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RESEARCH ARTICLE

Hypertension Monitoring by a Real Time Management System for Patients in Community and Its Data Mining by Vector Autoregressive Model

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ABSTRACT Blood pressure has a 24-hour repetitive and regular variation which shows circadian rhythm. Using the multivariate time series analysis method of vector autoregressive model, we could realize the simultaneous prediction for both systolic and diastolic blood pressures. We choose blood pressure from 6 AM to 10 AM in 3 weeks as an episode to construct a prediction model. Missing values were imputed by regression models. Subsequently, we defined segments as positive or negative segments according to blood pressure measurements. The predictions were accomplished by vector autoregressive model (VAR). Both positive and negative segments were randomly selected from each patient to summarize the effect of prediction models. In this study, the MAPE (Mean Absolute Percentage Error) of systolic blood pressure and diastolic blood pressure were both less than 10%, indicating that the VAR model was adaptable in predicting the blood pressure of hypertensive patients. Based on VAR, we could provide early warning to breakthrough of blood pressure thresholds. The sensitivity, specificity, and accuracy for patients in the training sets were 77.50%, 81.58 %, and 79.49% respectively, and the sensitivity, specificity, and accuracy for patients in the training sets were 76.92%, 80.00% and 78.43% respectively. This research took information of both systolic and diastolic blood pressures at the same time to establish the VAR models and enabled simultaneous prediction for systolic and diastolic blood pressure.

INDEX TERMS Time series, vector autoregressive model, hypertension.

I. INTRODUCTION

In general, hypertension is asymptomatic most time until acute events emerge [1], [2]. Raised blood pressure (BP) is the highest single risk factor contributing to an estimate of 10.4 million deaths [3], [5], [6], and estimate is still arising [4], [7], [8], [9]. Acute elevations of blood pressure are commonly associated with serious consequences requiring urgent interventions [10], [11], [12]. In a large-scale study from 17 countries, it was reported that only

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half of participants were aware of their condition including 57840 hypertensive adults [5]. It was shown that 72% of adults (aged 40∼79 years) from high-income countries were aware of their condition, while only 10.3% of hypertensive in low and middle-income countries had their BPs controlled [6]. It is a critical issue to manage blood pressure. It is now high time to raise BP awareness and attach importance to hypertension management.

Hypertensive patients could modify their blood pressure to reduce cardiovascular events and mortality by changing lifestyle and pharmacological interventions [13]. More importantly, measuring BP frequently is of great significance to health promotion [14]. At present, there are many kinds of sphygmomanometers to facilitate real-time monitoring. It could even automatically synchronize blood pressure measurements to the background [15], [16]. However, all the sphygmomanometers can only record historical physiological data. They are not able to forecast the blood pressure value at a certain future. It would be better if it could forecast the possibility of acute cardiovascular event so that send an alert timely [17].

Circadian rhythm of blood pressure that has a 24-hour repetitive and regular variation [18], [19]. There is autocorrelation in blood pressures. It is essential to handle autocorrelation properly in a model. Besides this, the uneven dynamic series of blood pressure may increase the inaccuracy of prediction [20]. Some researchers have applied time series models in biological rhythm time series successfully [21], [22], [23], [24]. Badu et al established an autoregressive integrated moving average (ARIMA) model to predict systolic blood pressure [25]. It was showed that ARIMA model was useful to predict fluctuations in the blood pressure sequence. However, there still need improvement in the prediction results. It is an another field that applying machine learning to identify people at high risk of hypertension [26]. Support vector regression (SVR), linear regression, or ridge regression models have been attempted at prediction in many researches [26], [27], [28], [29], [30].

An acute rising in the blood pressure is called a hypertensive crisis. It required prompt treatment, otherwise severe fluctuations in blood pressure will lead to irreversible damage [31], [32]. With emerging technology, telemedicine will be helpful with convenience and promptness [33]. In the past two decades, telemedicine technology has been evolving rapidly from simple blood pressure tele-monitoring to the combined monitoring with interventions [34], [35]. It provides an interactive platform between physicians and patients. In some case, it needs to monitor continuous blood pressure of hypertensive patients. For this, physiological sensors paired with artificial intelligence, particularly like PPG (Photoplethysmography) and ECG (Electrocardiography), are taken into consideration to predict blood pressure. It is simple, portable, and able to measure health parameters continuously and non-invasively. Our research was first to concentrate on the role of blood pressure values. We introduced sphygmomanometers which could automatically upload blood pressure in the background to monitor home blood pressure. These are automatic health tracking devices and record patients' health parameters for future use. In addition, our study takes personal heterogeneity into consideration in blood pressure dynamics. Unlike others' study, we established a unique auto vector regression model for each person, which would alarm the occurrence of emergencies or acute heart attacks.

TABLE 1. Characteristic of datasets.

Factors		Training set	Testing set
Gender	Male	12	13
	Female	22	13
Age		66±8	68±8

II. METHOD AND MATERIAL

A. DATA COLLECTION-INCLUSION CRITERIA AND EXCLUSION CRITERIA

1) INCLUSION CRITERIA AND EXCLUSION CRITERIA

All data in this study were derived from the 982 hypertensive patients in Banfu Town, Zhongshan City, Guangdong Province. Data collection began from December 2016 to September 2020. All patients had signed an informed consent form. Inclusion criteria were the followings: ① age larger than 18 years old; ② being able to operate a sphygmomanometer to monitor blood pressure by themselves. Exclusion criteria were as following: ① having acute and serious diseases in the past month, such as acute myocardial infarction, acute heart failure, acute cerebral infarction, malignant tumours; ② having visual, auditory and intellectual impairment, cognitive impairment; ③ with severe depression or a history of mental illness; ④ with abuse of alcohol or drug.

2) DEFINITION OF EPISODE

To a patient, it is common that variations of blood pressure occur frequently. Physicians need to determine treatment strategy by observed blood pressure measurements. According to the Chinese National Guidelines for the Prevention and Management of Primary Hypertension, it recommends that patients take twice more consultations within following four weeks after the first measurement of blood pressure by physicians. However, those extreme changes may be missed by the former recommendation. In order to detect the significant changes timely, we chose four weeks as an episode. In each episode, the accumulated length with no measurements provided should be no more than 3 days.

3) DEFINITION OF POSITIVE AND NEGATIVE SEGMENTS

The prediction in our research was performed in each episode (4 weeks). The first 3 weeks were used to construct model, while the fourth week was a segment being predicted.

In the fourth week, if the patient kept systolic blood pressure less than 140mmHg and diastolic blood pressure less than 90mmHg, then this segment was negative.

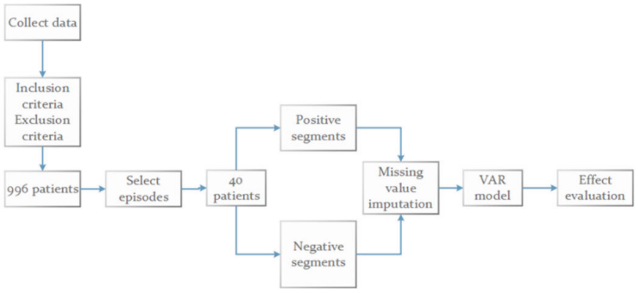

FIGURE 1. Analytic framework of hypertension prediction.

In the fourth week, if the patient had three or more systolic blood pressure values larger than 140mmHg or diastolic blood pressure larger than 90mmHg, then this segment was positive. This definition kept consistent with the Chinese National Guidelines for the Prevention and Management of Primary Hypertension. There was no overlap between positive segments and negative segments.

4) DATA SET AND ANALYTIC FRAMEWORK

Forty patients possess both positive and negative segments at the same time. We selected one negative segment and one positive segment from each patient as training sets to predict blood pressure.

Among the 40 patients mentioned above, 26 patients contained 2 or more positive segments. Despite of the 40 positive segments, we chose 26 new segments respectively from different patients. They are used as testing set for validation.

Their basic demographic characteristics were shown in Table 1 and analytic framework was shown in Fig. 1.

B. MEASUREMENT OF BLOOD PRESSURE VALUE

The *Lexin i5* or *Lexin i7 electronic blood pressure meters* were applied. Operation of measuring followed the China Blood Pressure Measurement Guidelines issued by the China Blood Pressure Measurement Working Group in 2011

Considering that daily blood pressure is a dipper shape with incomparable values at different time-points in a day, we chose the mean of blood pressure values measured from 6a.m. to 10 a.m. It was deemed to be missing values if patients did not upload measurements.

C. IMPUTATION OF MISSING VALUES

In Section II-A.2 definition of episode is given. If there exist any missing value at time-point t, the $x_{(t-1)}$, $x_{(t-2)}$, $x_{(t+1)}$, $x_{(t+2)}$ should be recorded. Otherwise, the influenced episodes were abandoned.

The missing value of $x_{(t-1)}$ missed was imputed by linear regression models without intercept. For Model I, constructing the regression model by backward selection strategy with significance level $\alpha = 0.10$. For Model II, constructing the regression model by all the $x_{(t-1)}, x_{(t-2)}, x_{(t+1)}, x_{(t+2)}$ without any exclusion.

We compared the effects of Model I and Model II with Mean Square Error (MSE), Akaike's Information Criterion (AIC), and Bayesian Information Criterion (BIC) [36]. AIC was adapted with a higher priority in case the results were not consistent.

TABLE 2. The coefficients of 40 regression models for imputation.

