A Temporal-Causal Network Model for Hypertension Among Young Adults

Reshma S and Dr. K Sunil Kumar
Department of Mechanical Engineering
College of Engineering Trivandrum, Thiruvananthapuram, Kerala
rameshreshma095@gmail.com, ksk_sunil@cet.ac.in

Abstract

Hypertension is a major public health problem because of its high ubiquity among around the world. Currently, hypertension in young adults is very common. It is because of the increase in lifestyle behaviors with advancement of technology and better standard of living. The factors responsible for hypertension among young adults are unspecified. The risk of hypertension is very high among young adults as it contributes to an early onset of coronary heart diseases, stroke and ephemeral ischemic attacks. The work mainly focuses on the identification of major facets responsible for hypertension in young adults and to develop a computational model for determining hypertension. The data collection is carried out among young adults in the community through clinical tests. A set of Questionnaires are prepared based on the study to analyze what are the risk factors for hypertension. Statistical analysis is done to identify the major contributing risk factors and Network-Oriented Modeling based on Temporal-Causal Network (TCN) is used for preparing the computational model for hypertension. The novelty of this paper is the usage of Temporal-Causal network modeling, which helps in depicting and cope- with causal dependencies, propagation over time. With the help of Statistical analysis and Network-Oriented Modeling using Temporal-Causal Network, facets contributing hypertension among young adults are identified and the progression of disease is modeled.

Keywords
Hypertension, Ischemic attacks, Statistical analysis, Network-Oriented Modeling, Temporal-Causal Networks.

1. Introduction
Globally, around 26% of the population suffer from Hypertension and it is estimated to undergo an increase in later years to 29% stated by World Health Organization (WHO). Due to the upsurge of advancement in the lifestyle of people, the prevalence of hypertension has augmented. Hypertension being a key factor in the onset of certain cardiovascular events such as heart diseases, strokes etc.; treatment and prediction of this disease must be done at the earliest. Many of the people sail through it asymptomatically, that is why hypertension being remarked as a "Silent Killer". Most of them are unaware of the disease and does not give much importance to an increase in blood pressure level thinking that it would be lowering accordingly. But certain times, the level of blood pressure upsurges in such a way that it can even lead to death.

Nowadays, especially in case of young adults, they barely check the blood pressure level. They do not give much seriousness to increase in blood pressure. Nevertheless, it can be seen that 19% of the young adults around the world suffer from an elevated blood pressure according to a study conducted by National Longitudinal Study of Adolescent Health. In fact, half of the young adults over the age of 20 have high blood pressure, even if they give the impression healthy. High blood pressure does not provide noticeable signs, but that does not mean it should be overlooked.

As said, hypertension does not show any symptoms and the factors affecting it are also unspecified. Most studies imply the physiological aspects of hypertension among older adults. But it can be taken into account that some psychological factors are also responsible for an elevated blood pressure among people. We can see with the advancement in technology and lifestyle of people, the younger generation are prone to various psychological issues because of lack of socializing abilities and other undesirable influences. A study regarding psychological aspects of hypertension and finding the facets leading to hypertension among young adults are being addressed here. For that the cognitive nature of people having hypertension are studied and it is finally modeled using Cognitive modeling techniques.

1.1 Objectives

Objectives of the study include:

1. To identify and analyze the factors leading to hypertension among young adults.
2. To develop a computational model for determining hypertension based on Temporal- Causal Network model.

2. Literature Review

Most of the population is prone to Hypertension. It is noticeable that hypertension is a key factor for the onset of several cardiovascular diseases. Many studies are being conducted to find out the prevalence of hypertension among individuals.

Bani-Salameh et al. (2021) explains that hypertension to be the most common illness among a wide range of population. The disease affects individuals of different age groups unfavorably. Hence, the treatment and prediction of the disease must be done ahead of time. Zhao et al. (2021) elucidates the prediction of risk factors responsible for hypertension using Machine Learning methods. The study basically focuses on the estimation and comparison of the four machine learning techniques- Random Forest, CatBoost, Multi-Layer Perceptron (MLP) and Logistic Regression (LR). It was found that Random Forest algorithm can predict the risk factor of hypertension deprived of clinical and genetic data.

