CLAIMS

1. A processor implemented method for anomaly detection in an input sensor signal, comprising:

deriving primary features associated with an input sensor signal based on discrete nature of the input sensor signal, the primary features being minima points, maxima points, next minima points and three consecutive extrema points, wherein the input sensor signal comprises a non-anomalous portion thereof;

detecting a pattern associated with the input sensor signal based on selective derived features obtained from the primary features and representing the detected pattern in the form of a function of the derived features;

identifying, using a semi-supervised approach, at least one defining feature from the derived features based on statistical properties and time and frequency domain properties of the input sensor signal, wherein the identified defining features are the derived features that satisfy conditions including:

(i) difference between mean values of the derived features of the non-anomalous portion of the input sensor signal and the mean values of the derived features of complete portion of the input sensor signal is larger than at least a pre-defined first threshold, the pre-defined first threshold being based on the type of the input sensor signal; and

(ii) standard deviation of the derived features of the non-anomalous portion of the input sensor signal is smaller than the standard deviation of the derived features of complete portion of the input sensor signal by at least a pre-defined second threshold, the pre-defined second threshold being based on the type of the input sensor signal;

performing self-learning of the input sensor signal based on the derived features and the at least one defining feature of the non-anomalous portion of the input sensor signal;

clustering portions of the input sensor signal based on values of the at least one defining feature associated thereof into clusters of varying density; and

automatically classifying the portions of the input sensor signal as anomalous portions and non-anomalous portions based on the density of the clusters and ground truth, wherein most dense clusters correspond to non-anomalous portions and least dense clusters correspond to anomalous portions of the input sensor signal,

wherein self-learning of the input sensor signal encompasses dynamic variation in pattern recognition to classify the anomalous portions and non-anomalous portions.

2. The processor implemented method of claim 1, wherein the derived features obtained from the primary features are (i) amplitude of maxima points, (ii) number of sampling points between two consecutive minima points, (iii) amplitude differences between minima points and next followed maxima points, (iv) number of sampling points between maxima points and next followed minima points and (v) consecutive amplitude and temporal differences of a number of sampling points in a pre-defined time frame detection window to identify trends thereof.

3. The processor implemented method of claim 1, wherein the step of clustering portions of the input sensor signal based on values of the at least one defining feature associated thereof is based on k-means clustering method.

4. The processor implemented method of claim 3, wherein the step of clustering portions of the input sensor signal is based on 3-means clustering method with k = 3.

5. The processor implemented method of claim 1, wherein the step of clustering comprises merging of two or more of the clusters.

6. A system for anomaly detection in an input sensor signal, comprising:

one or more data storage devices operatively coupled to one or more hardware processors and configured to store instructions configured for execution by the one or more hardware processors to:

derive primary features associated with the input sensor signal based on discrete nature of the input sensor signal, the primary features being minima points, maxima points, next minima points and three consecutive extrema points, wherein the input sensor signal comprises a non-anomalous portion thereof;

detect a pattern associated with the input sensor signal based on selective derived features obtained from the primary features and represent the detected pattern in the form of a function of the derived features;

identify, using a semi-supervised approach, at least one defining feature from the derived features based on statistical properties and time and frequency domain

properties of the input sensor signal, wherein the identified defining features are the derived features that satisfy conditions including:

(i) difference between mean values of the derived features of the non-anomalous portion of the input sensor signal and the mean values of the derived features of complete portion of the input sensor signal is larger than at least a pre-defined first threshold, the pre-defined first threshold being based on the type of the input sensor signal; and

(ii) standard deviation of the derived features of the non-anomalous portion of the input sensor signal is smaller than the standard deviation of the derived features of complete portion of the input sensor signal by at least a pre-defined second threshold, the pre-defined second threshold being based on the type of the input sensor signal;

perform self-learning the input sensor signal based on the derived features and the at least one defining feature of the non-anomalous portion of the input sensor signal;

cluster portions of the input sensor signal based on values of the at least one defining feature associated thereof into clusters of varying density; and

classify automatically, the portions of the input sensor signal as anomalous portions and non-anomalous portions based on the density of the clusters, wherein most dense clusters correspond to non-anomalous portions and least dense clusters correspond to anomalous portions of the input sensor signal,

wherein self-learning of the input sensor signal encompasses dynamic variation in pattern recognition to classify the anomalous portions and non-anomalous portions.

7. The system of claim 6, wherein the derived features obtained from the primary features are (i) amplitude of maxima points, (ii) number of sampling points between two consecutive minima points, (iii) amplitude differences between minima points and next followed maxima points, (iv) number of sampling points between maxima points and next followed minima points and (v) consecutive amplitude and temporal differences of a number of sampling points in a pre-defined time frame detection window to identify the trend thereof.

8. The system of claim 6, wherein the one or more hardware processors are further configured to cluster portions of the input sensor signal based on the values of the at least one defining feature associated thereof based on k-means clustering method.

9. The system of claim 8, wherein the one or more hardware processors are further configured to cluster portions of the input sensor signal based on 3-means clustering method with k = 3.

10. The system of claim 6, wherein the one or more hardware processors are further configured to cluster portions of the input sensor signal by merging of two or more clusters.

11. A computer program product comprising a non-transitory computer readable medium having a computer readable program embodied therein, wherein the computer readable program, when executed on a computing device, causes the computing device to:

derive primary features associated with an input sensor signal based on discrete nature of the input sensor signal, the primary features being minima points, maxima points, next minima points and three consecutive extrema points, wherein the input sensor signal comprises a non-anomalous portion thereof;

detect a pattern associated with the input sensor signal based on selective derived features obtained from the primary features and represent the detected pattern in the form of a function of the derived features;

identify, using a semi-supervised approach, at least one defining feature from the derived features based on statistical properties and time and frequency domain properties of the input sensor signal, wherein the identified defining features are the derived features that satisfy conditions including:

(i) difference between mean values of the derived features of the non-anomalous portion of the input sensor signal and the mean values of the derived features of complete portion of the input sensor signal is larger than at least a pre-defined first threshold, the pre-defined first threshold being based on the type of the input sensor signal; and

(ii) standard deviation of the derived features of the non-anomalous portion of the input sensor signal is smaller than the standard deviation of the derived features of complete portion of the input sensor signal by at least a pre-defined second threshold, the pre-defined second threshold being based on the type of the input sensor signal;

perform self-learning the input sensor signal based on the derived features and the at least one defining feature of the non-anomalous portion of the input sensor signal;

cluster portions of the input sensor signal based on values of the at least one defining feature associated thereof into clusters of varying density; and

classify automatically, the portions of the input sensor signal as anomalous portions and non-anomalous portions based on the density of the clusters, wherein most dense clusters correspond to non-anomalous portions and least dense clusters correspond to anomalous portions of the input sensor signal,

wherein self-learning of the input sensor signal encompasses dynamic variation in pattern recognition to classify the anomalous portions and non-anomalous portions.