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A novel group decision making model based on neutrosophic sets for heart disease diagnosis

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Abstract
In a developed society, people have more concerned about their health. Thus, improvement of medical field application has been one of the greatest active study areas. Medical statistics show that heart disease is the main reason for morbidity and death in the world. The physician's job is difficult because of having too many factors to analyze in the diagnosis of heart disease. Besides, data and information gained by the physician for diagnosis are often partial and immersed. Recently, health care applications with the Internet of Things (IoT) have offered different dimensions and other online services. These applications have provided a new platform for millions of people to receive benefits from the regular health tips to live a healthy life. In this paper, we propose a novel framework based on computer supported diagnosis and IoT to detect and monitor heart failure infected patients, where the data are attained from various other sources. The proposed healthcare system aims at obtaining better precision of diagnosis with ambiguous information. We suggest neutrosophic multi criteria decision making (NMCDM) technique to aid patient and physician to know if patient is suffering from heart failure. Furthermore, through dealing with the uncertainty of imprecision and vagueness resulted from the symmetrical priority scales of different symptoms of disease, users know what extent the disease is dangerous in their body. The proposed model is validated by numerical examples on real case studies. The experimental results indicate that the proposed system provides a viable solution that can work at wide range, a new platform to millions of people getting benefit over the decreasing of mortality and cost of clinical treatment related to heart failure.

Keywords Heart failure · Internet of things (IoT) · Neutrosophic multi criteria decision making · Biomedical data analysis

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1 Introduction

Heart disease is the most concerned problems that influence heart's potency to function normally. The most popular reason of heart disease is narrowing or blockage and protest of the coronary blood vessels, which supply blood or gore to the heart itself. Among the noncommunicable diseases, heart disease is the number one basis of death worldwide. In the last decade, the number of dooms occasioned by heart disease increased by 14.6% and attained 17.5 million people in 2016, which accounts for 31% of the global dooms [39]. Each year, heart disease is responsible for more than 70,000 deaths in the United Kingdom [39]. About 1 in 5 men and 1 in 9 women decease from heart disease [39]. Heart disease is the number one source of death among Egyptians, and there are 500 deaths per 100 thousand occur annually in Egypt due to cardiovascular diseases caused by acute heart disease, coronary insufficiency, and stroke [39].

However, as it is related with many symptoms and many pathologic features, the diagnosis of heart disease remains a great problem for **less experienced doctors** and physicians [48]. Commonly, a physician makes decision by estimating the actual examine results of a patient and by indicating to the prior decisions he made on other patients with comparable conditions. The previous relies heavily on the physician's knowledge while the last based on his experience. Considering the number of factors to be evaluated, this job cannot get easily done [22]. It is required to have an **accurate tool** that offers the diagnosis on patients with same or close to same factors.

Due to the importance of heart failure disease, there is a brief summary of researches on heart failure management as shown in Fig. **1**. **Remote health monitoring from the Internet of Things** (IoT) seems to be a hopeful solution that can work at large levels, to decrease death rate, and economic percentage of expenditure related to heart failure. However, the capability to gather, keep, store and handle great amount of data collected from the sensors in an operative, durable and dynamic style is considered a great challenge to great scale remote monitoring systems. Moreover, a really effective remote health surveillance system has to likewise be capable to implement smart analyses on aggregated data. This denotes the system should supply resources of methodical algorithms that can deduce valuable information or find out predictive styles from the data. Equipped with the data and information, early involvements can be made to stop medical events from occurrence. Regrettably, some existing studies on diabetic monitoring IoT system focus on improvement the response performance of the system, the security of database systems [25, 35], the other existing remote surveillance systems lack analytics abilities [18, 30] or no advanced decision making techniques are employed to improve the decision making skills.

In this research, we propose a **new group decision making model based on the IoT** for detecting and surveillance heart failure patients in real time. Details of the proposed system are as follows:

In the IoT system, sensors are responsible for gathering important information about patient's body for observation of diseases. A tracking process of the present status of the outbreak and recognizing infected users to treat them early for achieving a high rate of cure will be performed by the proposed system. Each user will register via mobile applications and insert all personal information. Then, a unique identification number (ID) is created automatically for each registered user for continuous communication among users and health care center. The data of heart failure symptoms from body sensors is gathered by user's mobile phone through the Bluetooth technology and transferred by a smart gateway to cloud database for storing it.

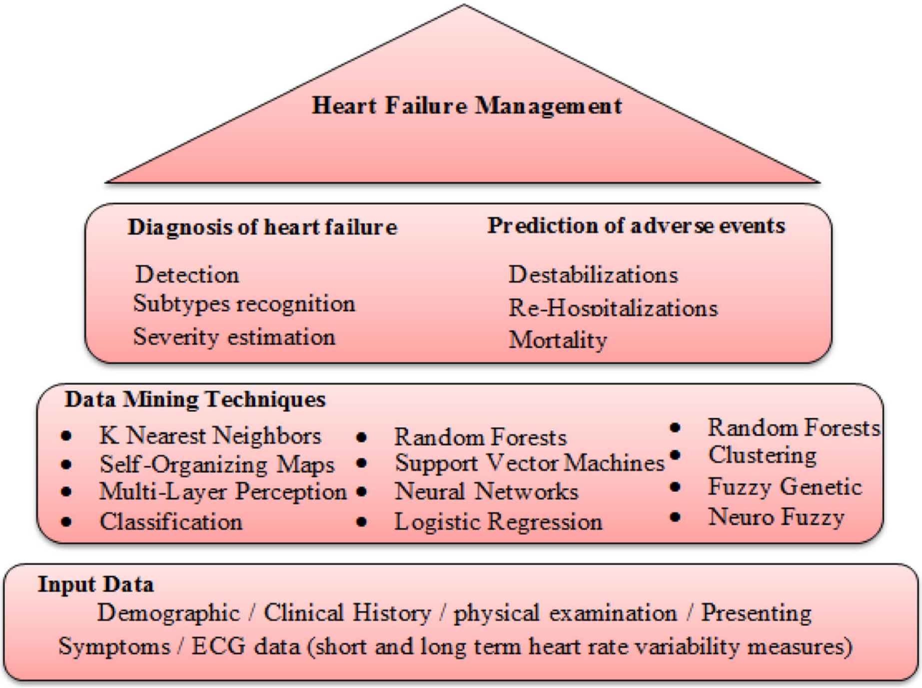

Fig. 1 Summary of researches on heart failure management

In the second phase, clinicians classify patients into several groups based on their symptoms. An electronic health record contains the diagnosis of disease and recommended advices is sent to patients via the shared interface. If the patient is infected, clinicians should determine the type and stage of heart failure for treatment. To lower the risk for complication, we propose a new group decision making model called N-MCDM for handling vague, uncertainty, incompleteness of reported symptoms and distancing clearly among heart failure or similar diseases in the symptoms.

Lastly, the proposed IoT system and N-MCDM technique integrates together for detecting, monitoring and controlling heart failure with minimum cost and time to predict the disease. The main contributions of the paper are summarized as follows:

- A complete implementation of a diagnosis IoT-Based system for monitoring heart disease patients in real time;
- A new group decision making model based on bipolar neutrosophic numbers;
- A new system established on WBAN for it mobility and wireless transference characteristics;
- Biomedical data analysis, warning the user and supporting doctor making decision.

The remainder of this research is structured as follows. Section 2 focuses on the related works. In Section 3, we draft the configuration for the IoT system. Section 4 presents N-MCDM technique for handling vagueness, uncertainty, incompleteness of reported symptoms and distancing clearly among percentage of disease (Heart Failure) in every patient. Sections 5 and 6 show the experiments and conclude the research and discuss future fields of research.

2 Literature review

First, we summarize some literatures on medical diagnosis based on machine learning techniques.

Poornima and Gladis [44] proposed a heart disease prediction system based on the hybrid optimization techniques. First, they used Orthogonal Local Preserving Projection method to reduce the function dimension of the input high-dimensional data. Then, they used the Levenberg-Marquardt training algorithm to determine the best network parameters that minimize the error. The proposed method increases the rate, the sensitivity and accuracy of the heart disease prediction system on Cleveland dataset.

Bhatla and Jyoti [12] made a research on reducing the number of attributes used in heart disease diagnosis with the desire to reduce the number of tests required to be taken on a patient. They proposed a system based on Decision Tree and Naive Bayes using fuzzy logic.

