

Utilizing Modular Neural Network for Prediction of Possible Emergencies Locations within Point of Interest of Hajj Pilgrimage

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Abstract

This paper utilize modular neural network for prediction of possible emergencies locations during hajj pilgrimage. Available location, localization and positioning determination systems become increasingly important for use in day-to-day activities. These systems dwells on various scientific tools which ensure that the systems will provide accurate response to the needed service at the right time. Unfortunately, some tools were faced with drawbacks, either their use was not appropriate or they do not give reliable results, or the results obtained in certain scenario might not be apply to other scenarios. For this reasons, we utilize modular neural network tool to examine the analysis of determining possible emergencies locations within point of Interest of Hajj Pilgrimage in Meccah Saudi Arabia. The prediction results are generated by the use of longitude, latitude and distances as the dataset. Modular neural network takes longitude and latitude as inputs and predict distances within pilgrim's possible point of interest. The learning systems were trained on the collected data. Experimental investigation demonstrated that modular network produce higher prediction accuracy compaired to other tools. This finding would contribute to the design of add-on applications which will deem to provide location based services for possible emergencies locations.

Keywords: Modular Neural Network, location, localization, positioning determination

1. Introduction

1.1 Background of the Problem

During Hajj pilgrimage in Mekkah Saudi Arabia, volunteer Doctors from different countries take part as medical team of their own country delegation's of the pilgrims. Most of the Doctors are general practitioners. The doctors sole responsibilities lies in an emergency situation, not treating patients, and if found they are liable for prosecution by the Saudi authorities. Most of the clinic for these foreign doctors during pilgrims in Makkah are set up in hotel rooms and open for most time during Hajj pilgrims. The doctors are always available in Al-haram; the name given to Al-Masjid Al-Haram the grand mosque where the holy Al Ka'ba building is located in center of Mecca, Saudi Arabia. There are 25 gates into the Mosque 8 from the north, 7 from the south, and 5 from the east and 5 from the west respectively. The distance of the holy Al Ka'ba to any gate is approximately 300 meters. In most cases the area of the Mosque is always overcrowded. The crowd situation is some cases sprawl up to 2KM radius from the

holy Ka'ba. There are high possibilities of emergency situation by pilgrims. The doctors from any affected delegation might be around with their medical kits. They could be in any point of interest. The possibilities that doctors could be at each point of Interest from the holy ka'ba could be predicted base on the prior knowledge of the point of interest and their distance from the holy Ka'ba. For that reason, this study aimed at exploring information on distance proximity which connects to other point of interest at about 10 kilometers radius from the holy Al Ka'ba building in order to show how far point of interest are separated from the grand mosque, and predict doctors locations relative to an emergencies situation position, in order to get doctors of close proximity to the point of emergencies. Hotels, malls, and almost the entire area 2km radius from Ka'ba are among the most important pilgrims point of interest.

Points of interest are key locations that when trying to predict position of an emergencies situation might require the attention of the closet medical doctors. People may have some choices based on specifics distance computed by the time it takes to move from point A to point B over the path generated by location facts, beliefs and experience of moving from one area to another. That is why there is point of interest. People always know where they are, and will always notice objects or location intended to visit in mind. However, individuals on the move do not notice distance in respect to their path than they do in respect of time for a short or long distance.

Going for pilgrimage somewhere else by pilgrims is associated with the perception of visiting ritual sites which could be one or many places and the distance apart from either one ritual site to the other or from pilgrim's accommodation to ritual sites and other places of visit are important to the visiting pilgrim's. Pilgrimage is a trip made to places with the purpose of worshiping in order to discharge some religious obligation by Christians, Hindus, Buddhists, Baha'is, Muslims etc, the assumption is that any person who travel for performing pilgrimage generally is willing to go to all the ritual sites regardless of distance between the rituals sides. The mode of transportation to the ritual sites is by car, ship, train, bus, lorry, or even by walk. No matter what the distance may be, pilgrimages have no alternatives. This typical scenario is observed in Mecca Saudi Arabia during Muslims pilgrimage. Going to Mecca in Saudi Arabia for performing hajj at least once during lifetime is the fifth pillar of Islam and one of the Muslim's duties which display the most significant manifestation of Islamic faith and unity with over 2.5 million people expected from all over the world annually. It is recommended for Hajj pilgrims to be in a holy Al Ka'bah, Mina, Mudzalifah and Arafat at the right time when performing hajj. However, the proximity of these locations to other point of interest is beneficial to hajj pilgrims in order to schedule visiting other places. Most hajj pilgrim during the hajj rituals prefer to walk due to the nature of crowd and the road networks. It's hard to reason how far hajj pilgrims will prefer to walk to the ritual sites (holy Al Ka'bah and other sites). The walk distances are graph-geodetic and converge to the shortest path distance while a long walk distance is described as approaching limit values which a person cannot withstand, thus the long walk distance is equal to the resistance distance (Pavell, 2012). It is important to provide actual distance proximities not based on roads network alone, but also including the entire pedestrian route to all possible point of interest within the principal ritual site (holy Al Ka'bah).

The focus of this paper is to apply modular network to built models for predicting locations of possible emergencies cases. Computational foundation of neural networks research was spring up by McCulloch and Pitts in the early 40's, details can be found in (Sharkey et al., 2000). There are numerous works in literature on comparing prediction performances of different architectural configurations of neural networks referred to as learning method in (Granitto et al., 2005). Feed forward neural networks are better than other architectures in terms of pattern recognition (Bishop, 2006). In Gencay and Liu (1997), feed forward and recurrent network were compared. Support vector machine and back propagation neural network were contrasted in (Cao & Tay, 2001; Tay & Cao, 2001). Recurrent network and multilayer feed forward neural network compared in (Kulkarni & Haidar, 2009). Time delay, recurrent and probabilistic neural networks compared in (Saad, 1998). Comparison of neural network and support vector machine is presented in (Fernandez, 2012). Multilayer perceptron feed forward neural network, recurrent neural network and Elman recurrent networks were compared in (Quek et al., 2008). Support vector machine and back-propagation neural network were contrasted in (Xie et al., 2008). Neuro-fuzzy inference system, multi-layer perceptron and radial basis function networks compared in Kaynar et al., 2010). Elman networks, feed forward neural network and adaptive neuro-fuzzy inference system compared in (Zimberg, 2008). Conventional support vector machine and improved cluster support vector machine contrasted in (Qi & Zhang, 2009). Back-propagation neural network, support vector machine regression and radial basis function neural network contrasted in (Yu et al., 2008). Multilayer feed forward network and support vector machine contrasted in (Byvatov et al., 2003). Finally, study in (Chen et al., 2011) compared support vector regression and radial basis function network. Results of these comparisons are presented in Table 11. There is lack of check for statistical significance difference in prediction performances among compared neural networks architectures. In this paper,

we experimentally investigate prediction performances of modular network in contrast to support vector machine within the context of distance prediction of location. We step further and check for correlation between values predicted by the two models. Lastly, we check whether there is statistical significance difference between prediction accuracy of the two models?

