Development of a deep learning-based anomaly detection model using multivariate time series manufacturing data

Industrial Intelligence Lab

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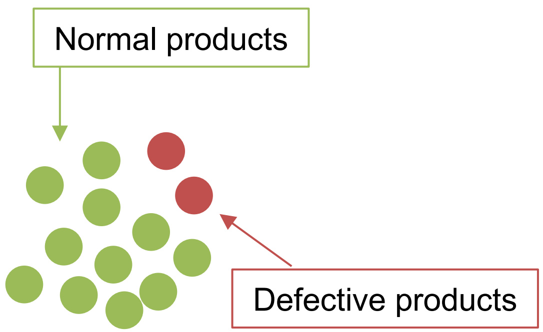
Introduction

- **Applications of deep learning in anomaly detection**
  - Manufacturing
    - Fault detection
    - Prognostics and health management (PHM)
  - Cyber security
    - Cyber intrusions
  - Finance
    - Fraud detection
  - Healthcare
    - Disease detection

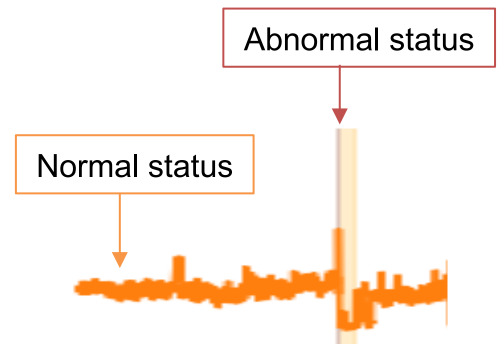
Introduction

In manufacturing fields

- With various data types, including time series and image data, **quality prediction** and **prognostics and health management** (PHM) are mainly conducted.
- **Data imbalance** between normal and abnormal data is existed.



Quality prediction



PHM

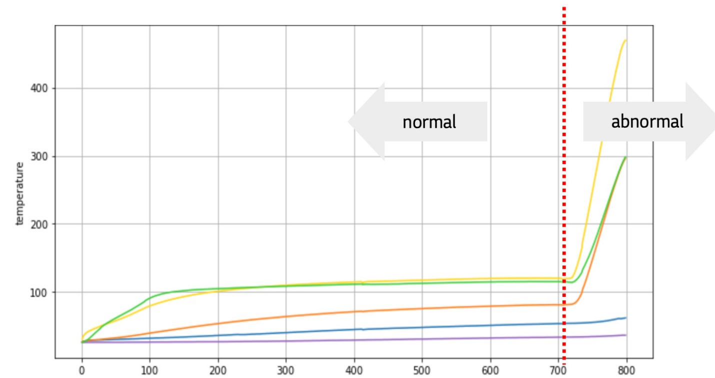
- To address a data imbalance issue, semi-supervised anomaly detection methods have been widely used.

Semi-supervised anomaly detection

- Using **normal data** only for training.
- Called “one-class anomaly detection”

