# I. INTRODUCTION

Every work sector, especially those in industries that rely on technical operations and infrastructure systems, is not im- mune to risk and potential damage. The oil and gas industry is a sector highly vulnerable to various types of operational disruptions, particularly in gas distribution through pipelines. The industry relies on pipelines to transport gas and oil on a large scale, essentially the lifeblood of the energy distribution system. However, with pipelines being widespread in length and operating in various extreme environmental conditions, the risk of damage is also higher [1], [2]. Even small, unde- tected damages can become significant problems threatening operational safety and the environment. One such conse- quence is leaks in pipelines, which lead to environmental pollution, increased carbon emissions, and harm to the health of the surrounding population [3]. If these pipeline leaks are left untreated, these impacts will occur, and accidents will result in considerable losses to the oil and gas industry.

Until now, the conventional method used to detect pipeline damage still relies on human manual monitoring. This approach usually involves operators monitoring pipelines through visual observation of operational data, using their experience and subjective judgment. However, this method tends to be inefficient and vulnerable to human error. Even with the increasing complexity of pipeline operations, this method can no longer accurately detect minor issues such as anomalies. To address this limitation, a solution that is gaining widespread application is the use of machine learning (ML) technology in anomaly detection, a form of artificial intelligence (AI) [4]. This anomaly detection technology en- ables real-time monitoring of pipelines, identifying abnormal patterns that might otherwise go undetected so that potential damage or leaks can be mitigated early.

Various machine learning models can be used to detect anomalies, which, of course, have advantages. One of these models is the traditional model, which is based on supervised learning using labeled data, such as K-Nearest Neighbors (KNN) [5], Support Vector Machine (SVM) [6], and Ran- dom Forest [7]. On the other hand, traditional unsuper- vised learning-based models such as K-Means Clustering and Principal Component Analysis (PCA) are often used to automatically detect anomalies without labeled data [8], [9]. However, traditional models for anomaly detection often rely on manually defined rules and thresholds, which can be time- consuming and difficult to optimize [10].

Deep learning-based approaches are increasingly being used as the need for more adaptive anomaly detection sys- tems grows. One study demonstrated that autoencoders could detect anomalies in unlabeled natural gas pipeline operational data, utilizing the Euclidean distance between the original and reconstructed data as the anomaly score and determining a threshold based on the statistical distribution of the score [11]. Meanwhile, another approach compared two popular deep learning architectures, namely Long Short-Term Memory (LSTM) and Temporal Convolutional Network (TCN), in de- tecting anomalies in multivariate time series data. The results show that TCN has advantages in terms of training stability and time efficiency over LSTM and produces slightly higher F1 scores in detecting anomalies [12]. The findings of both studies confirm the importance of selecting the exemplary model architecture in the development of anomaly detection systems, especially on unlabeled time series data such as oil and gas operational data.

Therefore, this research focuses on finding the best model by combining three deep learning approaches, namely TCN, LSTM, and Autoencoder, into two main variants: TCN- Autoencoder (TCN-AE) and LSTM-Autoencoder (LSTM- AE). The two models are compared to identify the most optimal model for detecting anomalies in oil and gas opera- tional data. Given that the data used is unlabeled, performance evaluation is conducted using the Mean Squared Error (MSE) metric as an indicator of reconstruction. In addition to MSE- based quantitative analysis, anomaly detection results are analyzed qualitatively through human visual interpretation to ensure that detected anomalies represent significant devia- tions in an operational context and can be identified in an applicable way. This research provides additional insights for the data science community by benchmarking deep learning architectures under unlabeled time-series conditions. It of- fers practical guidance in selecting lightweight yet effective real-time industrial anomaly detection models, especially in safety-critical domains where labeled data is scarce.