Anomaly Detection using Variational Autoencoder with Spectrum Analysis for Time Series Data

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***Abstract*—Uncertainty is an ever present challenge in life. To meet this challenge in data analysis, we propose a method for detecting anomalies in data. This method, based in part on Variational Autoencoder, identifies spiking raw data by means of spectrum analysis. Time series data are examined in the frequency domain to enhance detection of anomalies. In this paper, we validate the proposed method using standard datasets. Experimental results show that the comparison of the frequency domain with the original data can improve the validity and accuracy of anomaly detection. Therefore, analyzing time-series data using a combination of Variational Autoencoder and the frequency domain spectrum can be effective in detecting anomalies.**

***Contribution*— We have proposed an anomaly detection method based on an analysis of time series data using a combination of Variational Autoencoder and Spectrum analysis, and have benchmarked the method with reference to recent related research.**

Keywords—Anomaly Detection, Variational Autoencoder, Time Series Data

I. INTRODUCTION

Research in artificial intelligence has spurred advances in algorithms for identifying trends in complex data sets. However, the reliability and accuracy of these algorithms depend on the quality of the input data and metadata obtained from observations in the real world. Clearly data is essential for decision making, but some data sets are better than others.

Inescapably, data sets contain uncertain or noisy information which may reduce the accuracy of analysis. Thus it is critical to detect and avoid the use of abnormal data. Our research focuses on the development of methods for determining uncertain or anomalous data to help ensure the validity of data driven systems in areas of practical application in areas such as factory automation, medicine, and business.

Anomaly detection is analogous to outlier detection in traditional statistics, and is a species of novelty detection in an emerging area of data analysis. It attempts to identify data patterns that do not conform to the expected data characteristics. Identification of anomalies is of importance in a number of areas including credit card fraud, medical diagnosis, network intrusion, sensor network faults, and others.

Various methods for anomaly detection have been developed which focus on dimensional reduction. This method aims to reduce the number of features that describe data, retaining only the important features that characterize the data. This reduction is done either by selection or by extraction and can be useful in many situations that require low dimensional data. One of the earliest of these methods is principal component analysis (PCA). The Autoencoder is a new method for dimensionality reduction which is similar to but more flexible than PCA. An autoencoder is a specific type of feedforward neural network in which the input is the same as the output. Dimension reduction is achieved by stacking up layers in the process of encoding and decoding the data. By reducing the number of units in a certain layer, it is expected that the units will extract features that represent the data well [1].

Variational Autoencoder (VAE) is a recently developed deep learning, generative model based on Autoencoder that offers a powerful method for producing a faithful representation of data in a nonlinear and noisy environment which is suitable for practical applications. VAE outperforms autoencoders and PCA, as it provides a probability measurement instead of a reconstruction error as anomaly scores. Moreover, VAE also provides latent feature vectors [2] which could extract the key features of the data.

In this paper, we propose the variational autoencoder method with spiking raw data to detect anomalies by using the frequency domain for analysis and prediction. Moreover, we validate our proposed method by comparing the results of VAE with the original data derived from factory automation, wafer fabrication for integrated circuits, and ECG data from medical applications. The validation and verification are based on Area Under the Curve, Precision, Recall, and F1-score criteria.

II. BACKGROUND AND RELATED WORK

Anomaly detection is an active area research and has been investigated extensively, see, for example, [3]. It has been applied in a number of different fields. In robotics, it has been used to detect the failure of manipulation tasks such as grasping objects in factory automation, and for aerial robots in surveillance operations, known as Anomaly Detection and Cognizant Path Planning for Surveillance Operations using Aerial Robots. Popular techniques utilize classification approaches that learn a discriminative boundary around standard data, such as SVMs [4] for prediction requiring a set of vectors as input instead of time series data. Thus, they convert the time series into a phase-space using a time-delay embedding process, which involves creating overlapping subsequences from a given long sequence. These vectors are projected onto an orthogonal subspace which acts as a high pass filter used to exclude low-frequency components and allow only high-frequency ones (anomalies) [5].

