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Improved DNN and Auto-Encoder Based-Anomaly Recognition for Machine Sound

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ABSTRACT

In industry machine monitoring, anomaly recognition for machine sound is a critical task. It is extremely difficult to distinguish due to the lack of a dataset of sound anomalies. This paper uses the improved DNN and Auto-Encoder to present and test two deep learning methods for recognizing sound anomalies for industrial machine monitoring. The AUC and p-AUC of the proposed approaches are greater and better than the AUC and p-AUC of the baseline system, according to experimental results using the same dataset as the baseline system.

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Keywords:Anomaly Recognition, Sound Anomaly, Auto-Encoder, and Improved DNN.

I. Introduction

Anomaly detection in sound is now employed for a wide range of applications, including audio surveillance [1], animal husbandry [2], product inspection, and predictive maintenance [3]. Because it is used to indicate the signs of errors or malicious activity, early detection may help to avoid difficulties. We could utilize both supervised and unsupervised methods in machine learning to solve these problems. However, applying supervised algorithms to detect anomalies from machine noises is problematic due to the difficulty of collecting a high volume of aberrant sounds. In real-world contexts, the frequency of equipment failure is quite low, and the number of ways in which equipment might fail is also very great. As a result, gathering a sufficient amount of training sound data matching to abnormal operational conditions is not practicable. As a result, these methods are unsuitable for detecting anomalies in sound.

To address the problem, we present an upgraded DNN [4] and an Auto-Encoder based on Fully Connected for anomaly detection in sound. Our paper is organized as follows to clarify the proposed methods: The features that are employed are shown in Sec. 2. Sec. 3 describes the proposed methodology and experimental data, whereas Sec. 4 presents the conclusion..

II. Dataset and Features

As shown in Fig. 1, we employed a feature that is made up of six different characteristics, including Mel Frequency Campestral Coefficient, Short-Time Fourier Transform, Chroma Features, Mel Spectrogram, Spectral Contrast, and Tonnetz. The average feature of six features is then computed, and 1D feature vectors are constructed as the input layer of the proposed approach.

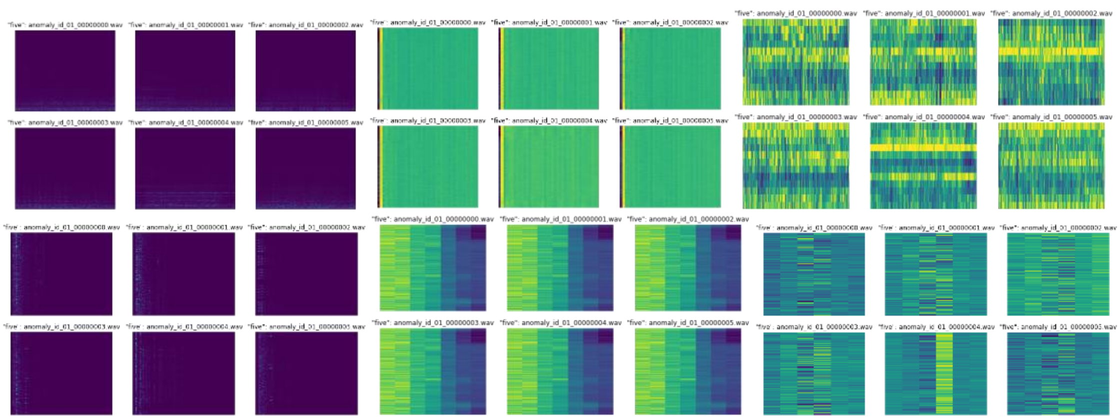

Fig. 1. Used Features

III. The Proposed Methods

A. Improved DNN

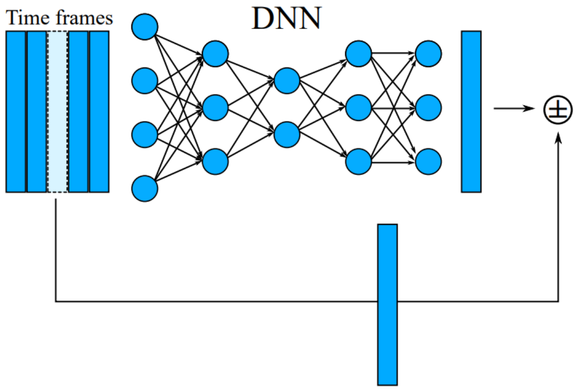

Fig. 2. Improved DNN

To feed the enhanced DNN, features are separated into time frames. Figure 2 depicts the modified DNN architecture. A batch norm layer and a Re-LU activation function follow each fully linked layer.