Analyzing risk factors of hypertension are carried out through several studies which include study of hypertension based on lifestyle habits. Manios et al. (2021) elucidates about the usage of tobacco and alcohol along with other lifestyle behaviors that leads to severe hypertension among individuals. Another impactful risk factor is social media as it can affect young adults in many ways as they ae mostly prone to use it. People nowadays are addicted to social media and it has tremendously affected their lives with various negative impacts including body shaming, crimes among youth, depression etc. (Mancheno et al. 2021). Yu et al. (2021) explains mental stress as a causal factor in the development of hypertension and cardiovascular diseases. Similarly, Aisha et al. (2021) provides a clear association of hypertension with stress and depression among different individuals. It can be noticed that family issues including conflicts with parents, child abusing, comparison of children by parents, peer pressure etc. can lead to depression and aggression among young which are basically risk factors for hypertension (East et al. 2020). Lack of sleep can cause increase in blood pressure and other stress; hence it can be considered as a risk factor for hypertension (Denise et al. (2018). Singh et al. (2017) elucidates about the preponderance of hypertension among people. It is noted that educational status, economical status, involvement of aerobic activities as well as consumption of alcohol and tobacco are major facets leading to hypertension. Aggression is considered to be a key factor as it increases blood pressure level in the body. Aggression is considered to be a cognitive maladaptive strategy and its effects can cause variable change in behavior (Tilov et al. 2016).

Several studies emphasize on the analyzing of risk factors of hypertension and modeling of hypertension based on socio-psychological factors are not being implemented. The studies focused on many network modeling techniques which includes Support Vector Machine (SVM), K-Nearest Neighbor (KNN), Multi-Layer Perceptron (MLP) neural network techniques etc. Network-Oriented modeling method which is a Cognitive modeling approach grounded on Temporal-causal networks is a suggestive dynamic Artificial Intelligence modeling method grounded on networks of causal relations that combines with a constant time dimension to prototypical dynamics (Treur et al. 2016). Dynamics is not combined in methods based on causal networks so as to avoid complexity which neglects the cyclic paths in causal network thereby not allowing time component to get involved in causal effects. The Network- Oriented modeling approach based on temporal- causal networks selected here can be detected as part of the tradition of causal modeling, as it comprises the dynamics which is grounded on constant time dimension that is exemplified by real numbers.

Basically, network models are too complex to deal with, but in case of temporal-causal network modeling which is a part of network-oriented modeling provides a simpler computational processing and modeling techniques. The simplicity of the model is the key factor that keep it as far better option compared to other network modeling methods (Figure 1).

3. Research Methodology

The research method used in this work is based on the clinical test and survey by means of a designed questionnaire. The data collected is analyzed to find out the most dominating factors responsible for hypertension using factor analysis. The factors are further used to build a computational model for hypertension.

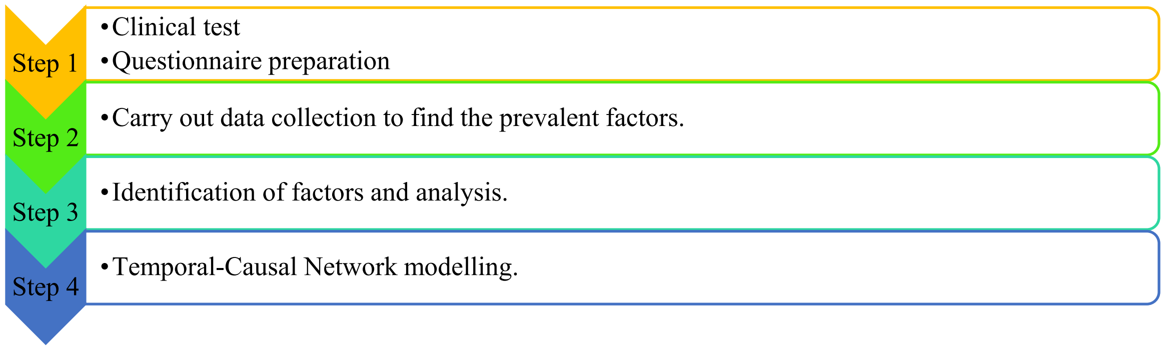


Figure 1. Research Methodology

4. Data Collection

Considering an infinite population, the study size was estimated at 10% precision and confidence interval 95% which came out to be 138. The data was collected in two different ways among young adults from 18-30 years of age. A clinical analysis was carried out for doing the clinical test to check height, weight, blood pressure-Systolic Blood Pressure (SBP) and Diastolic Blood Pressure (DBP). The height and weight were measured in order to calculate the Body Mass Index (BMI).