1.2 Modular Neural Network

Modular network was pioneered in (Jacobs et al., 1991). Committee machines are class of artificial neural network architecture that uses the idea of divide and conquer. In this technique, larger problems are partition into smaller manageable units easy to be solved and the solutions obtained from various units are recombined once more to have a complete solution to the problem. Therefore, a committee machine is a group of learning machines refers to as experts in which their results are integrated to yield an optimum solution better than solution of individual expert. Learning speed of modular network is superior to other class of neural networks when compared (Lopes et al., 2004). Individual output of each sub-network in modular network are modulated by gating sub-network to yield only one output of modular network as shown in Figure 1, gating sub network is responsible for assigning each expert network to suitable sub regions of the input space (Funand & Hagan, 1996). Learning of patterns is competed among experts and gating network serves as the competition mediator (Jacobs & Jordan, 1993). Therefore, output of the committee machine is determined by the gating unit (Sheikhan & Ali, 2012). There is another class of modular network without gating, where outputs of all experts are linearly combined (ensemble averaging) to produce one single output of the network as depicted in Figure 2. The gate values ranging from 1 to 0 are multiply with experts output so as to select the most highly relevant output. Struggle for selection among experts become tougher if gating value is either 1 or 0 otherwise “a certain degree of blending between the module outputs ensues, which is of particular interest in smoothing out the final result around the borders of the partition of the training data.” (Carcenac, 2008). The modular network in Figure 1 have output as follows

$$y = \sum_{i=1}^N g_i y_i , \tag{1}$$

where y = sum of modular network output.

y_i = output of expert i .

g_i = i th output gating subnetworks.

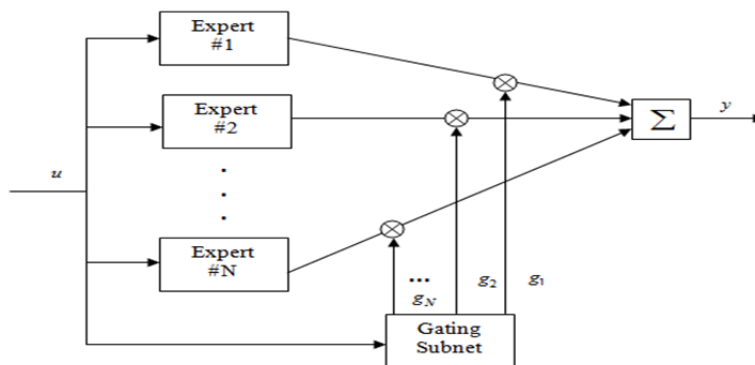


Figure 1. Committee Machine

Each expert is having multilayer network with varying configurations. Gating subnet may have a multiple network with soft-max activation function (g_i) at the last layer.

$$g_i = \frac{\ell^{s_i}}{\sum_{j=1}^N \ell^{s_j}} , \tag{2}$$

where S_i = network input to the transfer function at the last layer. Substituting Equation 2 in Equation 1, then we have Equation 3 as follow

$$y = \sum_{i=1}^N \left(\frac{\ell^{s_i}}{\sum_{j=1}^N \ell^{s_j}} \right) y_i. \tag{3}$$

Modular network performance index is given by

$$J(X) = \ln \sum_{i=1}^N g_i \ell^{-\frac{1}{2}(y^* - y_i)^T (y^* - y_i)}. \tag{4}$$

Substituting Equation 2 in Equation 4 we have Equation 5

$$J(X) = \frac{\ell^{s_i}}{\sum_{j=1}^N \ell^{s_j}} \left[\ln \sum_{i=1}^N g_i \ell^{-\frac{1}{2}(y^* - y_i)^T (y^* - y_i)} \right] \tag{5}$$

$$X = [r_1 r_2, \dots, r_N Z]^T, \tag{6}$$

Where r_j = parameter vector comprising weights and biases in the j -th expert sub-network. Z = vector comprising weights and biases of gating sub-network. y^* = desired output vector as given in (Funand & Hagan, 1996).

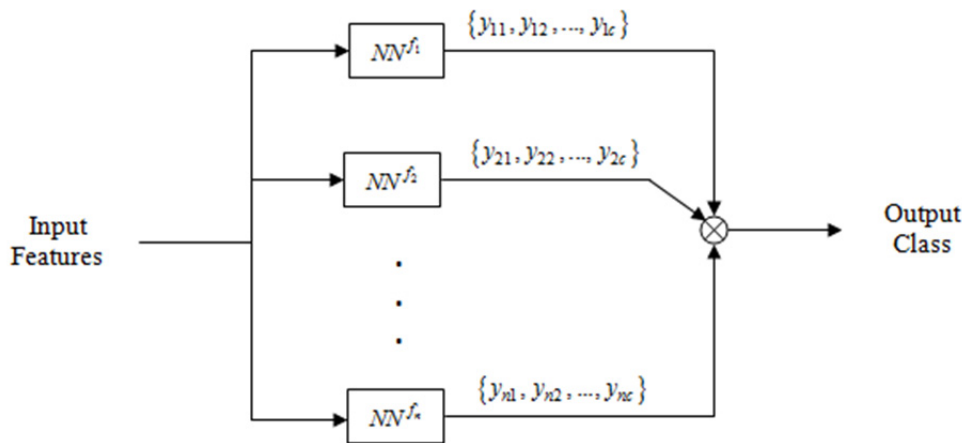


Figure 2. Modula neural networks without gating (Cho, 1997)

Gradient based algorithms are typically used to train modular network as pointed out in (Jacobs & Jordan, 1993). Performance index is minimized by network training and steepest ascent algorithms technique is the easier way to achieve it.

$$x_{k+1} = x_k + \alpha \frac{\partial j}{\partial x} \tag{7}$$

Computation of gradient is realized by computing partial derivative of Equation 7 with respect to network input of gating sub-network at the last layer.

$$\frac{\partial j}{\partial s_i} = h_i - g_i, \quad (8)$$

where

$$h_i = \frac{g_i \ell^{-\frac{1}{2}(y^* - y_i)^T (y^* - y_i)}}{\sum_{j=1}^N g_j \ell^{-\frac{1}{2}(y^* - y_j)^T (y^* - y_j)}}. \quad (9)$$