	Model I				Model II			
ID	$\beta_{1,(t-2)}$	$\beta_{1,(t-1)}$	$\beta_{1,(t+1)}$	$\beta_{1,(t+2)}$	$\beta_{2,(t-2)}$	$\beta_{2,(t-1)}$	$\beta_{2,(t+1)}$	$\beta_{2,(t+1)}$
77	0.15	0.38	0.34	0.13	0.23	0.30	0.27	0.20
88	0.25	0.25	0.25	0.25	0.26	0.24	0.24	0.26
97	0.22	0.27	0.27	0.24	0.19	0.31	0.30	0.20
113	0.17	0.32	0.32	0.19	0.28	0.22	0.20	0.30
182	0.34	0.16	0.15	0.35	0.34	0.16	0.16	0.34
196	0.13	0.37	0.37	0.13	0.17	0.33	0.34	0.16
212	0.11	0.37	0.34	0.18	0.14	0.31	0.28	0.27
241	0	0.08	0.62	0	0.25	0.25	0.24	0.26
302	0.20	0.30	0.30	0.20	0.17	0.33	0.33	0.17
316	0.16	0.34	0.34	0.16	0.28	0.22	0.23	0.27
331	0.21	0.26	0.30	0.23	0.09	0.39	0.43	0.09
361	0.26	0.24	0.24	0.26	0.26	0.24	0.24	0.26
385	0.29	0.21	0.20	0.30	0.30	0.20	0.18	0.32
421	0.24	0.26	0.25	0.25	0.16	0.35	0.35	0.14
425	0.24	0.25	0.24	0.27	0.24	0.21	0.20	0.35
447	0.18	0.32	0.32	0.18	0.22	0.28	0.27	0.23
466	0.15	0.35	0.35	0.15	0.17	0.33	0.33	0.17
478	0.27	0.23	0.24	0.26	0.39	0.12	0.12	0.37
578	0.22	0.27	0.28	0.23	0.25	0.25	0.26	0.25
580	0.17	0.33	0.33	0.17	0.18	0.31	0.32	0.19
594	0.17	0.32	0.31	0.20	0	0.12	0.86	0
605	0.15	0.35	0.35	0.15	0.18	0.32	0.32	0.18
643	0.31	0.19	0.17	0.33	0.24	0.26	0.26	0.24
669	0.22	0.27	0.28	0.23	0.32	0.18	0.18	0.32
685	0.16	0.34	0.34	0.16	0.20	0.30	0.30	0.20
697	0.24	0.26	0.25	0.25	0.22	0.28	0.26	0.24
728	0.19	0.31	0.31	0.19	0.14	0.36	0.36	0.14
760	0.23	0.27	0.27	0.23	0.23	0.27	0.27	0.23
766	0.27	0.23	0.23	0.27	0	0.11	1.22	0
784	0.17	0.33	0.34	0.16	0.19	0.31	0.31	0.19
810	0.18	0.31	0.31	0.20	0.17	0.33	0.32	0.18
822	0.16	0.34	0.34	0.16	0.29	0.21	0.21	0.29
835	0.20	0.30	0.30	0.20	0.22	0.28	0.28	0.22
847	0.20	0.30	0.31	0.19	0.27	0.24	0.24	0.25
881	0.21	0.27	0.26	0.26	0.22	0.27	0.27	0.24
898	0.21	0.28	0.28	0.23	0.22	0.27	0.27	0.24
912	0.24	0.27	0.26	0.23	0.33	0.17	0.17	0.33
937	0.18	0.32	0.32	0.18	0.19	0.31	0.31	0.19
941	0.17	0.33	0.31	0.19	0	0.10	0.07	0
951	0.21	0.29	0.29	0.21	0.19	0.31	0.31	0.19

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2 \tag{1}$$

where, n is the number of samples.

$$AIC = 2k - 2\ln(n) \tag{2}$$

where, k is the number of parameters of the model.

$$BIC = kln(n) - 2\ln(L) \tag{3}$$

where, L is the likelihood function.

We normalized regression coefficients so as to make the imputation is a linear combination to $x_{(t-1)}$, $x_{(t-2)}$, $x_{(t+1)}$, $x_{(t+2)}$ by a set of weights.

TABLE 3. The number of segments in 40 patients.

ID	Positive	Negative	ID	Positive	Negative
77	2	13	594	4	3
88	1	19	605	1	1
97	2	30	643	3	23
113	1	13	669	1	18
182	1	11	685	1	34
196	2	22	697	1	52
212	1	35	728	1	14
241	3	7	760	2	2
302	3	0	766	1	15
316	1	1	784	4	2
331	1	10	810	2	6
361	4	18	822	6	1
385	2	1	835	3	42
421	2	3	847	3	15
425	2	1	881	1	3
447	2	8	898	2	15
466	2	14	912	2	3
478	2	39	937	4	7
578	2	14	941	1	0
580	2	31	951	2	40

D. VECTOR AUTO REGRESSION MODEL

We introduced multivariate time series to combine patient's systolic and diastolic blood pressure and established a vector autoregression (VAR) model to predict both blood pressure values.

$$\begin{pmatrix} y_{1,t} \\ y_{2,t} \end{pmatrix} = \begin{pmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{pmatrix} + \begin{pmatrix} \beta_{11}y_{11} \\ \beta_{12}y_{12} \end{pmatrix} \begin{pmatrix} y_{1,t-1} \\ y_{2,t-1} \end{pmatrix} + \ldots + \begin{pmatrix} \beta_{1p}y_{1p} \\ \beta_{1p}y_{1\mathrm{p}} \end{pmatrix} \begin{pmatrix} y_{1,t-p} \\ y_{2,t-p} \end{pmatrix} \quad (4)$$

where $\begin{pmatrix} \beta_{1p}y_{1p} \\ \beta_{2p}y_{2p} \end{pmatrix}$ is the coefficient matrix, and $\begin{pmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{pmatrix}$ is the error matrix.

We used the Augmented Dickey-Fuller (ADF) test to determine the stationary of time series. The series is stable with p values larger than 0.05. If the sequence is unstable, the original sequence needs to be differentiated.

In order to utilize information in time series thoroughly, we determined the most appropriate lag with the AIC and Schwarz Criterion (SC). When both AIC and SC reach the minimum, the lag is the best. If the two results are inconsistent, we would introduce the likelihood ratio to choose lag.

The stability of the model was also assessed. The model would be stable and effective if all reciprocals of characteristic roots are less than 1.

E. EVALUATION OF VAR MODEL

In each episode, the data of the previous three weeks were utilized to build a VAR model to predict the patient's systolic and diastolic pressures simultaneously on the fourth week. We evaluated the effect of prediction by the mean absolute percentage error (MAPE) and model error.

$$MAPE = \frac{100}{n}\sum_{i=1}^{n}\left|\frac{\hat{y}_i - y_i}{y_i}\right| (\%) \quad (5)$$

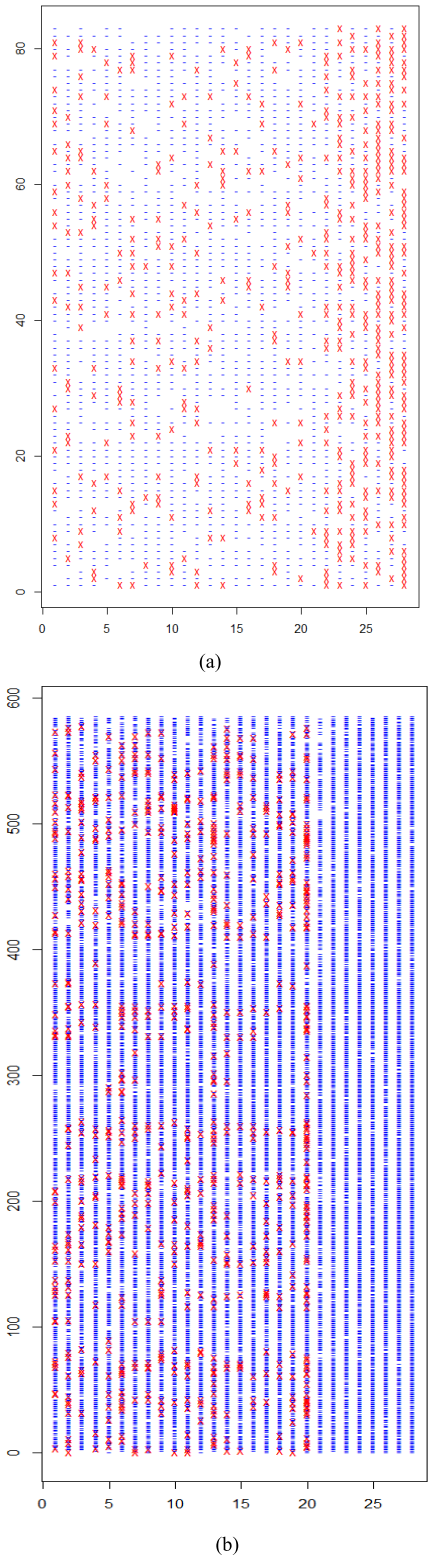

FIGURE 2. Details of all segments.

TABLE 4. Stationarity of episodes with positive segments (training set).

characteristic roots	minimum	maximum	number
1	0.27	0.99	40
2	0.27	0.99	40
3	0.64	0.99	40
4	0.64	0.99	40
5	0.47	0.99	40
6	0.04	0.90	40
7	0.13	0.90	36
8	0.06	0.85	36

△ More related characteristic roots to show stationarity were given in supplement table sVII-sIX. For episodes with positive segments (testing set), for episodes with negative segments (training set), and for episodes with negative segments (testing set).

TABLE 5. Assessment for VAR models by MAPE (%).

group		$MAPE_{SBP}$	$MAPE_{DBP}$	$MAPE_{model}$
Training set	Positive	7.98±3.73	7.50±3.44	7.87±3.28
	Negative	7.54±3.02	7.76±3.61	7.83±2.90
Testing set	Positive	7.71±3.63	7.60±3.73	7.83±3.26
	Negative	7.01±3.12	7.99±3.43	7.69±2.84

TABLE 6. Assessment for VAR models by three indices (%).

group	Sensitivity(95%CI)	Specificity (95%CI)	Accuracy(95%CI)
Training set	77.50(65.58,91.58)	81.58(70.14,94.88)	79.49(71.01,88.97)
Testing set	76.92(62.32,94.95)	80.00(65.76,97.32)	78.43(67.92,90.57)

$$error = \sqrt{\frac{MAPE^2_{Systolicpressure} + MAPE^2_{diastolicpressure}}{2}} \quad (6)$$

It demonstrates to be sensitive if VAR models will predict positive events in the fourth week successfully. On the other hand, the models are of high specificity if they could predict negative events correctly. We calculated accuracy, sensitivity, and specificity to testify the ability of prediction.

