CLAIMS

1. A method of producing an artificial neural network capable of predicting the survivability of a patient, the method comprising:

storing in an electronic database patient health data, the patient health data comprising a plurality of sets of data, each set having at least one of a first parameter relating to heart rate variability data and a second parameter relating to vital sign data, each set further having a third parameter relating to patient survivability;

providing a network of nodes interconnected to form an artificial neural network, the nodes comprising a plurality of artificial neurons, each artificial neuron having at least one input with an associated weight; and

training the artificial neural network using the patient health data such that the associated weight of the at least one input of each artificial neuron of the plurality of artificial neurons is adjusted in response to respective first, second and third parameters of different sets of data from the patient health data, such that the artificial neural network is trained to produce a prediction on the survivability of a patient.

2. The method of claim 1, wherein the heart rate variability data is extracted from an electrocardiogram (ECG) signal from at least one patient.

3. The method of claim 2, wherein extracting the heart rate variability data comprises

filtering the ECG signal to remove noise and artifacts;

locating a QRS complex within the filtered ECG signal;

finding a RR interval between successive QRS peaks of the QRS complex; and

processing the sequence of information within the RR interval to obtain the heart rate variability data.

4. The method of claim 3, wherein a band pass filter is used to filter the ECG signal and locate the QRS complex.

5. The method of claim 4, wherein the band pass filter frequency range is between about 5Hz to about 28Hz.

6. The method of claims 3 to 5, wherein the QRS peaks are located by:

locating a maximum peak data value first occurring in the filtered ECG signal;

determining an upper amplitude threshold and a lower amplitude threshold from the located maximum peak value;

locating a peak value

locating minimum values on either side of the peak value; and

denoting, when the peak value is above the upper amplitude threshold while the minimum values are below the lower amplitude threshold, the location of the peak value as a R position, the location of the minimum value occurring closest on the left side of the R position as a Q position, and the location of the minimum value occurring closest on the right side of the R position as a S position, so as to form the location of a QRS peak within the filtered ECG signal.

7. The method of claim 6, wherein the positions of other QRS peaks within the filtered ECG signal are located by iterating the process of:

locating another peak value;

locating other minimum values on either side of the another peak value; and

denoting, when the another peak value is above the upper amplitude threshold while the other minimum values are both below the lower threshold, the location of the peak value as a R position, the location of the minimum value occurring closest on the left side of the R position as a Q position, and the location of the minimum value occurring closest on the right side of the R position as a S position, so as to form the location of another QRS peak.

8. The method of claims 3 to 7, wherein processing the sequence of information within the RR interval further comprises removing outliers from the sequence of information within the RR interval by:

finding a median value and standard deviation value for the RR interval;

calculating a tolerance factor based on the standard deviation value;

retaining a portion of information that lies within the RR interval spanning either side of the median value by the tolerance factor, so that the heart rate variability data is obtained from the retained portion of information; and

discarding the remaining portion of the information from the sequence of information.

9. The method of claims 1 to 8, further comprising classifying the first parameter, the second parameter or a combination of the first parameter and the second parameter as feature vectors of the patient health data and training the artificial neural network with the feature vectors.

10. The method of claims 1 to 9, wherein the artificial neural network is implemented as instructions stored in a memory that when executed by a processor cause the processor to perform the functions of the artificial neural network.

11. The method of claim 10, wherein the artificial neural network is based on support vector machine architecture, wherein the associated weight of the at least one input of each artificial neuron of the plurality of artificial neurons is initialized from a library used by the support vector machine.

12. The method of claim 11, the support vector machine comprises a decision function, the decision function given by

$$f(x) = \mathrm{sgn}(\sum_{i=1}^{N} \alpha_i y_i k(x, x_i) + b)$$

wherein sgn() is a sign function; $(x;x_i)$ is set of feature vector; $k(x;x_i)$ is a kernel matrix constructed by x and x_i;y_i is 1 or -1; which is the label of feature vector x_i; a_i and b are parameters used to define an optimal decision hyperplane so that the margin between two classes of patterns can be maximized in the feature space.