Substitute Equation 2 and Equation 9 in Equation 8 to get Equation 10 as follow

$$\frac{\partial j}{\partial s_i} = \frac{g_i \ell^{-\frac{1}{2}(y^* - y_i)^T (y^* - y_i)}}{\sum_{j=1}^N g_j \ell^{-\frac{1}{2}(y^* - y_j)^T (y^* - y_j)}} - \frac{\ell^{s_i}}{\sum_{j=1}^N \ell^{s_j}}. \quad (10)$$

- Computation of j -derivative with respect to weights in getting sub-network (Z)
- Combine Equation 10 with $\frac{\partial s}{\partial z}$, standard back-propagation technique can be used for the computation.
- Compute derivative of j with respect to weights in expert sub-networks, r_i in this case there is the need for computation of j derivative with respect to expert sub-networks outputs.

$$\frac{\partial J}{\partial y_i} = h_i (y^* - y_i) \quad (11)$$

Combination of Equation 11 with dy_i/dr_i yields derivative of j with respect to weights in the expert sub-network. Back-propagation may be used for the computation (Jacobs & Jordan, 1993). Modular network provide alternative solution to problem of local minima normally experience by back propagation learning (Ishikawa, 1995). Modular network has been used for image transformation (Carcenac, 2008), fault diagnosis (Sheikhan & Ali, 2012), motion adaptive de-interlacing (Choi & Lee, 2011), prediction (Gradojevic et al., 2009), pattern recognition (Martinez et al., 2005), image processing (Srivastava et al., 2012) and classification (Anand et al., 2005).

2. Method

2.1 Dataset

The geographical distance between two or more locations measured along the surface of earth is usually obtained by considering each point as a geographic coordinate namely longitude and latitude. Longitude and Latitude are imaginary lines on earth which runs from east to west and north to south respectively, measure in angular degrees. Longitude is measure at an angle east or west from the Prime Meridian, ranging from 0° (refers to as Prime Meridian) to $+180^\circ$ eastward and -180° westward, while Latitude ranges from 0° (refers to as the Equator) to 90° north or south (refers to as poles). In geodesy and geophysics, data of global coverage are often given on a latitude–longitude grid of constant intervals in latitude and longitude called the gridded data, or referred to as spherical harmonic expansion (Guo & Shum, 2009).

A map projection transforms the Earth's spherical two-dimensional coordinate system to the plane or planimetric map surface. Throughout history, map projections have been developed to meet various mapping purposes (Kessler, F. C., 2009). The current availability of global positioning systems (GPS) that can rapidly and accurately determine latitude-longitude coordinates has the potential to produce large amounts of position data that may need to be plotted on a variety of map projections (Allison, 2005; Kaplan & Hegarty, 2006). The GPS system was developed by the U.S. Department of Defense under its NAVSTAR satellite program (Grewal et al., 2001). The GPS is a satellite-based radio-navigation system emitting special coded satellite signals that can be processed in a GPS receiver. This enables the receiver to compute position, velocity, and time. The system provides accurate, continuous, worldwide, three-dimensional position and velocity information to any user with the appropriate receiving equipment. It is also the source of coordinated universal time. The satellite constellation nominally

consists of 24 satellites arranged in six orbital planes with four satellites each. A worldwide ground control network monitors the condition and status of the satellites. This network also uploads navigation data and other data to the satellites. Normally, four GPS satellite signals are used to compute positions in three dimensions (latitude, longitude, altitude), and the time offset in the receiver clock. As a result, the GPS system has become prominent for providing navigation information for military and civilian applications in land vehicles, marine vessels, air transport, life safety, and many others (Wang et al., 2009). Most importantly, GPS can provide services to an unlimited number of users (Abubakar et al., 2011) whose role is limited to that of passive receivers. The system utilizes the concept of one-way time of arrival ranging. Satellite transmissions are referenced to highly accurate atomic frequency standards on board the satellites, which are in synchronism with a GPS time base.

Unfortunately the system does not provide information on distances between different locations on earth. The idea of calculating distance on earth surface deals with the science of measuring the structure and size of the earth (Geodesy) and the notion of either flat-earth, Spherical and Ellipsoidal earth. The distance between points flat-earth model for instance when given two points (A_1, B_1) and (A_2, B_2) within any place on earth the distance d between these points is given by

$$d = \sqrt{(A_2 - A_1)^2 + (B_2 - B_1)^2} \tag{12}$$

Pythagorean Theorem proves that the length of the third side (hypotenuse of right triangle) is sum of two other sides. In this case, the assumption is accurate and will apply to the flat-earth distance between two points when the lengths between the locations (a degree of longitude and latitude) are for short moderate distances (Erickson, 2007). However, considering the ellipsoid/spherical shape of the earth, the distance between two locations cannot be accurate if Equation 34 is used; rather Vincenty's formulae, law of cosines or haversine formula is more reliable because the distances between two points based on the spheroid structure of the earth is a special case of a more general spherical trigonometry. Therefore, given two longitude and latitude positions within any place, their distances will be evaluated using haversine formula (Robusto, 1957) as follows:

Let the longitude of two points (lon1 and lon2) be: $dlon = lon2 - lon1$

Let the latitude of two points (lat1 and lat2) be: $dlat = lat2 - lat1$

The haversine formula is given by:

$$a = \sin^2\left(\frac{dlat}{2}\right) + \cos(lat1) \times \cos(lat2) \times \sin^2\left(\frac{dlon}{2}\right) \tag{13}$$

The great circle distance in radians is given by

$$c = 2 \times a \tan 2\left(\sqrt{a}, \sqrt{1-a}\right) \tag{14}$$

While the lengths (distance) of degree of longitude and latitude is given as

$$d = R \times c \tag{15}$$

Table 1. Group 1, locations that are 300 meters away from the Al Ka'bah building but less than 1 kilometer to pilgrim's point of interest

Name	Distance(km)	Latitude	Longitude
Al-Ka`bah	0.32	21.423056	39.826389
La-Mecque	0.48	21.426666	39.826111
Al-Qushashiyah	0.48	21.425556	39.828609
Bi'r-Zamzam	0.80	21.424168	39.831665
Makkah	0.80	21.420000	39.830002
Al-Qararah	0.97	21.428888	39.828056
Ash-Shubaykah	0.96	21.420555	39.821110
Jadat-al-Bab	0.95	21.424168	39.819443
Suq-al-Layl	0.96	21.427221	39.833611
Ash-Shamiyah	0.97	21.429445	39.823055
An-Naqa	0.99	21.430555	39.826111

Where d the distance in kilometers between the two points, R is the mean radius of the earth (6371) and c is the

great circle distance in radians (Sinnott, 1984; Van Liere, 2010; Friedman et al., 2012).