Introduction

- A case study with real-world data from industrial electronics

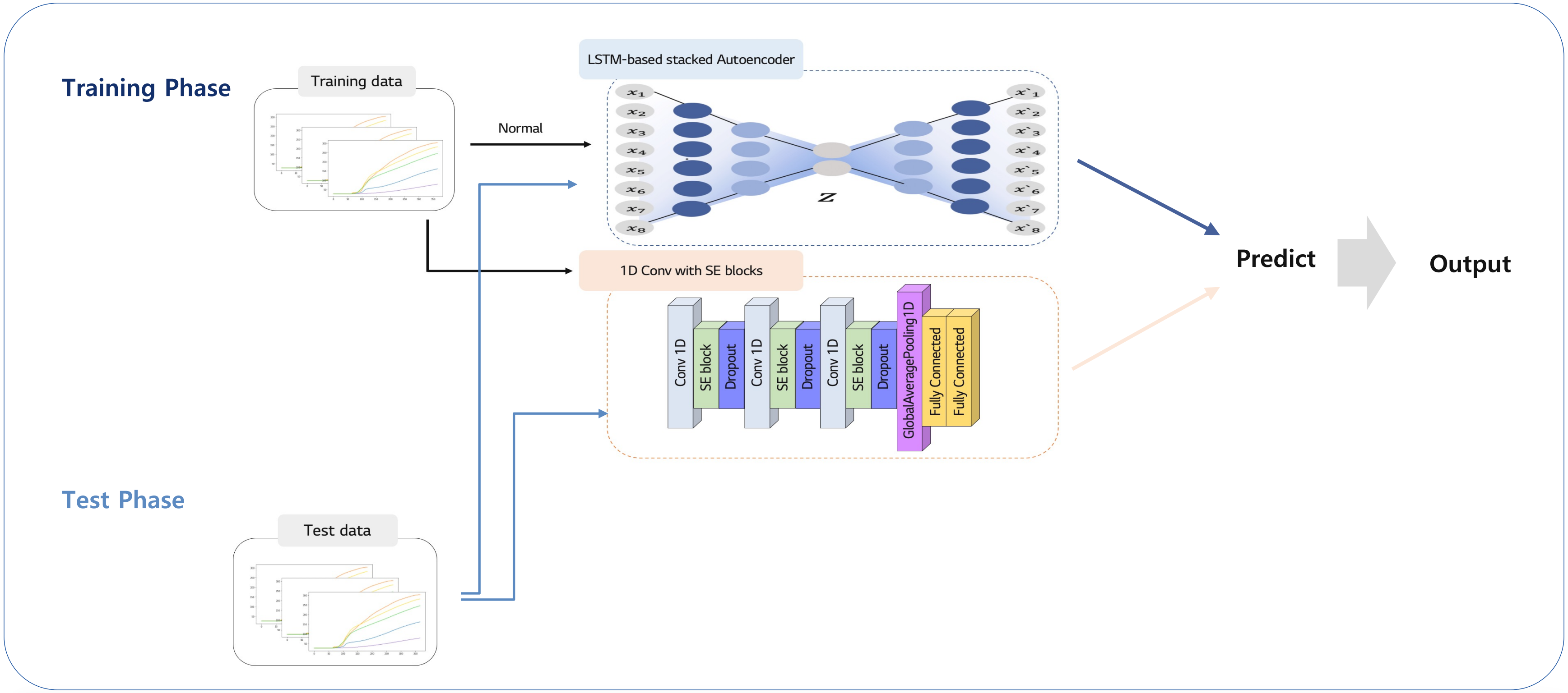


Task : To predict abnormal points with real-world data using a deep-learning framework.
The characteristics of the data:
- Multivariate time series data
- **Two types of abnormal** status
- All data are **labeled**

Introduction

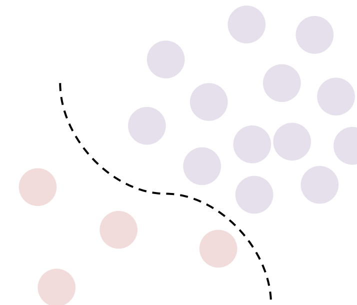
Proposed framework

➢ Combining **semi-supervised** and **supervised** methods to predict abnormal points.



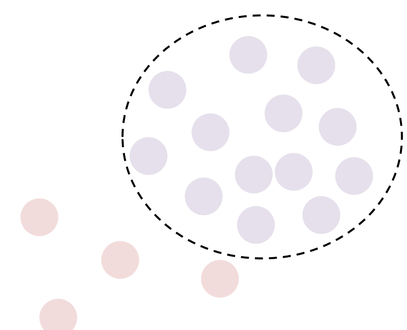
Related works

- **Deep learning (DL)-based approach for anomaly detection**
  - Supervised anomaly detection



    - Required labeled data
    - Learn the boundary between normal and abnormal data
    - Superior performance in accuracy and speed-wise
    - Difficult to apply for real-world data

      → ARIMA, Tree-based models, RNN-based models
  - Semi-supervised anomaly detection



    - Required normal data only
    - Learn the features of training (normal) data
    - Overfitting problems

    Representation learning from reconstruction

    → Autoencoders (AE), PCA, LSTM-AE,

    Generative learning

    → Variational autoencoders, GAN-based models (TadGAN, MadGAN,TAnoGAN, BeatGAN,,)

