Abstract—The increasing deployment of low-cost IoT sensor platforms in industry boosts the demand for anomaly detection solutions that fulfill two key requirements: minimal configuration effort and easy transferability across equipment. Recent advances in deep learning, especially long-short-term memory (LSTM) and autoencoders, offer promising methods for detecting anomalies in sensor data recordings. We compared autoencoders with various architectures such as deep neural networks (DNN), LSTMs and convolutional neural networks (CNN) using a simple benchmark dataset, which we generated by operating a peristaltic pump under various operating conditions and inducing anomalies manually. Our preliminary results indicate that a single model can detect anomalies under various operating conditions on a four-dimensional data set without any specific feature engineering for each operating condition. We consider this work as being the first step towards a generic anomaly detection method, which is applicable for a wide range of industrial equipment.

Index Terms—Internet of Things (IoT), Industry and Production 4.0, Predictive Maintenance, Unsupervised Machine Learning, Anomaly Detection

I. INTRODUCTION

Prognostics and health management approaches have been studied extensively across industrial applications, such as aircraft engines [1], wind turbines [2], and other expensive and mission critical machines. The application of IIoT sensors [3]–[5] enables continuous monitoring on previously unequipped industrial assets. The SITRANS multi sensor [5] enables affordable to monitor equipment and industry expects huge cost savings from the implementation of data-driven predictive maintenance techniques such as anomaly detection. However, the implementation of a traditional anomaly detection technique for some specific equipment often requires significant manual feature engineering [6], [7] and model optimization effort. Alternative approaches requiring less effort and transferability to similar equipment are therefore becoming increasingly relevant in industrial contexts. A number of anomaly detection methods for predictive maintenance have been proposed. Kato et al. [8] proposed a rule-based approach for fault detection in spacecrafts. Principal component analysis (PCA) based anomaly detection in networks was discussed by [9]. [10] showed that autoencoders can outperform PCA based approaches for telemetry data of spacecrafts. Unsupervised anomaly detection with deep autoencoders was shown by [11], [12].

Our aim is to develop an unsupervised anomaly detection method for a universally deployable IIoT sensor tag, which records multivariate data. It should learn anomalies automatically over time and thereby reduce manual feature engineering effort. Our specific contributions so far are: (i) define initial requirements and derive design rationals for minimal-configuration anomaly detection for IIoT Sensors (ii) provide a hand-crafted benchmark data set of evaluating anomaly detection approaches, and (iii) train various deep neural networks with autoencoder architectures and evaluated them against benchmark models.

II. INDUSTRIAL REQUIREMENTS AND DESIGN RATIONAL

A low-cost multi sensor should be applicable to any industrial asset. With the help of this multi- sensor, the conditions should be monitored without any meta information available. For this purpose, the healthy state with all typical operational conditions is recorded with and used as a reference for anomaly detection. The amount of healthy training data is not strictly limited and several days can be expected. The system should be minimal configurable. The only input parameter is
the healthy reference data. The system should be operable by a non-machine learning expert. The user should be a domain expert and select a time period with typical operational conditions as reference. Everything else is left to the model and the system. The decision for an unsupervised machine learning paradigm results from the requirements.

III. DATA SET CREATION

We have selected the peristaltic pump as it can be operated using various operating conditions and anomalies in the pipe’s water flow resistance can be applied easily. Further, the rotor of a peristaltic pump is representative for many rotary equipment in the industry, such as fans, compressors and turbines. Additionally, degradation is commonly observed and can be controlled as pipes can be replaced easily. Abrasion of the pipes will be used to predict failure of the pipe system in subsequent work. Peristaltic pumps are used for sterile or aggressive liquids, as the pump doesn’t contact the fluid. The flow of liquids is induced by a repeating sequential compression of a flexible tube that pushed the liquid in one direction.

We created our data set with a prototype of the SIEMENS SITRANS multi sensor specifically developed for industrial applications and harsh environments [5]. The sensor offers a multiple number of measurement parameters. In this work, we used the sensor tag that records three-axis vibration, each with a frequency of 6664 Hz, an audio signal with 16k Hz, and temperature. Due to restrictions in bandwidth, vibration and audio are measured sequentially for 1024 data points every 60 s. We mounted the sensor tag on the rotational axis of the pump’s rotor and documented the sensor’s angle and its horizontal axis. To simulate various operating conditions, we operated the pump under various conditions by changing the pump’s frequency. Further, we induced anomalies by restricting the water flow in the tube leading to the pipe. We scheduled the data acquisition to generate a data set that is balanced for operating conditions and anomalies. Additionally, we documented the replacement of the tube to allow analysis of the tube’s degradation and we also perform measurements with a rotated sensor to evaluate the models robustness against rotation. A model, which performs well if the sensor was rotated and reattached, is a candidate for architectures that are easily transferable across equipment and require minimal configuration effort. The data set contains 3041 samples with each 1024 data points for audio and the three vibration axis and will be made publicly available.

