CLAIMS:

1. A computer-implemented method for automated machine learning in industrial process control, the method being executed by one or more processors and comprising:

receiving, by the one or more processors, two or more time-series data sequences representative of a target process executed within a physical environment;

executing, by the one or more processors, automated time-series process segmentation to provide a plurality of subsequence segments for each of the two or more time-series data sequences, each subsequence segment corresponding to a phase of the target process, wherein the target process comprises a plurality of phases, and wherein each phase of the target process corresponds to a different time-series model,

wherein executing the automated time-series process segmentation comprises:

executing a deep learning model to process each time-series data sequence into an encoded vector, wherein the encoded vector includes a first encoded vector generated by an autoencoder concatenated with a variable transformation of the time-series data sequence generated by an additive and multiplicative effects network (AME);

processing, by the one or more processors, the plurality of subsequence segments using at least one time-series transformation to provide a feature data set for each subsequence segment;

applying, by the one or more processors, each feature data set of each subsequence segment to provide a plurality of time-series models for anomaly detection and forecasting, respectively, each time-series model i) corresponding to a phase of the target process, and ii) being provided as one of a recurrent neural network (RNN), a convolution neural network (CNN), and a generative adversarial network (GAN);

determining, by the one or more processors, anomaly scores based on the plurality of time-series models; and

selectively providing, by the one or more processors, an alert to one or more users, each alert indicating at least one anomaly and a respective probability.

2. The method of claim 1, wherein executing automated time-series process segmentation comprises processing each of the two or more time-series data sequences using a deep learning (DL) model provided as one of a bidirectional long short-term memory (LSTM) sequence classifier using supervised learning, and the autoencoder using unsupervised learning.

3. The method of claim 1, wherein the at least one time-series transformation comprises one or more of a temporal transformation, a spectral transformation, a shape transformation, a statistical transformation, an autoencoder transformation, and a decomposition transformation, and a pass-through transformation.

4. The method of claim 1, further comprising processing each feature data set through a reinforcement learning framework, in which rewards are applied based on minimal time deviation from a process set point within the target process.

5. The method of claim 4, further comprising automatically adjusting a controller based on reinforcement learning to reduce deviation from the process set point.

6. The method of claim 1, further comprising executing root cause analysis to determine a cause of an anomaly using one or more of classification, correlation, and RL-based action tracking for fault cause inference.

7. The method of claim 6, wherein the alert comprises a cause determined for the at least one anomaly.

8. The method of claim 1, wherein the two or more time-series data sequences are generated by one or more Internet-of-Things (IoT) devices located within the physical environment.

9. A non-transitory computer-readable storage medium coupled to one or more processors and having instructions stored thereon which, when executed by the one or more processors, cause the one or more processors to perform operations for automated machine learning in industrial process control, the operations comprising:

receiving two or more time-series data sequences representative of a target process executed within a physical environment;

executing automated time-series process segmentation to provide a plurality of subsequence segments for each of the two or more time-series data sequences, each subsequence segment corresponding to a phase of the target process, wherein the target process comprises a

plurality of phases, and wherein each phase of the target process corresponds to a different time-series model,

wherein executing the automated time-series process segmentation comprises:

executing a deep learning model to process each time-series data sequence into an encoded vector, wherein the encoded vector includes a first encoded vector generated by an autoencoder concatenated with a variable transformation of the time-series data sequence generated by an additive and multiplicative effects network (AME);

processing the plurality of subsequence segments using at least one time-series transformation to provide a feature data set for each subsequence segment;

applying each feature data set of each subsequence segment to provide a plurality of time-series models for anomaly detection and forecasting, respectively, each time-series model i) corresponding to a phase of the target process, and ii) being provided as one of a recurrent neural network (RNN), a convolution neural network (CNN), and a generative adversarial network (GAN);

determining anomaly scores based on the plurality of time-series models; and

selectively providing an alert to one or more users, each alert indicating at least one anomaly and a respective probability.