To judge the performance of the VAR model for identifying dangerous situations, we applied several indicators to evaluate.

Accuracy, or correct rate:

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \quad (7)$$

Precision, or Positive Predictive Value:

$$Precision = \frac{TP}{TP + FP} \quad (8)$$

Specificity, True Negative Rate (TNR):

$$Specificity = \frac{TN}{FP + TN} \quad (9)$$

True Positives (TP): the number of epochs correctly classified as positive epochs; False Positives (FP): the number of epochs misclassified as positive epochs; True Negatives (TN): the number of epochs correctly classified as negative epochs; False Negatives (FN): the number of epochs misclassified as negative epochs.

TABLE 7. Summary of related work by following Shallow Machine Learning techniques.

Biosensor	Feature Engineering	Performance	Significant Outlines
PPG	Discrete wavelet transform	SBP:5.1 ± 4.3 mmHg DBP:4.6 ± 4.3 mmHg	It uses the information PPG signal to predict by time–frequency decomposition.
PPG	Autoregressive coefficient Kaiser-Teager HR Spectral entropy Pulse wave	KAPPA score SBP: 0.99 DBP:0.99	Prediction are highly consistency.
PPG ECG	Pulse Arrival Time (PAT) Features In Time-domain signals)	SBP:11.1 ± 10.09mmHg DBP:5.35 ± 6.14mmHg	It applied time-domain information to prediction.
PPG	Autoregressive model Kaiser-Teager energy HR statistics Oxygen saturation Spectral entropy	Coefficients R = 0.91 SBP R = 0.89 DBP R = 0.90 BGL	This method was subject independent.
PPG	Multiple Parameters	SBP,DBP: less than 6 ± 6.5 mmHg	This study was conducted measure physiological parameters for blood pressure estimation.

III. RESULTS

A. IMPUTATION MODEL OF MISSING VALUE

In this study, we consider two kinds of regression model to impute missing data, and we apply AIC and MSE to choose adaptable imputation models. It was demonstrated that imputation model is more adaptable with smaller values of both AIC and MSE. The results of AIC and MSE were shown in the appendix Table 8. The results of regression coefficients were shown in Table 2. Considering that personal heterogeneity, each patient possessed a unique regression

TABLE 8. The effect of the two imputed regression models.

No.	Model 1[a] *MSE*	Model 2[a] *MSE*	Model1[a] *AIC*	Model 2[a] *AIC*	Model 1[a] *BIC*	Model 2[a] *BIC*	Model 1[b] *MSE*	Model 2[b] *MSE*	Model 1[b] *AIC*	Model 2[b] *AIC*	Model 1[b] *BIC*	Model 2[b] *BIC*
77	99.93	99.93	1185.89	1185.89	1201.20	1201.20	47.73	47.73	1069.13	1069.13	1084.45	1084.45
88	177.02	177.02	851.48	851.48	864.75	864.75	93.08	93.08	783.99	783.99	797.26	797.26
97	78.37	78.37	1788.22	1788.22	1805.76	1805.76	48.37	48.37	1669.04	1669.04	1686.59	1686.59
113	162.55	162.55	866.32	866.32	879.73	879.73	43.05	43.05	722.82	722.82	736.23	736.23
182	135.41	135.41	1040.25	1040.25	1054.70	1054.70	53.30	53.30	916.23	916.23	930.69	930.69
196	157.08	157.08	1715.24	1715.24	1732.12	1732.12	23.44	23.44	1304.33	1304.33	1321.21	1321.21
212	59.55	59.55	1457.28	1457.28	1473.99	1473.99	20.98	20.98	1239.18	1239.18	1255.90	1255.90
241	149.96	151.19	1140.14	1137.32	1154.99	1146.23	52.15	52.15	988.04	988.04	1002.89	1002.89
302	43.34	43.34	1939.25	1939.25	1957.63	1957.63	12.61	12.61	1578.80	1578.80	1597.19	1597.19
316	140.69	140.69	959.70	959.70	973.72	973.72	47.05	47.05	826.07	826.07	840.09	840.09
33	73.99	73.99	1145.56	1145.56	1160.90	1160.90	16.22	16.71	904.26	904.99	919.61	914.20
361	25.87	25.87	2287.99	2287.99	2307.61	2307.61	13.47	13.47	2044.02	2044.02	2063.65	2063.65
385	77.48	92.60	419.71	425.87	429.92	432.00	46.55	54.42	390.67	395.58	400.89	401.70
421	104.83	104.83	1043.64	1043.64	1058.28	1058.28	24.93	25.38	845.45	845.90	860.09	857.61
425	153.03	153.03	765.38	765.38	778.20	778.20	55.87	55.87	668.65	668.65	681.47	681.47
447	103.37	103.37	1400.57	1400.57	1416.69	1416.69	22.45	22.45	1116.56	1116.56	1132.68	1132.68
466	110.28	110.28	1917.84	1917.84	1935.51	1935.51	30.01	30.01	1588.57	1588.57	1606.24	1606.24
478	76.89	76.89	455.17	455.17	465.81	465.81	36.11	38.85	408.32	408.85	418.95	415.23
578	104.21	104.21	1619.13	1619.13	1635.98	1635.98	36.00	36.00	1390.62	1390.62	1407.47	1407.47
580	69.02	69.02	1947.79	1947.79	1965.86	1965.86	25.08	25.08	1670.38	1670.38	1688.44	1688.44
594	202.04	208.67	604.68	605.04	616.14	614.20	84.77	87.87	541.28	539.91	552.73	546.78
605	96.28	96.28	1705.77	1705.77	1722.93	1722.93	46.55	46.55	1539.37	1539.37	1556.54	1556.54
643	66.13	66.13	1626.79	1626.79	1643.98	1643.98	22.62	22.62	1380.02	1380.02	1397.21	1397.21
669	100.40	100.40	1000.45	1000.45	1014.91	1014.91	23.54	23.54	807.52	807.52	821.98	821.98
685	173.91	173.91	2960.68	2960.68	2980.23	2980.23	115.33	115.33	2809.10	2809.10	2828.65	2828.65
697	56.84	56.84	1990.92	1990.92	2009.24	2009.24	34.89	34.89	1850.35	1850.35	1868.67	1868.67
728	52.23	52.23	662.18	662.18	675.00	675.00	25.75	27.40	594.30	596.26	607.12	603.96
760	403.83	403.83	2670.50	2670.50	2689.03	2689.03	113.39	113.39	2288.19	2288.19	2306.73	2306.73
766	178.12	178.12	747.87	747.87	760.48	760.48	51.17	53.06	633.12	632.45	645.73	640.02
784	120.10	120.10	1542.86	1542.86	1559.38	1559.38	63.24	63.24	1413.96	1413.96	1430.47	1430.47
810	112.87	112.87	925.25	925.25	939.23	939.23	40.90	40.90	802.44	802.44	816.42	816.42
822	210.41	210.41	1008.81	1008.81	1022.83	1022.83	51.67	51.67	837.50	837.50	851.52	851.52
835	116.40	116.40	2584.66	2584.66	2603.79	2603.79	31.19	31.19	2138.20	2138.20	2157.33	2157.33
847	55.02	55.02	1290.12	1290.12	1306.27	1306.27	20.34	20.34	1104.02	1104.02	1120.18	1120.18
881	140.49	140.49	391.37	391.37	400.83	400.83	45.31	45.31	335.91	335.91	345.37	345.37
898	55.77	55.77	1134.89	1134.89	1150.39	1150.39	23.41	23.41	992.51	992.51	1008.01	1008.01
912	53.40	53.40	323.52	323.52	332.66	332.66	20.90	24.01	280.36	282.76	289.51	288.25
937	160.17	160.17	2890.74	2890.74	2910.22	2910.22	32.72	32.72	2312.67	2312.67	2332.15	2332.15
941	79.49	79.49	601.51	601.51	613.54	613.54	21.21	21.28	493.15	489.43	505.19	496.65
951	76.04	76.04	1200.08	1200.08	1215.64	1215.64	43.19	43.19	1106.19	1106.19	1121.75	1121.75

a: represents imputed regression model of the systolic pressure.
b: represents imputed regression model of the diastolic pressure.

imputation model. All coefficients were normalized. β_1, t was a coefficient to impute missing values of systolic pressure, β_2, t was for diastolic pressure. Take the 77$^{\text{th}}$ patient as an example. The predicted systolic pressure ($y_{1(t)}$) and diastolic pressure ($y_{2(t)}$) were showed in the following,

$$y_{1(t)} = 0.15x_{(t-2)} + 0.38x_{(t-1)} + 0.34x_{(t+1)} + 0.13x_{(t+2)} \tag{10}$$

$$y_{2(t)} = 0.23x_{(t-2)} + 0.30x_{(t-1)} + 0.27x_{(t+1)} + 0.20x_{(t+2)} \tag{11}$$

B. THE DETAILS OF ACQUIRED POSITIVE AND NEGATIVE SEGMENTS

According to definition of positive and negative segments in Section II-A.3, two patients failed to provide negative segments in training sets, and one patient failed to provide a positive segment in testing sets. Therefore, the training set included 40 positive segments and 38 negative segments. As for the testing set, it was composed of 26 positive segments and 25 negative segments. The number of segments provided by each patient was shown in Table 3.

The information of segments was shown in Fig. 2. The horizontal axis was 28 days, which was the length of time in an episode, and the vertical axis was the serial number of segments. The blue dots meant that the blood pressure value was normal, and the red cross meant to be abnormal. In positive episodes, there were once abnormal blood pressure value occurred in the fourth week at least. Take the 83rd positive segment as an example, three abnormal events occurred in the fourth week, without any abnormal events that happened in each previous three weeks. In Fig. 2(b), all blood pressure values were normal in the fourth week in negative episodes.