Another method uses fidelity of reconstruction to determine whether an example is abnormal. An important example is Principal Component Analysis (PCA) [4]. PCA is a dimensionality reduction method which works by transforming a large variable set into a small variable set that still contains most of the information in the original set. A relatively new method of dimensionality reduction is autoencoder. Autoencoders is quite similar to PCA, but its autoencoders are capable of modeling complex non-linear functions, whereas PCA is essentially a linear transformation. Yokkampon et al. [6] propose an autoencoder with spiking in the frequency domain to detect anomalies. This method offers good anomaly detection performance, analyzing time series data in the frequency domain.

Another novel approach is Variational Autoencoder (VAE) [7]. Unlike autoencoders, VAE does not use the encoding-decoding process to reconstruct an input. Instead, they impose a probability distribution on latent space and learn the distribution so that the distribution of outputs from the decoder matches that of the observed data. Then, it can generate new data by sampling from this distribution. Bayer and Osendorfer [8] proposed recurrent neural networks with latent variables to model time series data and introduced Stochastic Recurrent Networks (STORNs). Soelch et al. [9] proposed the Stochastic Recurrent Network (STORN) to detect robot anomalies by predicting unimodal signals. An and Cho [1] proposed the reconstruction probability from the variational autoencoder to predict anomaly detection and introduced a new probabilistic anomaly score. Zhang et al. [10] proposed the novel method using the variational autoencoder with re-Encoder and Latent Constraint network (VELC) to predict the time series anomaly detection.

In our current research, we propose the Variational Autoencoder method with spiking raw data to analyze and detect anomalies in time series data by using the frequency domain to improve performance. We also compare our results with those of previous research [6] which followed a somewhat different approach but also made use of frequency domain analysis. The frequency domain analysis helps to determine the absolute and relative stability of the closed-loop system, and it can also be extended to the analysis and design of nonlinear control systems. Moreover, we compare our results with research reported in [10], which also used variational autoencoder but did not use frequency domain analysis. Our approach is designed to avoid overfitting and ensure that the latent space has suitable properties that enable the generative process. Therefore, the variational autoencoder can be defined as being an autoencoder whose training is regularized, which implies that it can be design complex generative models of data and fit them to large datasets. This is where VAE works better than any other method currently available. To justify this claim, we briefly explain the VAE and frequency domain analysis in this section.

A. *Variational Autoencoder*

Autoencoders are neural networks architectures consisting of an encoder and a decoder which pass data through a 'bottleneck', and implement training designed to lose a minimal quantity of information during the encoding-decoding process. The training in this case is by gradient descent over the parameters of these networks to reduce the reconstruction error. Due to overfitting, the latent space of an autoencoder can be extremely irregular. Therefore, we cannot define a generative process that consists of sampling a point from the latent space and making it go through the decoder to get new data.

Variational autoencoders (VAE) are autoencoders that tackle the problem of the latent space irregularity by making the encoder return a distribution over the latent space instead of a single point and by adding in the loss function a regularization term over that returned distribution in order to ensure a better organization of the latent space.

VAE is a popular and widely used method. In general, VAE uses a deep neural network to learn representations from complex data without supervision (Kingma and Welling, 2013) [7]. VAE is an autoencoder in which distribution of encodings is regularized during the training to ensure that its latent space has suitable properties allowing for generation of some new data. Moreover, the term "variational" comes from the close relationship between the regularization and the variational inference method in statistics.

The variational autoencoder has three parts, namely, encoder, decoder and loss function. The encoder is a neural network. Its input is a datapoint x, its output is a hidden representation z, and it has weights and biases θ. The encoder's goal is to 'encode' the data into a latent (hidden) representation space z, which has many fewer dimensions than the data. This is commonly referred to as a 'bottleneck' because the encoder must learn an efficient compression of data into this lower-dimensional space. The encoder is represented by $q_\phi(z|x)$.

The decoder is another neural network. Its input is the representation z, it outputs a datapoint x, and has weights and biases ϕ. The decoder is denoted by $p_\phi(x|z)$. The decoder 'decodes' the low-dimensional latent representation z into the datapoint x.

The loss function of the variational autoencoder is the negative log-likelihood and a regularizer. The total loss is then $\sum_{i=1}^{N} l_i$ for N total datapoints. The loss function l_i for datapoint x_i is:

$$l_i(\theta,\phi) = -E_{z\sim q_\theta(z|x_i)}[\log p_\phi(x_i|z)] + KL\left(q_\theta(z|x_i) \,\|\, p(z)\right) \quad (1)$$

The first term is the reconstruction loss or expected negative log-likelihood of the i -th data point. This term promotes the decoder to learn to reconstruct the data. Poor reconstruction will incur many costs in this loss function.