After the clinical analysis it is apparent that some other factors are responsible for hypertension among young adults. It may be occurring due certain socio-psychological factors. For identifying certain socio-psychological factors responsible for hypertension, a set of questionnaires was adopted for the purpose of study and the data was collected among the 138 respondents.

5. Results and Discussion

5.1 Clinical Analysis

From clinical analysis of 138 respondents, both the graphs show correlation between BMI and Systolic blood pressure and Diastolic blood pressure which is being positively correlated with each other. It is noticeable that a person with high BMI(Overweight) tend to have high systolic blood pressure and diastolic blood pressure, which is around 17% of the total. Similarly, a person with low BMI(Underweight) tends to have prehypertension as they show a moderate systolic and diastolic blood pressure, that is around 7% of the total. Also, it is noticeable that a person with normal BMI tends to have prehypertension as they show a moderate systolic and diastolic blood pressure, that is around 9% of the selected population (Figure 2).

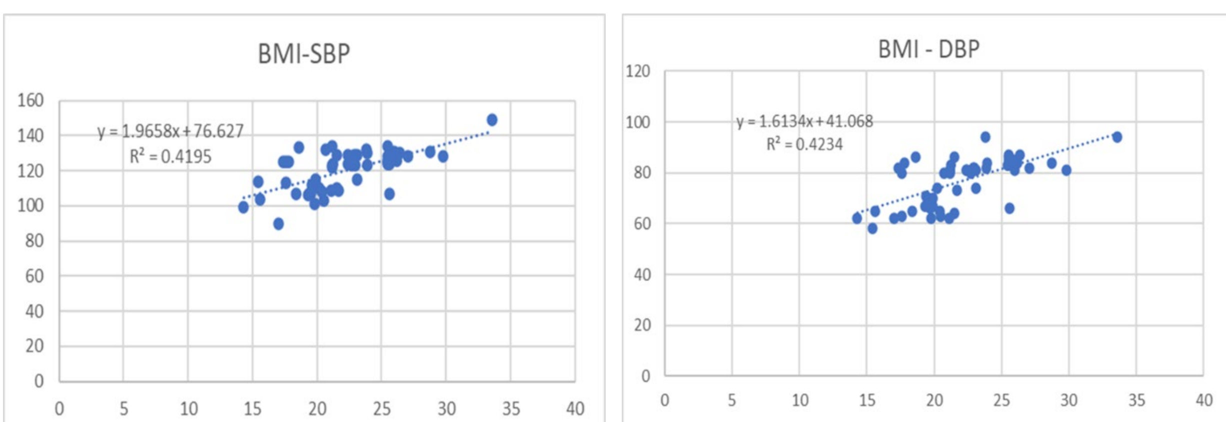


Figure 2. Graph showing correlation of BMI with SBP and DBP

5.2 Factor Analysis

The factor analysis was carried out in IBM SPSS26 software for identifying factors leading to hypertension. The Eigen values and Scree plot are obtained. The shape of the scree plot is used to determine the optimal number of factors to be taken in the final solution. The Scree plot is cut with two lines forming an elbow shape and the points or factors lying above the point of intersection of the two lines are being taken as the key components or factors for the factor analysis. The scree plot shows a linearity as it reaches the bottom stage as they indicate the undesirable factors during the analysis. On viewing the scree plot itself one can easily find out which all factors are being dominant and which are undesirable in nature (Figure 3).

The scree plot for the current analysis is being shown in below depicting mainly six factors or components in dominant positions (Table 1-3).