13. The method of claim 10, wherein the artificial neural network is based on an extreme learning machine architecture, wherein the associated weight of the at least one input of each artificial neuron of the plurality of artificial neurons is initialized through random selection by the extreme learning machine.

14. The method of claim 13, wherein the artificial neural network is realized as a single-layer feed-forward network, whereby the prediction on the survivability of the patient is derived from the function,

$$f_{\tilde{N}}(x_j) = \sum_{i=1}^{\tilde{N}} \beta_i g(w_i \cdot x_j + b_i) = t_j \quad j = 1,...,N$$

wherein x_j is an input vector to an input of one of the plurality of artificial neurons for j = 1, 2, ..., N input vectors; w_i is the associated weight of the input of the artificial neuron receiving the x_j input vector; $g(w_i.x_j + b_i)$ is an output of the artificial neuron receiving the x_j input vector... for i = 1, 2, ..., N artificial neurons; β_i is the output weight vector that associates an i^{th} hidden neuron with a respective output neuron; and b_i is the bias for the i^{th} hidden neuron.

15. The method of claims 1 to 14, wherein the training of the artificial neural network is based on back-propagation learning.

16. The method of claim 15, wherein the back-propagation learning uses the Levenberg-Marquardt algorithm.

17. The method of claims 1 to 16, wherein each of the plurality of artificial neurons has an activation function, the activation function being selected from a group of functions comprising hardlim, sigmoid, sine, radial basis and linear.

18. The method of claims 3 to 17, further comprising

partitioning the sequence of information within the RR interval into non-overlapping segments; and

using the non-overlapping segments to train the artificial neural network.

19. The method of claims 3 to 17, further comprising

extracting a length of signal within the RR interval of each of the filtered ECG signal;

partitioning the length of signal into non-overlapping segments; and

selecting at least one of the non-overlapping segments to train the artificial neural network.

20. The method of claim 19, wherein each of the non-overlapping segments is of substantially equal length.

21. The method of claim 19, wherein each of the non-overlapping segments is of an unequal length.

22. The method of claims 18 to 21, wherein the non-overlapping segments have a fixed length.

23. The method of claims 18 to 21, wherein the non-overlapping segments have an adjustable length.

24. The method of claims 1 to 23, wherein each set of the plurality of sets of data further comprises a fourth parameter relating to patient characteristics.

25. The method of claim 24, wherein the patient characteristics comprises any one or more of the following: age, gender and medical history.

26. A method of predicting the survivability of a patient, the method comprising

measuring a first set of parameters relating to heart rate variability data of a patient;

measuring a second set of parameters relating to vital sign data of the patient;

providing an artificial neural network comprising a network of interconnected nodes, the nodes comprising a plurality of artificial neurons, each artificial neuron having at least one input with an associated weight adjusted by training the artificial neural network using an electronic database having a plurality of sets of data, each set having at least a parameter relating to heart rate variability data and a parameter relating to vital sign data, each set further having a parameter relating to patient survivability;

processing the first set of parameters and the second set of parameters to produce processed data suitable for input into the artificial neural network;

providing the processed data as input into the artificial neural network; and

obtaining an output from the artificial neural network, the output providing a prediction on the survivability of the patient.

27. The method of claim 26, wherein the processed data of the first set of parameters and the processed data of the second set of parameters are represented as a feature vector.

28. The method of claim 26, wherein the processed data is the first set of parameters and the second set of parameters being represented as normalized data.

29. The method of claims 26 to 28,

wherein the processed data is partitioned into non-overlapping segments, so that the input into the artificial neural network comprises sets of one or more of the non-overlapping segments of processed data; and wherein

a result is obtained for each of the sets of one or more of the non-overlapping segments of processed data, so that each of the results is considered to predict the survivability of the patient.