The second term is the regularizer, Kullback-Leibler divergence between the encoder's distribution $q_\theta(z|x)$ and $p(z)$. It is a measure of how close q is to p.

VAE is the highly powerful generative tools because it can work with diverse types of data such as sequential or non-sequential, continuous or discrete, even labeled or completely unlabeled.

B. *Frequency Domain Analysis*

The frequency domain is the domain for analysis of mathematical functions or signals transformed from the time domain. Frequency domain analysis is widely used in fields such as control systems engineering, electronics, and statistics; it is typically applied to the analysis of periodic signals or functions recorded over time.

In the frequency domain, we can observe the relationship between amplitude and frequency. The amplitude of a wave or vibration is expressed in positive numbers, with the highest amplitude as a measure of deviation from its central value. The same signal can also be displayed in power versus frequency format. This will appear on the spectrum analyzer, which can analyze the frequency domain.

With frequency domain analysis, we can identify the key point in a data set without having to examine every variation which occurs in the time domain. A frequency domain graph shows either the phase shift or signal magnitude at each given frequency. It shows the proportion of the signal that lies within each specified frequency band over a range of frequencies. Signals can be described as the sum of many sine waves ("Fourier series") with different pulses, phases, and amplitudes.

The discrete Fourier transform (DFT) is one of the most powerful tools in digital signal processing. The DFT enables analysis and design of systems in the frequency domain. Note that part of the DFT's attractiveness stems from the fact that efficient algorithms can be used to calculate the DFT of a sequence. One particularly important algorithm is the so-called Fast Fourier Transform (FFT).

FFT is widely used in transforming signal representations from the time domain to the frequency domain. It converts the signal into individual spectral components and provides frequency information about the signal. Signals are sampled over a period of time and divided into frequency components. These components are single sinusoidal oscillations at distinct frequencies, each with its amplitude and phase. FFT is used for fault analysis, quality control, and condition monitoring of machines or systems. It is an algorithm that determines the Discrete Fourier Transform of an input significantly faster than computing it directly.

The FFT computes the DFT in an efficient manner. The DFT is defined given by

$$H_k = \sum_{i=0}^{n-1} x_i e^{2j\pi ik/n} \quad (2)$$

where j is the imaginary number $\sqrt{-1}$, and n is the number of points in T and F.

III. PROPOSED METHOD

In this section, we explain our proposed system for improving anomaly detection, and also discuss the data sets and the evaluation metric used. The architecture of our proposed method is shown in Fig. 1. As explained earlier, this system combines the variational autoencoder method with analysis of spiking raw data in the frequency domain for purposes of identifying anomalies.

The system consists of three parts. First is the input, second is the variational autoencoder method, and the last is the set of predicted results. The input part consists of the original time series data, which is transformed into the frequency domain in order to visualize the spike plot as a spectrum. The time series data and FFT values of each dataset are then combined. The next step is to input the two groups, i.e.., original data and original data combined with the frequency domain representation, to the variational autoencoder in order to identify anomalies by constructing the encoder and decoder. Next the results from the reconstruction value of the variational autoencoder are obtained.

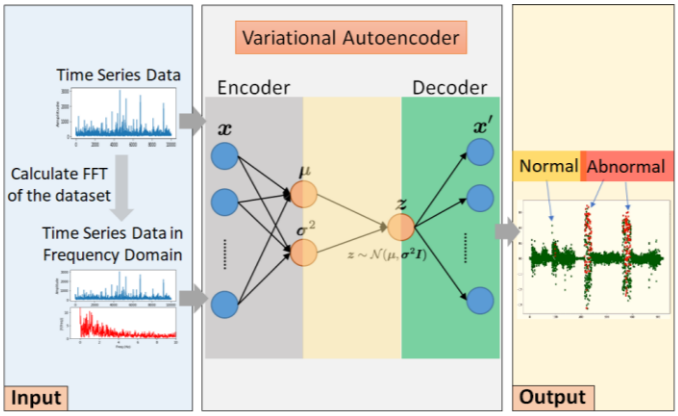


Figure 1. Concept of the proposed method.

