Intorduction

In gas supply infrastructure, gas pipeline networks play a crucial role in ensuring the safe and efficient distribution of gas to various consumption locations. However, gas pipelines can also encounter various technical issues that may jeopardize the integrity of the system and the environment. One common problem that frequently occurs is gas leakage, which can lead to serious consequences, including the risk of fire and explosions. Additionally, the leakage of gases such as isobutane and propane into the atmosphere has very dangerous effects on ozone layer depletion and global warming [1]. For example, data from the Environmental Protection Agency (EPA) shows that emissions of these gases significantly contribute to environmental damage and climate change. Therefore, early detection of gas leaks and other anomalies in pipeline networks is of utmost importance. The use of machine learning has gained widespread attention as it offers a range of advanced tools that provide promising results across various applications [2]. Traditional approaches to anomaly detection have been thoroughly explored using a variety of strategies [3]. However, in recent years, machine learning-based approaches, such as ensemble learning, have become the focus of research for detecting anomalies in gas distribution systems. Ensemble learning combines multiple machine learning algorithms to enhance the accuracy and reliability of anomaly detection. In this context, two algorithms that have proven effective are random forest [4], [5] and gradient boosting [6], [7]. These algorithms can be used to improve the quality of anomaly detection in gas pipelines. Previous studies have demonstrated the effectiveness of this approach, such as the work by Alobaidi et al.[8], who used semi-supervised machine learning to enhance accuracy in detecting pipeline failures, and Ihsan et al.[9], who developed an anomaly detection model based on deep learning using an autoencoder architecture for natural gas pipeline operational data. Additionally, Adebayo [10] conducted research using model development methods with observer design techniques on gas pipelines, while Chen et al. [11] aimed to develop an anomaly identification method specifically for oil pipelines. Nevertheless, this research is expected to fill a gap in the literature by developing a more robust anomaly detection method that can be widely applied in various operational contexts of gas pipeline networks.