In what follows, we summarize the latest trends on medical diagnosis via IoT. Generally, remote health observation influences three stages architecture: a WBAN involving of wearable sensing elements as the fact procuration component, networking and communication and the layer of service [7, 30].

For example, the authors [32] suggested a framework or scheme which enrolls wearable sensing elements to scale different bodily functional factors like body temperature and blood pressure. The gateway server receives gathered information collected by sensors via Bluetooth linking. The gateway server mutations data and information into a measurement and surveillance folder which contains many files on a distant custom server for subsequent recuperation by physicians. Using medical data store built on a comparable cloud, a healthiness surveillance framework is shown in [24] where medical staff can connect stored data over the Internet by performing a satisfied service. Aimed at presenting and applying a particular medical application, the remote monitoring and analysis system is associated with remote health to monitor patients with an increased risk of heart failure [11]. In the other manner, Tuan et al. [35] presented a Fog-based system for remoting health monitoring and fall detection of both e-health signals such as glucose, ECG, body temperature and contextual data such as room temperature, humidity, and air quality in real-time. Chao Li et al. [25] proposed a pervasive monitoring system that can send patients' physical signs (blood pressure, ECG, SpO2, heart rate, pulse rate, blood fat and blood glucose) to remote medical applications in real time.

Besides the knowledge for statistics collecting, storing and retrieve, medical information and data analyses and conception are crucial parameters of distant healthiness surveillance schemes. Careful diagnosis and surveillance of sick person's medical status depends on analyses of medicinal enrollments including many physiological features through a prolonged interval of time. Transaction with data and information of large dimension together time and quantum make data analyses mission depressing and fault prone for physicians. Even though the employ of data excavating and conception mechanizations had prior been addressed as a settlement to defy [13], these procedures have only lately acquired awareness in distant healthiness surveillance systems [47].

Through the incoming of electronic remote healthiness surveillance systems has hopeful to revolt the traditional healthiness patronage approaches, merging the IoT ideal into these systems can furthermore raise realization, operability and pliability [37]. Over the Internet, any device employing the IoT schema is distinctively accosted and recognizable at anywhere and anytime. IoT established devices in distant healthiness surveillance schemes are not only able of the traditional recognizing missions but can reciprocate information and data with each other, robotically relate to and reciprocation information and data with healthiness institutions and hospitals via Internet, safely facilitating constitute and management tasks. As exhibited in [49], such systems are capable to extend facilities like impulsive alarm to the adjacent healthcare institution in the happening of a climacteric incident for overseen patients [1–6, 10, 15, 26–29, 36, 42].

3 The proposed IoT system

The system configuration for a remote healthiness surveillance system (or the IoT system) are depicted as follows (Fig. 2):

(a) **Data acquirement** is achieved by various wearable sensors that measure body bio-markers, like aerobic rate, ECG, bearing (posture), skin fever and EMG muscle vigor. These sensors are located in data concentrator or network data aggregation, which is smartphone existed in the nearness of the sick person. The information and data transition elements of the framework and system are accountable for transferring enrollments of patients from household to the health care community with guaranteed confidentiality and safety, preferably in close actual period.

Usually, the sensual conquest stand is prepared with a stumpy domain transistor such as Bluetooth or ZigBee which utilizes to send convey sensing element data to the concentrator. Gathered information and data are moved to a healthcare community for prolonged storing using online connectivity on the concentrator, usually through cellular data connection or a smartphone's WiFi. Sensors in the data conquest portion compose an IoT established construction as every single sensor's data enable be retrieved out of network of the internet

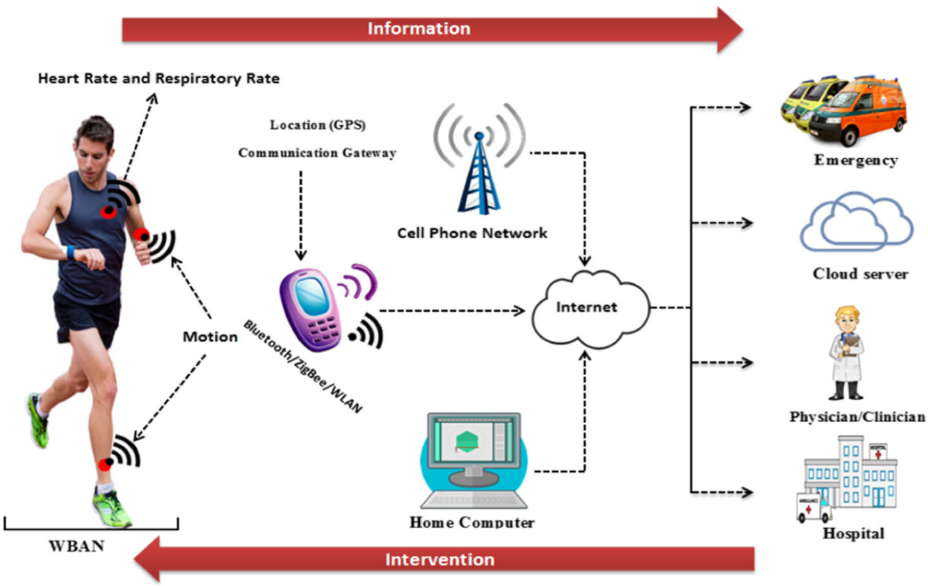

Fig. 2 Typical WBAN structure

through concentrator [17, 19]. Typically, a processing system or device in nearness of a portable person, occasionally indicated to as the Internet, is applied to increase its handling or storage ability whenever the native mobile possessions do not perfect the implementation's necessities [45].

(b) **A local processing unit** can be cloudlet (such a desktop computer) that is an immediately attainable by the concentrator meanwhile WiFi network. Besides supplying provisional storage previously to connecting of information and data to the processing unit (cloud), the cloudlet can be utilized for serious tasks on sick person's gathered information and data. Furthermore, the cloudlet can be utilized to convey the gathered data to the cloud in state of restriction on the mobile device like provisional shortage of energy or connectivity.

There are three distinguished components in cloud processing such as storing, conception and analytics. The scheme is intended for prolonged period storing of sick person's biomedical data likewise helping health consultants with diagnostic information. In this literature [14, 46] cloud built medical data and information storing and the tasks have been comprehensively classified. Analytics that utilized the sensor data forever with electronic healthiness enrollments that are appropriate prevailing can assist with diagnosis and prediction for a number of healthiness cases and diseases. In addition, visualization or conception is a key demand for any such system as it is impracticable to require clinicians to crucial over the huge statistics or analysis from wearable sensing elements. Conception procedures that form the data and analysis attainable to them in an easily edible shape are fundamental if the wearable sensing elements are to effect experimental practice.

Typically, health surveillance systems comprise many devices for gathering data from patient body and conveying it to visualization or transformation device through wires and cables for diagnosis and surveillance. The main drawbacks of such systems are the unsupported remote surveillance and mobility, which give rise to troubles for both patients and physicians.