Related works

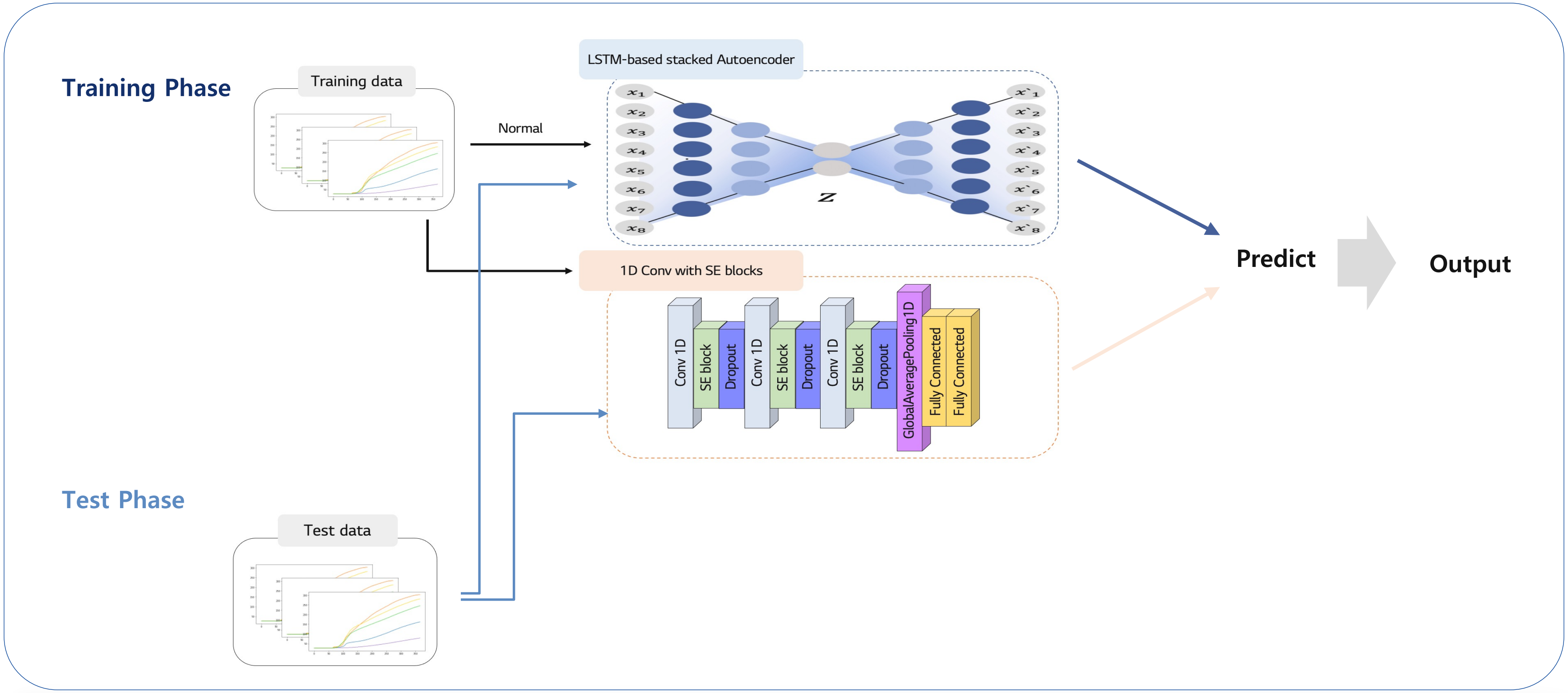
- **Applications of semi-supervised anomaly detection in real indu stry**
  - Convolutional recurrent autoencoder for IoT time series anomaly detection (Yin et al. 2022)
  - GAN variants called MADGAN for medical anomaly detection with brain MRI data (Han et al. 2021)
  - LSTM-based encoder-decoder for multi sensor anomaly detection (Malhotra et al. 2016)

- **Hybrid models for anomaly detection**
  - Combining unsupervised and supervised learning for detecting financial fra uds (Carcillo et al. 2021)
  - Combining LSTM-based models and DBN for PHM of aircraft (Che et al. 2019)
  - Combining three unsupervised algorithms to detect real-time cyber attacks (Carrera et al. 2022)

Proposed framework

Proposed framework

- Combining **LSTM-based stacked AE** and **1D Conv** to predict abnormal points more precisely.



