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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 the detection of anomalies. In this paper, we have used the standard data sets to validate the proposed method. Experimental results show that the comparison of the frequency domain with the original data for anomaly detection can improve validity and accuracy on all criteria. Therefore, analysis of time series data by combining Variational Autoencoder and frequency domain spectrum methods can effectively detect anomalies.**

***Contribution*— We have proposed an anomaly detection method based on the time series data analysis by combining 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 data analysis area. Anomaly detection attempts to identify data occurrences that deviate from expected patterns. 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 focusing on dimension reduction have been developed. As the name suggests, these methods aim to reduce the number features needed to characterize the data, retaining only the critical ones. This approach is useful in many situations requiring low dimensional data, and can be performed by selection or extraction. 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 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].

In recent years, the Variational Autoencoder (VAE) has been developed as a generative model based on Autoencoder. This method offers an effective way of producing a faithful representation of data in a non-linear and noisy environment, 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 data's key features.

In this work, we propose an anomaly detection method using variational autoencoders (VAE) with spiking raw data and the frequency domain for analysis and prediction. We validate the 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 AUC (area under the ROC curve), precision, recall, and F1-score criteria.

II. BACKGROUND AND RELATED WORK

Anomaly detection is an active area of research and has been investigated extensively, see, for example, [3]. It has been applied in a number of different fields. In factory operations dependent on robots, anomaly detection is used to analyze and detect failures in manipulation tasks such as pick and place. It is also used in automated aerial surveillance, as a method known as detecting anomalies and cognizant path planning. Popular techniques utilizing classification approaches that learn a discriminative boundary around standard data, such as SVMs [4] for prediction require a set of vectors as input to represent time-series data. Therefore, it uses a time delay embedding process to transform the time-series into phase space. The time delay embedding process involves identifying relatively short overlapping subsequences drawn from a given long sequence. All vectors are projected onto an orthogonal subspace, acting as a high-pass filter used to exclude low-frequency components, thus allowing only high-frequency ones [5].

Another method uses the fidelity of reconstruction to examine whether the data sets are abnormal. A major example is Principal Component Analysis (PCA) [4]. PCA is a dimensionality reduction technique that works by transforming a large variable set into a small variable set that still contains most of the information in the original set. One of the latest techniques for dimensionality reduction is Autoencoder, which is a neural network approach. The Autoencoder has much in common with PCA. However, the autoencoder method is 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 of time series data by combining Variational Autoencoder and frequency domain spectrum analysis.

Another novel approach is Variational Autoencoder (VAE) [7]. Unlike autoencoders, VAE can reconstruct the input without using an encoding-decoding process. Instead, it defines the probability distribution on the latent vector and learns a distribution in order to match the distribution of outputs inferred by the decoder to the observed data. Then, it can generate new data by sampling this distribution. Bayer and Osendorfer [8] proposed the recurrent neural networks with latent variables by using motion capture data to model time series data. Soelch et al. [9] proposed the Stochastic Recurrent Network (STORN) to detect and predict robot anomalies using 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 a new technique using the variational autoencoder together with re-Encoder and the Latent Constraint network (VELC) to perform time series anomaly detection. This method offers good performance.

In our current research, we propose the Variational Autoencoder technique to compare spiking raw data with original data for detection of anomalies. This approach makes use of the frequency domain to improve performance. We compare our results with those of previous research [6], which has followed a somewhat different approach, but also made use of frequency domain analysis. Analysis in the frequency domain can determine the absolute stability and relative stability of the closed-loop system. It can be extended for application to nonlinear control systems analysis and nonlinear control systems design. We also compare our results with research reported in [10], which used variational autoencoder but did not make use of frequency domain analysis. Our approach is designed to avoid overfitting and to make sure that the latent space is suitable for enabling the generative process. Therefore, VAE can be defined as an autoencoder whose training is regularized, which implies that it can design the complex generative data models and effect a fit to large datasets. These are the reasons that 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

Autoencoder is a neural network architecture consisting of two parts, the encoder, and decoder which pass data through a 'bottleneck', and implement training designed to lose the least amount of information during the encoder-decoder process. The training aims to reduce reconstruction error, which uses gradient descent over the network parameters. Because of over-fitting, the latent space of an autoencoder can be highly irregular. As a result, it is not feasible to rely on the generative process consisting of sampling a point from the latent space and making it through the decoder to get the new data.

Variational autoencoder (VAE) is an autoencoder that addresses the anomaly problem of the latent space by having the encoder return a distribution rather than just a single point, and by including a loss function and regularization term for that distribution to ensure that a better organization of the latent space.