C. VAR MODEL

After imputation, we could adopt VAR model to forecast future blood pressure. Firstly, we apply ADF test to determine whether original blood pressure values should be difference

TABLE 9. ADF of positive segments in training set.

No.	TIME OF DIFFERENCE	*ADF* OF SBP	*P*	*ADF* OF DBP	*P*
77	1	-4.77	0.01	-3.94	0.03
88	2	-6.49	0.01	-4.86	0.01
97	2	-5.04	0.01	-3.70	0.04
113	3	-4.94	0.01	-4.44	0.01
182	1	-3.73	0.04	-5.47	0.01
196	2	-3.75	0.04	-4.09	0.02
212	2	-5.64	0.01	-3.99	0.02
241	2	-4.51	0.01	-3.92	0.03
302	1	-3.85	0.03	-6.13	0.01
316	2	-4.95	0.01	-4.60	0.01
331	2	-3.95	0.03	-3.75	0.04
361	1	-4.31	0.01	-4.06	0.02
385	1	-4.16	0.02	-4.53	0.01
421	2	-4.33	0.01	-8.67	0.01
425	2	-6.24	0.01	-8.18	0.01
447	3	-4.05	0.02	-4.23	0.02
466	0	-4.43	0.01	-3.84	0.03
478	3	-4.40	0.01	-4.12	0.02
578	0	-3.76	0.04	-4.67	0.01
580	2	-4.23	0.02	-2.97	0.02
594	3	-4.41	0.01	-3.88	0.03
605	2	-3.75	0.04	-5.88	0.01
643	2	-5.54	0.01	-3.98	0.02
669	2	-3.75	0.04	-5.88	0.01
685	3	-4.85	0.01	-4.51	0.01
697	3	-4.61	0.01	-3.71	0.04
728	1	-3.99	0.02	-4.49	0.01
760	2	-3.76	0.04	-4.79	0.01
766	3	-4.01	0.02	-5.46	0.01
784	3	-3.89	0.03	-3.81	0.04
810	3	-4.85	0.01	-4.51	0.01
822	2	-4.93	0.01	-4.52	0.01
835	2	-3.99	0.02	-4.43	0.01
847	1	-4.28	0.01	-4.52	0.01
881	3	-4.75	0.01	-4.84	0.01
898	3	-4.61	0.01	-4.08	0.02
912	1	-3.74	0.04	-3.73	0.04
937	3	-4.90	0.01	-4.32	0.01
941	3	-3.75	0.04	-7.91	0.01
951	1	-3.72	0.04	-3.94	0.03

to handle unevenness. All results of ADF test and *P* values were shown in the Appendix Table 9∼12. If the time of difference was zero, it meant that there was no need to construct difference equations on original time series, like No.466 and No.568. It could construct VAR model on original series directly. For non-stationary sequences, the sequences are differentiated until the systolic and diastolic blood pressure sequences meet the homogeneous single integer. In Table 9-12, all *P* values of ADF were less than 0.05. It demonstrated that time series of systolic and diastolic pressure reached stableness after difference at last. Appendix Table 9-12 included ADF test of all the segments. Secondly, we determined the largest lag *p* of VAR when both AIC and SC were minimum. The results of lag order were shown in Table 13-16. Constantly, we use MSE to adjust coefficients. In the result of All reciprocals of characteristic roots in every VAR model were less than 1 (Table 4) that meant precondition

TABLE 10. ADF of negative segments in training set.

No.	Time of difference	*ADF* of SBP	*P*	*ADF* of DBP	*P*
77	1	-3.70	0.04	-4.14	0.02
88	2	-4.20	0.02	-4.50	0.01
97	0	-4.29	0.01	-5.08	0.01
113	1	-3.68	0.04	-4.30	0.01
182	0	-4.19	0.02	-3.70	0.04
196	1	-3.81	0.04	-3.62	0.05
212	0	-3.74	0.04	-4.36	0.01
241	2	-4.25	0.01	-4.81	0.01
316	2	-4.15	0.02	-3.63	0.05
331	2	-4.03	0.02	-4.29	0.01
361	0	-3.96	0.02	-3.60	0.05
385	2	-4.28	0.01	-5.51	0.01
421	0	-5.96	0.01	-5.40	0.01
425	1	-3.78	0.04	-3.97	0.02
447	2	-4.48	0.01	-4.28	0.01
466	1	-4.56	0.01	-4.42	0.01
478	1	-3.99	0.02	-3.68	0.04
578	2	-4.16	0.02	-3.89	0.03
580	1	-5.47	0.01	-5.99	0.01
594	1	-3.67	0.04	-4.45	0.01
605	2	-4.93	0.01	-5.47	0.01
643	0	-4.36	0.01	-3.79	0.04
669	1	-4.47	0.01	-4.02	0.02
685	1	-3.69	0.04	-3.96	0.02
697	0	-4.13	0.02	-3.69	0.04
728	2	-6.08	0.01	-3.72	0.04
760	1	-3.78	0.04	-4.32	0.01
766	0	-3.71	0.04	-5.05	0.01
784	0	-3.90	0.03	-3.68	0.04
810	1	-4.55	0.01	-4.06	0.02
822	2	-4.43	0.01	-4.42	0.01
835	1	-3.70	0.04	-3.77	0.04
847	2	-3.73	0.04	-5.01	0.01
881	2	-4.40	0.01	-5.75	0.01
898	0	-4.44	0.01	-4.01	0.02
912	1	-4.86	0.01	-6.18	0.01
937	1	-4.18	0.02	-3.97	0.02
951	0	-4.68	0.01	-5.82	0.01

for stationarity was satisfied. Most lags of the VAR models were 4. 4 models are suitable for lag 3(without the characteristic roots of 7 and 8).

D. EVALUATION OF PREDICTION

Based on previous recommended lags, we constructed a unique VAR model for each patient. The specific parameters of each equation were shown in Appendix Table 18. Take the 77^{th} patients as an example, the VAR model of prediction in vector form was the following,

$$\begin{aligned}\begin{pmatrix} y_{1,t} \\ y_{2,t} \end{pmatrix} &= \begin{pmatrix} 0.23 \\ 0.17 \end{pmatrix} + \begin{pmatrix} 0.03 & 0.65 \\ 0.53 & 0.59 \end{pmatrix} \begin{pmatrix} y_{1,t-1} \\ y_{2,t-1} \end{pmatrix} \\ &+ \begin{pmatrix} -0.05 & 0.90 \\ 0.10 & 0.27 \end{pmatrix} \begin{pmatrix} y_{1,t-2} \\ y_{2,t-2} \end{pmatrix} \begin{pmatrix} 0.76 & 0.34 \\ -0.08 & -0.40 \end{pmatrix} \\ &\times \begin{pmatrix} y_{1,t-3} \\ y_{2,t-3} \end{pmatrix} + \begin{pmatrix} 0.39 & 0.52 \\ -0.73 & -0.11 \end{pmatrix} \begin{pmatrix} y_{1,t-4} \\ y_{2,t-4} \end{pmatrix} \end{aligned} \quad (12)$$

TABLE 11. ADF of positive segments in testing set.

No.	TIME OF DIFFERENCE	*ADF* OF SBP	*P*	*ADF* OF DBP	*P*
77	2	-4.54	0.01	-5.63	0.01
97	1	-5.52	0.01	-4.28	0.01
196	1	-4.02	0.02	-3.74	0.04
241	1	-4.05	0.02	-4.13	0.02
361	2	-3.86	0.03	-5.51	0.01
385	2	-4.28	0.01	-5.51	0.01
421	2	-4.83	0.01	-4.13	0.02
425	1	-3.78	0.04	-3.97	0.02
447	2	-3.80	0.04	-5.39	0.01
466	2	-4.81	0.01	-6.22	0.01
478	1	-4.27	0.01	-6.38	0.01
578	2	-4.28	0.01	-5.67	0.01
580	1	-4.15	0.02	-4.03	0.02
594	2	-3.82	0.03	-4.52	0.01
643	1	-4.09	0.02	-4.19	0.02
760	2	-3.73	0.04	-4.24	0.01
784	2	-3.84	0.03	-4.62	0.01
810	2	-4.53	0.01	-4.10	0.02
822	2	-4.43	0.01	-4.42	0.01
835	1	-4.98	0.01	-4.85	0.01
847	2	-4.54	0.01	-6.84	0.01
898	1	-4.95	0.01	-3.82	0.03
912	1	-5.02	0.01	-4.61	0.01
937	0	-4.28	0.01	-3.66	0.05
951	0	-4.67	0.01	-3.98	0.02

TABLE 12. Lag of negative segments in testing set.

No.	Time of difference	*ADF* of SBP	*P*	*ADF* of DBP	*P*
77	2	-4.61	0.01	-5.47	0.01
97	1	-5.31	0.01	-4.05	0.02
196	1	-5.48	0.01	-4.07	0.02
241	2	-4.15	0.02	-4.60	0.01
302	2	-4.30	0.01	-4.78	0.01
361	2	-4.68	0.01	-3.70	0.04
385	1	-4.68	0.01	-3.70	0.04
421	1	-3.79	0.04	-3.93	0.03
425	3	-3.95	0.03	-5.48	0.01
447	3	-5.67	0.01	-3.77	0.04
466	2	-5.00	0.01	-4.72	0.01
478	1	-3.83	0.03	-5.27	0.01
578	2	-3.98	0.02	-3.53	0.04
580	3	-4.09	0.02	-3.75	0.04
594	2	-3.71	0.04	-4.11	0.02
643	3	-3.76	0.04	-3.70	0.04
760	3	-3.99	0.02	-3.89	0.03
784	1	-4.98	0.01	-4.75	0.01
810	0	-3.84	0.03	-3.76	0.04
822	3	-4.43	0.01	-5.50	0.01
835	3	-4.90	0.01	-4.32	0.01
847	3	-4.47	0.01	-4.41	0.01
898	3	-4.90	0.01	-4.32	0.01
912	4	-3.94	0.03	-4.83	0.01
937	2	-3.90	0.03	-4.80	0.01
951	3	-4.29	0.01	-7.41	0.01

$MAPE_{\text{model}}$ in each situation was less than 10%, which meant VAR had a relatively good prediction effect. The results were shown in Table 5. In Table 6, it displayed moderately effective in prediction. All the indices are approximately 80%.