Proposed framework

Model

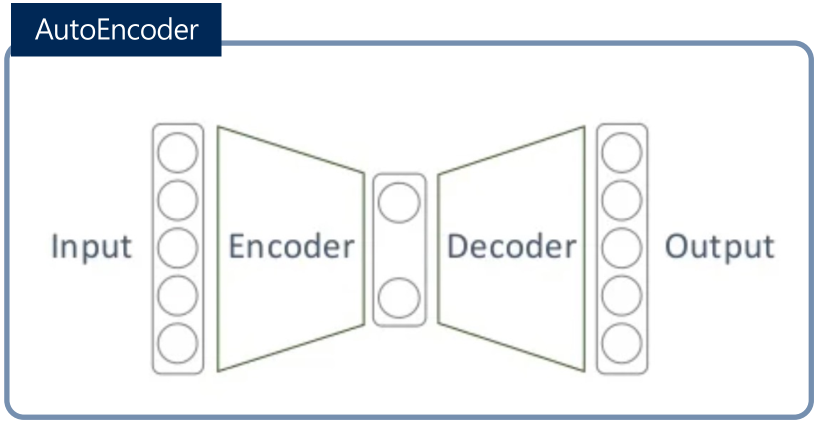
LSTM-based stacked autoencoder

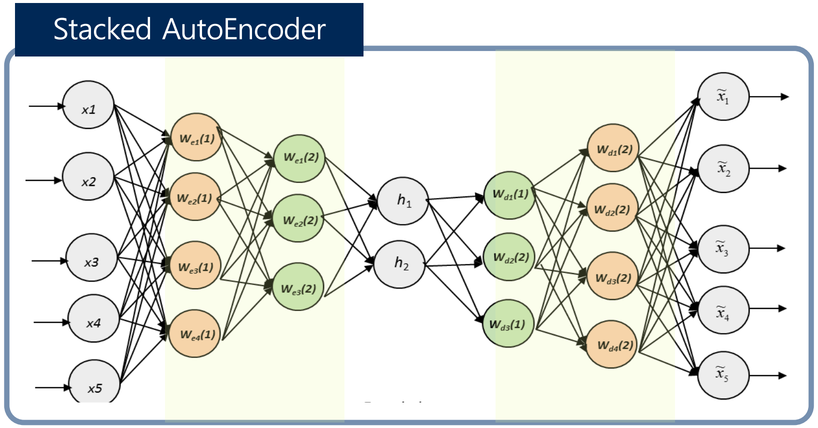
→ Autoencoder variant which can learn compressed representation of sequence data

→ Encoder compresses input data into the representation vector.

→ Decoder decompresses and reconstructs the representation vector.

→ Extract more features than autoencoder.