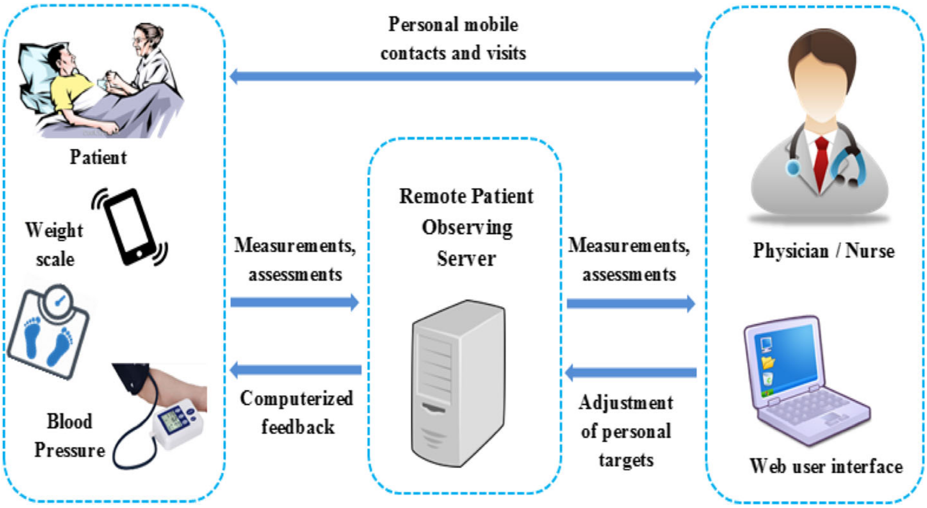

Fig. 3 Inclusive architecture for remote patient surveillance

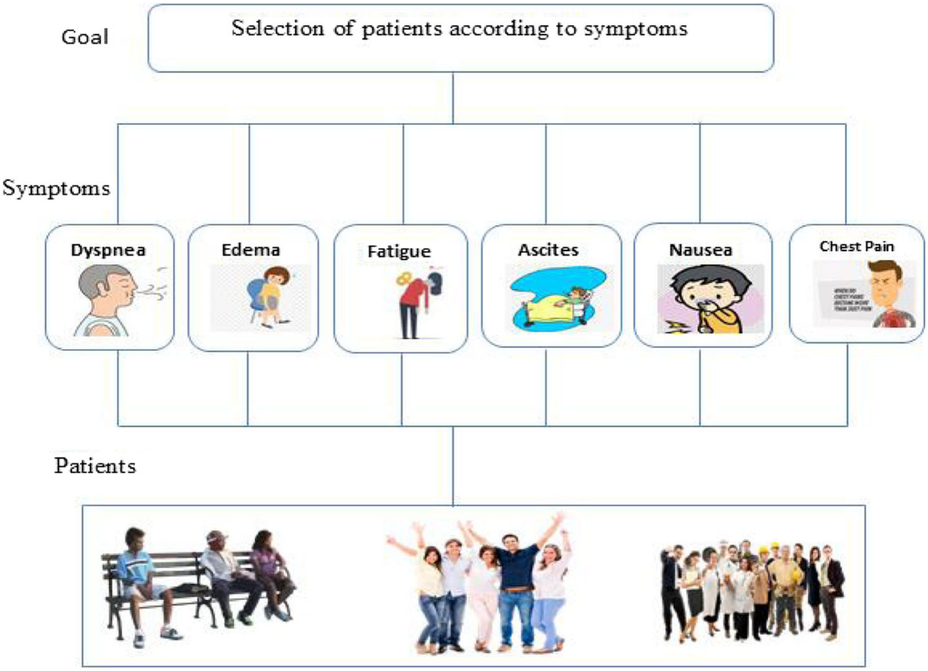

Fig. 4 The hierarchy for selecting the patients by heart failure

In conventional systems, patient must carry numerous devices and cables during long time of surveillance hours in such cases of diseases and any motion activity of patient will give rise to incorrect gathering of data. For instance, diabetes type one, two and Coronary heart disease need continuous surveillance twenty-four hours a day, seven days a week.

We **suggest a new system established on WBAN** for its mobility and wireless transference characteristics, and then be capable to classify conventional systems shortcomings. The suggested system consists of the following **components**:

– The first portion of suggested healthcare system is WBAN or **medical sensor** node. It is a collection of numerous physical devices including sensors which are wearable and combined to a small wireless module for gathering data that assist physicians to detect

Table 1 Linguistic variables for diagnosing alternatives (patients) with respect to each symptom and weighting symptoms

Linguistic variables	Bipolar neutrosophic numbers $\langle T^{+}(x), I^{+}(x), F^{+}(x), T^{-}(x), I^{-}(x), F^{-}(x)\rangle$
Excessively Dangerous/Disease (ED)	$\langle 0.9, 0.2, 0.0, 0.0, -0.7, -0.8\rangle$
Extremely Dangerous/Disease (EXD)	$\langle 0.8, 0.6, 0.5, -0.1, -0.9, -0.8\rangle$
Very Strongly Dangerous/Disease (VSD)	$\langle 0.9, 0.7, 0.4, -0.3, -0.4, -0.6\rangle$
Strongly Dangerous/Disease (SD)	$\langle 0.5, 0.3, 0.2, -0.2, -0.1, -0.4\rangle$
Moderately Dangerous/Disease (MD)	$\langle 0.4, 0.3, 0.4, -0.5, -0.1, -0.2\rangle$
Equally Dangerous/Disease (EQD)	$\langle 0.3, 0.3, 0.7, -0.4, -0.2, -0.1\rangle$
Less Dangerous/Disease (LD)	$\langle 0.4, 0.6, 0.8, -0.9, -0.1, -0.1\rangle$

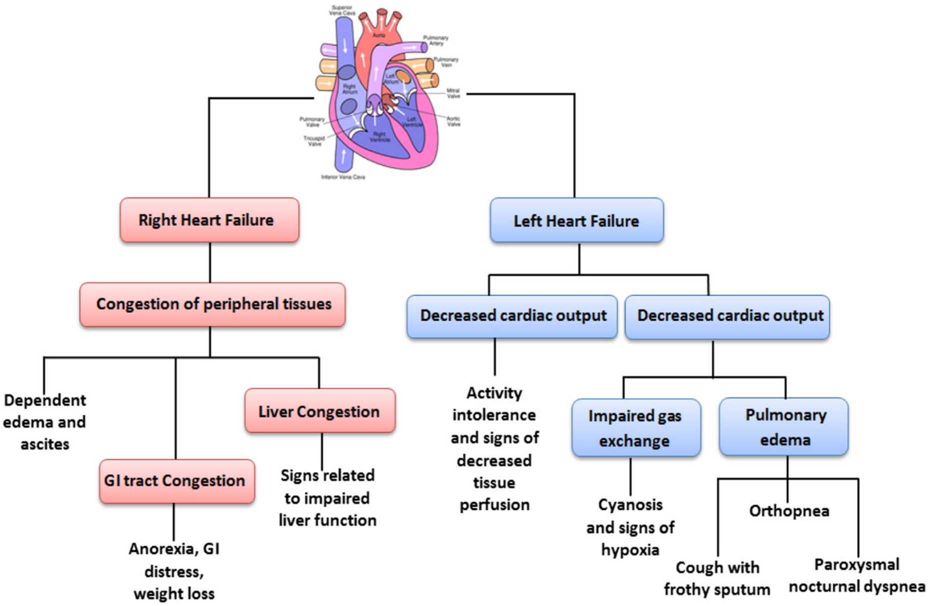

Fig. 5 Symptoms of right and left heart failure

heart failure disease in the early stages. These sensors involve: blood pressure, heart rate and respiratory rate, glucose detection, motion activity.

- After utilizing sensors and mobile application interface for gathering patient data, personal information of patients must be collected also and generating ID to patients in the system. The data extracted from WBAN convey are sent to the mobile application through Bluetooth or ZigBee and stored in the cloud server to store, process and broadcast data.
- After then, physicians are able to determine the percentage of heart failure disease of patients through the N-MCDM model. If patient is infected person has high percentage of heart failure then, physicians will send an electronic health report to patient. The role of this report is to inform patient with the result of diagnosis and need to be in the hospital for performing more checks.
- An ambulance will be sent to patient for bringing him to perform more checks and receive treatment, if he/she is in critical case. The components of monitoring system summarized as in Fig. 3.

Table 2 General symptoms of heart disease

Symptoms	Value “YES”	Value “NO”
Dyspnea	EXD, ED, MD, VSD, SD, EQD, LD	NO
Edema	EXD, ED, MD, VSD, SD, EQD, LD	NO
Fatigue	EXD, ED, MD, VSD, SD, EQD, LD	NO
Ascites	EXD, ED, MD, VSD, SD, EQD, LD	NO
Nausea	EXD, ED, MD, VSD, SD, EQD, LD	NO
Chest pain	EXD, ED, MD, VSD, SD, EQD, LD	NO

Table 3 Personal data of users

S. no.	Attribute	Characterization	S. no.	Attribute	characterization
1	MFP	Medical file of the patient	11	Mob	Mobile of user
2	UID	User identification number	12	Family member mobile number	Family member mobile number
3	Name	Username	13	Family member name	Name of the family member
4	DOB	Date of Birth	14	Previous health information	User previous health information
5	Gender	Male or Female	15	RH	Regular Habits
6	Age	User Age	16	VR	Vital Rates
7	Job	Job of patient	17	CD	Chronic Diseases
8	Email	Mail of User	18	CM	Current Medicines
9	Address	User Address	19	VA	Vaccinations
10	Nat	Nationality	20	INC	Insurance

4 Proposed N-MCDM technique

The purpose of this section is to additional examine and forecast percentage of patients affected by heart disease or heart failure based on reported symptoms of patient. This proposed technique combines **MCDM technique with bipolar neutrosophic numbers** for dealing with the uncertainty of imprecision and vagueness which created from the proportional priority scales of different factors of symptoms. This approach can assist physicians and users to determine the weight of heart failure disease in the patient's body based on the symptoms and scores selected by the users thereby offering quality of life assistance services.

