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Precision Pipeline Leakage Detection Through Deep Learning and Infrared Sensing

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ABSTRACT

Leaks of chemicals and gas pipes left unrepaired or lost in distribution networks can result in hazards with significant harm to the environment, people, and property, causing economic losses amounting to billions of dollars annually. Conventional inspection techniques, which depend on sporadic inspection schedules, routine checks, and localized sensors, are inadequate since they frequently miss tiny breaches because of their low sensitivity. This paper presents an innovative approach that leverages machine learning algorithms combined with infrared thermal imaging to enhance early detection of minor leaks. We developed a dataset comprising 1035 thermal images of leak scenarios and 1036 images of no-leak scenarios, captured using a thermal camera in a controlled setup. The final dataset has 1035 images of leakages and 1036 images of no-leakage scenarios. Our experiments with a Multi-Layer Perceptron model achieved the highest accuracy of 95.41%. To augment the system's detection capabilities, we integrated it with traditional flow sensor-based methods. The resulting portable device merges thermal imaging and deep neural network analysis, offering a powerful tool for detecting leaks in both household and industrial settings, as well as in agricultural applications.

Introduction

Leaks of chemicals and gasses present significant dangers to the environment, public health, and the global economy [1]. Hazardous spills resulting from industrial accidents cause thousands of deaths, substantial environmental harm, and economic losses amounting to billions of dollars annually. A notable example is the Deepwater Horizon oil spill in 2010, which resulted in the release of approximately 134 million gallons of oil into the Gulf of Mexico, causing long-term environmental damage and costing BP over 20 billion dollars in settlements and compensation [9]. Another notable example is the 1984 Bhopal gas disaster left over 3,000 people dead right away and permanently damaged the environment, making soil unfit for farming and groundwater unusable [5]. These events highlight the necessity of efficient detection and preventive mechanisms to lessen these dangers.

Several factors, such as human error, shaky pipelines, inadequate monitoring systems, and restricted access to real-time monitoring technologies, contribute to chemical and gas leaks, which can result in significant harm [2]. If left unchecked, minor leaks can become large-scale catastrophes injuring a large area. The discharged chemicals have the potential to seep into subterranean water systems, causing chronic poisoning that can harm people for years and render the land hazardous. Conventional inspection techniques, which depend on sporadic inspection schedules, routine checks, and localized sensors, are inadequate since they frequently miss tiny breaches because of their low sensitivity [6]. This lapse in detection exacerbates small leaks and becomes a threat. Although helpful, localized sensors are usually only effective for large flow variations and frequently lack the sensitivity to identify small interval leakages. This implies that minor leaks that develop slowly may go undiscovered until they become serious problems.

My research introduces an innovative approach to address the inefficiencies of conventional leak detection methods by employing machine learning algorithms and infrared thermal imaging. Thermal imaging, with its sensitivity to minute temperature changes caused by leaks, enables early detection and containment. This smart leakage detection system enhances the ability to identify minor leaks in real-time, significantly reducing the need for manual inspections. By integrating infrared sensing with deep learning, this technology offers a more effective solution for early leak detection and prevention, mitigating the risks and economic losses associated with traditional methods.

Early and precise leak detection helps avert the grave effects of chemical and gas spills, safeguarding the environment and public health. A promising answer to the problems with conventional techniques is the combination of deep learning and thermal imaging, which results in a more successful and efficient way of leak detection and prevention.

The rest of the paper is organized in the following ways. The next sections explore related work in this field. Next, we have the materials and methods section which presents the procedure and the tools used for data collection, training the model, and building the hardware device. Then we have a results section presenting the results of the training. Finally, we have discussions and a conclusion section.

Related Work

Finding pipeline breaches is a significant problem for many different businesses, but it's especially difficult in the gas, oil, and water supply sectors. Numerous research studies have examined how improvements in machine learning and sensor technology have improved leak detection systems. For example, in [10], [4], [7] researchers have used data from Wireless Sensor Networks (WSN) or SCADA systems and performed deep learning to detect leakages in oil, gas, and water pipelines. The problem with the data collected from these systems is they can detect only big changes in pressure and flow. This means the detection will be done when the leak has already become big and might not be easy to prevent.