VAE is a popular and widely used method. VAE learns how to represent complex data without supervision by using a deep neural network (Kingma and Welling, 2013) [7]. To ensure that the latent space of VAE has suitable properties for the generation of the new data, VAE has to ensure that the distribution produced by the encoder is regularized during the training. Note that the term "variational" is derived from the close relationship between regularization and the variational inference approach based on statistical properties.

Variational autoencoder has three parts, namely, encoder, decoder, and loss function. Both encoder and decoder are neural networks. An encoder's input is a data point x, an encoder's output is a latent representation z, having weights and biases θ. The encoder aims to "encode" the data into a latent representation space z, which has a lower dimension than the data (input). In general, the latent space is commonly referred to as a "bottleneck". The encoder learns to compress the data from input to lower-dimensional space. The encoder is represented by the conditional probability $q_\phi(z|x)$.

The decoder's input is denoted by z, the decoder's output is denoted by a datapoint x. Weights and biases are represented by ϕ, and $p_\phi(x|z)$ represents the decoder. The decoder aims to "decode" the low dimensional latent space representation z into the data point x (output).

The loss function of VAE uses negative log-likelihood and a regularizer. The overall loss is given by $\sum_{i=1}^{N} l_i$ a total of N datapoints. A loss function l_i for datapoint x_i is given by:

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

The first term represents the reconstruction loss of the negative log-likelihood of the i -th data point. This term prompts the decoder to reconstruct the data. Poor reconstruction will incur many costs associated with this loss function.

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

VAE is a highly powerful generative tool because it can be used with various data types such as sequence or non-sequence, continuous or non-continuous, even labeled or completely unlabeled data.

B. Frequency Domain Analysis

The frequency domain is the domain of analysis of mathematical functions or signals transformed from the time domain. The frequency domain has played an important role in communications, engineering, electronics, image processing, statistics, and various other fields. It is typically used with the analysis of periodic signals or functions recorded over time.

In general, we can observe the relationship between amplitude and frequency. Wave amplitude or vibration amplitude is shown as a positive number, with the highest amplitude being a measure of the deviation from the median. These signals can also be expressed in power versus frequency format. This will appear on the spectrum analyzer, which can analyze the frequency domain.

We can identify the key point in all datasets by analyzing the frequency domain without having to examine all variations occurring in the time domain. The graph of frequency domain expresses either the phase shift or signal magnitude at each given frequency. It expresses the number of signals in each specified frequency band over a range of frequencies. Therefore, signals can be explained as the sum of many sine waves ("Fourier series") with different pulses, phases, and amplitudes.

Discrete Fourier Transform (DFT) is most commonly used in the processing, especially in the digital signal, both real-time or non-real-time. In the frequency domain, we can use the DFT to analyze and design the system. Note that DFT is attractive because efficient algorithms exist for its computation. The so-called Fast Fourier Transform (FFT) is of particular importance.

FFT has been widely used in transforming signal representations between time and frequency domains. FFT transforms the signals into the individual frequency components and also provides the frequency information about the signal. The frequency components come from sampling the signal over a period of time and then breaking it down into frequency components. Each component is a single sinusoidal oscillation at a particular frequency, with certain amplitude and phase. FFT is most commonly used in the analysis of anomalies in operations such as quality control and machine condition checking, as well as other applications. An FFT algorithm can determine the DFT of input sequences much faster than direct calculation.

FFT computes the DFT defined as follows:

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

where j represents the complex number $\sqrt{-1}$, and

n denotes the number of points in time and frequency.

III. PROPOSED METHOD

The proposed system for improving anomaly detection, and the data sets and the evaluation metric used, are described here. Fig. 1 shows the architecture of the proposed method. As explained earlier, this system combines the variational autoencoder approach with the analysis of spiking raw data in the analysis of signal (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 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, including FFT values of each data set, are then combined. 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.

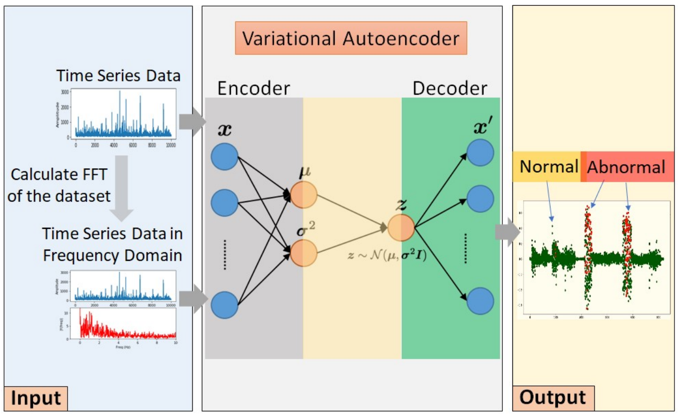


Figure 1. Concept of the proposed method.