A. *Spike Plot*

The Fourier transform is represented as spikes in the frequency domain, the spike height showing the amplitude of the wave of that frequency. By transforming the input signal to the frequency domain, the spike like representations in the plot denote the frequency components of the signal. The Larger spike length, the highest frequency component, and the smaller the spike length, the lower the frequency component. Spikes represent any number of horizontal or vertical line segments with fixed or variable heights. For example, if the time signal is created as a sum of three sine waves, the spectrum will have spikes corresponding to each of the sine components.

Spikes are commonly used in time series plots. They may also be useful in showing deviation from a general value such as the mean or median, more domain-specific cases, such as visualizing spike trains for neurophysiology or spectrograms in physics and chemistry applications.

B. Data sets

To illustrate the effectiveness of our proposed method, time series data was obtained from a UCR public data set [11] and a UCI public data set [12]. All datasets are given in time series format, and every data point is manually labeled. For all datasets, we chose the minority class as an anomaly class. The details about datasets are shown in Table 1. For each dataset, 80% of the normal data were used for the training phase and the remaining 20% and all the anomalies were used for testing.

TABLE I. THE DETAILS OF TIME SIRIES DATA SETS

Datasets	Length	Number of instances	Anomaly Ratio
ItalyPowerDemand	24	1096	0.49
Wafer	152	7164	0.11
SonyAIBORobotSurface2	65	980	0.38
ECGFiveDays	136	884	0.50
TwoLeadECG	82	1162	0.50
MoteStrain	84	1272	0.46
Arrhythmia	274	452	0.40

C. Performance Evaluation

We evaluate the accuracy of the anomaly detection method using Area under the curve of the receiver operating characteristic (AUC), Precision (Pre), Recall (Rec), and F1-Score, which are defined as follows:

$$\text{Pre} = \frac{TP}{TP+FP} \tag{3}$$

$$\text{Rec} = \frac{TP}{TP+FN} \tag{4}$$

$$\text{F1} = 2 \times \frac{\text{Pre}\times\text{Rec}}{\text{Pre}+\text{Rec}} \tag{5}$$

where TP is the correctly detected anomaly, FP is the falsely detected anomaly, TN is the correctly assigned normal, and FN is the falsely assigned normal.

IV. RESULTS AND DISCUSSION

We evaluate the anomaly detection performance for both spiking raw data and combined frequency domain using the Variational autoencoder method. In the combined frequency case, we calculated the FFT values of all datasets and spike plot. The example of a spike plot is shown in Fig. 2 in which the features in the image are extracted by spectrum analysis in real time. The result is from the wafer dataset for spike plot. We extract the data over time by sampling.