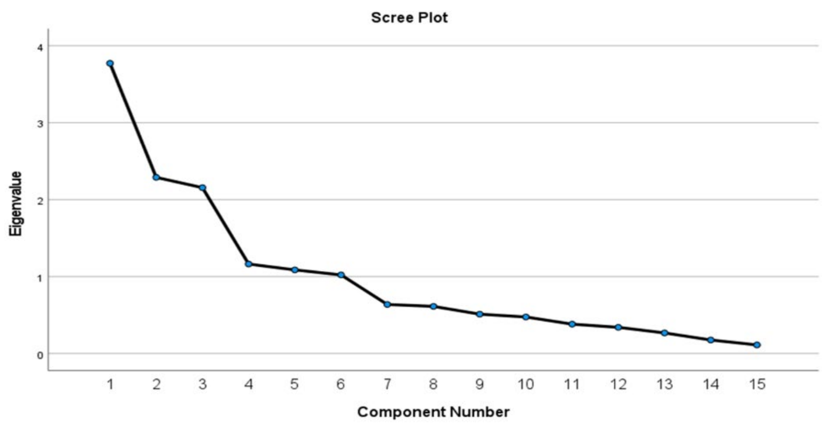


Figure 3. Scree plot

Table 1. Eigen values of the components

Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	3.772	25.150	25.150	3.772	25.150	25.150	2.411	16.074	16.074
2	2.289	15.262	40.412	2.289	15.262	40.412	2.242	14.946	31.020
3	2.156	14.373	54.786	2.156	14.373	54.786	1.937	12.911	43.931
4	1.163	7.753	62.538	1.163	7.753	62.538	1.846	12.305	56.236
5	1.087	7.245	69.783	1.087	7.245	69.783	1.551	10.340	66.576
6	1.022	6.811	76.594	1.022	6.811	76.594	1.503	10.017	76.594
7	.637	4.249	80.842						
8	.612	4.082	84.924						
9	.511	3.407	88.331						
10	.475	3.164	91.495						
11	.381	2.543	94.038						
12	.340	2.267	96.305						
13	.267	1.783	98.088						
14	.175	1.170	99.258						
15	.111	.742	100.000						

Extraction Method: Principal Component Analysis.

According to the eigenvalue measures, the factors having more than one eigenvalue are included in the model. Here, it can be noted that the eigenvalue for the six components shows above one and they are being selected as the key factors. It can be seen that percentage variance of the six factors are coming as 25.15%, 15.26%, 14.38%, 7.75%,7.25% and 6.8% respectively.

These six factors are then chosen to fit in the main model as they have eigen values more than one respectively. Another key element that is used to determine the significance of factors are the communalities of the factor analysis. The communality of the scale which shows the amount of variance in each dimension, is also measured to confirm acceptable levels of elucidation.

From the eigen value and the communalities is clear that it is significant enough to carry out the further analysis of the data. With keeping six factors as the key elements of the analysis, the grouping of other components under six factors are done.

During the grouping, the most similar and dominant components are clustered together meanwhile the undesirable components are being extracted away and thus a clustered set of factors are obtained.

Table 2. Communalities of factors

Components	Initial	Extraction
MS1	1.000	0.705
MS2	1.000	0.713
MS3	1.000	0.727
MS4	1.000	0.693
A1	1.000	0.760
A2	1.000	0.639
D1	1.000	0.857
D2	1.000	0.853
FS1	1.000	0.926
FS2	1.000	0.917
LH1	1.000	0.754
LH2	1.000	0.678
FH1	1.000	0.692
FH2	1.000	0.825
FH3	1.000	0.750

Table 3. Factor loadings of the factors

Items	1	2	3	4	5	6
Mental Stress						
MS1	.716					
MS2	.819					
MS3	.748					
MS4	.695					
Food Habits						
FH1		.787				
FH2		.891				
FH3		.851				
Family Support						
FS1			.948			
FS2			.946			
Depression						
D1				.883		
D2				.862		
Lifestyle Habits						

LH1					.855	
LH2					.787	
Aggression						
A1						.854
A2						.702

The Table 3 shows factor loadings of each factor. These values are above 0.50 and hence they are significant in nature. All the values so obtained are far above 0.50 and nearly 0.9 which imparts how well each factor correlate with each other. The communalities obtained were above 0.50 and the factor loadings obtained for every 6 factors and its components are above 0.50. The six factors found out through factor analysis are Mental stress, Food habits, Family support, Depression, Lifestyle habits and Aggression.

5.3 Validation of Factor analysis

The validation of the results is done through reliability test of the given set of components. The implication of the correlation matrix through Bartlett's Test of Sphericity, which provides a degree of the arithmetical probability that the correlation matrix has significant correlations among some of its components.