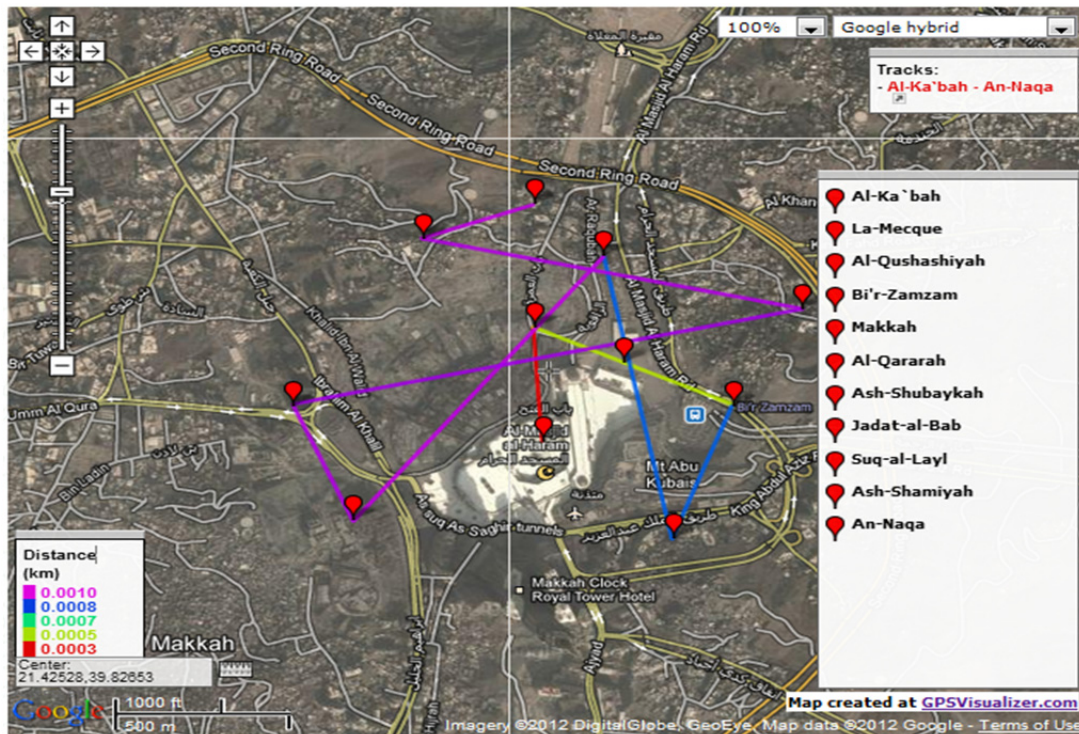


Figure 3. Group 1, locations that are 300 meters away from the kabah building but less than 1 kilometer to pilgrim’s point of interest

Data were collected from the municipality situated around 10 km radius from the holy Al Ka’bah as shown in Figure 6, which indicates some randomly selected points around the holy Al Ka’bah, some of which are the locations required to be known by hajj pilgrims for performing hajj and umrah. These locations (see Figures 3–8) are drawn using GPS Visualizer, an online platform for drawing maps from Google map for any place on the earth. There are three important locations which is obligatory for hajj pilgrims to visits in the holy Al Ka’bah’s surroundings which include: Al Ka’bah building, for performing Tawaf; Safa, the hill on which the hajj pilgrim begins his/her walking is about 200 meters southeast of Al ka’bah building; Marwa the hill on which hajj pilgrim end his/her walking is about 250 meters northeast of kabah building and the well of ZamZam for drinking ZamZam water, is about 150 meters southeast of Al Ka’bah building. (Note 1)

Table 2. Group 2, locations that are 300 meters away from the Al Ka’bah building but less than 3 kilometers to pilgrim’s point of interest

Name	Distance (KM)	Latitude	Longitude
Al-Ka`bah	0.32	21.423056	39.826389
Al-Masfalah	1.8	21.415556	39.821945
Ajyad	1.8	21.420279	39.836666
Shi`b` Amir	2.1	21.433611	39.834721
Jarwal	2.2	21.432777	39.818611
Sha`b` Amir	2.2	21.433611	39.834721
At-Tundubawi	2.3	21.417223	39.814724
As-Sulaymaniyah	2.9	21.438889	39.827778

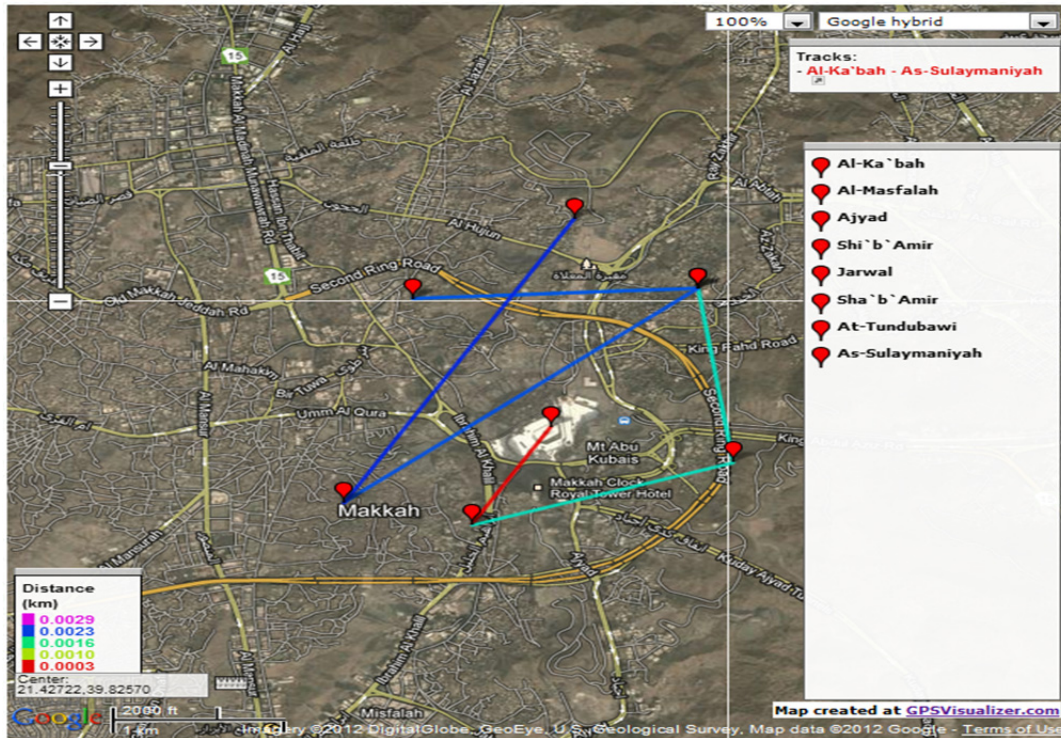


Figure 4. Group 2, locations that are 300 meters away from the Al ka`bah building but less than 3 kilometer to pilgrim’s point of interest