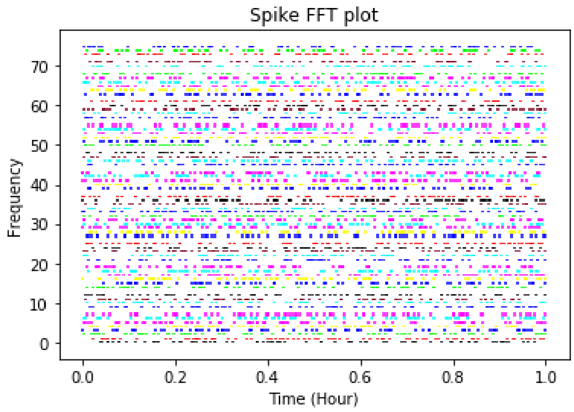
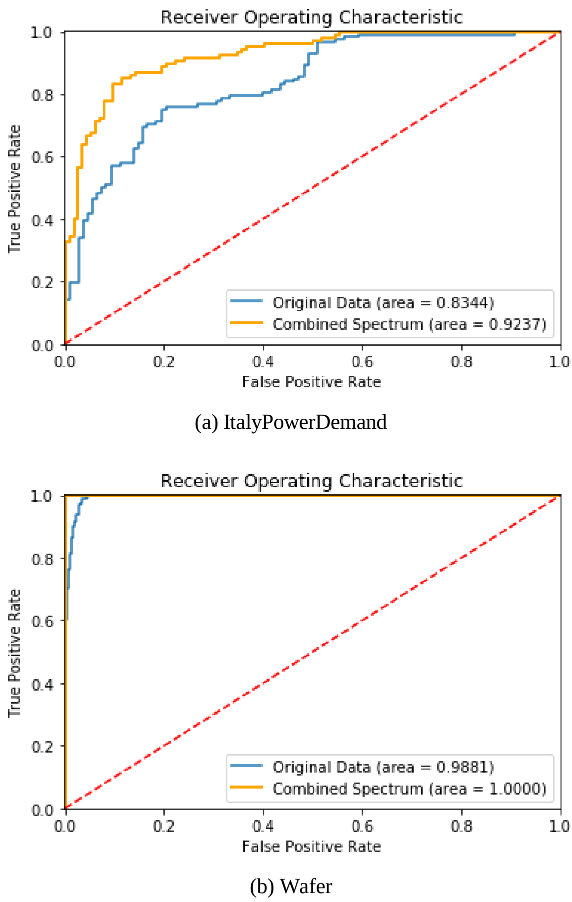
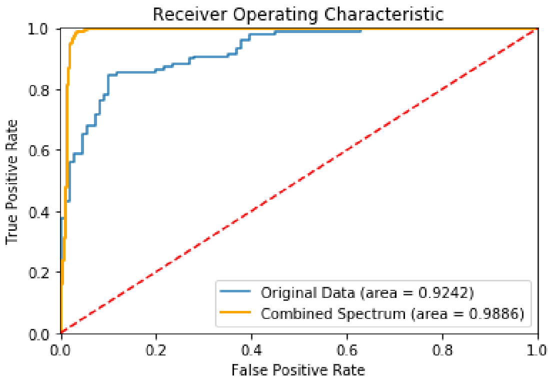


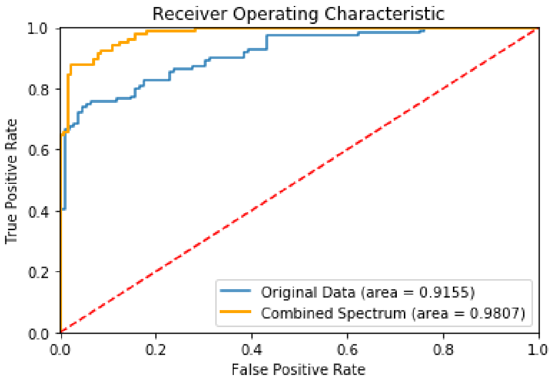
Figure 2. The example of spike plot.

We performed the anomaly detection experiments for accuracy in seven data sets and used AUC as the criterion. From Fig. 3, the blue line is the AUC value of the original data, and the orange line represents the AUC value of raw data combined with frequency domain. It is clear that our proposed method could improve outcomes in AUC values higher than the original data from all data sets. Thus, our proposed methods can be used to improve the effectiveness of anomaly detection for time series data.