TABLE 13. Lag of positive segments in training set.

No.	Lag order recommended by AIC	Lag order recommended by SC	Personal biggest lag order
77	4	4	4
88	3	3	3
97	4	4	4
113	4	4	4
182	4	4	4
196	3	3	3
212	4	4	4
241	4	4	4
302	3	3	4
316	4	4	4
331	4	4	4
361	3	3	4
385	4	4	4
421	3	3	4
425	4	4	4
447	4	4	4
466	4	4	4
478	3	3	4
578	4	4	4
580	4	4	4
594	4	4	4
605	4	4	4
643	3	3	4
669	4	4	4
685	4	4	4
697	3	3	3
728	4	4	4
760	4	4	4
766	4	4	4
784	4	4	4
810	4	4	4
822	4	4	4
835	4	4	4
847	4	4	4
881	4	4	4
898	4	4	4
912	4	4	4
937	3	3	4
941	3	3	3
951	4	4	4

IV. DISCUSSION

Blood pressure (BP) is a significant indicator of cardiovascular health that can be managed to prevent cardiovascular disease [37]. BP measured at home (home BP) is strongly associated with cardiovascular disease (CVD) than BP values measured at a hospital [38], [39], [40], [41], [42]. Therefore, guidelines recommend that individuals regularly measure BP at home for management. Acute CVD events such as stroke, coronary artery disease, sudden death occur in the morning with high probability. The morning hypertension especially exaggerated morning surge in BP is the risk factor of these CVD events [43]. Thus, all values of blood pressure used in establishing models in our research were in the morning.

On account of forgetting to upload BP someday, there would be missing values for monitoring BP. Comparing with

TABLE 14. Lag of negative segments in training set.

No.	Lag order recommended by AIC	Lag order recommended by SC	Personal biggest lag order
77	4	4	4
88	4	4	4
97	4	4	4
113	4	4	4
182	4	4	4
196	4	4	4
212	4	4	4
241	3	3	4
316	4	4	4
331	4	4	4
361	4	4	4
385	4	4	4
421	3	3	4
425	4	4	4
447	4	4	4
466	4	4	4
478	4	4	4
578	4	4	4
580	4	4	4
594	4	4	4
605	4	4	4
643	4	4	4
669	4	4	4
685	4	4	4
697	4	4	4
728	4	4	4
760	4	4	4
766	4	4	4
784	4	4	4
810	4	4	4
822	4	4	4
835	4	4	4
847	4	4	4
881	3	3	4
898	4	4	4
912	4	4	4
937	3	3	4
951	3	3	4

other imputation models for missing values [5], [44], [45], we selected an imputation regression model for both systolic and diastolic blood pressures. As the fluctuation of BP depends on the individuals' physiological characteristics, changes in manners, hypertension treatments, or other factors, we established a distinguished imputed model for one patient. Moreover, considering BP of different time points may make different significance, imputed coefficient possessed dissimilar weights. It not only utilizes information of time points but also considers the biological heterogeneity.

In the most recent research, systolic blood pressure (SBP) is studied widely and understood deeply. It is a variable applied in most cardiovascular risk scores, which is even among the strongest predictors of stroke [9]. However, according to Kanegae [36], it was found that among newly onset hypertension patients under 50 years old, the risk ratio of diastolic blood pressure (DBP) alone was 1.67 times than SBP. Worse diastolic function from earlier midlife tended to cause cardiovascular dysfunction [46]. This effect would have

TABLE 15. Lag of positive segments in testing set.

No.	Lag order recommended by AIC	Lag order recommended by SC	Personal biggest lag order
77	4	4	4
97	3	3	4
196	3	3	3
241	4	4	4
302	4	4	4
361	4	4	4
385	4	4	4
421	4	4	4
425	4	4	4
447	3	3	4
466	4	4	4
478	4	4	4
578	4	4	4
580	4	4	4
594	4	4	4
643	4	4	4
760	4	4	4
784	4	4	4
810	4	4	4
822	3	3	4
835	3	3	4
847	3	3	4
898	3	3	4
912	3	3	4
937	4	4	4
951	3	3	4

TABLE 16. Lag of negative segments in testing set.

No.	Lag order recommended by AIC	Lag order recommended by SC	Personal biggest lag order
77	4	4	4
97	4	4	4
196	4	4	4
241	4	4	4
361	3	3	4
385	4	4	4
421	4	4	4
425	4	4	4
447	3	3	4
466	4	4	4
478	3	3	4
578	4	4	4
580	4	4	4
594	4	4	4
643	3	3	4
760	4	4	4
784	4	4	4
810	4	4	4
822	3	3	4
835	4	4	4
847	4	4	4
898	4	4	4
912	4	4	4
937	3	3	4
951	4	4	4

an influence on not only people with hypertension but also those who would go on to develop hypertension when assessing diastolic function [47]. Thus, to realize hypertension

TABLE 17. VAR models of positive segments in training set.