Table 3. Group 3, locations that are 300 meters away from the Al Ka`bah building but less than 5 kilometer to pilgrim’s point of interest

Name	Distance (KM)	Latitude	Longitude
Al-Ka`bah	0.32	21.423056	39.826389
AlJummayzah	3.4	21.441389	39.834721
Al`Utaybiyah	3.7	21.443890	39.826946
Ar-Rawdah	3.9	21.436666	39.845554
Al-Hijun	4.2	21.444723	39.815834
Al-Faysaliyah	4.2	21.428888	39.851387
Jabal-Khandama	4.3	21.401945	39.839722
Az-Zahra	4.7	21.431110	39.800556
Al-Hindawiyah	4.7	21.419167	39.799168

Other important locations that are required to be visited by the hajj pilgrims in order to complete the hajj obligations are outside the holy Al Ka`bah environment, which include Mina, about 9.6 kilometers from the holy Al Ka`bah, Muzdalifa, about 10.1 kilometers from holy Al Ka`bah, and mount Arafat about 23 kilometers from the holy Al Ka`bah. However, for the purpose of this research, randomly selected locations within 10 kilometers radius of the holy Al Ka`bah environment are collected. The distances for each point were obtained base on road network distances. Locations were retrieved in groups, group 1 are these locations situated 300 meters away from the Al Ka`bah building but less than 1 kilometer as shown in Table 1, Figure 3. Group 2 are these locations situated 300 meters away from the Al Ka`bah building but less than 3 kilometers as shown in Table 2, Figure 4. Group 3 are these locations situated 300 meters away from the Al Ka`bah building but less than 5 kilometers as shown in Table 3, Figure 5. Group 4 are these locations situated 300 meters away from the Kabah building but less than 6.4 kilometers as shown in Table 4, Figure 6. Group 5 are locations situated 300 meters away from the Al Ka`bah building but less than 8 kilometer to pilgrim’s point of interest as shown in Table 5, Figure 7 and finally Group 6 are locations situated 300 meters away from the Al Ka`bah building but less than 10.1 kilometer to pilgrim’s point of interest as shown in Table 6, Figure 8.

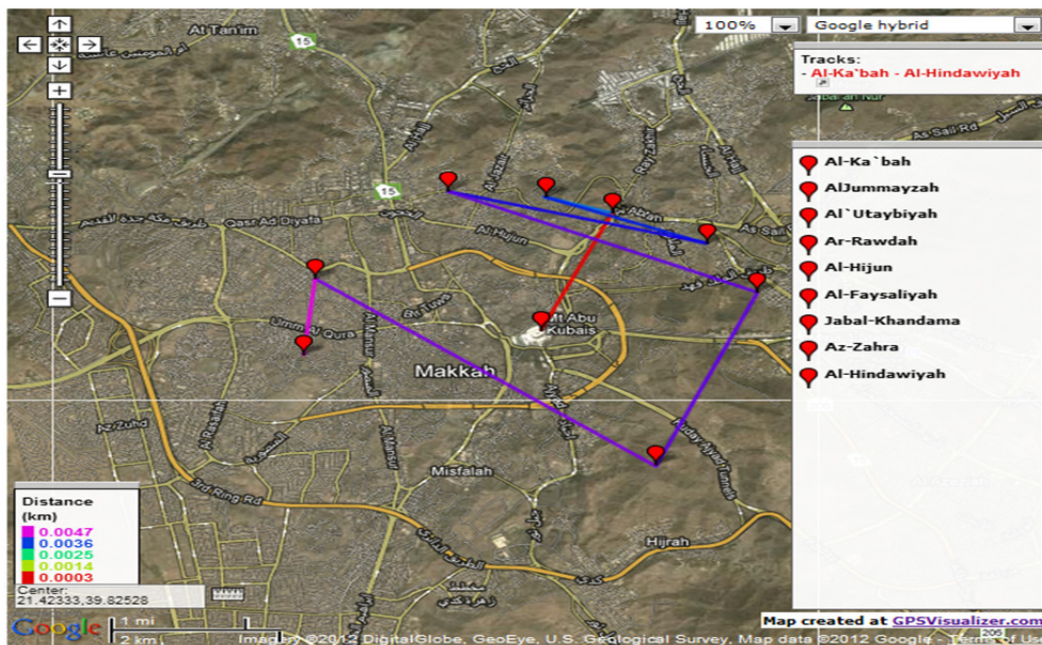


Figure 5. Group 3, locations that are 300 meters away from the Al Ka’bah building but less than 5 kilometers to pilgrim’s point of interest

Table 4. Group 4, locations that are 300 meters away from the Al Ka’bah building but less than 6.4 kilometers to pilgrim’s point of interest

Name	Distance (KM)	Latitude	Longitude
Al-Ka’bah	0.32	21.423056	39.826389
Jabal-Qaws-anNikashah	5.0	21.396389	39.819168
Marwa	5.0	21.450001	39.816666
Al-Khansak	5.1	21.426390	39.858612
Al-Badr	6.0	21.392500	39.840557
Al’Adl	6.0	21.443611	39.856110
Al-Ma’abidah	6.3	21.449722	39.852222