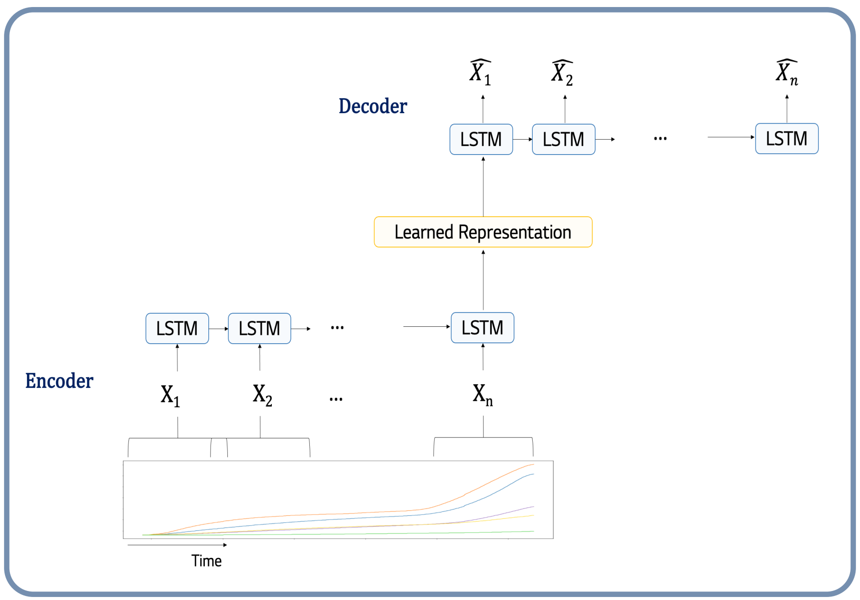


Proposed framework

Model

LSTM-based stacked autoencoder

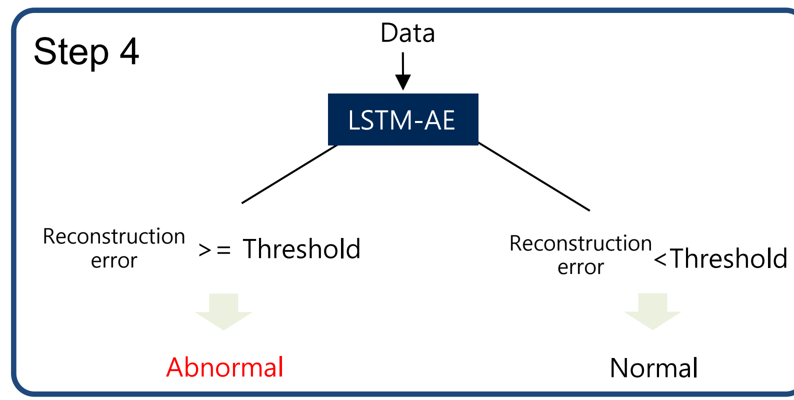
LSTM-based AE



Step 1. Train with normal data.

Step 2. Set the threshold.

Step 3. Test with abnormal data.