30. The method of claim 29, wherein majority voting is used to determine the prediction on the survivability of the patient, the majority voting represented by the function

$$\hat{y} = \max_{j=1}^{2} \sum_{m=1}^{M} D_{m,j}$$

wherein $D_{m,j}$ is an intermediate variable for final decision making, $D_{m,j}$ assigned a value of 1 if a m^{th} classifier chooses class j in the decision ensemble, and 0 otherwise.

31. The method of claims 26 to 30, wherein the result of the artificial neural network is coded as a two class label, so that the method further comprises

applying a label-based algorithm to each of the two class label results to decide the output from the artificial neural network, thereby providing a prediction on the survivability of the patient.

32. The method of claims 1 to 31, wherein the heart rate variability data comprises time domain data, frequency domain data and geometric domain data.

33. The method of claim 32, wherein the time domain data comprises information on any one or more of the following parameters: mean of RR intervals (mean RR), standard deviation of RR intervals (STD), mean of the instantaneous heart rate (mean HR), standard deviation of the instantaneous heart rate (STD_HR), root mean square of differences between adjacent RR intervals (RMSSD), number of consecutive RR intervals differing by more than 50 ms (NN50), and percentage of consecutive RR intervals differing by more than 50 ms (pNN50).

34. The method of claims 32 or 33, wherein the frequency domain data comprises information on any one or more of the following parameters: power in very low frequency range (<= 0.04Hz) (VLF), power in low frequency range (0.04 to 0.15 Hz) (LF), power in high frequency range (0.15 to 0.4 Hz) (HF), total power which is estimated from the variance of NN intervals in the segment and is measured in ms^2 (TP), ratio of LF power to HF power (LF/HF), LF power in normalized units: LF/(TP-VLF)x100 (LFnorm), and HF power in normalized units: HF/(TP-VLF)x100 (HFnorm).

35. The method of claims 32 to 34, wherein the geometric domain data comprises information on any one of the following data: total number of all RR intervals divided by

height of histogram of intervals (HRV Index) and base width of triangle fit into RR histogram using least squares method (TINN).

36. The method of claims 1 to 35, wherein the vital sign data comprises any one or more of the following: systolic blood pressure, diastolic blood pressure, pulse rate, pulse oximetry, respiratory rate, glasgow coma scale (GCS), pain score, temperature and age.

37. The method of claims 1 to 36, wherein the patient health data used to train the artificial neural network are standard deviation of the instantaneous heart rate (STD_HR), power in low frequency range (0.04 to 0.15 Hz) in normalized units (LFnorm), age, pulse rate, pulse oximetry, systolic blood pressure and diastolic blood pressure.

38. The method of claims 24 to 37, wherein the measured first set of parameters are standard deviation of the instantaneous heart rate (STD_HR) and power in low frequency range (0.04 to 0.15 Hz) in normalized units (LFnorm); and the measured second set of parameters are age, pulse rate, pulse oximetry, systolic blood pressure and diastolic blood pressure.

39. The method of claims 1 to 38, wherein the prediction on the survivability of the patient is either death or survival of the patient.

40. A patient survivability prediction system comprising:

a first input to receive a first set of parameters relating to heart rate variability data of a patient;

a second input to receive a second set of parameters relating to vital sign data of the patient;

a memory module storing instructions to implement an artificial neural network comprising a network of interconnected nodes, the nodes comprising a plurality of artificial neurons, each artificial neuron having at least one input with an associated weight adjusted by training the artificial neural network using an electronic database having a plurality of sets of data, each set having at least one a parameter relating to heart

rate variability data and a parameter relating to vital sign data, each set further having a parameter relating to patient survivability;

a processor to execute the instructions stored in the memory module to perform the functions of the artificial neural network and output a prediction on the survivability of the patient based on the first set of parameters and the second set of parameters; and

a display for displaying the prediction on the survivability of the patient.

41. The patient survivability prediction system of claim 40, further comprising a port to receive the first set of parameters from the first input and the second set of parameters from the second input.