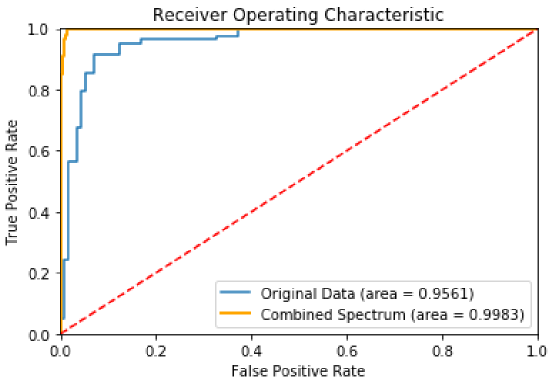




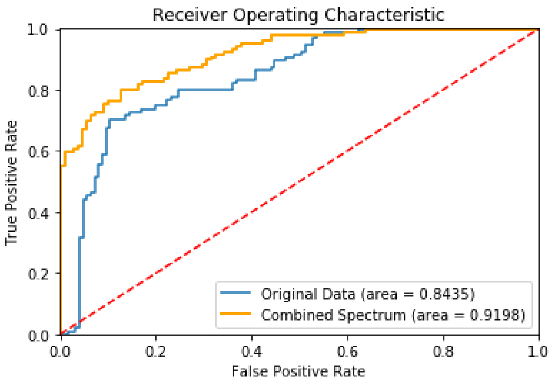
(c) SonyAIBORobotSurface 2



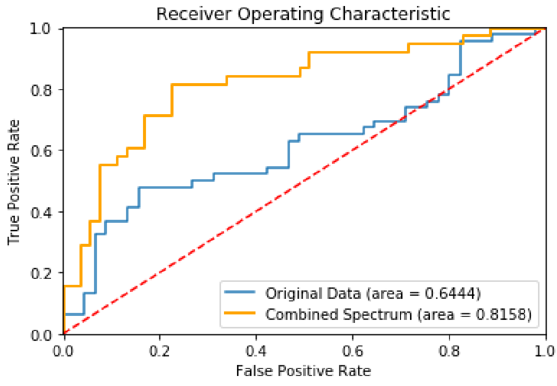
(d) ECGFiveDays



(e) TwoLeadECG



(f) MoteStrain



(g) Arrhythmia

Figure 3. AUC comparisons between original data and combine frequency domain.

The results of anomaly detection and comparisons are summarized in Table 2. We presented the results with 7 data set for discussion. The results show that our proposed method could outperform comparing computed to original data in all aspects and datasets. For the Arrhythmia data set, the result of AUC of Original data yields 64.44%, but our method can improve the results to 81.58%. In addition, the F1-Score of Original data yields only 70.71% compared with 84.75% for our method. The Wafer dataset results for AUC, Precision, Recall, and F1-Score all show our method to be superior. Moreover, SonyAIBORobotSurface2, ECGFiveDays, and TwoLeadECG datasets show perfect recall results, and the precision results for the MoteStrain dataset are also perfect.

We also compared our results in previous research, “Autoencoder with spiking in frequency domain for anomaly detection of uncertainty event” [6], which used a somewhat different method. For three common datasets, the method proposed in this paper can improve the accuracy of all results reported in our previous paper. The results obtained in the earlier research are shown in Table 3, for comparison with those of the improved method displayed in Table 2.

Yet another comparison is presented here, i.e., our latest results with those reported in “Time Series Anomaly Detection with Variational Autoencoders” [10] in 2019. There are six common datasets utilized in our method, namely, ItalyPowerDemand, Wafer, ECGFiveDays, TwoLeadECG, MoteStrain, and Arrhythmia. The results in terms of AUC are shown in Table 4. These results show that our method could improve outcome AUC outcome values more than the approach taken in [10] for all six datasets. In general, the results show that our method constitutes an improvement in anomaly detection performance for time series data relative to the results reported in the literature.

V. Conclusion

The method proposed here uses Variational autoencoder method based on negative log-likelihood loss function together with a comparison between the original data and frequency spectrum data, as well as visualization of the spike spectrum plot to estimate the anomalies based on AUC, Precision, Recall and F1-Score criteria. The experiments on anomaly detection show that our proposed method can improve the accuracy of detecting anomalies on all criteria through the use of spiking spectrum data based on frequency analysis. Therefore, the incorporation of frequency domain analysis has been shown to improve anomaly detection in time series data.

In future research, we intend to create various custom loss functions for use in variational autoencoder to detect anomalies in time series data.

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REFERENCES

[1] J. An, and S. Cho, "Variational autoencoder based anomaly detection using reconstruction probability," Special Lecture on IE 2, no. 1, 2015.

[2] J. Sun, X. Wang, N. Xiong, and J. Shao. "Learning sparse representation with variational auto-encoder for anomaly detection," IEEE Access, 6, pp.33353-33361, 2018.

[3] V. Chandola, A. Banerjee, and V. Kumar, "Anomaly detection: A survey," ACM Computing Surveys, vol. 41(3), 2009.

[4] H. Zenati, C. S. Foo, B. Lecouat, G. Manek, and V. R. Chandrasekhar, "Efficient GAN-Based Anomaly Detection," arXiv preprint arXiv:1802.06222, 2018.

[5] J. Ma and S. Perkins, "Time-series novelty detection using one-class support vector machines," IEEE Neural Networks vol. 3, pp. 1741–1745, July 2003.