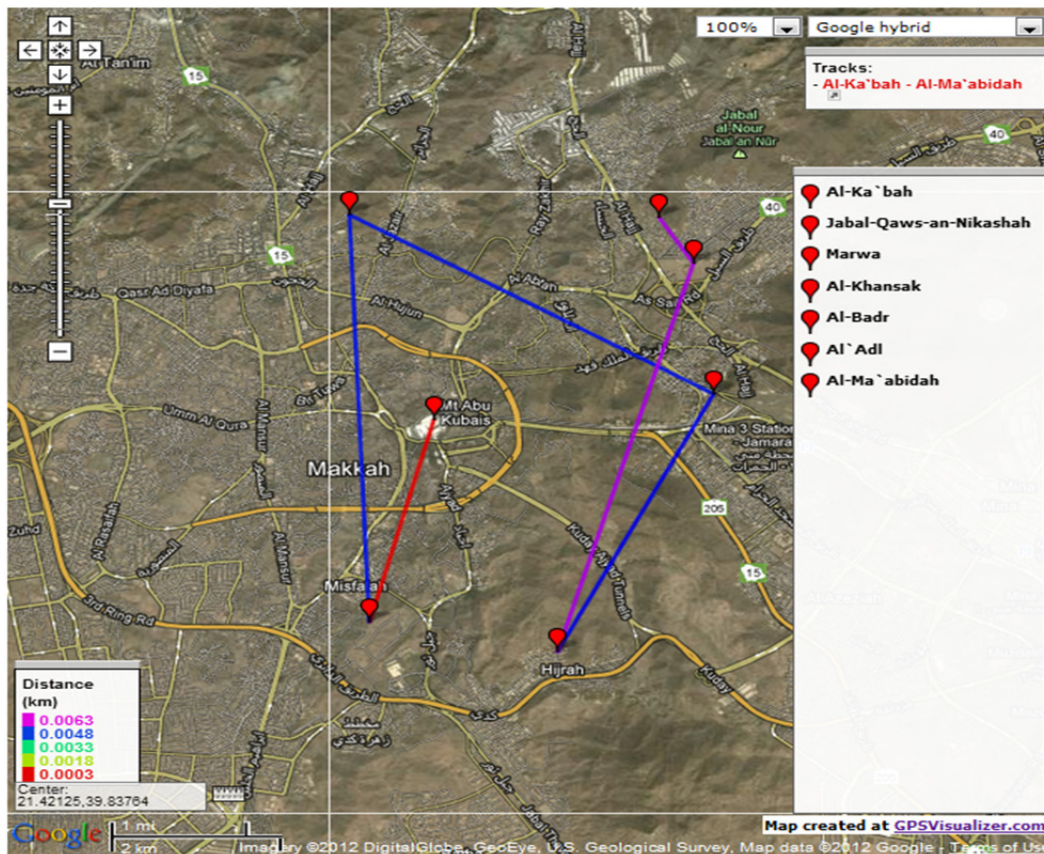


Figure 6. Group 4, locations that are 300 meters away from the Al Ka’bah building but less than 7 kilometers to pilgrim’s point of interest

Table 5. Group 5, locations that are 300 meters away from the Al Ka’bah building but less than 8 kilometers to pilgrim’s point of interest

Name	Distance (KM)	Latitude	Longitude
Al Ka’bah,	0.32	21.423056	39.826389
Az Zahir	6.4	21.449444	39.801109
Mahgar Elkabch	6.8	21.416666	39.866665
Ar Rusayfah	6.8	21.414722	39.787498
Ash Shuhada	6.8	21.456667	39.808613
Ar Rasifah	6.8	21.414722	39.787498
An Nuzhah	6.8	21.431389	39.786667
Jami’at Umm al Qura	6.8	21.407223	39.867500
An Nikashah	7.7	21.385555	39.803612

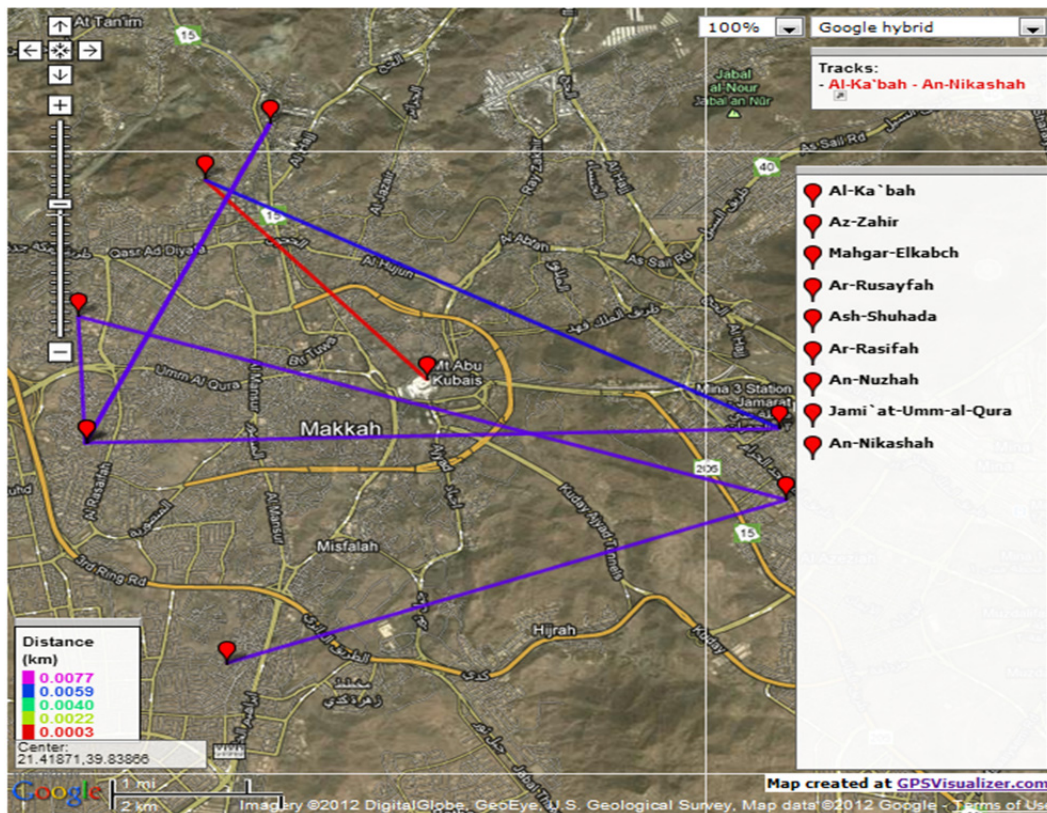


Figure 7. Group 5, locations that are 300 meters away from the Al Ka’bah building but less than 8 kilometers to pilgrim’s point of interest

Table 6. Group 6, locations that are 300 meters away from the Al Ka’bah building but less than 9.9 kilometers to pilgrim’s point of interest

Name	Distance (KM)	Latitude	Longitude
Al Ka’bah	0.32	21.423056	39.826389
Umm al Jud,	8.0	21.449444	39.787777
Jabal an Nur	8.2	21.458055	39.861389
Jabal Thughbah	8.2	21.436945	39.875278
As Safra	8.2	21.468056	39.839169
Al Aziziyah	8.2	21.403055	39.871944
Al Iskan	8.2	21.394167	39.788334
Wadi al Jalil	8.2	21.462500	39.855000
Gabal Alnoor	8.2	21.458055	39.861389
Jabal as Sarid,	8.5	21.376944,	39.818054
Al Hamra,	8.9	21.428055	39.774445
Al Ghassalah	9.0	21.448055	39.875000
Jabal Thawr	9.3	21.376667	39.851112
Suq al Hatab	9.3	21.375278,	39.806946
As Sifyani,	9.7	21.475555	39.843056
Jabal al Quways	9.8	21.432222,	39.884998
Bi’r Umm ad Dud,	10	21.433332	39.766666