42. The patient survivability prediction system of claim 40, further comprising

a first port to receive the first set of parameters from the first input; and

a second port to receive the second set of parameters from the second input.

43. A method of predicting the survivability of a patient, the method comprising:

measuring a first set of parameters relating to heart rate variability data of a patient;

measuring a second set of parameters relating to vital sign data of the patient;

obtaining a third set of parameters relating to patient characteristics;

providing the first set of parameters, the second set of parameters and the third set of parameters as sets of normalized data values, where required, to a scoring model implemented in an electronic database, the scoring model having a respective category associated to each parameter of the first set of parameters, the second set of parameters and the third set of parameters, each category having a plurality of pre-defined value ranges, each of the plurality of value ranges having a pre-defined score;

determining a score for each parameter of the first set of parameters, the second set of parameters and the third set of parameters by assigning the sets of normalized data to respective pre-defined value ranges, encompassing the sets of normalized data values, of the plurality of value ranges of the category associated to the respective parameter of the first set of parameters, the second set of parameters and the third set of parameters;

obtaining a total score, being a summation of the score for each parameter of the first set of parameters, the second set of parameters and the third set of parameters, the total score providing an indication on the survivability of the patient.

44. The method of claim 41, wherein the scoring model further comprises a plurality of risk categories, each category having a pre-defined range of values, the method further comprising assigning the total score to the category having the pre-defined range of values encompassing the total score, to determine which of the plurality of risk categories the total score belongs to.

45. A system for the detection of impending acute cardiopulmonary medical events that, left untreated, would with a reasonable likelihood result in either severe injury or death comprising:

an electro-cardiogram (ECG) module including a plurality of electrodes for sensing a patient's ECG and having an ECG output;

a sensor for sensing a patient's physiologic parameter other than ECG;

a first input for receiving the ECG output;

a second input for receiving signals from the sensor for sensing a patient's physiologic parameter other than ECG;

a third input constructed and arranged to receive:

parametric information describing at least one element of a patient's demographic information; and

parametric information describing a patient's medical history;

a digitizing unit for digitizing the ECG and the physiologic signal other than ECG;

a housing containing a memory unit and processing unit, for storing and processing, respectively, the ECG, the physiologic signal other than ECG, patient demographic information and medical history; and

a user communication unit;

wherein the processing unit calculates at least one measure of heart rate variability (HRV), combines that at least one measure of HRV with at least one parameter each of

patient demographic information and medical history, and calculates a statistical probability of an ACP event within 72 hours of the calculation.

46. The system of claim 45 constructed and arranged to be carried by the patient in a wearable configuration.

47. The system of claim 45 wherein the sensor measures the perfusion status of the microvasculature.

48. The system of claim 47 wherein the sensor is a pulse oximeter.

49. The system of claim 45 further comprising:
an electromagnetic stimulator of physiologic tissue.

50. The system of claim 49 wherein the electromagnetic stimulator stimulates cardiac tissue.

51. The system of claim 45 wherein the user communication unit has key entry.

52. The system of claim 51 wherein the third input is a key entry.

53. The system of claim 45 wherein the user communication unit is in the main housing;

54. The system of claim 45 wherein the user communication unit is separate from main housing.

55. The system of claim 45 wherein the user communication unit is a display.

56. The system of claim 50 wherein the stimulation is pacing.

57. The system of claim 50 wherein the stimulation is defibrillation.

58. The system of claim 50 wherein the stimulation is magnetic stimulation.

59. A system for predicting mortality of a patient being treated for trauma or as part of a mass casualty occurrence, comprising:

an electro-cardiogram (ECG) module including a plurality of electrodes for sensing a patient's ECG and having an ECG output;

a sensor for sensing a patient's physiologic parameter other than ECG;

a first input for receiving the ECG output;

a second input for receiving signals from the sensor for sensing a patient's physiologic parameter other than ECG;

a third input constructed and arranged to receive:

parametric information describing at least one element of a patient's demographic information; and

parametric information describing a patient's medical history;

a digitizing unit for digitizing the ECG and the physiologic signal other than ECG;

a housing containing a memory unit and processing unit, for storing and processing, respectively, the ECG, the physiologic signal other than ECG, patient demographic information and medical history; and

a user communication unit;

wherein the processing unit calculates at least one measure of heart rate variability (HRV), combines that at least one measure of HRV with at least one parameter each of patient demographic information and medical history, and calculates a statistical probability of mortality for the patient.