The results were substantial, X^2 $(n = 138)$ = 1249.294 that specifies its appropriateness for the factor analysis.
The Kaiser-Meyer-Olkin measure of sampling adequacy, that specifies the appropriateness of the data for factor analysis was 0.762.

Finally, the factor solution resulting from this analysis produced six factors for the given data set, which defined for 76.59 percentage of the dissimilarity in the data.
Another validity for the analysis is the reliability of the analysis which can be determined through Cronbach alpha coefficients obtained. The reliability of the analysis is given in Table 4 shows above 0.7 which is valid in all terms.

Table 4. Reliability Table

FACTORS	CRONBACH ALPHA
Mental Stress	0.7445
Food Habits	0.843
Family Support	0.947
Depression	0.8725
Lifestyle Habits	0.821
Aggression	0.778

For the purpose of validation of the factors, hypothesis is being set and regression analysis is carried out. The hypothesis is set as:H_0 = All the selected factors have significant effect on Hypertension.H_1 = Not all the factors selected have significant effect on Hypertension (Table 5).

Table 5. F-value and P-value

FACTORS	F-VALUE	P-VALUE
Mental Stress	1.985	0.4865
Food Habits	0.997	0.6706
Family Support	0.395	0.542
Depression	0.555	0.4245
Lifestyle Habits	0.855	0.285
Aggression	4.165	0.2585

Analysis shows that all P-values are above the critical value of 0.05, hence the Null hypothesis is accepted. That is all the factors selected have significant effect on hypertension.

5.4 Temporal-Causal Network (TCN) model for hypertension

The conceptual representation of the Temporal-Causal Network model for hypertension is shown in the above Figure 3 . The various factors identified are taken as the input which is connected to the respective sensor state and further connections goes till the output which is the emotional response. The network structure consists of 23 states, from which following are the input factors: MS- Mental Stress, D- Depression, A- Aggression, FS- Family Support, FH- Food Habits and LH- Lifestyle Habits

ss_x - Sensor state for input x. The person observes the input state through the sensor state, which provides sensory input.

srs_x - Sensory Representation state for input x. It is the internal representation of sensory input.

cs – Control state. It's for emotion b (negative emotion) monitors feelings and preparation for emotion b. If an unwanted emotion b occurs, the control state suppresses it.

fs – Feeling state. It's affected before performing an action through the preparation state ps.

ps – Preparation state. It's responsible for the preparation of the body for a response involving emotion b.

es – Emotional response state. The decision of ps activates the expressed emotional response es which is the actual execution of the emotional response of b by the person that expresses the level of hypertension. A high output of es means a high level of hypertension.

bs – Belief state. It is responsible for the interpretation of the world information, in this case, for emotion b.

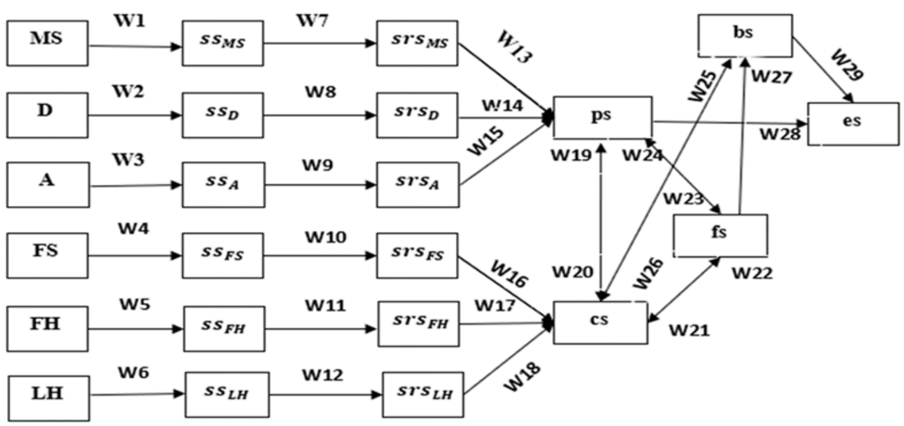


Figure 4. TCN model for Hypertension

The states are connected to each other that shows the causal relations (Figure 4). The connections from one state to another are weighted connections which ranges between 0 to 1. Such weight value expresses the strength of influence of state at the tail end of arrow on the state at the head end. The weight is represented by w_{XY} and for each state, there is a speed factor ηY. This expresses how fast the state Y will change with time. The states are being affected by one or more states which leads to the causation to have an aggregate impact on the state at the head end of the arrow. This aggregate impact is determined using a combination function which as such in this case is taken as advanced logistic sum combination function which is given by Equation 1:

alogistic$_{\sigma}$,τ$(V_1,\ldots,V_k)$ = $[(1/1+e^{-\sigma(V_1+\cdots+V_k-\tau)}))-(1/1+e^{\sigma\tau}))](1+e^{-\sigma\tau})$ (Treur et al. 2016)