The **weighted sum model** (WSM) is the straightforward and the most ordinarily used method in MCDA. The basic precept beyond this method is the collective utility presumption. That is, if the rendering of each alternative in terms of each criterion in the decision problem (i.e., a_{ij} the values) is commensurable and is of the same unit where higher is preferable, the alternate with the great accumulative value is the preferable. A well-known method to make decision by analyzing, determining complex problems, and evaluating the best feasible solution from different conflicting objectives is the MCDM technique [20, 41]. The benefit of this approach is the simplicity and proportional linear conversion of the raw data. The limitation of traditional WSM method is that it fails to deal with vague and uncertain information. This uncertainty and vagueness cannot be measured precisely (i.e. using crisp values). For solving theses drawbacks, we **enlarge the proposed model by using bipolar neutrosophic numbers.** The steps of the suggested model are as follows:

Step 1. Selecting group of consultants who have robust background about the signification of problem. Since the problem scope in our paper is the medical diagnosis then, we selected physicians who are consultants.

Step 2. Determine symptoms which are recorded via the suggested health care system in the first part of the research.

Step 3. Determine all available alternatives who are patients which have common symptoms with heart disease.

Step 4. Construct the hierarchical structure of the problem for facilitating and visualizing it obviously, via clarifying main goal, criteria and available alternatives as in Fig. 4.

Table 4 The aggregated decision matrix of symptoms

Symptoms	Dyspnea	Edema	Fatigue	Ascites	Nausea	Chest pain
Dyspnea	$\langle 0.5, 0.5, 0.5, -0.5, -0.5, -0.5 \rangle$	$\langle 0.4, 0.3, 0.4, -0.5, -0.1, -0.2 \rangle$	$\langle 0.5, 0.3, 0.2, -0.2, -0.1, -0.4 \rangle$	$\langle 0.4, 0.3, 0.4, -0.5, -0.1, -0.2 \rangle$	$\langle 0.4, 0.3, 0.4, -0.5, -0.1, -0.2 \rangle$	$\langle 0.3, 0.3, 0.7, -0.4, -0.2, -0.1 \rangle$
Edema	$\langle 0.3, 0.3, 0.7, -0.4, -0.2, -0.1 \rangle$	$\langle 0.5, 0.5, 0.5, -0.5, -0.5, -0.5 \rangle$	$\langle 0.9, 0.7, 0.4, -0.3, -0.4, -0.6 \rangle$	$\langle 0.5, 0.3, 0.2, -0.2, -0.1, -0.4 \rangle$	$\langle 0.9, 0.7, 0.4, -0.3, -0.4, -0.6 \rangle$	$\langle 0.5, 0.3, 0.2, -0.2, -0.1, -0.4 \rangle$
Fatigue	$\langle 0.4, 0.3, 0.4, -0.5, -0.1, -0.2 \rangle$	$\langle 0.9, 0.2, 0.0, 0.0, -0.7, -0.8 \rangle$	$\langle 0.5, 0.5, 0.5, -0.5, -0.5, -0.5 \rangle$	$\langle 0.8, 0.6, 0.5, -0.1, -0.9, -0.8 \rangle$	$\langle 0.8, 0.6, 0.5, -0.1, -0.9, -0.8 \rangle$	$\langle 0.4, 0.3, 0.4, -0.5, -0.1, -0.2 \rangle$
Ascites	$\langle 0.5, 0.3, 0.2, -0.2, -0.1, -0.4 \rangle$	$\langle 0.8, 0.6, 0.5, -0.1, -0.9, -0.8 \rangle$	$\langle 0.3, 0.3, 0.7, -0.4, -0.2, -0.1 \rangle$	$\langle 0.5, 0.5, 0.5, -0.5, -0.5, -0.5 \rangle$	$\langle 0.4, 0.3, 0.4, -0.5, -0.1, -0.2 \rangle$	$\langle 0.8, 0.6, 0.5, -0.1, -0.9, -0.8 \rangle$
Nausea	$\langle 0.4, 0.6, 0.8, -0.9, -0.1, -0.1 \rangle$	$\langle 0.9, 0.7, 0.4, -0.3, -0.4, -0.6 \rangle$	$\langle 0.4, 0.6, 0.8, -0.9, -0.1, -0.1 \rangle$	$\langle 0.4, 0.3, 0.4, -0.5, -0.1, -0.2 \rangle$	$\langle 0.5, 0.5, 0.5, -0.5, -0.5, -0.5 \rangle$	$\langle 0.4, 0.6, 0.8, -0.9, -0.1, -0.1 \rangle$
Chest pain	$\langle 0.9, 0.7, 0.4, -0.3, -0.4, -0.6 \rangle$	$\langle 0.3, 0.3, 0.7, -0.4, -0.2, -0.1 \rangle$	$\langle 0.3, 0.3, 0.7, -0.4, -0.2, -0.1 \rangle$	$\langle 0.8, 0.6, 0.5, -0.1, -0.9, -0.8 \rangle$	$\langle 0.4, 0.3, 0.4, -0.5, -0.1, -0.2 \rangle$	$\langle 0.5, 0.5, 0.5, -0.5, -0.5, -0.5 \rangle$

Table 5 The normalized decision matrix of symptoms

Symptoms	Dyspnea	Edema	Fatigue	Ascites	Nausea	Chest pain
Dyspnea	0.50	0.42	0.55	0.42	0.42	0.37
Edema	0.37	0.50	0.59	0.55	0.59	0.55
Fatigue	0.42	0.87	0.50	0.72	0.72	0.42
Ascites	0.55	0.72	0.37	0.50	0.42	0.72
Nausea	0.22	0.59	0.22	0.42	0.50	0.22
Chest pain	0.59	0.37	0.37	0.72	0.42	0.50

Step 5. After structuring the hierarchy, the importance of each symptom and evaluation of alternatives (patients) must be calculated. The consultants will make their judgments on the criteria and alternatives via using linguistic variables.

Step 6. The suitable neutrosophic linguistic variables for both Symptoms and alternatives will be presented by consultants. A seven-point scale is used by consultants in this evaluation process as in Table 1.

Step 7. Construct comparison matrix of symptoms according to each consultant and aggregate the neutrosophic evaluation values of experts by using the geometric mean operator as in Eq. (1). For doing this, the major operations of bipolar neutrosophic numbers [16] are illustrated with details.

$$\tilde{a}_{ij} = \overset{1}{\tilde{a}_{ij}} + \overset{2}{\tilde{a}_{ij}} + \overset{3}{\tilde{a}_{ij}} + \ldots + \overset{z}{\tilde{a}_{ij}}/Z \tag{1}$$

where Z is the number of consultants and $\tilde{a}_{ij}$ is the aggregated value of neutrosophic rating of symptoms.