No.		c	$d(y_1)_{t-1}$	$d(y_1)_{t-2}$	$d(y_1)_{t-3}$	$d(y_1)_{t-4}$	$d(y_2)_{t-1}$	$d(y_2)_{t-2}$	$d(y_2)_{t-3}$	$d(y_2)_{t-4}$
77	$d(y_1)$	0.23	0.03	-0.05	0.76	0.39	0.53	0.10	-0.08	-0.73
	$d(y_2)$	0.17	0.65	0.90	0.34	0.52	0.59	0.27	-0.40	-0.11
88	$d(y_1)$	0.30	-0.97	-0.07	-0.08	0.00	-0.19	0.50	0.59	0.00
	$d(y_2)$	0.35	-0.02	-0.32	-0.15	0.00	-0.08	-0.52	-0.59	0.00
97	$d(y_1)$	-0.13	-0.10	-0.13	-0.65	0.16	0.48	0.50	0.94	0.08
	$d(y_2)$	-0.38	-0.04	-0.11	0.27	0.17	-0.80	-0.16	-0.20	-0.39
113	$d(y_1)$	0.40	-0.32	-0.74	0.07	0.21	-0.36	-0.75	-0.56	-0.72
	$d(y_2)$	0.53	0.06	0.11	0.35	0.27	-0.47	-0.19	-0.96	-0.38
182	$d(y_1)$	0.21	-1.21	-1.02	-0.56	-0.33	-0.36	-0.40	-0.48	-0.15
	$d(y_2)$	0.51	-0.03	-0.05	0.05	0.04	-0.52	-1.35	-0.06	-0.49
196	$d(y_1)$	0.67	-0.03	0.26	0.05	0.00	-0.25	-0.21	-0.94	0.00
	$d(y_2)$	-0.50	0.47	0.53	0.23	0.00	0.12	-0.67	-0.33	0.00
212	$d(y_1)$	0.64	0.29	-0.31	-0.03	-0.16	0.24	0.55	0.18	-0.24
	$d(y_2)$	-0.16	-0.69	-0.14	-0.10	0.20	0.77	-0.22	0.10	-0.69
241	$d(y_1)$	0.82	-0.11	-0.32	-0.03	-0.12	-0.18	0.35	0.71	0.09
	$d(y_2)$	0.20	-0.01	0.78	-0.31	-0.07	0.94	-0.98	0.53	-0.39
302	$d(y_1)$	0.54	-0.76	-0.42	-0.05	-0.19	0.81	0.10	0.21	0.49
	$d(y_2)$	0.65	0.12	-0.42	-0.25	-0.63	-0.37	-0.17	0.00	0.70
316	$d(y_1)$	0.53	-0.56	-0.21	-0.21	0.16	0.03	0.14	0.36	-0.16
	$d(y_2)$	0.50	-0.38	-0.50	-0.21	0.11	-0.12	-0.10	-0.82	0.72
331	$d(y_1)$	0.08	-0.73	-0.55	0.73	-0.36	0.81	0.15	0.90	0.49
	$d(y_2)$	-0.05	-0.09	-0.11	-0.23	-0.09	-0.79	-0.64	-0.14	-0.16
361	$d(y_1)$	-0.93	0.44	0.40	0.90	-0.71	-0.21	-0.93	-0.16	0.24
	$d(y_2)$	-0.52	-0.23	0.00	0.07	-0.26	-0.46	-0.78	-0.22	0.14
385	$d(y_1)$	-0.90	-0.18	0.41	-0.15	-0.26	-0.49	-0.26	0.13	0.13
	$d(y_2)$	-0.85	0.04	0.12	-0.28	0.50	-0.68	0.35	0.46	-0.27
421	$d(y_1)$	0.43	-0.12	-0.54	-0.69	-0.68	-0.15	0.39	0.18	0.66
	$d(y_2)$	0.63	-0.18	-0.01	0.02	-0.27	-0.16	-0.74	0.31	0.66
425	$d(y_1)$	-0.44	-0.22	-0.22	0.39	0.05	0.92	0.19	-0.20	-0.19
	$d(y_2)$	-0.27	0.29	-0.19	0.28	-0.24	0.05	-0.01	-0.19	0.39
447	$d(y_1)$	-0.89	-0.76	-0.73	-0.15	-0.50	0.51	0.45	0.63	0.99
	$d(y_2)$	0.54	-0.07	-0.08	0.03	0.03	-0.28	-0.88	-0.44	-0.23
466	$d(y_1)$	163.02	-0.29	-0.34	0.06	0.23	-0.20	0.21	-0.13	-0.19
	$d(y_2)$	75.95	-0.36	-0.02	-0.16	0.23	0.34	-0.21	0.01	0.00
478	$d(y_1)$	0.63	-0.57	-0.07	-0.06	-0.01	0.72	0.85	-0.60	-0.24
	$d(y_2)$	0.81	-0.29	0.33	-0.12	-0.46	-0.48	-0.58	-0.70	-0.25
578	$d(y_1)$	105.65	0.08	0.70	-0.61	0.35	0.85	-0.59	0.58	-0.54
	$d(y_2)$	52.86	0.10	0.32	-0.33	0.32	0.2	-0.5	0.06	-0.34
580	$d(y_1)$	0.45	0.82	-0.30	0.10	-0.08	-0.51	-0.22	-0.27	0.18
	$d(y_2)$	0.92	-0.08	-0.22	-0.67	-0.33	-0.01	-0.78	-0.51	-0.62
594	$d(y_1)$	0.71	-0.31	-0.85	-0.58	-0.27	0.31	-0.16	0.13	-0.30
	$d(y_2)$	0.27	0.51	0.45	0.03	0.36	-1.69	-0.09	-0.23	-2.40
605	$d(y_1)$	-0.10	-0.74	-0.88	-0.29	-0.35	0.07	0.46	0.32	0.57
	$d(y_2)$	0.24	0.14	-0.13	-0.21	-0.29	-0.97	-0.46	0.32	0.36
643	$d(y_1)$	-0.11	-0.72	-0.04	-0.41	0.37	-0.58	-0.38	0.61	-0.72
	$d(y_2)$	0.27	0.51	0.45	0.03	0.36	-0.69	-0.09	-0.23	-0.40
669	$d(y_1)$	-0.15	-0.79	-0.24	0.17	-0.18	0.15	0.17	0.43	0.27
	$d(y_2)$	-0.32	0.02	0.19	0.10	-0.10	-0.27	-0.40	-0.48	0.17
685	$d(y_1)$	0.95	-0.03	-0.82	-0.88	-0.41	-0.33	-0.71	-0.10	-0.14
	$d(y_2)$	-0.27	-0.56	-0.79	-0.25	0.06	0.81	-0.11	0.28	0.11
697	$d(y_1)$	-0.36	-0.40	-0.03	-0.73	0.00	0.26	0.12	0.70	0.00
	$d(y_2)$	0.52	-0.50	-0.07	-0.21	0.00	-0.51	-0.85	0.18	0.00
728	$d(y_1)$	0.18	-0.17	0.69	-0.14	-0.51	-0.67	-0.11	0.14	0.33
	$d(y_2)$	0.11	0.24	0.28	-0.14	0.22	-0.72	-0.74	-0.39	-0.36
760	$d(y_1)$	-0.70	-0.72	-0.22	0.10	0.21	-0.79	-0.32	-0.31	-0.51
	$d(y_2)$	-0.18	0.34	0.59	0.33	0.11	-0.64	-0.75	-0.12	-0.36
766	$d(y_1)$	-0.75	-0.21	-0.11	-0.14	-0.19	-0.35	-0.22	-0.54	-0.81
	$d(y_2)$	0.21	-0.04	0.14	0.30	0.28	-0.31	-0.73	-0.21	-0.76
784	$d(y_1)$	0.62	-0.59	-0.29	-0.55	-0.32	-0.81	-0.45	0.06	-0.19
	$d(y_2)$	0.96	-0.17	0.04	-0.49	-0.13	-0.68	-0.14	0.47	-0.36
810	$d(y_1)$	0.36	0.41	-0.06	0.92	0.13	-0.21	-0.75	-0.16	0.20
	$d(y_2)$	0.41	0.81	0.29	0.94	0.14	-2.22	-0.84	-0.09	0.16
822	$d(y_1)$	0.38	0.28	0.24	-0.09	-0.04	0.22	-0.22	-0.05	0.02
	$d(y_2)$	0.74	0.05	0.40	0.08	-0.05	-0.72	-0.07	-0.56	-0.33
835	$d(y_1)$	0.73	-0.69	-0.74	-0.08	0.11	0.08	0.05	-0.23	-0.16
	$d(y_2)$	0.83	-0.23	-0.26	-0.05	-0.03	-0.48	-0.43	-0.20	-0.14
847	$d(y_1)$	0.71	-0.70	-0.67	-0.54	-0.32	-0.31	0.21	0.12	-0.14
	$d(y_2)$	0.28	-0.19	-0.16	-0.47	-0.06	-0.60	-0.18	0.01	-0.40
881	$d(y_1)$	0.36	-0.36	-0.31	-0.91	-0.13	0.42	0.06	0.36	0.22
	$d(y_2)$	0.47	0.16	0.05	-0.31	-0.92	-0.35	-0.50	-0.01	0.26
898	$d(y_1)$	0.25	-0.13	-0.15	-0.25	-0.01	-0.69	-0.76	-0.22	-0.32
	$d(y_2)$	0.90	0.30	0.29	0.54	0.29	-0.79	-0.81	-0.50	-0.02
912	$d(y_1)$	-0.09	-0.76	0.62	0.86	-0.54	0.55	-0.20	-0.14	0.82
	$d(y_2)$	-0.37	-0.16	0.01	0.51	-0.27	-0.24	-0.38	-0.95	0.12
937	$d(y_1)$	-0.14	-0.09	0.05	-0.24	-0.51	0.72	-0.24	-0.30	0.73
	$d(y_2)$	0.44	-0.33	0.25	0.31	-0.20	0.28	0.41	-0.70	0.23
941	$d(y_1)$	-0.33	0.68	-0.14	-0.07	0.00	-0.36	-0.33	-0.27	0.00
	$d(y_2)$	-0.80	0.08	0.02	0.02	0.00	-0.46	-0.51	-0.82	0.00
951	$d(y_1)$	-0.25	-0.03	-0.46	-0.21	0.10	0.26	-0.61	0.94	0.50
	$d(y_2)$	-0.93	-0.09	0.21	0.27	0.01	-0.32	-0.95	0.93	0.88

precaution and control, it is necessary to pay attention to both systolic blood pressure and diastolic blood pressure. SBP and DBP often appear in pairs with a certain internal relevance, which is adaptable to construct a VAR model.

TABLE 18. VAR models of negative segments in training set.

No.		c	$d(y_1)_{t-1}$	$d(y_1)_{t-2}$	$d(y_1)_{t-3}$	$d(y_1)_{t-4}$	$d(y_2)_{t-1}$	$d(y_2)_{t-2}$	$d(y_2)_{t-3}$	$d(y_2)_{t-4}$
77	$d(y_1)$	0.03	-1.09	-1.11	-0.45	-0.40	-0.10	0.17	-0.08	0.13
	$d(y_2)$	0.05	0.04	0.05	0.15	0.01	-1.35	-1.14	-0.91	-0.32
97	$d(y_1)$	0.07	0.21	0.36	0.33	-0.46	-1.38	-0.75	-1.11	-0.64
	$d(y_2)$	1.09	0.53	0.85	0.51	0.16	-1.61	-1.56	-1.40	-0.85
196	$d(y_1)$	0.87	-0.27	-0.79	-0.36	0.00	0.90	-0.33	-0.17	0.00
	$d(y_2)$	0.38	-0.11	0.16	-0.01	0.00	-0.56	-0.30	-0.37	0.00
241	$d(y_1)$	-0.50	0.11	-0.31	-0.64	-0.30	-0.62	-0.02	-0.09	0.79
	$d(y_2)$	-0.51	0.18	0.42	0.41	0.07	-0.42	0.25	-0.09	-0.31
302	$d(y_1)$	-0.66	-0.30	-0.89	-0.87	-0.13	-0.86	0.75	0.51	-0.26
	$d(y_2)$	-0.19	0.54	-0.07	0.01	0.34	-1.51	-0.20	-0.61	-0.67
361	$d(y_1)$	-0.67	-0.66	-0.29	0.76	-0.20	0.14	0.26	0.84	0.82
	$d(y_2)$	-0.32	-0.30	0.15	-0.21	-0.04	0.82	-0.42	-0.24	0.19
385	$d(y_1)$	0.31	-0.79	-0.40	-0.18	0.51	-0.40	-0.32	0.18	-0.57
	$d(y_2)$	0.87	0.30	0.26	-0.34	0.84	-0.73	-0.58	0.47	-0.09
421	$d(y_1)$	0.39	-0.30	0.31	-0.06	0.22	-0.11	0.39	-0.33	-0.01
	$d(y_2)$	-0.52	0.85	0.47	0.39	0.75	-0.03	0.23	-0.59	-0.12
425	$d(y_1)$	0.23	0.83	-0.84	0.09	0.13	-1.02	0.95	-0.26	-0.37
	$d(y_2)$	0.64	-0.10	-0.12	0.42	0.05	-0.52	-0.45	-0.37	-0.29
447	$d(y_1)$	-0.39	-0.97	0.06	0.15	0.13	-0.51	-0.20	-0.44	-0.35
	$d(y_2)$	0.75	0.37	0.73	0.61	0.17	-0.05	-0.61	-0.12	-0.02
466	$d(y_1)$	0.30	-0.21	-0.06	-0.36	0.45	0.85	0.27	0.01	0.28
	$d(y_2)$	0.58	-0.34	-0.51	-0.21	0.30	0.57	-0.40	0.86	-0.18
478	$d(y_1)$	0.65	-0.25	-0.37	-0.03	0.02	-0.56	-0.78	-0.84	0.03
	$d(y_2)$	0.58	0.29	0.21	0.19	0.01	-1.09	-1.06	-0.52	0.20
578	$d(y_1)$	-0.05	-0.13	-0.11	-1.00	-0.63	-0.28	-0.07	0.39	0.22
	$d(y_2)$	0.69	-0.21	0.76	-0.98	-0.64	0.69	-0.22	-0.29	0.04
580	$d(y_1)$	0.45	-0.37	-0.03	0.22	0.45	0.37	-0.47	-0.24	-0.03
	$d(y_2)$	0.18	0.40	0.73	0.39	0.46	-0.50	-0.15	0.75	-0.85
594	$d(y_1)$	-0.69	-0.78	0.03	-0.50	0.28	-0.09	-0.65	0.21	-0.59
	$d(y_2)$	-0.29	-0.38	-0.06	-0.58	0.20	-0.77	-0.02	-0.03	-0.48
643	$d(y_1)$	-0.49	-0.78	0.17	0.01	0.17	0.26	-0.33	0.11	-0.28
	$d(y_2)$	0.51	-0.18	0.39	-0.03	-0.26	0.12	-0.51	0.09	0.33
760	$d(y_1)$	0.98	-0.68	-0.08	-0.47	-0.27	0.62	-0.25	-0.18	0.57
	$d(y_2)$	-0.13	-0.55	-0.58	-0.30	-0.25	-0.44	-0.40	-0.33	-0.08
784	$d(y_1)$	0.19	-0.67	0.00	-0.18	0.45	-0.46	-0.68	-0.07	-0.73
	$d(y_2)$	0.76	-0.53	0.12	0.01	0.20	-0.32	-0.25	-0.55	-0.61
810	$d(y_1)$	94.55	0.98	0.09	0.21	-0.22	-1.01	0.39	-0.40	-0.24
	$d(y_2)$	82.73	-0.20	0.47	-0.10	0.11	0.43	-0.42	0.01	-0.49
822	$d(y_1)$	-0.17	-0.95	-0.69	0.21	0.17	0.35	0.85	0.56	0.58
	$d(y_2)$	0.08	-0.31	0.83	-0.84	-0.35	0.23	-0.26	-0.03	-0.18
835	$d(y_1)$	0.13	-0.45	-0.22	-0.21	0.23	-0.39	-0.08	-0.54	-0.43
	$d(y_2)$	0.32	0.17	-0.11	-0.17	-0.18	-0.42	-0.34	-0.14	-0.64
847	$d(y_1)$	0.81	-0.25	-0.56	-0.16	-0.51	0.84	0.62	0.12	0.78
	$d(y_2)$	0.19	-0.10	0.62	0.95	0.36	-0.40	-0.28	-0.18	-0.52
898	$d(y_1)$	-0.94	0.95	-0.53	-0.16	-0.23	-0.17	-0.40	-0.45	0.20
	$d(y_2)$	0.33	-0.05	0.07	0.19	-0.04	-0.60	-0.52	0.92	-0.21
912	$d(y_1)$	-0.90	-0.49	-0.20	-0.77	-0.54	0.07	-0.13	0.18	-0.04
	$d(y_2)$	-0.88	-0.06	0.10	0.22	0.56	-0.56	-0.21	-0.40	0.25
937	$d(y_1)$	-0.24	-0.96	0.74	-0.60	-0.54	0.99	0.70	0.15	0.46
	$d(y_2)$	-0.23	-0.12	-0.19	-0.29	-0.16	-0.95	-0.67	-0.12	0.38
951	$d(y_1)$	-0.30	-0.79	-0.60	-0.96	-0.79	0.53	0.70	0.51	0.89
	$d(y_2)$	0.53	0.26	0.14	-0.52	-0.41	-0.87	-0.72	-0.72	0.21