Proposed framework

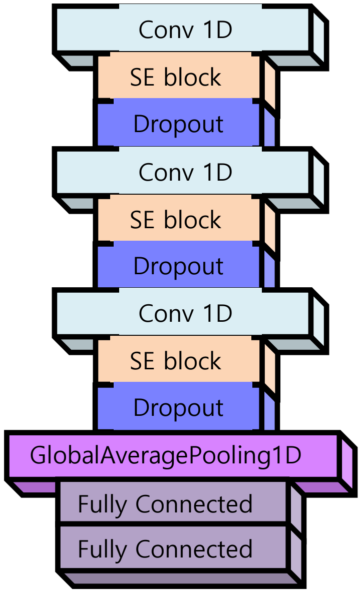
Model

1D-Conv-based model

→ Contemplate spatial correlation in data

→ Suitable for multivariate time series data

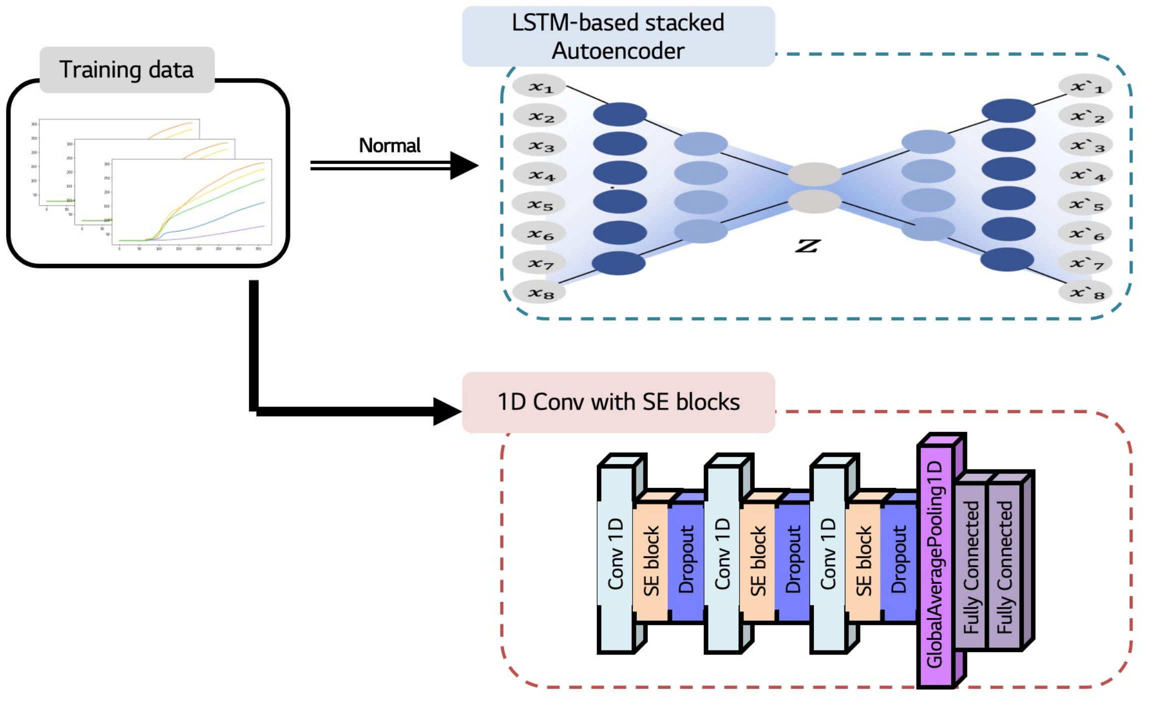
→ By adding SE blocks, consider the global feature