Step 8. Deneutrosophic weight values for obtaining crisp values of weights by using the following equation: Let $\langle T^{+}(a), I^{+}(a), F^{+}(a), T^{-}(a), I^{-}(a), F^{-}(a)\rangle$ be a single valued bipolar neutrosophic number, then, the score function are as follows:

$$\tilde{S}\left(\tilde{a}\right) = \langle T^{+}(a) + 1 - I^{+}(a) + 1 - F^{+}(a) + 1 + T^{-}(a) - I^{-}(a) - F^{-}(a)\rangle/6 \tag{2}$$

Step 9. Calculate weight of symptoms as follows: After constructing comparison matrix of symptoms, take the average of normalized matrix raw values then,

Table 6 The weight of symptoms

Symptoms	Dyspnea	Edema	Fatigue	Ascites	Nausea	Chest pain
Agg. crisp	0.45	0.53	0.62	0.55	0.36	0.49
Normalized weight	0.15	0.18	0.21	0.18	0.12	0.16

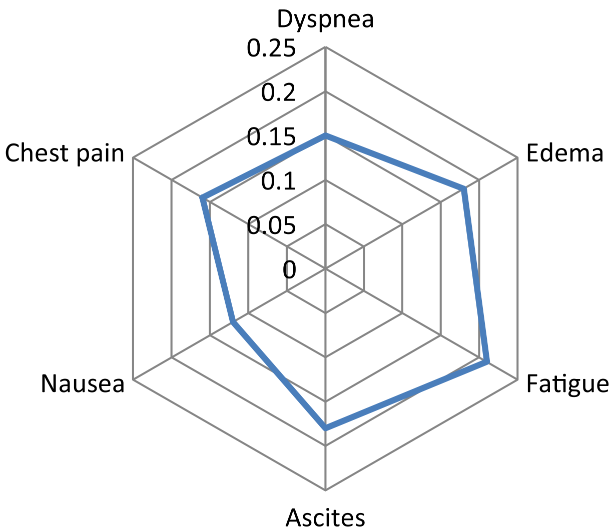

Fig. 6 The chart for weight of symptoms

$$\tilde{x}_i = \frac{\sum_{j=1}^{n} \tilde{a}_{ij}}{n} \tag{3}$$

Then, we make the normalization process.

Step 10. Start to rank alternatives (patients) using Neutrosophic WSM as follows:

- Utilize seven-point scales which presented in Table 3 and construct decision matrix of alternatives according to each symptom. Aggregate consultants' opinions as we exhibited in Step 7.
- Use Eq. (2) to obtain crisp matrix of alternatives.
- The normalized decision matrix must be calculated for symptom as follows:

$$x_{ij} = \frac{x_{ij}}{x_j^*} \mathrm{I} = 1, .., , \mathrm{n}, \mathrm{j} = 1, \ldots, \mathrm{m} \tag{4}$$

- Evaluating using neutrosophic weight sum model (NWSM):

$$\mathrm{A_i}^{\mathrm{wsm}} = \sum_{j=1}^{n} \mathrm{w_j}\ \mathrm{x_{ij}}.$$

Table 7 The diagnosing of patients based on neutrosophic scale

Patients / Symptoms	Patient 1	Patient 2	Patient 3	Patient 4	Patient 5
Dyspnea	$\langle 0.9, 0.2, 0.0, 0.0, -0.7, -0.8 \rangle$	$\langle 0.3, 0.3, 0.7, -0.4, -0.2, -0.1 \rangle$	$\langle 0.4, 0.6, 0.8, -0.9, -0.1, -0.1 \rangle$	$\langle 0.8, 0.6, 0.5, -0.1, -0.9, -0.8 \rangle$	$\langle 0.4, 0.6, 0.8, -0.9, -0.1, -0.1 \rangle$
Edema	$\langle 0.8, 0.6, 0.5, -0.1, -0.9, -0.8 \rangle$	$\langle 0.8, 0.6, 0.5, -0.1, -0.9, -0.8 \rangle$	$\langle 0.3, 0.3, 0.7, -0.4, -0.2, -0.1 \rangle$	$\langle 0.3, 0.3, 0.7, -0.4, -0.2, -0.1 \rangle$	$\langle 0.4, 0.6, 0.8, -0.9, -0.1, -0.1 \rangle$
Fatigue	$\langle 0.5, 0.3, 0.2, -0.2, -0.1, -0.4 \rangle$	$\langle 0.9, 0.2, 0.0, 0.0, -0.7, -0.8 \rangle$	$\langle 0.3, 0.3, 0.7, -0.4, -0.2, -0.1 \rangle$	$\langle 0.9, 0.2, 0.0, 0.0, -0.7, -0.8 \rangle$	$\langle 0.8, 0.6, 0.5, -0.1, -0.9, -0.8 \rangle$
Ascites	$\langle 0.4, 0.3, 0.4, -0.5, -0.1, -0.2 \rangle$	$\langle 0.5, 0.3, 0.2, -0.2, -0.1, -0.4 \rangle$	$\langle 0.9, 0.7, 0.4, -0.3, -0.4, -0.6 \rangle$	$\langle 0.4, 0.3, 0.4, -0.5, -0.1, -0.2 \rangle$	$\langle 0.9, 0.7, 0.4, -0.3, -0.4, -0.6 \rangle$
Nausea	$\langle 0.8, 0.6, 0.5, -0.1, -0.9, -0.8 \rangle$	$\langle 0.4, 0.6, 0.8, -0.9, -0.1, -0.1 \rangle$	$\langle 0.8, 0.6, 0.5, -0.1, -0.9, -0.8 \rangle$	$\langle 0.9, 0.2, 0.0, 0.0, -0.7, -0.8 \rangle$	$\langle 0.9, 0.2, 0.0, 0.0, -0.7, -0.8 \rangle$
Chest pain	$\langle 0.9, 0.2, 0.0, 0.0, -0.7, -0.8 \rangle$	$\langle 0.4, 0.6, 0.8, -0.9, -0.1, -0.1 \rangle$	$\langle 0.4, 0.6, 0.8, -0.9, -0.1, -0.1 \rangle$	$\langle 0.8, 0.6, 0.5, -0.1, -0.9, -0.8 \rangle$	$\langle 0.4, 0.6, 0.8, -0.9, -0.1, -0.1 \rangle$

Patients / Symptoms	Patient 6	Patient 7	Patient 8	Patient 9	Patient 10
Dyspnea	$\langle 0.4, 0.6, 0.8, -0.9, -0.1, -0.1 \rangle$	$\langle 0.3, 0.3, 0.7, -0.4, -0.2, -0.1 \rangle$	$\langle 0.4, 0.3, 0.4, -0.5, -0.1, -0.2 \rangle$	$\langle 0.4, 0.6, 0.8, -0.9, -0.1, -0.1 \rangle$	$\langle 0.4, 0.3, 0.4, -0.5, -0.1, -0.2 \rangle$
Edema	$\langle 0.9, 0.2, 0.0, 0.0, -0.7, -0.8 \rangle$	$\langle 0.8, 0.6, 0.5, -0.1, -0.9, -0.8 \rangle$	$\langle 0.9, 0.2, 0.0, 0.0, -0.7, -0.8 \rangle$	$\langle 0.9, 0.2, 0.0, 0.0, -0.7, -0.8 \rangle$	$\langle 0.8, 0.6, 0.5, -0.1, -0.9, -0.8 \rangle$
Fatigue	$\langle 0.5, 0.3, 0.2, -0.2, -0.1, -0.4 \rangle$	$\langle 0.9, 0.2, 0.0, 0.0, -0.7, -0.8 \rangle$	$\langle 0.8, 0.6, 0.5, -0.1, -0.9, -0.8 \rangle$	$\langle 0.4, 0.3, 0.4, -0.5, -0.1, -0.2 \rangle$	$\langle 0.3, 0.3, 0.7, -0.4, -0.2, -0.1 \rangle$
Ascites	$\langle 0.8, 0.6, 0.5, -0.1, -0.9, -0.8 \rangle$	$\langle 0.9, 0.2, 0.0, 0.0, -0.7, -0.8 \rangle$	$\langle 0.9, 0.7, 0.4, -0.3, -0.4, -0.6 \rangle$	$\langle 0.4, 0.6, 0.8, -0.9, -0.1, -0.1 \rangle$	$\langle 0.9, 0.7, 0.4, -0.3, -0.4, -0.6 \rangle$
Nausea	$\langle 0.8, 0.6, 0.5, -0.1, -0.9, -0.8 \rangle$	$\langle 0.4, 0.3, 0.4, -0.5, -0.1, -0.2 \rangle$	$\langle 0.4, 0.6, 0.8, -0.9, -0.1, -0.1 \rangle$	$\langle 0.8, 0.6, 0.5, -0.1, -0.9, -0.8 \rangle$	$\langle 0.8, 0.6, 0.5, -0.1, -0.9, -0.8 \rangle$
Chest pain	$\langle 0.9, 0.2, 0.0, 0.0, -0.7, -0.8 \rangle$	$\langle 0.4, 0.6, 0.8, -0.9, -0.1, -0.1 \rangle$	$\langle 0.4, 0.6, 0.8, -0.9, -0.1, -0.1 \rangle$	$\langle 0.8, 0.6, 0.5, -0.1, -0.9, -0.8 \rangle$	$\langle 0.9, 0.2, 0.0, 0.0, -0.7, -0.8 \rangle$