B. Fully-Connected Auto-Encoder

Figure 3 depicts the proposed technique. Except for the bottleneck layer, which does not have batch norm or Re-LU activation function, each layer is a fully linked layer, followed by batch norm and the Re-LU activation function. The two things that are special about this architecture is that:

- The immediate layer after the input layer has a higher dimension (1024) than the input layer. This goes against the convention of under-complete auto-encoder architecture.
- The bottleneck layer is not followed by batch norm and activation functions like other layers.

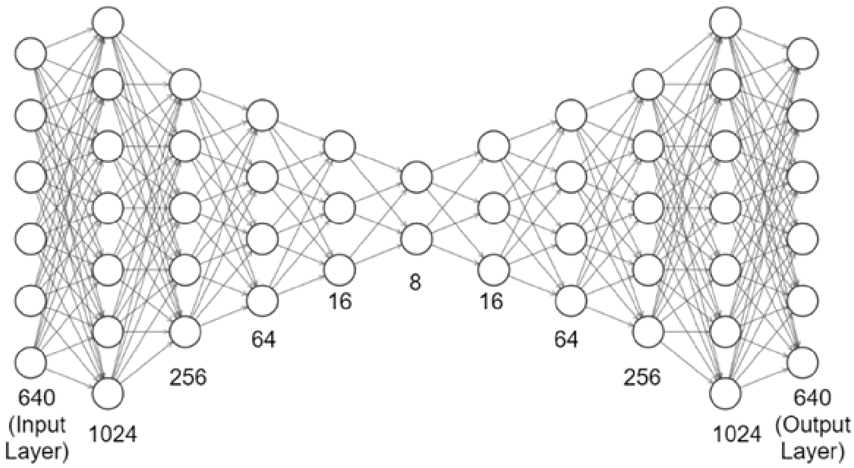

Fig. 3. Fully-Connected Auto-Encoder.

C. Experimental Results

We used the Toy ADMOS [5] and the MIMII Dataset [6], both of which contain the normal/anomalous functioning noises of six different types of toy/real machines. Each recording is a 10-second single-channel audio file that includes both the target machine's operational sound and ambient noise. Toy-car, Toy-conveyor, Valve, Pump, Fan, and Slide rail are the six types of toy/real machines employed. The outcomes of our experiments are compared to the findings of the baseline system. The baseline system is a simple anomaly score calculator based on an auto-encoder (AE). The area under the operating receiver characteristic curve (AUC) and partial-AUC (p-AUC) are the evaluation metrics utilized for this work [7, 8]. All of our approaches' AUC and p-AUC values are greater than the baseline system's AUC and p-AUC, as shown in Figs. 4 and 5.

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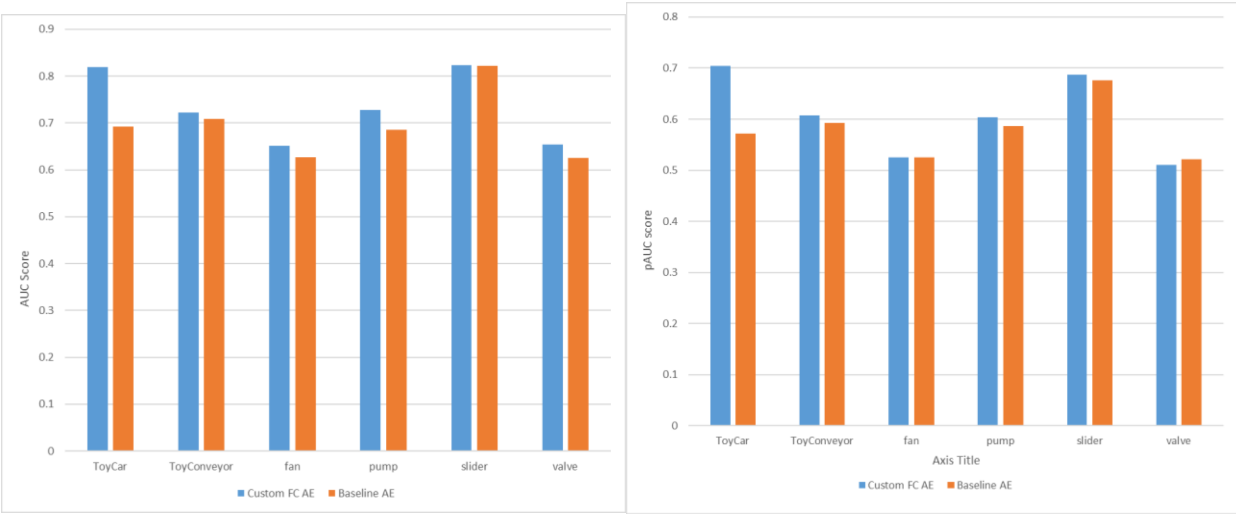

Fig. 4. Experimental result with Fully Connected Auto-Encoder.

