Operation and Maintenance

Unsupervised Deep Learning Image Processing for Anomaly Detection in Offshore Wind Turbines

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ABSTRACT & INTRODUCTION

Offshore Wind Turbines (OWTs) require continuous monitoring to maintain their efficiency and prolong their service life, relying on detailed analysis of turbine components for optimal performance and prompt anomaly detection. SCADA data is invaluable, collected from various sensors, including those monitoring the temperature of the gearbox, a crucial part of OWTs that experiences the most faults. Through the application of advanced signal-to-image processing algorithms, this signal data is transformed into visual formats, enabling the use of Convolutional Neural Networks (CNNs) and autoencoders to identify anomalies in an unsupervised manner. The main objective of this research is to construct an extensive model that decreases false positives and enhances the precision and trustworthiness of anomaly detection. The approach also seeks to increase the sustainability of OWT monitoring by reducing the amount of training data needed and the subsequent storage requirements. Furthermore, the effectiveness of data-driven methods is heavily dependent on data quality. Despite the prevalence of imperfect data, this research addresses six key data quality criteria—Consistent Representation, Completeness, Feature Accuracy, Target Accuracy, Uniqueness, and Target Class Balance—to assess the robustness of the proposed method. This technique aims to facilitate effective, long-term data utilization, minimizing the dependence on vast, flawless datasets and contributing to the sustainability of monitoring systems in renewable energy sectors.

METHODOLOGY

Converting time series data into images offers a visual emphasis on local patterns, enhancing the detection of trends, seasonality, or cycles that are not readily apparent in raw form. This transformation captures and encapsulates crucial information, enabling the application of complex image processing techniques and convolutional neural networks for more effective anomaly detection. This method facilitates the use of data augmentation techniques, which bolster the training of more robust machine learning models by introducing a varied range of scenarios. This image-based representation also enhances the encapsulation of complex features such as shape and texture, providing enriched information that could be missed in numerical data. Moreover, it enables the incorporation of multivariate time series into a unified framework, allowing each variable to be represented as separate channels, thus offering an integrated view of the data's multidimensional nature.

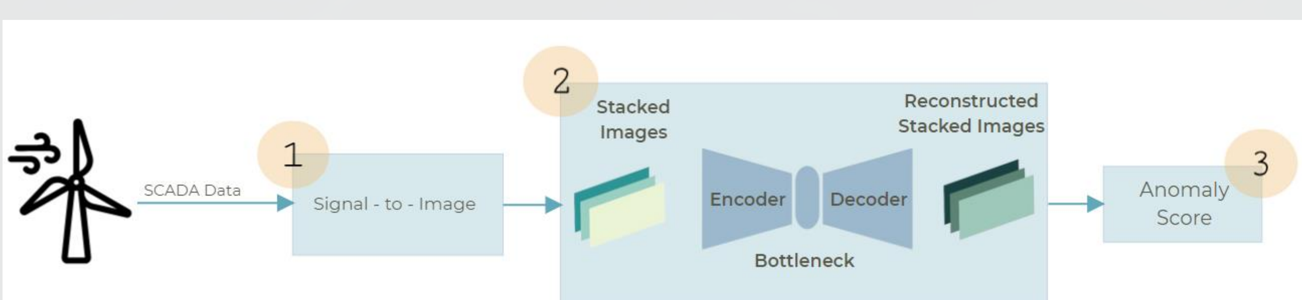
Signal-to-Image Algorithms

In the context of fault detection within generator bearings of offshore wind turbines (OWTs), this research explores various methodologies for mapping time series data to image representations. The study primarily investigates a range of signal-to-image encoding algorithms, including **Gramian Angular Field**, **Markov Transition Field**, **Recurrence Plot**, **Greyscale Encoding**, **Spectrogram**, and **Scalogram**, for the purpose of converting time series data into image-like formats. It is observed that the selection of the encoding technique plays a pivotal role in influencing the results when these techniques are integrated into deep learning frameworks.