The advanced alogistic sum combination function and identity function id(...) are preferred over the other combination functions in Formolo et al. (2017) because the former has the property that the activation levels 0 are mapped 0 and it keeps values below 1.

The numerical representation of the temporal-causal network model for hypertension are given by the input factors (Variables): MS- Mental Stress, D- Depression, A- Aggression, FS- Family Support, FH- Food Habits and LH- Lifestyle Habits

- *Input* ——> *Output*$_1$

The first set of nodes (Input variables) are transformed to second set of nodes (Sensory state) using Equation 2.

$$ss_x(t + \Delta t) = ss_x(t) + \eta_1[\omega_j x(t) - ss_x(t)]\Delta t \quad (2)$$

where, x - Input Variables, j - 1,2,3….6 for all inputs.

- *Output*$_1$ ——> *Output*$_2$

The second set of nodes (Sensory state) are transformed to third set of nodes (Sensory Representation state) using Equation 3:

$$srs_x(t + \Delta t) = srs_x(t) + \eta_2[\omega_j ss_x(t) - srs_x(t)]\Delta t \quad (3)$$

where, j – 7, 8,…..12 for all ss_x; x - Input Variables.

- *Output*$_2$ ——> *Output*$_3$

The third set of nodes (Sensory Representation state) are transformed to fourth set of nodes (Control state, Preparation state, Feeling state, Belief state) using Equation 4 to 7.

$$cs_b(t + \Delta t) = cs_b(t) + \eta_3[alogistic_{\sigma\tau}(xy) - cs_b(t)]\Delta t \quad (4)$$

where x,y denotes, $x = \omega_{16}, \omega_{17}, \omega_{18}, \omega_{22}, \omega_{24}$ and, $y = srs_{FS}(t), srs_A(t), srs_{LH}(t), fs_b(t), ps_b(t)$ respectively.

$$ps_b(t+\Delta t) = ps_b(t)+\eta_3[alogistic_{\sigma\tau}(xy)-ps_b(t)]\ \Delta t \quad (5)$$

where x,y denotes, $x = \omega_{13}, \omega_{14}, \omega_{15}, \omega_{21}, \omega_{22}$, and,
$y = srs_{MS}(t), srs_A(t), srs_D(t), cs_b(t), fs_b(t)$ respectively.

$$fs_b(t + \Delta t) = fs_b(t) + \eta_3[alogistic_{\sigma\tau}(xy) - fs_b(t)]\Delta t \quad (6)$$

where x,y denotes, $x = \omega_{23}, \omega_{24}$ and, $y = cs_b(t), ps_b(t)$ respectively.

$$bs_b(t + \Delta t) = bs_b(t) + \eta_3[alogistic_{\sigma\tau}(xy) - bs_b(t)]\Delta t \quad (7)$$

where x,y denotes, $x = \omega_{25}, \omega_{27}$ and, $y = cs_b(t), fs_b(t), bs_b(t)$ respectively.

- *Output*$_3$ ——> *Output*$_4$

The fourth set of nodes (Control state, Preparation state, Feeling state, Belief state) are transformed to fifth node (Emotional response state) using Equation 8:

$$es_b(t + \Delta t) = es_b(t) + \eta_4[alogistic_{\sigma\tau}(\omega_{28} bs_b(t), \omega_{29} ps_b(t)) - bs_b(t)]\Delta t \quad (8)$$

- Finally, the adaptive connections are modeled according to the following Hebbian learning rule for the connections from state X to state Y, the relation is given by Equation 9:

$$\omega_{X,Y}(t+\Delta t) = \omega_{X,Y}(t)+[\eta X(t)Y(t)(1-\omega_{X,Y}(X,Y)(t))-\zeta\omega_{X,Y}(t)]\Delta t \quad (9)$$