The proposed 1D-Conv based model

Proposed framework

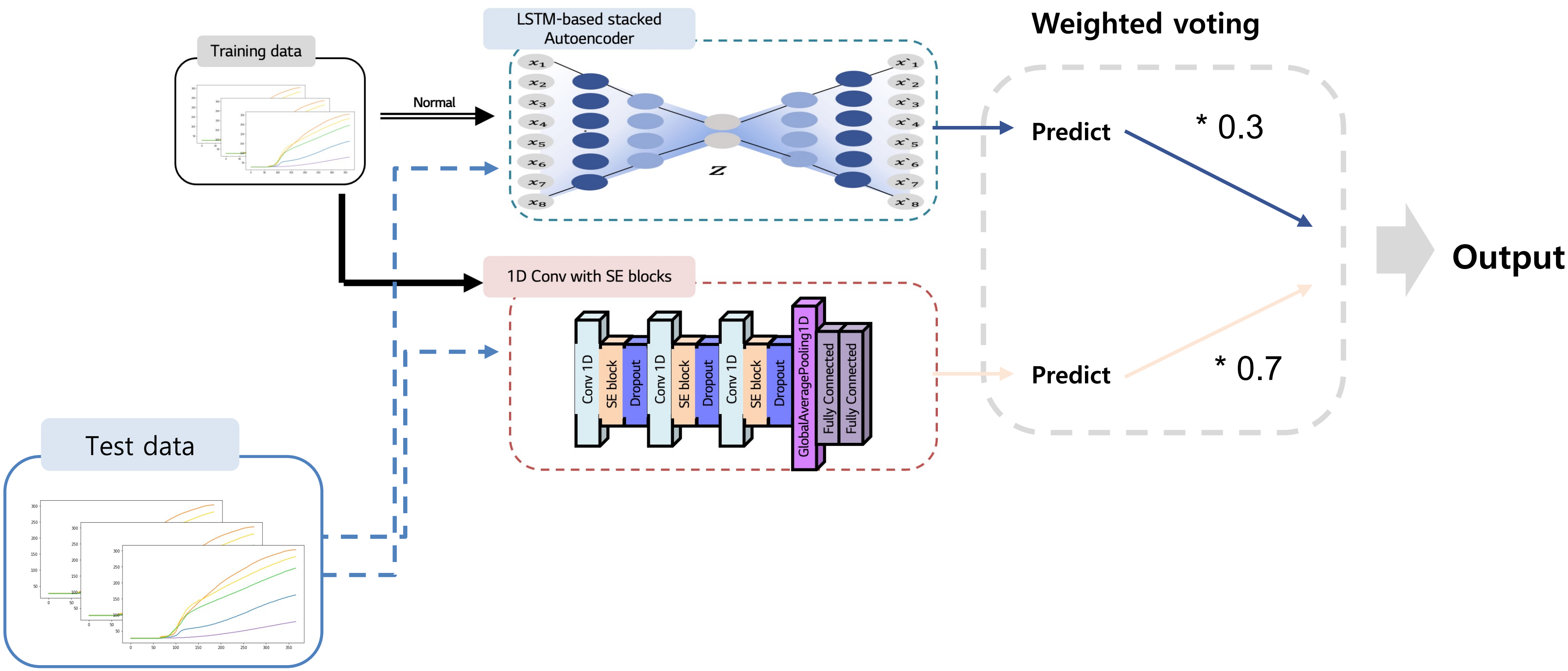
Training Phase



- Train two models separately.
- LSTM-based stacked autoencoder trained with normal data.

Proposed framework

Test Phase



- Test with both normal and abnormal data.
- Considering that the supervised method has higher accuracy, set the higher weighted for final prediction than the semi-supervised method.

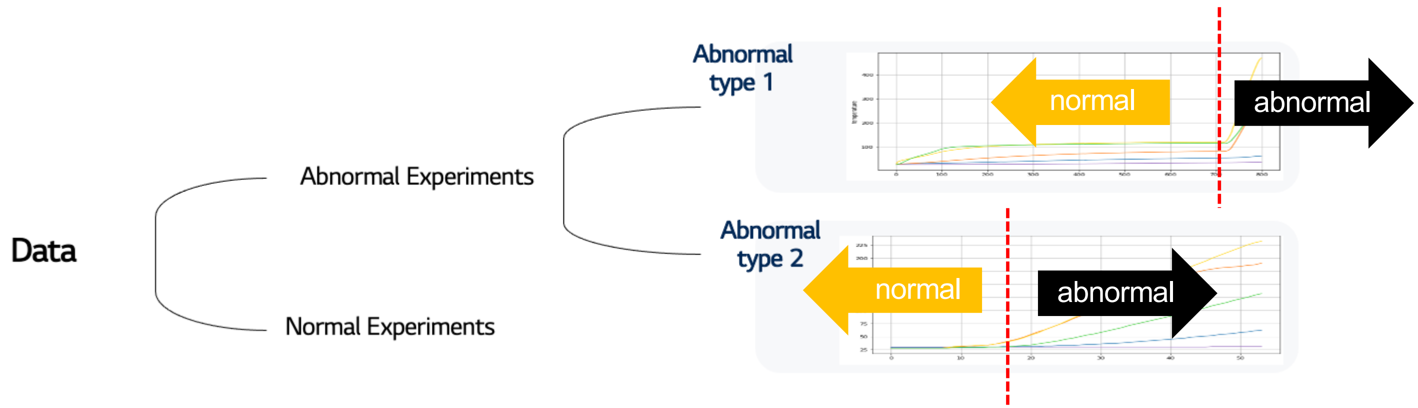
Experiments

Datasets:

- **Real-world data from industrial electronics**
  - Total 417 experiments
    - ➢ Normal experiments : 175
    - ➢ Abnormal experiments : 242

      : the number of normal status : 120117

      the number of abnormal status: 23379



- Evaluation metrics: precision, recall, F1 score, AUC

Experiments

Experiment settings:

- Data split :

Training : Validation : Test = 60:20:20

TRAINING	VALIDATION	TESTING

- Window size: 40
- Size of data shift: 4 (for training)

Ex) Size of data shift =2

	LeqOrigin_Moving	TopSensor	InverterPowerRMS	status
306	4800.0	61.0	3237.0	0
307	4824.0	61.0	3209.0	0
308	4855.0	61.0	3210.0	0
309	4890.0	62.0	3213.0	0
310	4932.0	61.0	3210.0	1
311	4979.0	62.0	3184.0	1
312	5013.0	62.0	3192.0	1

	LeqOrigin_Moving	TopSensor	InverterPowerRMS	status
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Results