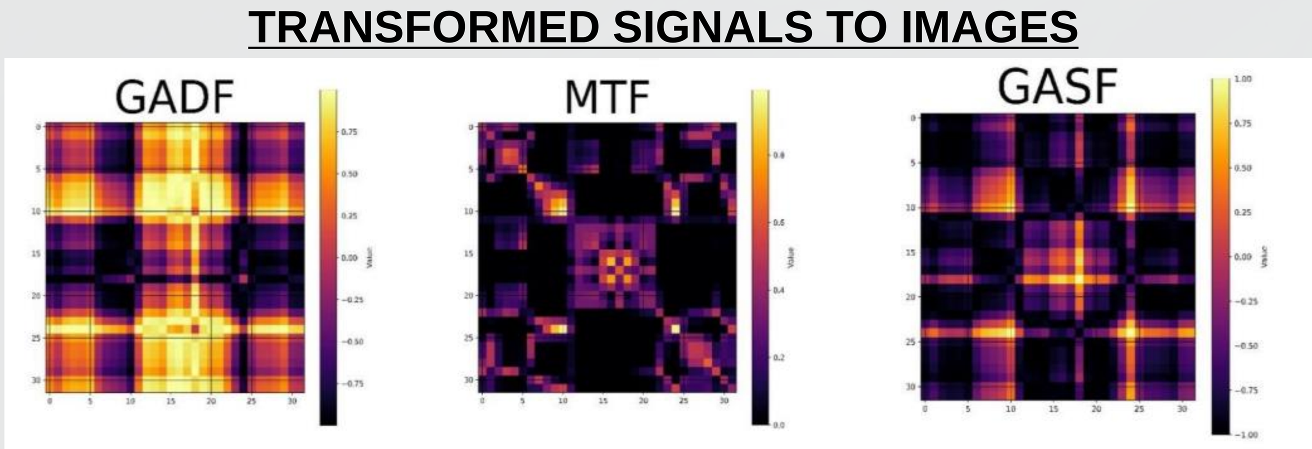
Convolutional Autoencoder:

Convolutional Autoencoders are designed to assimilate the attributes of normal data through training on a dataset comprising normal images. Subsequently, a predefined threshold is applied to the error metric during the evaluation phase, which encompasses a mixture of normal and test datasets. If the error associated with an image reconstructed by the autoencoder exceeds this threshold, it is classified as an anomaly. This methodology facilitates a reduction in the requisite data volume for training and testing, and enables the implementation of an unsupervised learning approach.