Table 8 The crisp matrix of patients diagnosing

Symptoms	Dyspnea	Edema	Fatigue	Ascites	Nausea	Chest pain
Patient 1	0.87	0.72	0.55	0.42	0.72	0.87
Patient 2	0.37	0.72	0.87	0.55	0.22	0.22
Patient 3	0.22	0.37	0.37	0.59	0.72	0.22
Patient 4	0.72	0.37	0.87	0.42	0.87	0.72
Patient 5	0.42	0.22	0.72	0.59	0.87	0.22
Patient 6	0.22	0.87	0.55	0.72	0.72	0.87
Patient 7	0.37	0.72	0.87	0.87	0.42	0.22
Patient 8	0.42	0.87	0.72	0.59	0.22	0.22
Patient 9	0.22	0.87	0.42	0.22	0.72	0.72
Patient 10	0.42	0.72	0.37	0.59	0.72	0.87

5 Case study

5.1 Results of the proposed method

In this section, we help patient to know which symptoms that he/she has a chance to be infected by it, and then he/she will be able to go to the right consultant and out of the confusion of disease. We will use the seven linguistic variable levels for contrasting the varied elements of the symptoms. By using the suggested healthcare framework, the patients enter these symptoms that he suffers from such as Dyspnea, Edema, Fatigue, Ascites, Nausea, Chest pain. After then, the consultants send a report to patient by email, for informing that the percentage that the patient suffer from heart failure (Fig. 5).

In this case study, we use the database that contains the symptoms data possessed from various times for same patients. Medical data which obtained from sensors can be used to detect symptoms of heart failure as in Table 2.

The residual symptoms will enter via mobile application interface of patients. These symptoms will enter by users or patients in the forms of "Yes" or "No". The personal information of patients should be gathered also, after utilizing mobile application interface and sensors for gathering patients' data. Table 3 presents the personal information of the users which stores in database.

Table 9 The normalized matrix of patients diagnosing

Symptoms	Dyspnea	Edema	Fatigue	Ascites	Nausea	Chest pain
Patient 1	1	0.83	0.63	0.48	0.83	1
Patient 2	0.43	0.83	1	0.63	0.25	0.25
Patient 3	0.25	0.43	0.43	0.68	0.83	0.25
Patient 4	0.83	0.43	1	0.48	1	0.83
Patient 5	0.48	0.25	0.83	0.68	1	0.25
Patient 6	0.25	1	0.63	0.83	0.83	1
Patient 7	0.43	0.83	1	1	0.48	0.25
Patient 8	0.48	1	0.83	0.68	0.25	0.25
Patient 9	0.25	1	0.48	0.25	0.83	0.83
Patient 10	0.48	0.83	0.43	0.68	0.83	1

Table 10 The final patients diagnosing

Patients	Diagnosing (WSM)	Patients	Diagnosing (WSM)
Patient 1	0.7734	Patient 6	0.7588
Patient 2	0.6073	Patient 7	0.7015
Patient 3	0.4672	Patient 8	0.6187
Patient 4	0.7511	Patient 9	0.5957
Patient 5	0.5737	Patient 10	0.6937

Now, we illustrate the algorithm:

Step 1. We choose three consultants who are specialists for helping us in our study.
Step 2. Construct hierarchical structure of medical problem for facilitating it.
Step 3. Use the bipolar neutrosophic standard which is exhibited in Table **1** for constructing decision matrix of symptoms according to each consultant's opinion. Then, aggregate all opinions of consultants via using geometric mean as in Eq. (1). The aggregated matrix of three consultants as exhibited in Table **4**.

Step 4. Determine weight of symptoms:

- Deneutrosophic weight values for obtaining crisp values of weights by using Eq. (2). The weights of symptoms are summarized in Table **5**.
- Then, take the average of each row of symptoms by using Eq. (3).
- After then, normalized the weight values of symptoms as exhibited in Table **6**.
- The weights of symptoms as summarized according to Table **6** and Fig. **6**.
- w_1= 0.15, w_2= 0.18, w_3= 0.21, w_4= 0.18, w_1= 0.12, w_1= 0.16.

Step 5. Utilize neutrosophic standard which exhibited in Table **1** and make decision matrix of alternatives (patients) according to symptoms. Then, synthesizing consultant matrices. The aggregated matrix presented in Table **7** shows the diagnosis of patients based on neutrosophic scale.

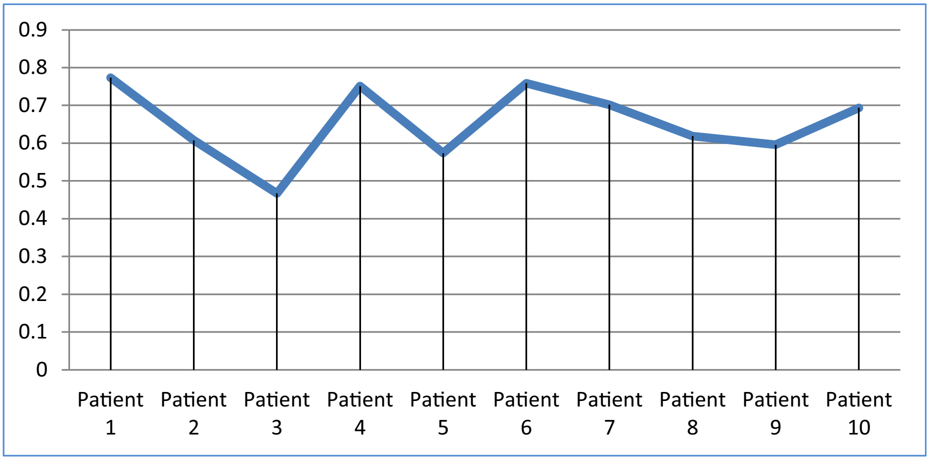

Fig. 7 The final diagnosis of patients

Table 11 The weighted values of pairwise matrix according to TOPSIS method

Symptoms	Dyspnea	Edema	Fatigue	Ascites	Nausea	Chest pain
Patient 1	0.087	0.059	0.055	0.041	0.041	0.074
Patient 2	0.038	0.059	0.088	0.054	0.013	0.019
Patient 3	0.023	0.031	0.038	0.058	0.041	0.019
Patient 4	0.072	0.031	0.088	0.041	0.050	0.061
Patient 5	0.042	0.018	0.071	0.058	0.050	0.019
Patient 6	0.023	0.072	0.055	0.070	0.041	0.074
Patient 7	0.038	0.059	0.088	0.085	0.024	0.019
Patient 8	0.042	0.072	0.071	0.058	0.013	0.019
Patient 9	0.023	0.072	0.042	0.022	0.041	0.061
Patient 10	0.042	0.059	0.038	0.058	0.041	0.074

Step 6. Final step for obtaining the diagnosis:

- Calculate crisp matrix of alternatives (patients) and compare with symptoms as presented in Table 8, by using Eq. (2).
- Build the normalized decision matrix by using Eq. (4) as presented in Table 9.
- Begin to estimate each patient, the result presented in Table 10.
- Evaluating using neutrosophic weight sum model (NWSM) $A_i^{wsm} = \sum_{j=1}^{n} w_j\, x_{ij}$.
- Obviously, the diagnosis shows that the patient 1 has all symptoms very high proportion according to the suggested method.
- Based on the Fig. 7, it is clear that the patient 1 suffers from heart failure by 77.34%, the patient 2 by 60.73%, the patient 3 by the 46.72% …etc., and based on these ratios, clinicians are able to determine any stage of the treatment of the patients.

5.2 Comparative analysis with decision making methods

In this section, we conduct comparative and sensitivity analyses to prove the intellectuality and the feasibility of the suggested approach against the well-known decision making models such as TOPSIS and SAW.