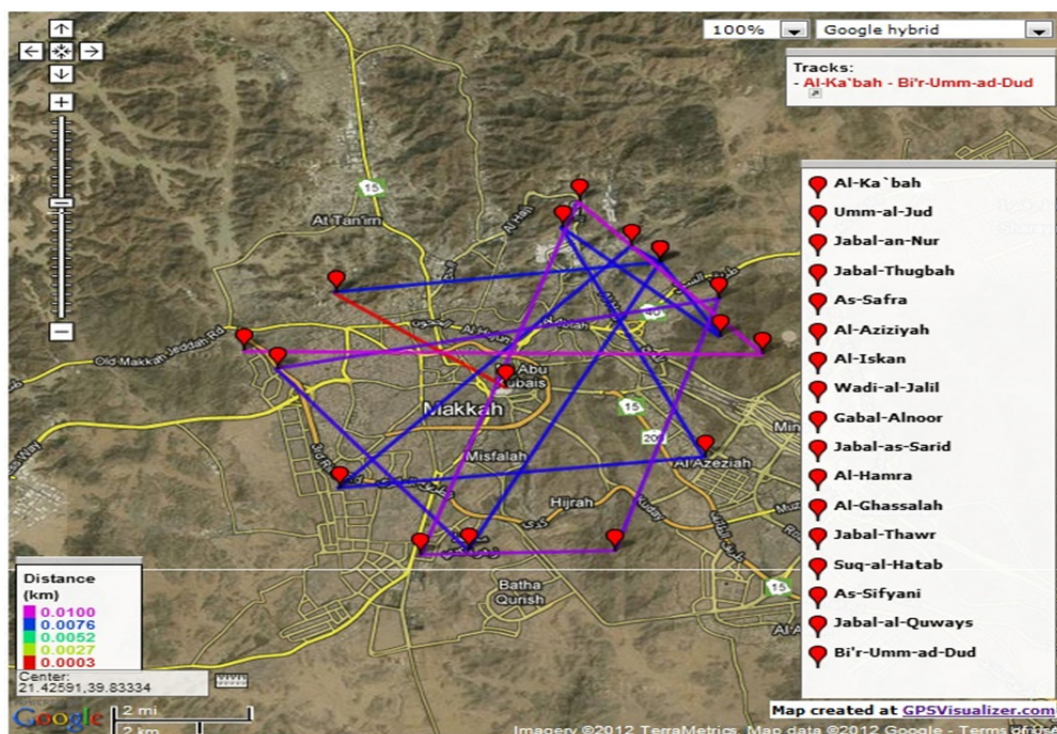


Figure 8. Group 6, locations that are 300 meters away from the Al Ka'bah building but less than 9.9 kilometers to pilgrim's point of interest

2.2 Experiment

The longitude, latitude and distances collected (see Tables 1–6) from Al Ka'ba to several pilgrim's points of interest in Mecca are grouped together and used for building modular network and support vector machine model in our experiments. In The present work, experiments are conducted in two phases: in first phase data was not normalized and randomized. Second phase data was not normalized but randomized.

The raw data was randomized to improve prediction performance of our models. Experiments were repeated with the randomized data in which data partition ratio (training: cross validation: testing), number of epochs, transfer functions, learning rule and other model configurations used in the first phase of the experiments are maintained in this second phase. Figure 9–10 reported training results for modular network and support vector machine. To ensure good generalization ability of a model, data set which the models have never seen was reserved for testing performance ability. The part of data to be reserved for testing has to be a section of a data in the target population. In this experiment, 25% (15) of our target data was reserved for testing generalization ability in terms of predicting distances from Al Ka'ba to point of interest within Al Haram. The reserved data was executed on modular network and support vector machine. Figure 11 and Table 7 present simulated results.

3. Results

This section presented training results of modular network and support vector machine models. The results of the study suggest the effect of both algorithm on efficiency and proficiency of prediction. The error in the training set are drastically decreasing as a function of training set as indicated in Figures 9–10 and the straight lines in both Figures indicated convergence. From Figure 9, the minimum and final MSE during in sample simulation (training) is $6.63E-05$ and $6.68E-05$ respectively at epoch 152. Minimum and final MSE of cross validation during hold out are 0.001849 and 0.002198 respectively at epoch of 53.

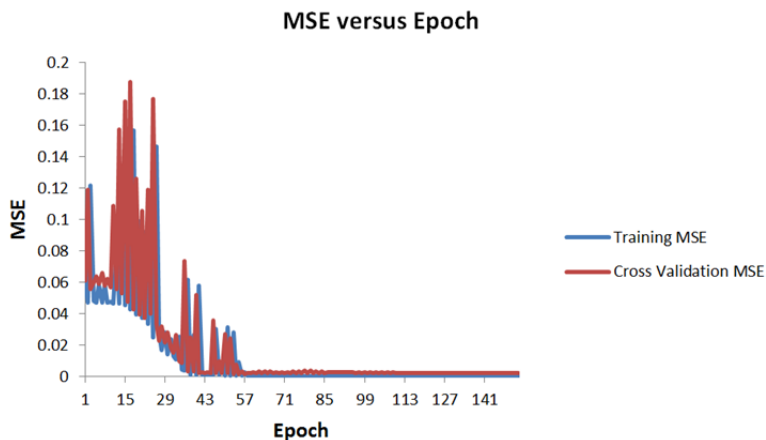


Figure 9. Plot of training and cross validation MSE versus epoch for modular network

From Figure 10, the minimum and final MSE during in sample simulation (training) are 0.041865 and 0.077334 respectively, at epoch of 63. Minimum and final MSE of cross validation during hold out are 0.085142 and 0.086398 respectively at epoch of 306.

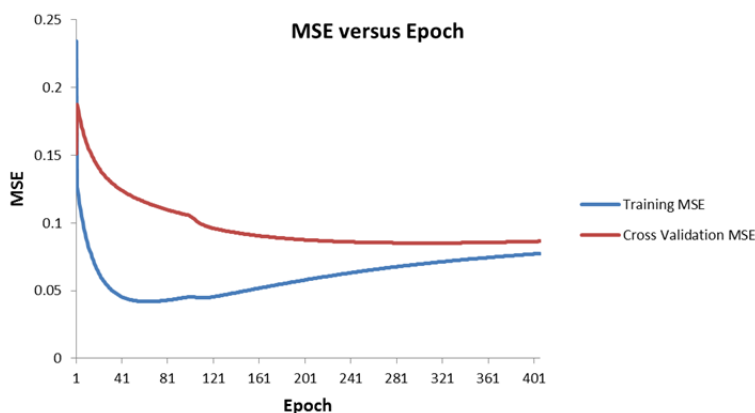


Figure 10. Plot of training and cross validation MSE versus epoch for support vector machine

The data reserved for testing our models are used on modular network and support vector machine. Figure 11 is a plot of distances predicted by both models and actual distances. Table 7 reported performance effectiveness of each model.