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 converting an input signal to the frequency domain, a spike like representations in the plot denote the frequency components of the signal. The Larger spike length, the higher frequency component, and the smaller the spike length, the lower the frequency component. The spikes show the number of sections of horizontal or vertical lines with a constant or variable height. For example, if we generated a sum of four sine waves time signal, we will get the spectrum with spikes corresponding to each of the sine components.

Spikes are typically used in time series plots and can also show deviation from a general value such as average, mode, mean. They are used, for example, in train-spike visualizations in neurophysiology.

B. Datasets

The results reported in this paper made use of ten time series data sets obtained from a UCR public dataset [11] and a UCI public dataset [12]. All data sets were given in time series format, in which every data point is labeled. We define the minority class as an anomaly class. The details about data sets are shown in Table 1. In our analysis of each data set, 80% of normal data was used in the training part and 20% of the normal and all anomaly data were used in the testing.

TABLE I. THE DETAILS OF TIME SERIES DATA SETS

Data sets	Time Series Length	Total Instances	Anomaly Rate
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. Benchmark Method

The proposed method was evaluated using standard criteria of anomaly detection, namely, area under the curve of the receiver operating characteristic, precision, recall, and F1-Score, computed as follows:

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

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

$$\text{F1-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{5}$$

where TP denotes accurately detected anomalies, FP stands for the falsely detected anomalies, TN denotes the accurately defined normal, and FN, the falsely defined normal.

IV. EXPERIMENTAL RESULTS

Performance of the proposed method for detecting anomalies in time series data using the Variational autoencoder approach is described in this section. In the combined frequency case, we have calculated the FFT values of all data sets and spike plots. Fig. 2 shows the spike plot example in which image features are extracted by spectrum analysis in real-time. The result is from the wafer dataset for the spike plot. We extract the data over time by sampling.

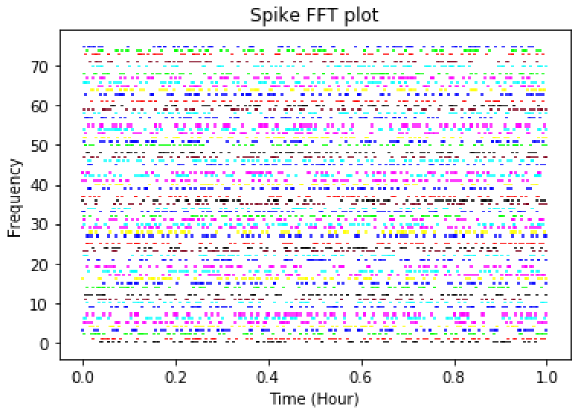
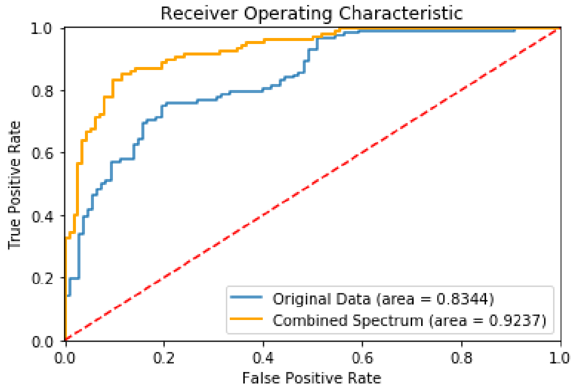
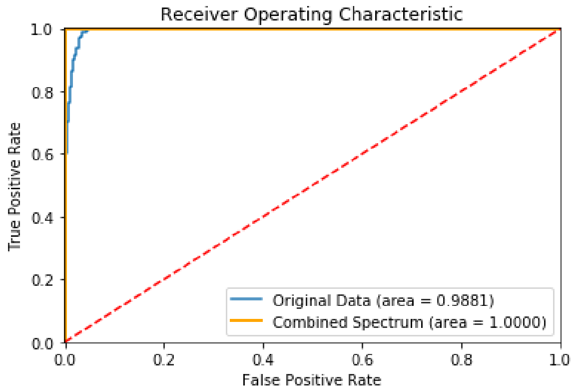


Figure 2. The spike plot example.