60. The system of claim 59 constructed and arranged to be carried by the patient in a wearable configuration.

61. The system of claim 59 wherein the sensor measures the perfusion status of the microvasculature.

62. The system of claim 61 wherein the sensor is a pulse oximeter.

63. A method of treating a cardiac condition of a patient, comprising:

measuring heart rate variability (HRV) of the patient;

measuring vital sign data of the patient;

predicting, using a computing apparatus constructed and arranged for the purpose, a likelihood of survival of the patient to one or more selected time limits based on HRV in combination with the measured vital sign data; and

treating the cardiac condition as indicated by the vital sign data when the likelihood of survival of the patient to one or more selected time limits is below a desired threshold.

64. The method of claim 63, further comprising:

collecting at least one of patient demographic information and patient history information; wherein predicting further comprises:

computing the likelihood of survival additionally in view of the collected patient demographic information and patient history information.

65. The method of claim 63, further comprising:

selecting a time limit of between 4 and 24 hours.

66. The method of claim 63, further comprising:

selecting a time limit of between 4 and 72 hours.

67. Apparatus for predicting a likelihood of survival of a patient to one or more selected time limits due to cardiac causes, comprising:

a heart rate sensor having a heart rate output;

a vital sign sensor having a vital sign output;

a computational module receiving the heart rate output and the vital sign output, and performing:

computing heart rate variability (HRV) related measures from the heart rate output received; and

computing the likelihood of survival of the patient to the one or more selected time limits due to cardiac causes, from a combination of the HRV related measures computed and the vital sign output; and,

an output device displaying to a user the likelihood of survival of the patient to the one or more selected time limits due to cardiac causes.

68. The apparatus of claim 67, further comprising:

a data input device constructed and arranged to collect at least one of patient demographic information and patient history information; and

computing the likelihood of survival additionally in view of the collected patient demographic information and patient history information.

69. The apparatus of claim 67, further comprising:

a time limit of between 4 and 24 hours.

70. The method of claim 67, further comprising:

a time limit of between 4 and 72 hours.

CLAIMS

1. A method of producing an artificial neural network capable of predicting the survivability of a patient, the method comprising:

storing in an electronic database patient health data, the patient health data comprising a plurality of sets of data, each set having at least one of a first parameter relating to heart rate variability data and a second parameter relating to vital sign data, each set further having a third parameter relating to patient survivability;

providing a network of nodes interconnected to form an artificial neural network, the nodes comprising a plurality of artificial neurons, each artificial neuron having at least one input with an associated weight; and

training the artificial neural network using the patient health data such that the associated weight of the at least one input of each artificial neuron of the plurality of artificial neurons is adjusted in response to respective first, second and third parameters of different sets of data from the patient health data, such that the artificial neural network is trained to produce a prediction on the survivability of a patient within the next 72 hours.

2. The method of claim 1, wherein the heart rate variability data is extracted from an electrocardiogram (ECG) signal from at least one patient.

3. The method of claim 2, wherein extracting the heart rate variability data comprises filtering the ECG signal to remove noise and artifacts; locating a QRS complex within the filtered ECG signal;

finding a RR interval between successive QRS peaks of the QRS complex; and processing the sequence of information within the RR interval to obtain the heart rate variability data.