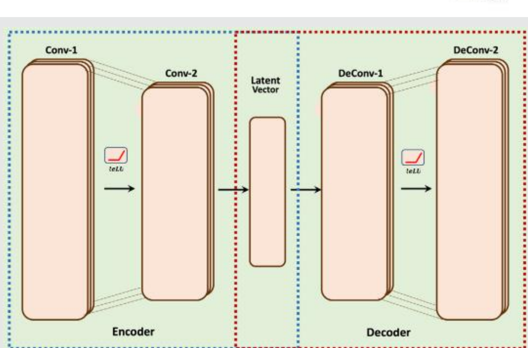
METHODOLOGY ARCHITECTURE



TRANSFORMED SIGNALS TO IMAGES

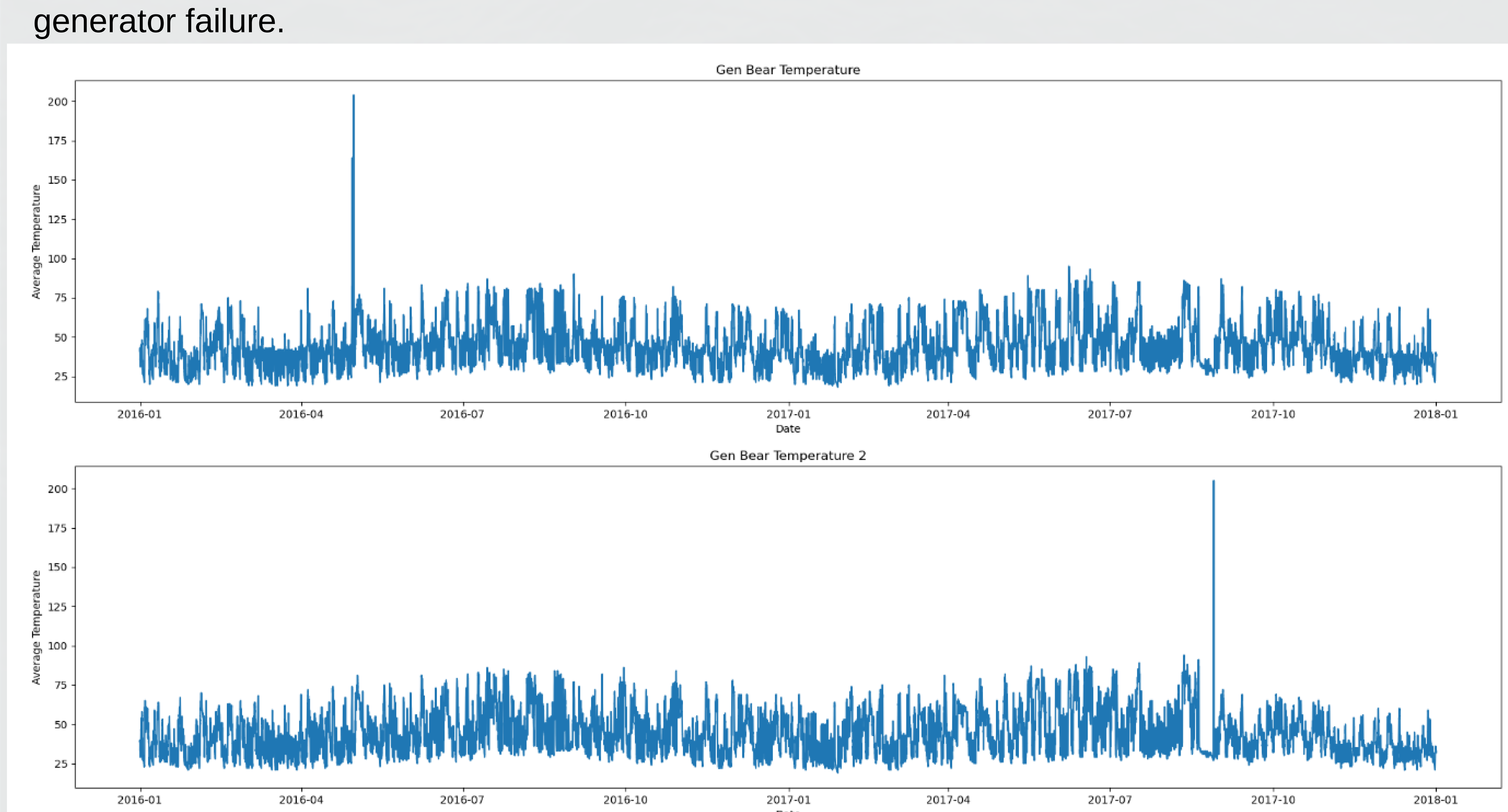


Convolutional Autoencoder Architecture:



GENERATOR BEARING TEMPERATURE

The experimental dataset employed in the preliminary evaluations of this study encompassed the readings gathered from two Generator Bearing Temperature sensors, which were affixed to a solitary wind turbine over a biennial period. Throughout this interval, the autoencoder model underwent training utilizing the dataset procured from one sensor, followed by validation against the dataset derived from the alternate sensor. It is noteworthy that both datasets exhibited a pair of pronounced excursions, manifesting as substantial spikes, temporally aligned with incidences of generator failure.



ANALYSIS & RESULTS: ENCODING ALGORITHMS COMPARED TO BENCHMARK METHODS

The findings of the present study suggest that the Markov Transition Field (MTF) and Gramian Angular Summation Field (GASF) encoding methodologies outperform the benchmark model that utilizes a one-dimensional signal data. In particular, the MTF encoding technique yields the most advantageous results, characterized by zero incidence of errors and the most expedient prediction latency. Although the MTF image processing may necessitate an elevation in resource consumption and protract the training phase, its distinguished accuracy in performance and temporal efficacy in prediction, which are pivotal for practical application, distinguish it from the alternative methods examined.

FURTHER STUDY

Subsequent endeavours will encompass the application of this methodology to a more expansive dataset, enriched with a greater incidence of anomalies. Preliminary evaluations have indicated that this technique harbours significant promise for detailed investigation. It demonstrates an adeptness in anomaly detection requiring minimal data input while still maintaining high precision, even in the presence of a solitary anomaly within the dataset. The methodology has proficiently managed most of the six-dimensional data quality parameters. Further empirical validation will be undertaken in the ensuing stages of this research endeavour.

CONCLUSIONS

Based on the results the following conclusion could be drawn:

- The study demonstrated the promise of unsupervised deep learning and image-based encoding in improving anomaly detection for wind energy generation, which could significantly contribute to the optimization and longevity of renewable energy infrastructure.
- Image-based encoding methods, especially Markov Transition Field (MTF) and Gramian Angular Summation Field (GASF), proved to be more efficient than traditional 1D autoencoders, with MTF showing the highest precision and time efficiency in anomaly detection.
- Subsequent research will involve the application of this methodology to a dataset of increased magnitude, which is slated for investigation in the forthcoming phases of the study.

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