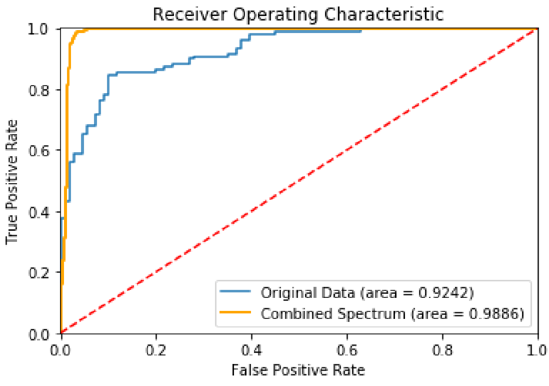
The anomaly detection experiment was conducted to improve the accuracy in seven time series datasets using area under the curve (AUC) criteria. In Fig. 3, the blue line represents the AUC value of the original data, and the orange line represents the AUC value of original data combined with frequency domain information. It is clear that our proposed method can improve outcomes in AUC values to a greater extent than the original data from all data sets. Thus, our proposed methods can be used to improve the effectiveness of anomaly detection in time series data.



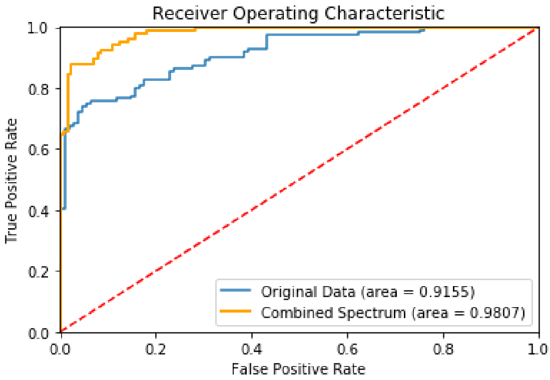
(a) ItalyPowerDemand



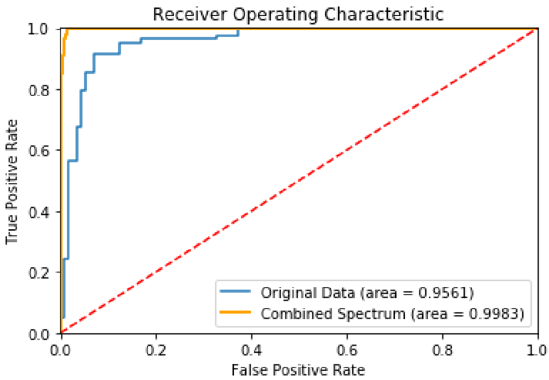
(b) Wafer



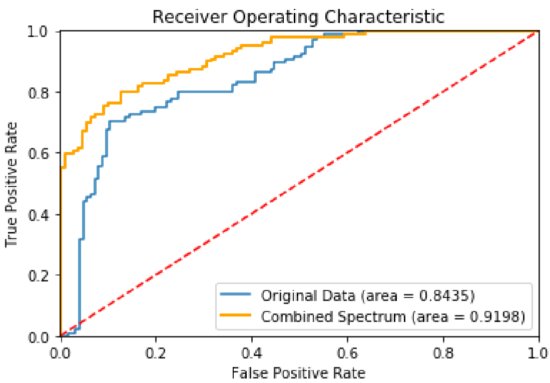
(c) SonyAIBORobotSurface 2



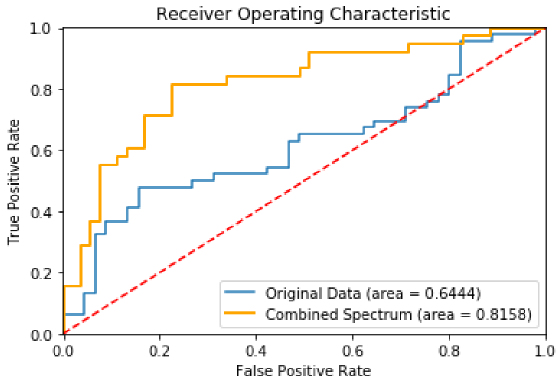
(d) ECGFiveDays



(e) TwoLeadECG



(f) MoteStrain



(g) Arrhythmia

Figure 3. AUC comparison between original data and combined frequency domain.

Table 2. shows the summary and comparison results of anomaly detection. We presented the results with 7 data sets for discussion. The results show that our method could improve performance relative to relying on original data for all criteria and data sets. For the Arrhythmia data set, the AUC value associated with original data was 64.44%, whereas our method gave an improved result of 81.58%. In addition, the F1-Score of original data was 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 current results to those obtained in previous research reported in “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 over those 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 the application of 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 the proposed method can improve the AUC values more than the approach taken in [10] for all six datasets. In general, the results show that the proposed system constitutes an improvement of performance in detecting anomalies 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 according to the AUC, Precision, Recall and F1-Score criteria. Experiments on anomaly detection indicate that our proposed method can enhance the validity and 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.

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

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TABLE II. VAE COMPARE OF ORIGINAL DATA AND COMBINED FREQUENCY DOMAIN

Data sets	Original Data				Combined 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

Data sets	Original Data				Combined 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

Data sets	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**