4. The method of claim 3, wherein a band pass filter is used to filter the ECG signal and locate the QRS complex.

5. The method of claim 4, wherein the band pass filter frequency range is between about 5 Hz to about 28 Hz.

6. The method of claim 3, wherein the QRS peaks are located by:

locating a maximum peak data value first occurring in the filtered ECG signal; determining an upper amplitude threshold and a lower amplitude threshold from the located maximum peak value;

locating a peak value

locating minimum values on either side of the peak value; and

denoting, when the peak value is above the upper amplitude threshold while the minimum values are below the lower amplitude threshold, the location of the peak value as a R position, the location of the minimum value occurring closest on the left side of the R position as a Q position, and the location of the minimum value occurring closest on the right side of the R position as a S position, so as to form the location of a QRS peak within the filtered ECG signal.

7. The method of claim 6, wherein the positions of other QRS peaks within the filtered ECG signal are located by iterating the process of:

locating another peak value;

locating other minimum values on either side of the another peak value; and

denoting, when the another peak value is above the upper amplitude threshold while the other minimum values are both below the lower threshold, the location of the peak value as a R position, the location of the minimum value occurring closest on the left side of the R position as a Q position, and the location of the minimum value occurring closest on the right side of the R position as a S position, so as to form the location of another QRS peak.

8. The method of claim 3, wherein processing the sequence of information within the RR interval further comprises removing outliers from the sequence of information within the RR interval by:

finding a median value and standard deviation value for the RR interval;

calculating a tolerance factor based on the standard deviation value;

retaining a portion of information that lies within the RR interval spanning either side of the median value by the tolerance factor, so that the heart rate variability data is obtained from the retained portion of information; and

discarding the remaining portion of the information from the sequence of information.

9. The method of claim 3, further comprising

partitioning the sequence of information within the RR interval into non-overlapping segments; and

using the non-overlapping segments to train the artificial neural network.

10. The method of claim 9, wherein the non-overlapping segments have a fixed length.

11. The method of claim 9, wherein the non-overlapping segments have an adjustable length.

12. The method of claim 3, further comprising

extracting a length of signal within the RR interval of each of the filtered ECG signal; partitioning the length of signal into non-overlapping segments; and

selecting at least one of the non-overlapping segments to train the artificial neural network.

13. The method of claim 12, wherein each of the non-overlapping segments is of substantially equal length.

14. The method of claim 12, wherein each of the non-overlapping segments is of an unequal length.

15. The method of claim 1, further comprising classifying the first parameter, the second parameter or a combination of the first parameter and the second parameter as feature vectors of the patient health data and training the artificial neural network with the feature vectors.

16. The method of claim 1, wherein the artificial neural network is implemented as instructions stored in a memory that when executed by a processor cause the processor to perform the functions of the artificial neural network.

17. The method of claim 16, wherein the artificial neural network is based on support vector machine architecture, wherein the associated weight of the at least one input of each

artificial neuron of the plurality of artificial neurons is initialized from a library used by the support vector machine.

18. The method of claim 17, the support vector machine comprises a decision function, the decision function given by

$$f(x) = \mathrm{sgn}\left(\sum_{i=1}^{N} \alpha_i y_i k(x, x_i) + b\right)$$

wherein sgn( ) is a sign function; $(x;x_i)$ is set of feature vector; $k(x;x_i)$ is a kernel matrix constructed by x and x_i;y_i is 1 or -1; which is the label of feature vector x_i; α_i and b are parameters used to define an optimal decision hyperplane so that the margin between two classes of patterns can be maximized in the feature space.

19. The method of claim 16, wherein the artificial neural network is based on an extreme learning machine architecture, wherein the associated weight of the at least one input of each artificial neuron of the plurality of artificial neurons is initialized through random selection by the extreme learning machine.