This study constructed a VAR model to predict both SBP and DBP in the meantime, which could make better use of relevant biological law. Algorithms proposed in our study will predict two kind of BP values on the fourth segment

TABLE 19. VAR models of positive segments in testing set.

No.		c	$d(y_1)_{t-1}$	$d(y_1)_{t-2}$	$d(y_1)_{t-3}$	$d(y_1)_{t-4}$	$d(y_2)_{t-1}$	$d(y_2)_{t-2}$	$d(y_2)_{t-3}$	$d(y_2)_{t-4}$
77	$d(y_1)$	0.03	-0.90	-0.11	-0.45	-0.40	-0.10	0.17	-0.08	0.13
	$d(y_2)$	0.05	0.04	0.05	0.15	0.01	-0.35	-0.14	-0.01	-0.32
97	$d(y_1)$	0.07	0.21	0.36	0.33	-0.46	-1.38	-0.75	-0.11	-0.64
	$d(y_2)$	0.09	0.53	0.85	0.51	0.06	-0.61	-0.56	-0.40	-0.85
196	$d(y_1)$	0.87	-0.27	-0.79	-0.36	0.00	0.90	-0.33	-0.17	0.00
	$d(y_2)$	0.38	-0.11	0.16	-0.01	0.00	-0.56	-0.30	-0.37	0.00
241	$d(y_1)$	-0.50	0.11	-0.31	-0.64	-0.30	-0.62	-0.02	-0.09	0.79
	$d(y_2)$	-0.51	0.18	0.42	0.41	0.07	-0.42	0.25	-0.09	-0.31
302	$d(y_1)$	-0.66	-0.30	-0.89	-0.87	-0.13	-0.86	0.75	0.51	-0.26
	$d(y_2)$	-0.19	0.54	-0.07	0.01	0.34	-1.51	-0.20	-0.61	-0.67
361	$d(y_1)$	-0.67	-0.66	-0.29	0.76	-0.20	0.14	0.26	0.84	0.82
	$d(y_2)$	-0.32	-0.30	0.15	-0.21	-0.04	0.82	-0.42	-0.24	0.19
385	$d(y_1)$	0.31	-0.79	-0.40	-0.18	0.51	-0.40	-0.32	0.18	-0.57
	$d(y_2)$	0.87	0.30	0.26	-0.34	0.84	-0.73	-0.58	0.47	-0.09
421	$d(y_1)$	0.39	-0.30	0.31	-0.06	0.22	-0.11	0.39	-0.33	-0.01
	$d(y_2)$	-0.52	0.85	0.47	0.39	0.75	-0.03	0.23	-0.59	-0.12
425	$d(y_1)$	0.23	0.83	-0.84	0.09	0.13	-0.72	0.95	-0.26	-0.37
	$d(y_2)$	0.64	-0.10	-0.12	0.42	0.05	-0.52	-0.45	-0.37	-0.29
447	$d(y_1)$	-0.39	-0.97	0.06	0.15	0.13	-0.51	-0.20	-0.44	-0.35
	$d(y_2)$	0.75	0.37	0.73	0.61	0.17	-0.05	-0.61	-0.12	-0.02
466	$d(y_1)$	0.30	-0.21	-0.06	-0.36	0.45	0.85	0.27	0.01	0.28
	$d(y_2)$	0.58	-0.34	-0.51	-0.21	0.30	0.57	-0.40	0.86	-0.18
478	$d(y_1)$	0.65	-0.25	-0.37	-0.03	0.02	-0.56	-0.78	-0.84	0.03
	$d(y_2)$	0.58	0.29	0.21	0.19	0.01	-0.90	-1.06	-0.52	0.20
578	$d(y_1)$	-0.05	-0.13	-0.11	-1.00	-0.63	-0.28	-0.07	0.39	0.22
	$d(y_2)$	0.69	-0.21	0.76	-0.98	-0.64	0.69	-0.22	-0.29	0.04
580	$d(y_1)$	0.45	-0.37	-0.03	0.22	0.45	0.37	-0.47	-0.24	-0.03
	$d(y_2)$	0.18	0.40	0.73	0.39	0.46	-0.50	-0.15	0.75	-0.85
594	$d(y_1)$	-0.69	-0.78	0.03	-0.50	0.28	-0.09	-0.65	0.21	-0.59
	$d(y_2)$	-0.29	-0.38	-0.06	-0.58	0.20	-0.77	-0.02	-0.03	-0.48
643	$d(y_1)$	-0.49	-0.78	0.17	0.01	0.17	0.26	-0.33	0.11	-0.28
	$d(y_2)$	0.51	-0.18	0.39	-0.03	-0.26	0.12	-0.51	0.09	0.33
760	$d(y_1)$	0.98	-0.68	-0.08	-0.47	-0.27	0.62	-0.25	-0.18	0.57
	$d(y_2)$	-0.13	-0.55	-0.58	-0.30	-0.25	-0.44	-0.40	-0.33	-0.08
784	$d(y_1)$	0.19	-0.67	0.00	-0.18	0.45	-0.46	-0.68	-0.07	-0.73
	$d(y_2)$	0.76	-0.53	0.12	0.01	0.20	-0.32	-0.25	-0.55	-0.61
810	$d(y_1)$	94.55	0.98	0.09	0.21	-0.22	-1.01	0.39	-0.40	-0.24
	$d(y_2)$	82.73	-0.20	0.47	-0.10	0.11	0.43	-0.42	0.01	-0.49
822	$d(y_1)$	-0.17	-0.95	-0.69	0.21	0.17	0.35	0.85	0.56	0.58
	$d(y_2)$	0.08	-0.31	0.83	-0.84	-0.35	0.23	-0.26	-0.03	-0.18
835	$d(y_1)$	0.13	-0.45	-0.22	-0.21	0.23	-0.39	-0.08	-0.54	-0.43
	$d(y_2)$	0.32	0.17	-0.11	-0.17	-0.18	-0.42	-0.34	-0.14	-0.64
847	$d(y_1)$	0.81	-0.25	-0.56	-0.16	-0.51	0.84	0.62	0.12	0.78
	$d(y_2)$	0.19	-0.10	0.62	0.95	0.36	-0.40	-0.28	-0.18	-0.52
898	$d(y_1)$	-0.94	0.95	-0.53	-0.16	-0.23	-0.17	-0.40	-0.45	0.20
	$d(y_2)$	0.33	-0.05	0.07	0.19	-0.04	-0.60	-0.52	0.92	-0.21
912	$d(y_1)$	-0.90	-0.49	-0.20	-0.77	-0.54	0.07	-0.13	0.18	-0.04
	$d(y_2)$	-0.88	-0.06	0.10	0.22	0.56	-0.56	-0.21	-0.40	0.25
937	$d(y_1)$	-0.24	-0.96	0.74	-0.60	-0.54	0.99	0.70	0.15	0.46
	$d(y_2)$	-0.23	-0.12	-0.19	-0.29	-0.16	-0.95	-0.67	-0.12	0.38
951	$d(y_1)$	-0.30	-0.79	-0.60	-0.96	-0.79	0.53	0.70	0.51	0.89
	$d(y_2)$	0.53	0.26	0.14	-0.52	-0.41	-0.87	-0.72	-0.72	0.21

simultaneously. Besides, each patient possessed a unique prediction model. These models will capture fluctuation in BP timely ahead of follow-up time stated in the Chinese National Guidelines for the Prevention and Management of Primary Hypertension.

