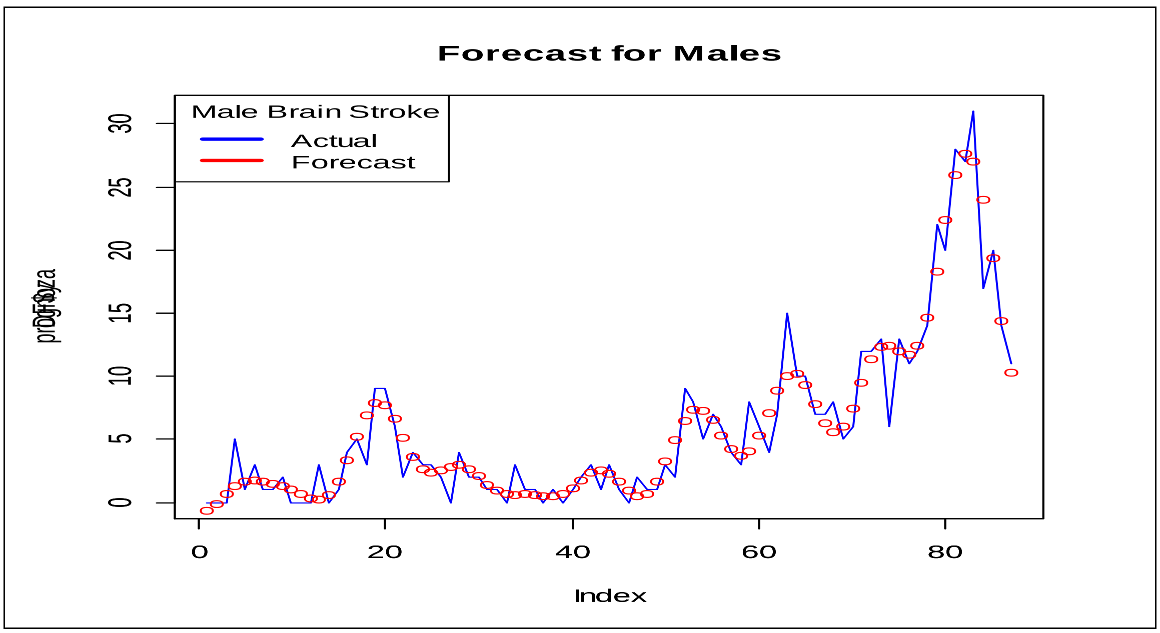
Table(6) Error measures between ARIMA and SVM

Error measures				
	ARIMA		SVM	
Index	Male	Female	Male	Female
mae	5.92	4.68	**3.22**	**2.275**
mse	49.29	36.52	**16.018**	**18.50705**
rmse	7.020684	6.043178	**4.002249**	**4.301982**
mape	0.3366809	0.218675	**0.176143**	**0.082015**



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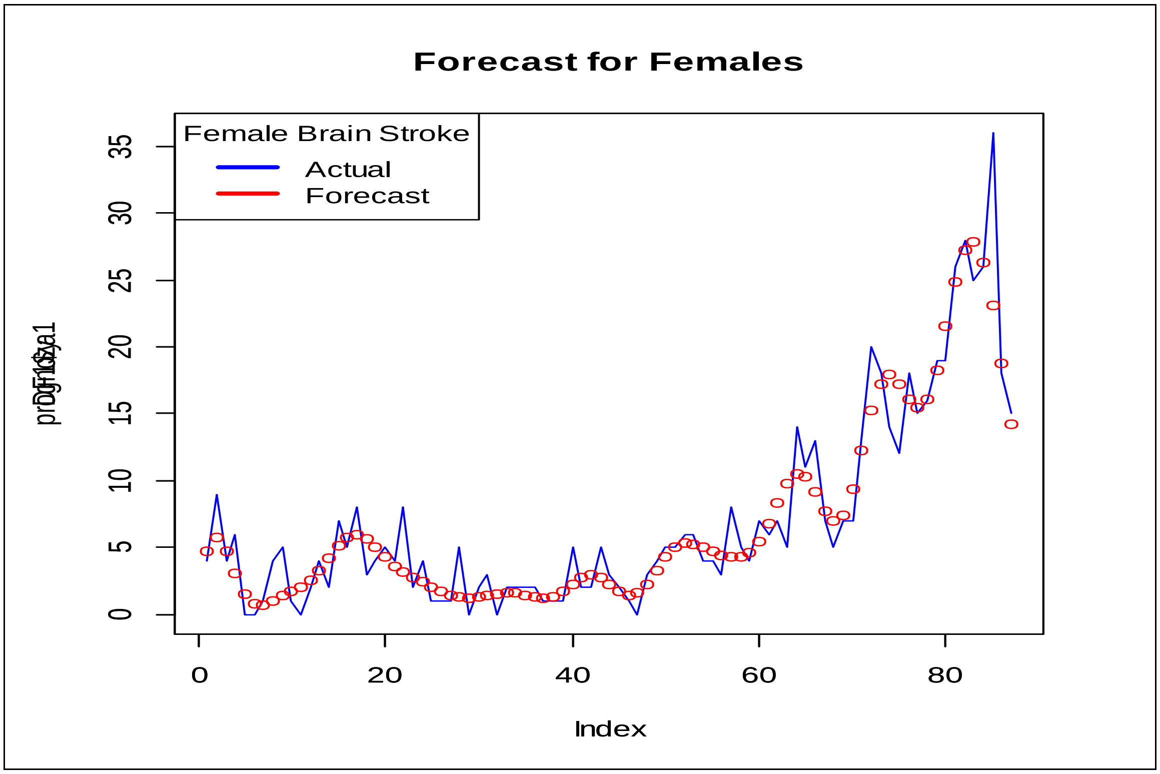

Fig(5): SVM forecast from 1/6/2018 to 31/3/2019.

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Table(7) SVM prediction from 1/4/2019 to 31/12/2019

Using SVM to predict number of brain stroke from 1/4/2019 to 31/12/2019			
Date	≈Male	≈Female	≈Total
1/4/2019	8	10	19
1/5/2019	8	8	16
1/6/2019	10	6	17
1/7/2019	14	6	20
1/8/2019	18	7	24
1/9/2019	21	8	29
1/10/2019	23	8	32
1/11/2019	24	9	33
1/12/2019	24	9	33

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