IV. EXPERIMENTAL SETUP

We trained unsupervised machine learning models to detect the anomalies in our dataset by using autoencoders based on a fully connected deep neural network (DNN), long short-term memory (LSTM) networks and convolutional neural networks (CNN). Autoencoder networks are trained to reproduce a input signal by minimization the error between input and output signal, which is called the reconstruction error. This is done by setting the input values as the target values. If there is a layer with a feature space lower than the input space, the autoencoder is forced to learn a compressed representation and therefore needs to generalize and approximate the input. In other words, a bottleneck in the network requires the encoder to extract the most substantial information.

For anomaly detection, autoencoders are trained to reconstruct only healthy machine data. It is assumed that the autoencoder learns to reconstruct the input for healthy machine data, as it was trained to do so, but will fail to reconstruct anomaly data. The reconstruction error — the error between input and output signal — can be used as an anomaly score. A reconstruction error above a threshold indicates an anomaly. The threshold is calculated on a subset of the healthy data that was excluded from training, by calculation mean + standard deviation of the reconstruction error on the subset. We evaluated the effectiveness of the anomaly detection using standard accuracy (Ac.), precision (P), recall (R) and the F1-score.

We compared the performance of our models on a variety of features. We used the audio and the vibration (vib. 3D) signal separately as well as a combinations of both. Further, we use raw signal and the fast Fourier transform (FFT) of the signals. In order to achieve invariance towards rotation of the sensor, we also use the euclidean norm of the three-dimensional vibration signal, which is denoted as vib. 1D. Feature names are generated from the options mentioned in this paragraph and are shown in Table I. For example, “vib. 1D & audio” denotes the raw audio signal in combination with the euclidean norm of the raw vibration signal. Feature vectors are then min-max normalized based on values of the train set.
The DNN model consists of six fully connected layers of varying dimension. With $x$ being the length of the input signal and $n$ being the characteristic number of neurons, the layers are of dimensions $x, n, \frac{n}{2}, \frac{n}{4}, \frac{n}{8}, \frac{n}{16}, n, x$. All units use the tanh activation function and $n$ is selected from the range 64 to 200, depending on the selected feature. For multivariate features and DNN we stack the feature vectors to achieve one-dimensional features, whereas CNN and LSTM operate directly on the two-dimensional features. Due to the high feature size (1024) compared to the number of samples, we use a rolling window of dimension 64 to create more and smaller feature vectors, that make a smaller model possible. The models threats each sub-vector independently and a decision for a original sample is created by majority vote on the sub-vectors from the rolling window.

The LSTM models consists of stacked LSTMs networks, with increasing dimension that create a two dimensional output by returning an output for every time step. The bottleneck layer reduces the dimension by returning only the last output for every time step. Then the number of neurons is decreased opposed to the encoder. With $n$ being the number of units, the dimensions of the layers are $n, \frac{n}{2}, \frac{n}{4}, \frac{n}{8}, \frac{n}{16}, \frac{n}{32}, \frac{n}{64}, n$ (rounded) with a lower cap of 16 and $n = 150$.

The CNN's encoder consists of an alternating sequence of convolutional and max pooling layers, each of dimension two, with the number of filters for the layers in the encoder being 16, 32, 64, 128. A fully connected layer as a bottleneck and a reversed encoder as a decoder.

We have implemented an end to end pipeline to evaluate the key requirement: “minimal configuration effort”. Further, we compare our model to simple statistical benchmarks based on the reconstruction error using principal component analysis (BM PCA) (see. Fig. 2) and an approach similar to boxplots, where values outside of the mean $\pm 1.5 \cdot$ iqr, with iqr being the interquartile range, are threaded as outliers (BM IQR).

Our aim was to define initial requirements for minimal-configuration anomaly detection for IIoT sensors. Based on the requirements, we focused on unsupervised machine learning and did not perform any equipment specific feature engineering. We created a hand-crafted benchmark data and made it publicly available. We experimented with three with three different neural network architectures for anomaly detection in the tube system of a peristaltic pump. Our preliminary results show an important step towards minimal-configuration anomaly detection for IIoT sensors. With all three networks we were able to outperform a benchmark based on the reconstruction error of a principal component analysis. However, it benchmark performed best with the 3-D vibration signal in both raw and Fourier-transformed form. Thus, our best model outperformed the benchmark by 10 %. However, the simple benchmark based on the interquartile range outperforms our autoencoders and the PCA benchmark by 1 % with a F1-Score of 0.63.