Compare the performance of prediction models

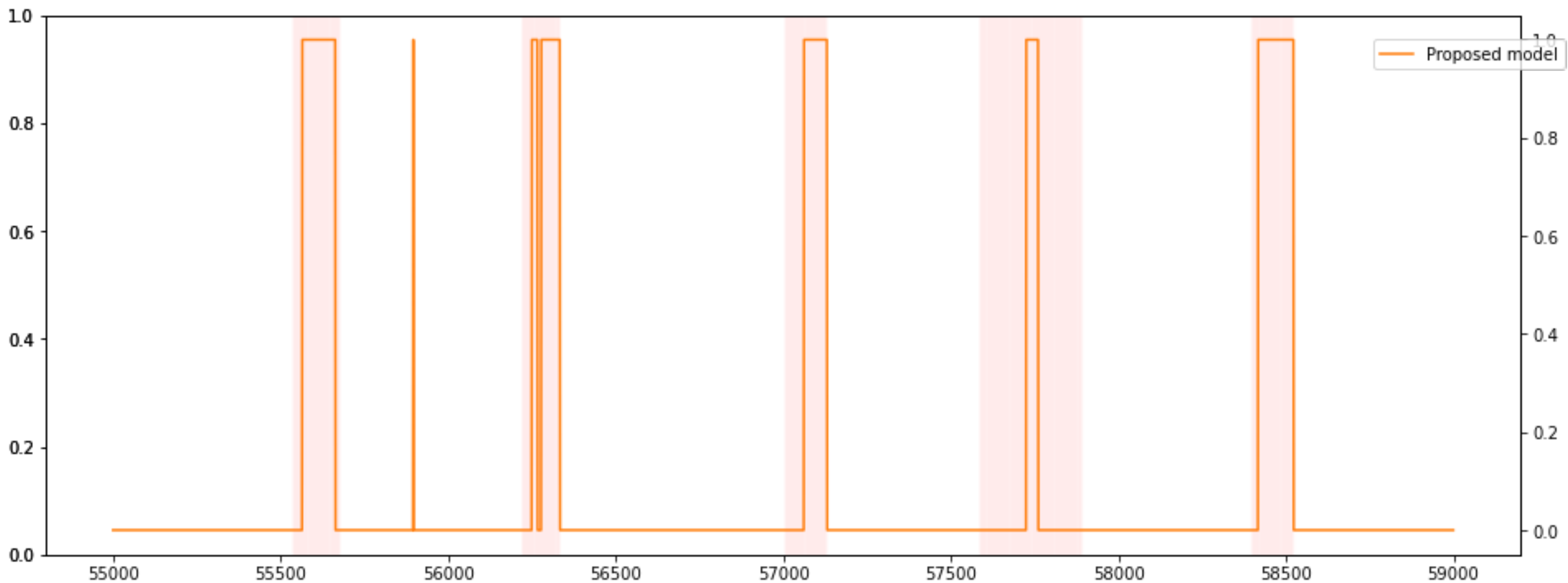
Method	Precision	Recall	F1 score	AUC
Isolation forest	0.117	0.377	0.178	0.598
LOF	0.06	0.516	0.11	0.508
KNN	0.43	0.528	0.474	0.742
LSTM-AE (w/o curve shift)	0.05	0.029	0.037	0.655
LSTM-AE (w/ curve shift)	0.06	0.005	0.010	0.769
LSTM- stacked AE (w/o curve shift)	0.055	0.034	0.042	0.827
LSTM- stacked AE (w/ curve shift)	0.273	0.276	0.274	0.667
1D Conv with SE-blocks (w/o curve shift)	0.418	0.362	0.388	0.793
1D Conv with SE-blocks (w/ curve shift)	0.627	**0.509**	**0.561**	0.832
Proposed model	0.679	0.471	0.556	0.840

Results

Visualization

abnormal

normal



* shade : real-abnormal point

Conclusion

- Develop the DL-based anomaly detection model for real-world time series data.
- The proposed model which is combined with LSTM-AE and 1D-Conv outperforms the base-line models.

Contribution

- Suggest the hybrid model (semi-supervised and supervised) to maximize the data usage and performance.

Future works

- Apply better methods for combining the results.

감사합니다

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