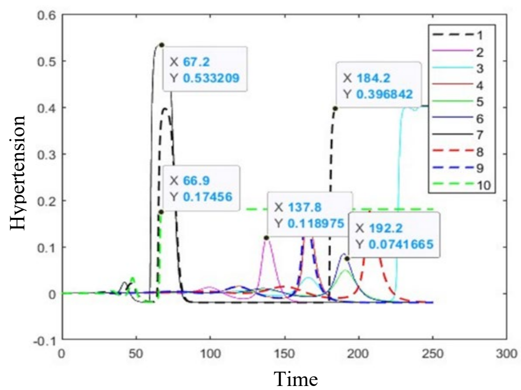
where, σ − Steepness = 4, τ − Threshold = 0.500, ηk − Speedfactor = 0.02, η – Learning rate = 0.02,

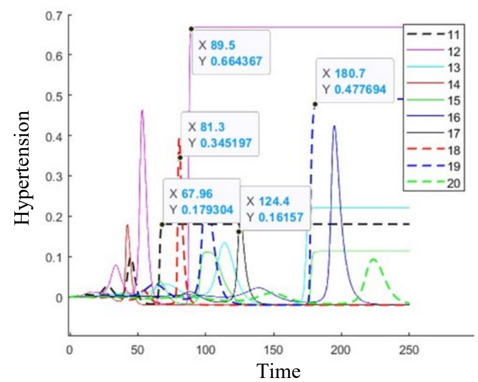
ζ − Extinction rate = 0.001

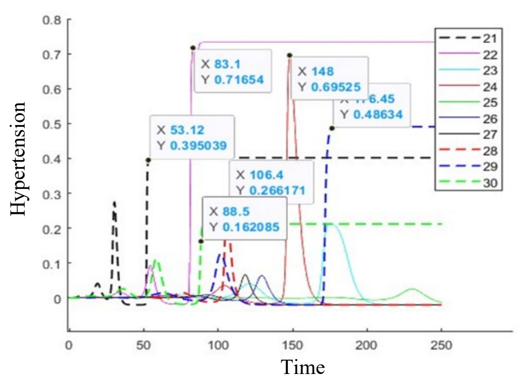
The values of the parameters are taken as per the values used in Formolo et al. (2017). The numerical illustration is shown for only a single time step for a single sample. The following section shows the validation of the first 60 samples using the parameter values mentioned in section 5.5.

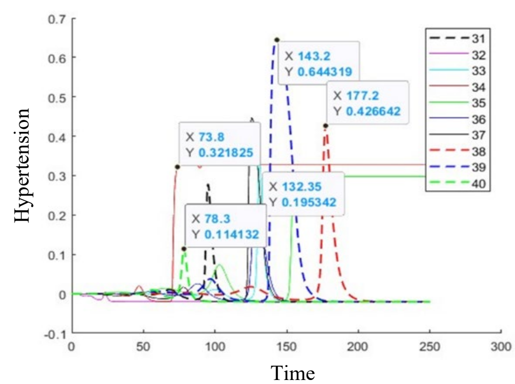
5.5 Validation of the Model

The model is developed in MATLAB R2022a. In order to find out the model as valid, validation of the model is required. This section deals with validation of the model. Out of 138 respondents, 60 respondents' data are validated for the purpose.









Hypertension

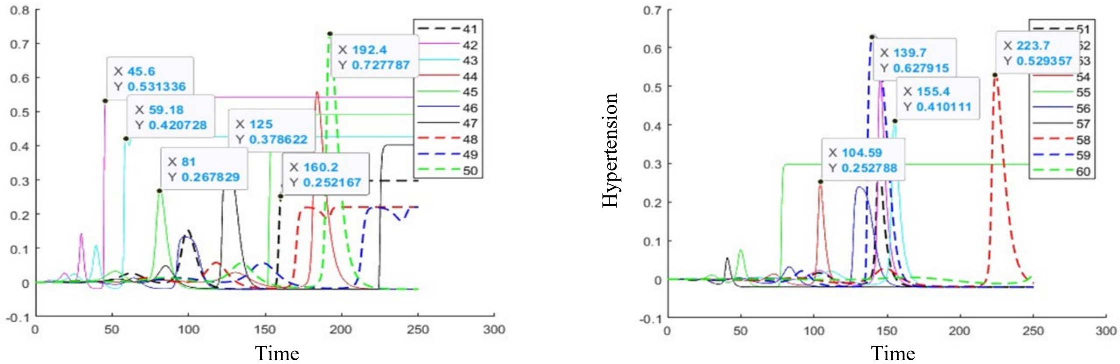


Figure 5. Graphs showing level of hypertension among 60 respondents

The model is run for the input values collected in survey (Figure 5); the hypertension level (output) curves obtained is marked with the matching output values collected in survey. The curve proliferates through a time. The time measured here has no specific unit but it just represents the passage of time.