20. The method of claim 19, wherein the artificial neural network is realized as a single-layer feed-forward network, whereby the prediction on the survivability of the patient within the next 72 hours is derived from the function,

$$f_{\tilde{N}}(x_j) = \sum_{i=1}^{\tilde{N}} \beta_i g(w_i \cdot x_j + b_i) = t_j \quad j = 1, \ldots, N$$

wherein x_j is an input vector to an input of one of the plurality of artificial neurons for j=1, 2, . . . , N input vectors; w_i is the associated weight of the input of the artificial neuron receiving the x_j input vector; $g(w_i,x_j+b_i)$ is an output of the artificial neuron receiving the x_j input vector . . . for i=1, 2, . . . , N artificial neurons; β_i is the output weight vector that associates an i^{th} hidden neuron with a respective output neuron; and b_i is the bias for the i^{th} hidden neuron.

21. The method of claim 1, wherein the training of the artificial neural network is based on back-propagation learning.

22. The method of claim 21, wherein the back-propagation learning uses the Levenberg-Marquardt algorithm.

23. The method of claim 1, wherein each of the plurality of artificial neurons has an activation function, the activation function being selected from a group of functions comprising hardlim, sigmoid, sine, radial basis and linear.

24. The method of claim 1, wherein each set of the plurality of sets of data further comprises a fourth parameter relating to patient characteristics.

25. The method of claim 24, wherein the patient characteristics comprises any one or more of the following: age, gender and medical history.

26. The method of claim 24, wherein the measured first set of parameters are standard deviation of the instantaneous heart rate (STD_HR) and power in low frequency range (0.04 to 0.15 Hz) in normalized units (LFnorm); and the measured second set of parameters are age, pulse rate, pulse oximetry, systolic blood pressure and diastolic blood pressure.

27. The method of claim 1, wherein the vital sign data comprises any one or more of the following: systolic blood pressure, diastolic blood pressure, pulse rate, pulse oximetry, respiratory rate, glasgow coma scale (GCS), pain score, temperature and age.

28. The method of claim 1, wherein the patient health data used to train the artificial neural network are standard deviation of the instantaneous heart rate (STD_HR), power in low frequency range (0.04 to 0.15 Hz) in normalized units (LFnorm), age, pulse rate, pulse oximetry, systolic blood pressure and diastolic blood pressure.

29. The method of claim 1, wherein the prediction on the survivability of the patient within the next 72 hours is either death or survival of the patient.

30. A method of predicting the survivability of a patient, the method comprising

measuring a first set of parameters relating to heart rate variability data of a patient;

measuring a second set of parameters relating to vital sign data of the patient;

providing an artificial neural network comprising a network of interconnected nodes, the nodes comprising a plurality of artificial neurons, each artificial neuron having at least one input with an associated weight adjusted by training the artificial neural network using an

electronic database having a plurality of sets of data, each set having at least a parameter relating to heart rate variability data and a parameter relating to vital sign data, each set further having a parameter relating to patient survivability;

processing the first set of parameters and the second set of parameters to produce processed data suitable for input into the artificial neural network;

providing the processed data as input into the artificial neural network; and

obtaining an output from the artificial neural network, the output providing a prediction on the survivability of the patient within the next 72 hours.

31. The method of claim 30, wherein the processed data of the first set of parameters and the processed data of the second set of parameters are represented as a feature vector.

32. The method of claim 30, wherein the processed data is the first set of parameters and the second set of parameters being represented as normalized data.

33. The method of claim 30,

wherein the processed data is partitioned into non-overlapping segments, so that the input into the artificial neural network comprises sets of one or more of the non-overlapping segments of processed data; and wherein

a result is obtained for each of the sets of one or more of the non-overlapping segments of processed data, so that each of the results is considered to predict the survivability of the patient within the next 72 hours.

34. The method of claim 33, wherein majority voting is used to determine the prediction on the survivability of the patient within the next 72 hours, the majority voting represented by the function

$$\hat{y} = \max_{j=1}^{2} \sum_{m=1}^{M} D_{m,j}$$

wherein $D_{m,j}$ is an intermediate variable for final decision making, $D_{m,j}$ assigned a value of 1 if a m^{th} classifier chooses class j in the decision ensemble, and 0 otherwise.