Building a warning system prior to the occurrence of abnormal blood pressure will improves individualized optimal BP management over the long term [48]. many studies have reported a telemedicine system for BP management [40], [42], [49], [50]. To expand the application of

TABLE 20. VAR models of negative segments in testing set.

No.		c	$d(y_1)_{t-1}$	$d(y_1)_{t-2}$	$d(y_1)_{t-3}$	$d(y_1)_{t-4}$	$d(y_2)_{t-1}$	$d(y_2)_{t-2}$	$d(y_2)_{t-3}$	$d(y_2)_{t-4}$
77	$d(y_1)$	0.61	-2.23	-2.81	-1.25	-0.85	1.99	2.95	1.92	1.41
	$d(y_2)$	0.11	-0.41	-1.36	-1.00	-0.81	-0.32	0.92	1.20	1.18
97	$d(y_1)$	0.14	-1.07	-1.77	-0.66	-0.87	0.38	1.42	-0.11	0.74
	$d(y_2)$	-0.30	-0.36	-0.43	-0.07	-0.27	-0.23	0.07	-0.53	-0.20
196	$d(y_1)$	0.44	-0.43	-0.19	-0.06	-0.08	1.09	0.80	0.81	0.90
	$d(y_2)$	-0.91	-0.06	-0.07	0.09	-0.06	-0.31	-0.07	-0.20	-0.06
241	$d(y_1)$	2.40	-0.23	-1.02	-0.25	-0.26	-0.07	0.30	0.09	-0.65
	$d(y_2)$	0.49	0.19	-0.22	0.01	-0.19	-0.22	0.53	-0.29	-0.38
361	$d(y_1)$	-0.55	-1.60	-0.85	0.22	0.37	-0.34	-1.65	-2.69	-1.59
	$d(y_2)$	-0.45	-0.26	0.30	0.49	0.63	-1.29	-1.88	-1.96	-1.46
385	$d(y_1)$	0.98	-0.44	0.02	-0.41	-0.54	-0.73	-1.15	-0.58	-0.07
	$d(y_2)$	0.91	0.55	0.71	0.21	-0.26	-1.76	-1.93	-1.18	-0.25
421	$d(y_1)$	-0.36	-0.76	-0.81	0.04	0.37	-0.39	1.25	-0.98	-0.18
	$d(y_2)$	0.10	-0.09	-0.08	0.10	0.17	-1.27	-0.57	-0.45	-0.64
425	$d(y_1)$	-0.16	-0.42	0.53	0.09	0.01	-0.58	-1.43	-0.74	-0.33
	$d(y_2)$	-0.04	0.14	0.54	0.14	0.04	-1.03	-1.29	-0.39	-0.12
447	$d(y_1)$	0.20	-1.06	-0.58	0.00	0.21	0.14	-0.72	-0.39	-0.41
	$d(y_2)$	-0.45	0.37	0.64	0.54	0.26	-1.37	-1.72	-0.96	-0.82
466	$d(y_1)$	-0.73	-0.89	-0.73	-0.23	0.00	-0.56	-0.35	-0.69	-0.69
	$d(y_2)$	-0.02	-0.01	-0.12	0.08	-0.05	-1.08	-0.98	-1.13	-0.18
478	$d(y_1)$	-2.04	-0.76	-1.11	-0.61	-0.28	-0.17	0.21	0.63	0.83
	$d(y_2)$	0.18	-0.04	-0.23	0.01	0.10	-1.41	-0.83	-0.57	-0.25
578	$d(y_1)$	-0.95	-1.13	-0.90	-0.62	-0.22	0.94	0.83	0.91	0.73
	$d(y_2)$	-0.38	-0.18	-0.16	0.04	0.10	-1.09	-0.78	-0.69	-0.39
580	$d(y_1)$	0.16	-0.79	-0.73	-0.01	0.30	0.81	0.95	-0.01	-0.25
	$d(y_2)$	-0.77	0.04	-0.01	0.10	0.40	-0.29	-0.20	-0.36	-0.53
594	$d(y_1)$	0.74	-0.88	-0.98	0.00	-0.91	0.09	0.10	-0.31	0.81
	$d(y_2)$	0.22	-0.55	-0.56	0.04	-0.46	-0.46	-0.37	-0.52	0.45
605	$d(y_1)$	0.31	0.13	-0.23	-0.22	0.26	-0.40	0.21	-0.16	-0.03
	$d(y_2)$	-0.18	0.40	0.50	0.10	0.60	-1.17	-1.01	-1.11	-0.90
760	$d(y_1)$	1.21	-1.68	-1.08	-0.48	-0.53	0.90	0.61	0.58	0.76
	$d(y_2)$	-1.18	-0.59	-0.38	0.00	-0.29	-0.20	-0.10	-0.16	0.31
784	$d(y_1)$	-1.01	-1.77	-1.18	-0.89	-0.21	0.17	0.04	-0.05	-0.02
	$d(y_2)$	-0.81	-0.07	0.47	0.37	-0.02	-1.02	-0.81	-0.46	-0.13
810	$d(y_1)$	0.91	-1.81	-1.57	-1.22	-0.51	1.64	1.77	1.04	0.63
	$d(y_2)$	0.21	-0.22	0.07	-0.06	-0.04	-0.41	-0.74	-0.51	-0.37
822	$d(y_1)$	-1.77	-0.73	0.31	-0.05	-0.32	-0.64	-1.18	-0.21	-0.06
	$d(y_2)$	-0.82	0.26	0.25	-0.36	-0.45	-1.57	-1.23	-0.14	0.10
835	$d(y_1)$	1.62	-0.71	-0.98	-0.50	-0.31	-0.57	0.50	0.20	0.24
	$d(y_2)$	0.46	-0.06	-0.43	-0.32	-0.29	-1.14	-0.56	-0.25	0.07
847	$d(y_1)$	0.32	-0.92	-0.57	-0.42	-0.06	-0.22	-0.20	-0.11	-0.08
	$d(y_2)$	-0.08	0.15	0.03	-0.10	0.10	-0.93	-0.67	0.00	0.32
898	$d(y_1)$	-0.14	0.46	0.53	-0.02	-0.05	-0.14	-0.17	0.84	0.65
	$d(y_2)$	-0.39	0.85	0.75	0.13	0.14	-1.93	-1.01	0.46	0.11
912	$d(y_1)$	-0.12	-0.99	-0.43	-0.18	0.15	-0.12	-1.13	-1.96	-1.28
	$d(y_2)$	0.43	0.12	0.00	0.07	0.21	-0.41	-0.30	-0.25	-0.06
937	$d(y_1)$	132.23	-0.14	0.34	-0.45	-0.01	1.25	-0.03	0.39	0.19
	$d(y_2)$	47.20	-0.21	0.43	-0.11	-0.16	0.58	0.01	-0.37	0.22
951	$d(y_1)$	129.61	0.11	0.32	-0.07	0.59	-0.49	-1.04	-0.91	-1.22
	$d(y_2)$	85.07	-0.19	0.33	-0.33	0.33	0.18	-0.44	-0.07	-0.71

telemedicine, On the one hand, our research introduced sphygmomanometers uploading blood pressure automatically in the background to monitor home BP. On the other hand, our VAR models predict blood pressure based on data collected by sphygmomanometer in the background. It makes sense especially for people who are at risk of developing hypertension, yet do not get their blood pressure checked regularly. Our VAR models perform a relatively good effect on early warning. As a tool for predicting blood pressure, it is helpful to use our models can as a component of an expert system related to medical consultations. Supposed the blood pressure of a person is not available or the person is at a remote location, when the predicted values are larger than the hypertension alarmed level, users could be given a warning promptly.

Comparing with other studies, we are the first to apply VAR model to predict both systolic and diastolic blood pressure. With the progress of artificial intelligence, we could estimate cardiovascular risk for patients with primary hypertension using with low-cost, routine clinical data. One study prove XGBoost model can perform global cardiovascular risk with the 127 clinical variables in ACC (0.72), F1-score (0.79), and AUC (0.77) [51]. 139 hypertension patients' real clinical ECG data are applied, and the overall precision is 0.95 [52]. López et al apply the National Health and Nutrition Examination Survey to predict hypertension, and the precision value is 0.58, the accuracy value is 0.73, the f1-score value is 0.47, and the AUC value is 0.77 [53]. In the study of Kim et al, they used health and nutrition examination survey to predict hypertension with the accuracy of 0.81 [54]. Zhang et al use Neural network model to predict hypertension with AUC value of 0.77 [55]. Yang-Hoon Chung et al made a prediction of blood pressure with deep learning, and the macro-average F1 scores of the datasets ranged from 0.68 to 0.72 [56].

These studies applied machine learning to classify patients who could develop cardiovascular disease, ignoring timely manner of blood pressure [51], [57]. They mainly focused on facilitating physician to identify hypertensive patients at risk. Our VAR models could perform a relatively good effect on early warning of emergent events timely. From a survey, results of researches based on blood pressure estimation were shown in following Table 7. These researches applied many kinds of models to predict blood pressure. Comparing with them, the relative error of our model to blood pressure varied 0.07-0.1. What' more, the model was only with passed BP, more completely used information of BP.

There are some limitations in our study. Firstly, the limited amount of data could bias the representativeness of VAR models. Other limitation is the lack of consideration for several temporal variables. There are still many other factors that also affect changes in blood pressure. To increase accuracy and specificity, further research should include more factors that affect patients' blood pressure changes, such as diet and exercise patterns, sleep, smoking, and drinking, etc. Then we should incorporate some variables that are meaningful to blood pressure changes into the entire study and conduct a more comprehensive data analysis. At last, while picking up positive segments, we only consider extreme urgent situation that three or more three or more systolic blood pressure values larger than 140mmHg or diastolic blood pressure larger than 90mmHg occur in the fourth segments. More various situation should be taken into account.

APPENDIX

There are Table 8-20 for supplement.

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