Table 12 The ideal (best) and (worst) values

Symptoms	Dyspnea	Edema	Fatigue	Ascites	Nausea	Chest pain
V^{+}_{j}	0.087	0.072	0.088	0.085	0.050	0.074
V^{-}_{j}	0.023	0.018	0.038	0.022	0.013	0.019

Table 13 The final patients diagnosing using TOPSIS method

Symptoms	D_i^+	D_i^-	CC_i
Patient 1	0.057	0.101	0.6392
Patient 2	0.089	0.073	0.4506
Patient 3	0.110	0.047	0.2993
Patient 4	0.063	0.092	0.5935
Patient 5	0.094	0.064	0.4050
Patient 6	0.074	0.096	0.5647
Patient 7	0.079	0.088	0.5269
Patient 8	0.086	0.075	0.4658
Patient 9	0.102	0.074	0.4204
Patient 10	0.074	0.084	0.5316

5.2.1 TOPSIS method

We conduct a comparative analysis between the proposed method and TOPSIS method (The Technique for Order of Preference by Similarity to Ideal Solution) in terms of diagnosis as follows:

- Here, we utilize the obtained weights of the symptoms as in Table 6.
- The normalized weighted comparison matrix of patients related to each symptom is shown in Table 11.
- Table 12 indicates for the ideal best and worst values.
- Finally, the final diagnosis of patients shown in Table 13 and in Fig. 8.

5.2.2 SAW method

We conduct a comparative analysis between the suggested method and Simple Additive Weighting (SAW) method as follows:

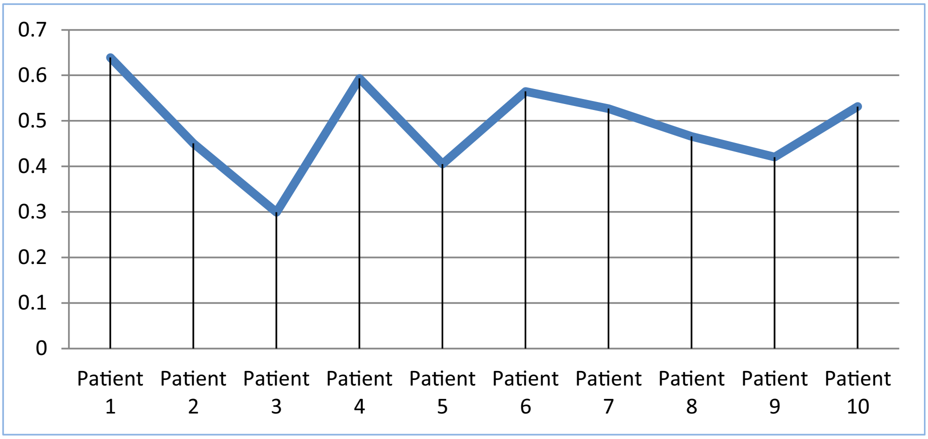

Fig. 8 The final diagnosis of patients using TOPSIS method

Table 14 The normalized matrix of patients diagnosing using SAW method

Symptoms	Dyspnea	Edema	Fatigue	Ascites	Nausea	Chest pain
Patient 1	0.25	0.31	0.67	0.52	0.31	0.25
Patient 2	0.59	0.31	0.43	0.40	1	1
Patient 3	1	0.59	1	0.37	0.31	1
Patient 4	0.31	0.59	0.43	0.52	0.25	0.31
Patient 5	0.52	1	0.51	0.37	0.25	1
Patient 6	1	0.25	0.67	0.31	0.31	0.25
Patient 7	0.59	0.31	0.43	0.25	0.52	1
Patient 8	0.52	0.25	0.51	0.37	1	1
Patient 9	1	0.25	0.88	1	0.31`	0.31
Patient 10	0.52	0.31	1	0.37	0.31	0.25

- Here, we utilized the obtained weights of the symptoms as in Table **6**.
- The normalized weighted comparison matrix of patients related to each symptom shown in Table **14**.
- Finally, the final diagnosis of patients shown in Table **15** and in Fig. **9**.

- To facilitate the problem of diagnosing, we compare the obtained results of all applied methods used in this research as shown in Fig. **10**.

5.3 Comparative analysis with related methods

In this subsection, we conduct comparisons with other decision making techniques to compare the suggested group medical decision making method with existing decision making techniques.

The *first method* [31] measured the diagnoses of each patient and medical knowledgebase using **fuzzy analytical hierarchy process** and **fuzzy inference system**. Researchers used a convinced weight allocating mechanism, which can locate the weight based on consultants' particular opinions [31]. The more likely the patients to have this type of disease "heart failure", the greater the weight of the symptoms. The final results of this method are shown in Table **16** and in Fig. **11**. The patients are classified by the final result ascending, and the larger the value of result, the more likely the patient suffers from a large proportion of the disease.

From Table **16**, it is obvious that patient 1 most likely suffers from heart failure, similar with our suggested approach, which is identical to the following two methods, which are mentioned in [31, 40]. Nevertheless, there are some dissimilarity in the ordering results among the proposed approach and other two methods. According to ranking by the approach [31], some

Table 15 The final patients diagnosing using SAW method

Patients	Diagnosing (SAW)	Patients	Diagnosing (SAW)
Patient 1	0.4048	Patient 6	0.4687
Patient 2	0.5866	Patient 7	0.5020
Patient 3	0.7300	Patient 8	0.5767
Patient 4	0.4162	Patient 9	0.6466
Patient 5	0.6217	Patient 10	0.4876

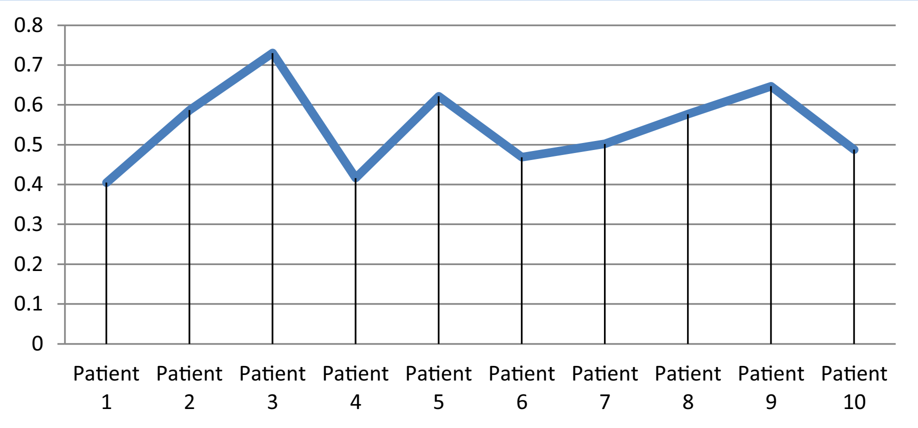

Fig. 9 The final diagnosis of patients using SAW method

alternatives vary in order where a patient 10 in place of patient 7, but arrange the rest of the patients as in the proposed approach. According to ranking by the approach [40], some alternatives vary in order where a patient 10 in place of patient 7 and patient 9 in place of patient 2, but arrange the rest of the patients as in the proposed approach.

Moreover, except the difference of two alternatives in approach [31] and the difference of four alternatives in approach [40], the ordering of patients in our suggested method is almost identical as obtained by the two method, which refers that the proposed method works rationally, logically and well. Furthermore, the reason why the suggested method is eligible

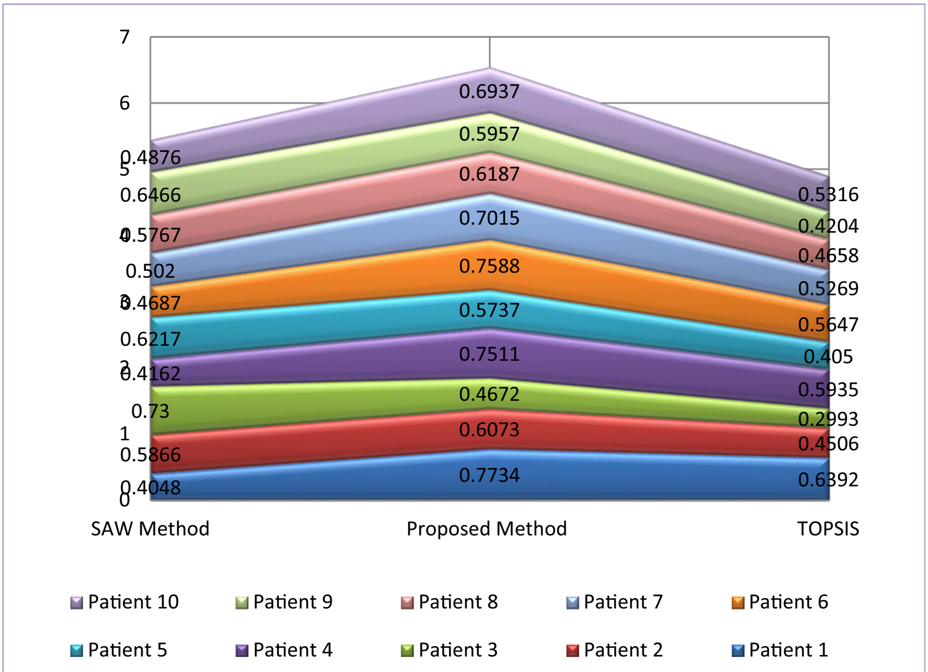

Fig. 10 Final diagnosis of patients using various decision making methods

Table 16 Assessments of patients according to method in [31]