[6] U. Yokkampon, S. Chumkamon, A. Mowshowitz, and E. Hayashi, "Autoencoder with Spiking in Frequency Domain for Anomaly Detection of Uncertainty Event," Journal of Robotics, Networking and Artificial Life, vol. 6, no. 4, pp. 231-234, 2020.

[7] D. P. Kingma, M. Welling, "Auto-encoding variational Bayes," Proc. 2nd Int. Conf. Learn. Represen., April 2014.

[8] J. Bayer, C. Osendorfer, "Learning stochastic recurrent networks," Proc. NIPS 2014 Workshop Advances Variational Inf., 2014.

[9] M. Sölch, J. Bayer, M. Ludersdorfer, P. van der Smagt, "Variational inference for on-line anomaly detection in high-dimensional time series," Proc. ICML 2016 Anomaly Detection Workshop, 2016.

[10] C. Zhang, and Y. Chen, "Time Series Anomaly Detection with Variational Autoencoders," CoRR, abs/1907.01702, 2019.

[11] H. A. Dau, E. Keogh, K. Kamgar, C.-C. M. Yeh, Y. Zhu, S. Gharghabi, C. A. Ratanamahatana, Yanping, B. Hu, N. Begum, A. Bagnall, A. Mueen, and G. Batista, "The ucr time series classification archive," October 2018, https://www.cs.ucr.edu/∼eamonn/time_series_data_2018/.

[12] D. Dua and C. Graff, "UCI machine learning repository," 2017. [Online]. Available: http://archive.ics.uci.edu/ml

TABLE II. VAE COMPARISONS BETWEEN ORIGINAL DATA AND COMBINE FREQUENCY DOMAIN

Datasets	Original Data				Combine Frequency Domain			
	AUC	*Precision*	*Recall*	*F1-Score*	*AUC*	*Precision*	*Recall*	*F1-Score*
ItalyPowerDemand	0.8344	0.9643	0.7941	0.8710	0.9237	0.9667	0.9355	0.9508
Wafer	0.9881	0.9787	1.0000	0.9892	**1.0000**	**1.0000**	**1.0000**	**1.0000**
SonyAIBORobotSurface2	0.9242	0.8846	0.9583	0.9200	0.9886	0.9600	**1.0000**	0.9796
ECGFiveDays	0.9155	0.8624	0.9615	0.9091	0.9807	0.9642	**1.0000**	0.9818
TwoLeadECG	0.9561	0.9333	1.0000	0.9655	0.9983	0.9688	**1.0000**	0.9841
MoteStrain	0.8435	1.0000	0.9556	0.9773	0.9198	**1.0000**	0.9778	0.9888
Arrhythmia	0.6444	0.7447	0.6731	0.7071	0.8158	0.8621	0.8333	0.8475

TABLE III. THE AUTOENCODER RESULTS FROM OUR PREVIOUS PAPER

Datasets	Original Data				Combine Frequency Domain			
	AUC	*Precision*	*Recall*	*F1-Score*	*AUC*	*Precision*	*Recall*	*F1-Score*
ItalyPowerDemand	0.5917	0.7091	0.5166	0.5977	0.9031	**0.9727**	0.7279	0.8327
Wafer	0.9820	0.7349	0.9979	0.8464	**0.9963**	0.8008	**1.0000**	0.8894
SonyAIBORobotSurface2	0.8999	0.9043	0.7647	0.8287	0.9520	0.9565	0.8333	**0.8907**

TABLE IV. COMPARING AUC OF VAE RESULTS FROM THE RECENT RESEARCH

Datasets	OUR*	ANOGAN	ALAD	MLP-VAE	IF
ItalyPowerDemand	0.761	0.516	0.538	**0.768**	0.763
Wafer	**0.965**	0.558	0.587	0.790	0.847
ECGFiveDays	**0.970**	0.970	0.694	0.910	0.678
TwoLeadECG	**0.891**	0.554	0.515	0.731	0.760
MoteStrain	**0.840**	0.746	0.504	0.750	0.762
Arrhythmia	**0.758**	0.576	0.515	0.747	0.530
KDD99	**0.958**	0.887	0.950	0.622	0.929
GunPointAgeSpan	**0.881**	0.515	0.547	0.821	0.612
ToeSegmentation2	**0.846**	0.547	0.544	0.816	0.787
Herring	0.659	0.488	0.569	0.627	**0.698**