A transfer learning method is presented in a paper by Han and colleagues, to forecast chemical dispersion in real time [3]. This approach mainly focuses on dispersion prediction after a leak has occurred, even if it successfully lowers processing costs and keeps excellent accuracy. To identify leaks before they cause major dispersion, on the other hand, my research takes a proactive approach.

Consider the research conducted by Li and colleagues in 2021 [8]; their approach achieved exceptional accuracy in leak identification by using convolutional neural networks (CNNs) to analyze aural input. However, their method is limited to leaks that generate audible noises and cannot detect minor, silent leaks.

In the above-mentioned works, leaks are detected only when they become big. In contrast, our technology leverages thermal imaging to identify leaks by monitoring temperature variations, allowing us to detect even the smallest leaks that might not produce any sound. This enhanced detection capability significantly improves the resilience and dependability of pipeline leak detection, ensuring that our system can operate effectively in a wider range of conditions.

Materials and Methods

Dataset

The data for developing the deep learning model was gathered by creating a simulated leakage setup and employing an infrared thermal sensor to capture images. The dataset was generated by recording two distinct scenarios: a no-leakage scenario and a leakage scenario, each captured over a 30-minute duration using the thermal camera. The resulting dataset comprised 2071 samples, with 1035 images representing the leakage scenario and 1036 images representing the no-leakage scenario. The images were flattened into pixel values and stored in a CSV file. The dataset was then divided into disjoint training and validation subsets for model development and evaluation.

Machine Learning Model

We employed the Multi-Layer Perceptron (MLP) technique to develop the classification model. To optimize our hyperparameters, we varied the number of neurons in the hidden layer (ranging from 100 to 10,000), the learning rates (0.0001 to 0.001), and the number of epochs (200 to 900). Training the model with these different hyperparameters resulted in accuracies ranging from 88 to 95 percent.

The model was deployed in the cloud and made accessible via an API. We constructed a hardware device using an ESP32 module and a thermal camera (MLX90640) to capture thermal images. The device communicates with the API to obtain predictions for the captured images. The final predictions are displayed on a computer dashboard. The thermal camera's precise imaging capabilities enabled the analysis of temperature fluctuations indicative of potential leak locations, allowing the system to differentiate between normal and leaking sections of the pipe. Additionally, integrating flow sensors added an extra layer of validation by measuring flow rates and detecting significant deviations caused by leaks.

Device

The system comprises three major components. The first device is the two flow sensors, the ESP32 (DOIT), along with the LCD to display the flow sensor data. The second device is the ESP32-S2, along with the thermal camera (MLX90640), which acts as a portable thermal scanner.

The thermal camera with the prediction from the AI model and flow sensors' results were combined to determine whether a leak existed. The combination of two data sources enabled a thorough study, increasing the accuracy of the leak detection system.

Results

The results of our study underscore the effectiveness of combining deep learning algorithms with infrared thermal imaging to detect pipeline leaks at an early stage. To identify the optimal model, we experimented with various configurations of hidden layers, iterations, and learning rates.

During our experiments, the Multi-Layer Perceptron (MLP) model was trained with multiple con figurations. The most effective configuration featured a single hidden layer with 460 neurons, 900 iterations, and a learning rate of 0.001. This setup achieved an accuracy of 95.41%, demonstrating the model's high precision in leak detection. The results indicate the model's robustness and potential for practical applications. The results are summarized in table 1.