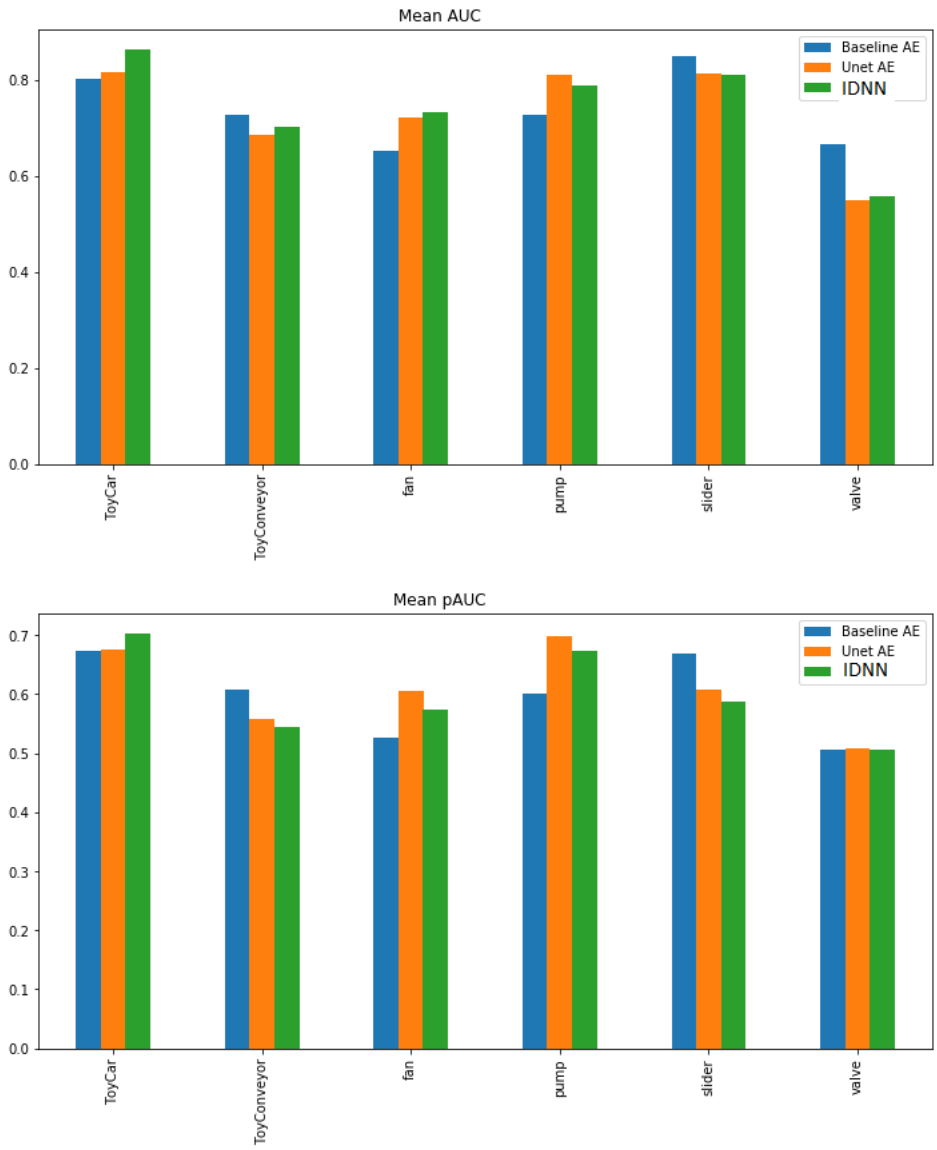

Fig. 5. Experimental Results with Improved DNN.

V. Conclusion

We developed two strategies for detecting sound anomalies for industrial machine monitoring in this research. The proposed methods have been tested on normal datasets that do not contain any aberrant data. The results of the experiments confirmed that our methods are superior to the previously mentioned baseline system. In the future, we'll aim to develop algorithms that can detect even difficult-to-detect sounds.

Acknowledgement

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