Fig. 2. Example of autoencoder input (measured signal) and output (reconstructed signal) from healthy data. The reconstruction error is derived input and output difference and used for anomaly detection.

V. PRELIMINARY RESULTS

We present the results of our initial experiments for all combinations of model and features in Table I and our benchmarks in Table II. In terms of F1-score, which is a trade off between precision and recall, our models beat the PCA benchmark in 15 out of 24 experiments. We achieve our best result with an LSTM network and the Euclidean norm of the 3-D vibration signal (vib. 1D) resulting in a F1-score of 0.64, a precision of 0.68 and a recall of 0.6. The PCA benchmark performed best with the 3-D vibration signal in both raw and Fourier-transformed form. Thus, our best model outperformed the benchmark by 10 %. However, the simple benchmark based on the interquartile range outperforms our autoencoders and the PCA benchmark by 1 % with a F1-Score of 0.63.

VI. DISCUSSION

Our aim was to define initial requirements for minimal-configuration anomaly detection for IIoT sensors. Based on the requirements, we focused on unsupervised machine learning and did not perform any equipment specific feature engineering. We created a hand-crafted benchmark data and made it publicly available. We experimented with three with three different neural network architectures for anomaly detection in the tube system of a peristaltic pump. Our preliminary results show an important step towards minimal-configuration anomaly detection for IIoT sensors. With all three networks we were able to outperform a benchmark based on the reconstruction error of a principal component analysis. However, it
remains unclear whether the respective sensor combination can be applied to a broad number of assets. Further, the impact of sensor position and the transferability towards identical assets remain unclear. Therefore, in the future, we will perform experiments on a data set that was recorded using different sensor positions to investigate the transferability of our models.

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**TABLE II**

RESULTS OF ANOMALY PREDICTION FOR EACH COMBINATION OF FEATURE SET AND MODEL.

| Features                  |(convolutional neural network (CNN)) |                |                |                |
|---------------------------|-------------------------------------|----------------|----------------|----------------|
|                           | Acc. F1 P R                          |                |                |                |
| Vibrations 1D             | 0.47 0.47 0.44 0.50                  |                |                |                |
| Audio                     | 0.46 0.53 0.44 0.67                  |                |                |                |
| Vibrations 3D             | 0.54 0.62 0.50 0.8                   |                |                |                |
| Vibrations 1D & Audio     | 0.46 0.53 0.44 0.67                  |                |                |                |
| FFT Vibrations 1D         | 0.54 0.00 0.00 0.00                  |                |                |                |
| FFT Audio                 | 0.53 0.46 0.49 0.44                  |                |                |                |
| FFT Vibrations 3D         | 0.54 0.04 0.57 0.02                  |                |                |                |
| FFT Vibrations 1D & Audio | 0.56 0.08 1.00 0.04                  |                |                |                |

| Features                  |(fully connected neural network (DNN)) |                |                |                |
|---------------------------|---------------------------------------|----------------|----------------|----------------|
|                           | Acc. F1 P R                           |                |                |                |
| Vibrations 1D             | 0.49 0.53 0.46 0.61                  |                |                |                |
| Audio                     | 0.46 0.54 0.45 0.68                  |                |                |                |
| Vibrations 3D             | 0.54 0.62 0.50 0.81                  |                |                |                |
| Vibrations 1D & Audio     | 0.47 0.54 0.45 0.68                  |                |                |                |
| FFT Vibrations 1D         | 0.59 0.47 0.59 0.39                  |                |                |                |
| FFT Audio                 | 0.50 0.45 0.46 0.44                  |                |                |                |
| FFT Vibrations 3D         | 0.49 0.43 0.44 0.41                  |                |                |                |
| FFT Vibrations 1D & Audio | 0.50 0.45 0.45 0.44                  |                |                |                |

| Features                  |(long short-term memory neural network (LSTM)) |                |                |                |
|---------------------------|-----------------------------------------------|----------------|----------------|----------------|
|                           | Acc. F1 P R                                   |                |                |                |
| Vibrations 1D             | 0.47 0.48 0.44 0.53                           |                |                |                |
| Audio                     | 0.46 0.53 0.44 0.67                           |                |                |                |
| Vibrations 3D             | 0.55 0.62 0.51 0.79                           |                |                |                |
| Vibrations 1D & Audio     | 0.46 0.53 0.44 0.67                           |                |                |                |
| FFT Vibrations 1D         | 0.53 0.02 0.40 0.01                           |                |                |                |
| FFT Audio                 | 0.52 0.48 0.48 0.48                           |                |                |                |
| FFT Vibrations 3D         | 0.60 0.37 0.71 0.25                           |                |                |                |
| FFT Vibrations 1D & Audio | 0.63 0.42 0.74 0.30                           |                |                |                |