With the passage of time, the variation of hypertension level is obtained through the model, therefore, unit of time has no specific significance. Hence, the values shown in x-axis only shows the increment of time and values have no specific significance.

From the graphs given above it can be seen that input variables – mental stress, aggression, depression. family support, lifestyle and food habits affect hypertension as there shows a steep increase in curves obtained. The progression of the disease along with time are being validated here. The values less than 0.25 denotes normal level of hypertension. The values of curves between 0.26 and 0.5 shows prehypertension among the respondents. The curves showing values between 0.51 and 0.75 gives an account on stage 1 hypertension meanwhile values above 0.76 represents stage 2 hypertension.

The validation of the model brings one observation into light, that is, irrespective of the hypertension value, the level of hypertension is significantly affected by the mental stress, lifestyle habit and food habitual values that keeps the level from dropping to zero.

It can be also noted that 16% of the respondents who are having lower family support along with mild depression and aggression significantly affecting hypertension.

6. Conclusion

The existing work focuses on the identification and analysis of the factors that leads to hypertension among the young adults and used these factors to develop a computational model based on temporal-causal network to determine hypertension among the young adults. The model used was a neurologically inspired computational model based on temporal-causal network for determining hypertension level using certain input factors. The input factors responsible for elevating and alleviating hypertension were identified from literature review and discussion with medical practitioners. The factors were analyzed through Exploratory factor analysis. The questionnaire consists of 28 questions and the analysis was carried out for each of the 28 questions. These 28 components were extracted after factor analysis to compress into 15 set of components. These 15 sets of components are being grouped into 6 factors through factor analysis and are sorted according to their function. The exploratory factor analysis revealed the presence of six factors exceeding 1, explaining 25.15%, 15.26%, 14.38%, 7.75%, 7.25% and 6.81% of the variance respectively. The six factors found out through factor analysis are Mental stress, Food habits, Family support, Depression, Lifestyle habits and Aggression. The computational model developed based on Temporal-causal Network to determine hypertension is valid since it passes validation test conducted for 60 data points out of 138 data points.

The validation of the model brings one observation into light, that is, irrespective of the hypertension value, the level of hypertension is significantly affected by the mental stress, lifestyle habit and food habitual values that keeps the level from dropping to zero. It can be also noted that 16% of the respondents who are having lower family support along with mild depression and aggression significantly affecting hypertension. The model helps to know about the progression of hypertension with the input values for the find out factors such as mental stress, aggression, depression, family support, lifestyle and food habits. Hence, factors leading to hypertension are identified, analyzed and modeled using Temporal-causal network. The study population is restricted to a portion of Thiruvananthapuram district. Studies can be extended to other districts of Kerala and to other age groups also. The factors identified in this work only applies to the young adults whereas there are different other factors that leads to hypertension among other age groups. So, the model can be extended to include the other factors for a person having hypertension.

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Biographies

Dr. K Sunil Kumar is graduated in Mechanical Engineering from College of Engineering Trivandrum, Kerala, India and post-graduated in Industrial Engineering and Operations Research from IIT Bombay, India. He has got his PhD from IIT Bombay, India. Presently, he is serving as Professor in Mechanical Engineering at College of Engineering Trivandrum, Thiruvananthapuram, Kerala, India. He has published several papers in international journals, participated and chaired sessions in several conferences. He is also a member in Indian Society for Technical Education (India)and Indian Institution of Industrial Engineering (India).

Reshma S is a postgraduate student in the Department of Mechanical Engineering in College of Engineering Trivandrum, Thiruvananthapuram, Kerala, India. She graduated from Nehru College of Engineering and Research Centre, India with a Bachelor's Degree in Mechatronics Engineering in 2019. Her research interests include Data analytics and Simulation.