10. The computer-readable storage medium of claim 9, wherein executing automated time-series process segmentation comprises processing each of the two or more time-series data sequences using a deep learning (DL) model provided as one of a bidirectional long short-term memory (LSTM) sequence classifier using supervised learning, and the autoencoder using unsupervised learning.

11. The computer-readable storage medium of claim 9, wherein the at least one time-series transformation comprises one or more of a temporal transformation, a spectral transformation, a shape transformation, a statistical transformation, an autoencoder transformation, and a decomposition transformation, and a pass-through transformation.

12. The computer-readable storage medium of claim 9, wherein operations further comprise processing each feature data set through a reinforcement learning framework, in which rewards are applied based on minimal time deviation from a process set point within the target process.

13. The computer-readable storage medium of claim 12, wherein operations further comprise automatically adjusting a controller based on reinforcement learning to reduce deviation from the process set point.

14. The computer-readable storage medium of claim 9, wherein operations further comprise executing root cause analysis to determine a cause of an anomaly using one or more of classification, correlation, and RL-based action tracking for fault cause inference.

15. The computer-readable storage medium of claim 14, wherein the alert comprises a cause determined for the at least one anomaly.

16. The computer-readable storage medium of claim 9, wherein the two or more time-series data sequences are generated by one or more Internet-of-Things (IoT) devices located within the physical environment.

17. A system, comprising:

one or more processors; and

a computer-readable storage device coupled to the one or more processors and having instructions stored thereon which, when executed by the one or more processors, cause the one or more processors to perform operations for automated machine learning in industrial process control, the operations comprising:

receiving two or more time-series data sequences representative of a target process executed within a physical environment;

executing automated time-series process segmentation to provide a plurality of subsequence segments for each of the two or more time-series data sequences, each subsequence segment corresponding to a phase of the target process, wherein the target process comprises a

plurality of phases, and wherein each phase of the target process corresponds to a different time-series model,

wherein executing the automated time-series process segmentation comprises:

executing a deep learning model to process each time-series data sequence into an encoded vector, wherein the encoded vector includes a first encoded vector generated by an autoencoder concatenated with a variable transformation of the time-series data sequence generated by an additive and multiplicative effects network (AME);

processing the plurality of subsequence segments using at least one time-series transformation to provide a feature data set for each subsequence segment;

applying each feature data set of each subsequence segment to provide a plurality of time-series models for anomaly detection and forecasting, respectively, each time-series model i) corresponding to a phase of the target process, and ii) being provided as one of a recurrent neural network (RNN), a convolution neural network (CNN), and a generative adversarial network (GAN);

determining anomaly scores based on the plurality of time-series models; and

selectively providing an alert to one or more users, each alert indicating at least one anomaly and a respective probability.

18. The system of claim 17, wherein executing automated time-series process segmentation comprises processing each of the two or more time-series data sequences using a deep learning (DL) model provided as one of a bidirectional long short-term memory (LSTM) sequence classifier using supervised learning, and the autoencoder using unsupervised learning.

19. The system of claim 17, wherein the at least one time-series transformation comprises one or more of a temporal transformation, a spectral transformation, a shape transformation, a statistical transformation, an autoencoder transformation, and a decomposition transformation, and a pass-through transformation.

20. The system of claim 17, wherein operations further comprise processing each feature data set through a reinforcement learning framework, in which rewards are applied based on minimal time deviation from a process set point within the target process.

21. The system of claim 20, wherein operations further comprise automatically adjusting a controller based on reinforcement learning to reduce deviation from the process set point.

22. The system of claim 17, wherein operations further comprise executing root cause analysis to determine a cause of an anomaly using one or more of classification, correlation, and RL-based action tracking for fault cause inference.

23. The system of claim 22, wherein the alert comprises a cause determined for the at least one anomaly.

24. The system of claim 17, wherein the two or more time-series data sequences are generated by one or more Internet-of-Things (IoT) devices located within the physical environment.