35. The method of claim 30, wherein the result of the artificial neural network is coded as a two class label, so that the method further comprises

applying a label-based algorithm to each of the two class label results to decide the output from the artificial neural network, thereby providing a prediction on the survivability of the patient within the next 72 hours.

36. The method of claim 1, wherein the heart rate variability data comprises time domain data, frequency domain data and geometric domain data.

37. The method of claim 36, wherein the time domain data comprises information on any one or more of the following parameters: mean of RR intervals (mean RR), standard deviation of RR intervals (STD), mean of the instantaneous heart rate (mean HR), standard deviation of the instantaneous heart rate (STD_HR), root mean square of differences between adjacent RR intervals (RMSSD), number of consecutive RR intervals differing by more than 50 ms (NN50), and percentage of consecutive RR intervals differing by more than 50 ms (pNN50).

38. The method of claim 36, wherein the frequency domain data comprises information on any one or more of the following parameters: power in very low frequency range (<=0.04 Hz) (VLF), power in low frequency range (0.04 to 0.15 Hz) (LF), power in high frequency range (0.15 to 0.4 Hz) (HF), total power which is estimated from the variance of NN intervals in the segment and is measured in ms^2 (TP), ratio of LF power to HF power (LF/HF), LF power in normalized units: LF/(TP-VLF).times.100 (LFnorm), and HF power in normalized units: HF/(TP-VLF)x100 (HFnorm).

39. The method of claim 36, wherein the geometric domain data comprises information on any one of the following data:

total number of all RR intervals divided by height of histogram of intervals (HRV Index) and base width of triangle fit into RR histogram using least squares method (TINN).

40. A patient survivability prediction system comprising:

a first input to receive a first set of parameters relating to heart rate variability data of a patient;

a second input to receive a second set of parameters relating to vital sign data of the patient;

a memory module storing instructions to implement an artificial neural network comprising a network of interconnected nodes, the nodes comprising a plurality of artificial neurons, each artificial neuron having at least one input with an associated weight adjusted by training the artificial neural network using an electronic database having a plurality of sets of data, each set having at least one a parameter relating to heart rate variability data and a parameter relating to vital sign data, each set further having a parameter relating to patient survivability;

a processor to execute the instructions stored in the memory module to perform the functions of the artificial neural network and output a prediction on the survivability of the patient within the next 72 hours based on the first set of parameters and the second set of parameters; and

a display for displaying the prediction on the survivability of the patient within the next 72 hours.

41. The patient survivability prediction system of claim 40, further comprising a port to receive the first set of parameters from the first input and the second set of parameters from the second input.

42. The patient survivability prediction system of claim 40, further comprising

a first port to receive the first set of parameters from the first input; and

a second port to receive the second set of parameters from the second input.

43. A method of predicting the survivability of a patient, the method comprising: measuring a first set of parameters relating to heart rate variability data of a patient; measuring a second set of parameters relating to vital sign data of the patient; obtaining a third set of parameters relating to patient characteristics;

providing the first set of parameters, the second set of parameters and the third set of parameters as sets of normalized data values, where required, to a scoring model implemented in an electronic database, the scoring model having a respective category associated to each parameter of the first set of parameters, the second set of parameters and

the third set of parameters, each category having a plurality of pre-defined value ranges, each of the plurality of value ranges having a pre-defined score;

determining a score for each parameter of the first set of parameters, the second set of parameters and the third set of parameters by assigning the sets of normalized data to respective pre-defined value ranges, encompassing the sets of normalized data values, of the plurality of value ranges of the category associated to the respective parameter of the first set of parameters, the second set of parameters and the third set of parameters;

obtaining a total score, being a summation of the score for each parameter of the first set of parameters, the second set of parameters and the third set of parameters, the total score providing an indication on the survivability of the patient within the next 72 hours.

44. The method of claim 43, wherein the scoring model further comprises a plurality of risk categories, each category having a pre-defined range of values, the method further comprising assigning the total score to the category having the pre-defined range of values encompassing the total score, to determine which of the plurality of risk categories the total score belongs to.