Table 7. Performance metrics for modular network and support vector machine

	Performance measures			
	MSE	NMSE	MAE	r
MN	0.803	0.073	0.686	0.963
SVM	5.073	0.459	1.744	0.868

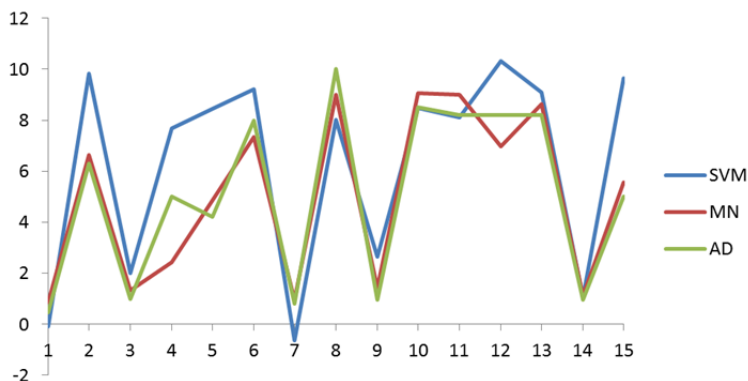


Figure 11. Predicted distances by modular network and support vector machine against actual distances (AD)

3.1 Correlation and T-Test Results

The distances from Al Ka’ba to point of interest predicted by modular network and support vector machine models are correlated in order find correlation between the two set of predicted values. The correlation between the two set of predicted distances is 0.836 as reported in Table 8.

Table 8. Correlation between predicted values of modular network and support vector machine

	N	Correlation	Sig.
Pair 1 SVM & MN	15	0.836	0.00

Table 9. Paired sample test

	Paired Differences					t	df	Sig. (2-tailed)
	Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval of the Difference				
				Lower	Upper			
Pair 1 SVM- MN	1.23940	2.18190	0.56336	0.03111	2.44770	2.200	14	0.045

Table 9 reported results of t–test analysis conducted between values of distances predicted by modular network and support vector machine, each model predicted 15 values. Degree of freedom is 14, 95% (0.05) confidence level, t computed is 2.2 and critical value is 2.14.

Table 10. Established Results of comparison between different neural networks architectures

Refs	Results
(Gencay & Liu, 1997))	Elman recurrent network perform better than feed forward neural network
(Cao & Tay, 2001)	Support vector machine outperform Back propagation neural network
(Tay & Cao, 2001)	Support vector machine outperform Back propagation neural network
(Kulkarni S., & Haidar, I. (2009)	Multilayer feed forward network perform better than recurrent network
(Saad et al., 1998)	Recurrent neural network perform better than time delay and probabilistic neural networks
(Fernandez, 2012)	First case (neural network perform better than support vector machine), Second case (support vector machine outperform neural network)
(Quek et al., 2008)	Recurrent network perform better than multilayer perceptron and Elman neural network
(Xie et al., 2008)	Support vector machine outperform Back propagation neural network
(Kaynar et al., 2010)	Neuro-fuzzy inference system perform better than multilayer perceptron

	and radial basis function network
(Zimberg, 2008)	Adaptive neuro-fuzzy inference system perform better than Elman neural network and feed forward neural network
(Qi & Zhang, 2009)	Cluster support vector machine perform better than conventional support vector machine
(Yu et al 2008)	First case (radial basis function network perform better than support vector machine and back propagation network), second case (support vector machine outperform radial basis function network and back propagation neural network)
(Byvatov et al., 2003)	Support vector machine outperform neural network
(Chen et al., 2001)	Support vector regression perform better than radial basis function network

4. Discussion

Performance measures listed in Table 7 indicated modular network and support vector machine perform very poor as r between values predicted by support vector machine and actual values shows there is no correlation (see Figure 9). For modular network the r value is very poor as well as MSE, NMSE and MAE for both models but the two compared results suggested modular network is the best of the worst. This signified very poor convergence for both models. Training results for modular network and support vector machine presented in Figures 9–10 and values of MSE for training and cross validation for both models suggested good convergence. It was found that difference between values of minimum and final training MSE varies a little bit so also minimum and final cross validation MSE, though not substantially. Values of cross validation MSE are better than training MSE. Generally, the training results suggested modular network training and cross validation MSE are superior to support vector machine training and cross validation MSE. Therefore, convergence of modular network is better than support vector machine. Figure 11 and Table 7 report a brief summary of basis to rely upon to take decision on performance effectiveness of our models. All the statistical indices listed in Table 7 measured prediction accuracy of modular network and support vector machine. MSE, NMSE, MAE and r clearly suggested that modular network perform better than support vector machine in predicting distances from Al Ka'ba based on longitude and latitude to pilgrim's point of interest. A careful examination of Figure 11 further revealed correlation between distances predicted by both models and actual distances. The plot indicated patterns predicted by modular network is closer to actual distances than patterns predicted by support vector machine. Therefore, have better generalization capability. Values of MSE, NMSE, MAE and r for support vector machine indicated the model is also good in terms of generalization ability. Training, cross validation and test results shows performance of modular network is consistent. Generally, it was observed that prediction accuracy significantly improved with randomized data. Probably, is due to data randomization. Table 8 Shows correlation between values predicted by modular network and support vector machine is statistically significant. Table 9 reported results of t-test in which H_0 is accepted and H_1 rejected suggesting prediction accuracy of modular network is better than support vector machine but the difference is not statistically significant. Table 10 reported established results in literature. Different neural networks architectural configurations are used to built a model and prediction results generated by the models are compared to assessed performance accuracy. Previous comparison results as pointed out in Table 10 clearly showed no any single neural network architecture perform better in all cases. Probably is because of different problem domain in which the neural networks are applied. What is common among the literature is lack of check whether prediction performance among compared architectures is statistically significant or not. Correlation of values predicted between compared models is also lacking

5. Conclusion

This paper offer informative comparisons of modular network and support vector machine within the context of distance prediction from Al Ka'ba to point of interest based on longitude and latitude. Having prior approximate distances within Al Haram to point of interest can enable pilgrims to properly plan for time cost when the needs for getting to a point of interest arise within Masjid Al-haram while performing Hajj and Umrah "the Muslim ritual". In addition, this also offers flexibility in making choices on places of interest within Al-haram and convenience in planning for many activities within Al-haram. Experimental investigation demonstrated that modular network applied in this research produce higher prediction accuracy than support vector machine. Correlation between the values predicted by both models is statistically significant but the difference in prediction accuracy between the two models is not statistically significant as revealed by the experimental results and analysis. This contribution May provide insight for researchers in choosing appropriate neural network architectural configuration for

application in a particular problem domain. In a specific problem domain, it seems several neural network architectures (feed forward network, recurrent network and support vector machine) has to be experimentally tried since no particular architecture is superior to others in solving all types of problems. Therefore, searching for suitable and optimum neural network requires several architectures to be experimentally tried and adopt the best.

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Notes

Note 1. GPSVisualiza.com

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