Patients	Unchangeable factors	Controllable factors	Changeable factors	Likelihood of heart disease
Patient 1	0.5448	0.6282	0.7336	0.6345
Patient 2	0.3866	0.4223	0.4567	0.4218
Patient 3	0.2789	0.2980	0.2345	0.2718
Patient 4	0. 5277	0.4898	0.5873	0.5369
Patient 5	0.3978	0.4056	0.4033	0.4025
Patient 6	0.5589	0.5523	0.5698	0.5623
Patient 7	0.5243	0.5145	0.5299	0.5246
Patient 8	0.4598	0.4656	0.4623	0.4612
Patient 9	0.4166	0.4187	0.4124	0.4153
Patient 10	0.5389	0.5287	0.5326	0.5342

is assigned to its own uniqueness. The two approaches in [31, 40] are measures based on fuzzy analytical hierarchy process which have identical characteristics so that the ranking and results incline to be similar. However, the suggested approach is neutrosophic WSM measures. The properties are diverse and the outcomes are rationally conflicting. Moreover, the existent techniques that are compared in the research all pay to the weight factor. In addition, the proposed method considers both subjective and objective to obtain the weight factor. While the two approaches in [31, 40] only take single subjective of objective parameter.

Generally, the best alternative “patient” least affected by the disease is P_3 while the worst alternative “patient” most affected by the disease is P_1, obtained by our suggested method and other approaches, which means the suggested method is perfect and it considers both the objective and subjective parameters. The ordering result may change with various methods, but the approach suggested in this research considers more valuation information.

Furthermore, the weights of decision makers are acquired by establishing an integrated weight determination model, which considers all the objective and subjective parameters in to consideration and can consider more valuation information and data. In addition, the weights are extracted from the neutrosophic WSM with the maximizing variation technique to assist the experts select the most appropriate candidate. To sum up, the arranging result gained by the suggested group medical diagnosis is more inclusive, rational and reasonable. The comparative results of all applied showed in Table **17** and Fig. **12**.

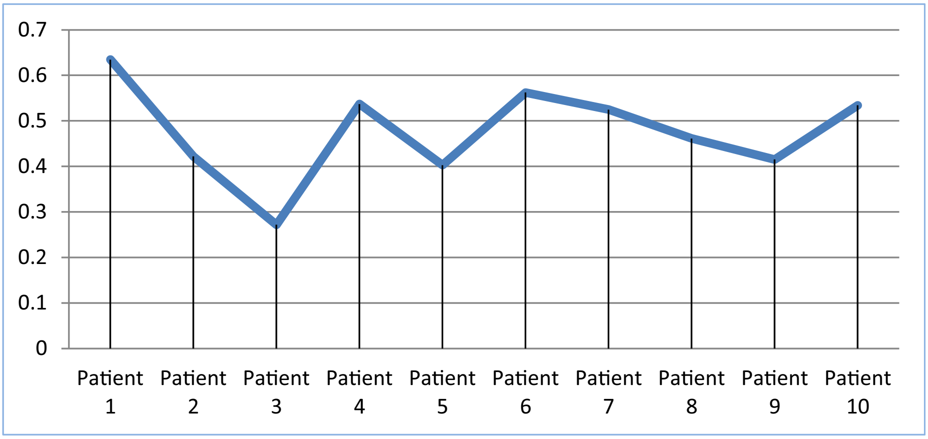

Fig. 11 The final diagnosis of patients using method in [31]

Table 17 Comparison results of MCDM methods in heart disease problem

Method	Diagnosis Result	Ranking
Proposed Method	Heart disease	$P_1 > P_6 > P_4 > P_7 > P_{10} > P_8 > P_2 > P_9 > P_5 > P_3$
Fuzzy Inference - Fuzzy Analytic Hierarchy Process [31]	Heart disease	$P_1 > P_6 > P_4 > P_{10} > P_7 > P_8 > P_2 > P_9 > P_5 > P_3$
Artificial neural networks and FAHP [40]	Heart disease	$P_1 > P_6 > P_4 > P_{10} > P_7 > P_8 > P_9 > P_2 > P_5 > P_3$

6 Conclusion

Despite the recent technological developments in the medical field, the number of deaths from heart failure disease is still on the raise [38], and this could be attributed to inappropriate diagnostic tools. In this research, we proposed a new IoT based decision making model for detecting and monitoring patients with heart failure. The social interactions and symptoms of user's body are captured via using WBAN and mobile application interface. After gathering personal data, information and symptoms, we classified users into infected or uninfected people. As part potential to improve a decision support schedule for the precise prediction of heart failure risks in patients, a hybrid technique based on both bipolar neutrosophic and weighted sum model was suggested in this study. Consequently, with the results from the research, we could view that the suggested hybrid technique would be hopeful in promoting a

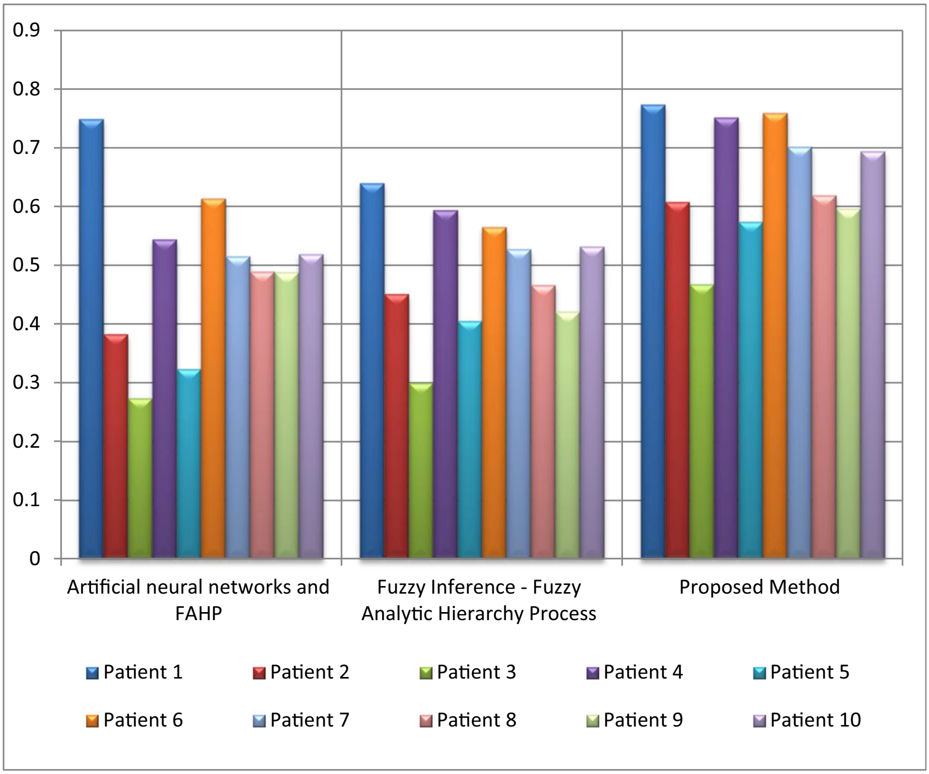

Fig. 12 The comparative results of all applied methods

decision support system for the precise prediction of heart failure risks in patients. If user is infected person, then the type, stage, and treatment method of heart failure determines through the suggested system. Some open problems for the future works:

- to enhance the accuracy prediction by using advanced machine learning methods [8, 9, 21, 23, 33, 34, 43];
- to integrate the patient data cloud computing systems with blockchain platform to secure the personal information on cloud database
- to extend the system to the other platform cloud by using surge computing.

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