Table 1. Performance of Multi-Layer Perceptron (MLP) Models with Varying Hyperparameters

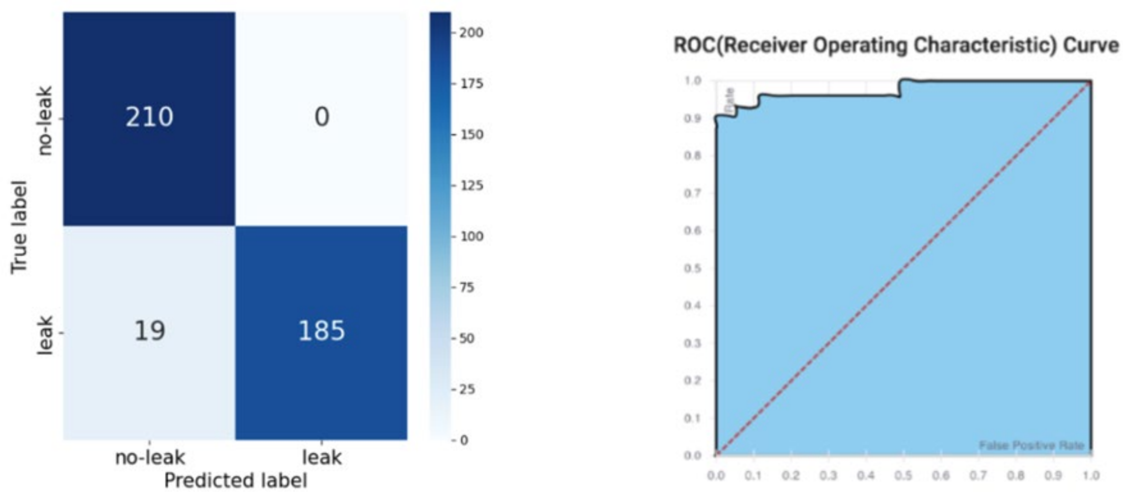
Learning Rate	# of Neurons (Hidden Layer)	# of Iterations	Accuracy
0.001	1000	200	91.06%
	100000	300	92.75%
	800	600	88.41%
	2000	350	93.24%
	460	900	95.41%

	100	200	85.99%
0.0001	500	600	89.61%

Even while the accuracy was high generally, we noticed some surprising variations in the model's performance among the various setups. For instance, the model with 350 iterations and 2000 neurons outperformed the prediction, obtaining an accuracy of 93.2367%.

The confusion matrix for the optimal model configuration demonstrates a high level of predictive accuracy. Figure 1a illustrates that the model exhibits a high true positive rate and a low false positive rate, confirming its robustness in leak detection.

The Receiver Operating Characteristic (ROC) curve for the best model configuration, as shown in Figure 1, further validates the model's performance. The area under the curve (AUC) is close to 1, indicating excellent classification ability.



1a 1b

Figure 1. Test Confusion Matrix & Accuracy Across Epochs

Discussion and Future Work

Our research developed a highly accurate leak detection model with an accuracy of 95.41%. Utilizing deep learning algorithms and thermal imaging, our model detects small breaches often missed by traditional methods. This approach integrates flow sensor readings with thermal data, providing a comprehensive solution that surpasses existing methods reliant on isolated sensors or periodic checks.

Our findings are consistent with similar research, such as the study "Evaluation of Deep Learning Algorithms for Oil and Gas Pipeline Leak Detection Using Wireless Sensor Networks," which also highlighted the effectiveness of machine learning models in improving detection accuracy. Our results further emphasize the importance of combining multiple data sources to enhance the robustness and reliability of leak detection systems.

Despite promising results, our study has limitations. The infrared camera's frame rate, limited to two pictures per second, may hinder the system's ability to detect sudden changes in leak dynamics. Additionally, the flow sensors were more effective for identifying larger leaks, potentially missing smaller, gradual ones. The model was trained on a dataset created in a controlled environment, which may not fully represent real-world variability.

Future research should focus on enhancing the thermal camera's frame rate and sensitivity to better detect minor leaks. Exploring advanced deep learning architectures, such as convolutional neural networks (CNNs), could improve the model's accuracy and robustness. Integrating additional data sources, such as acoustic sensors, could provide more comprehensive leak detection capabilities. Real world testing and validation under various environmental conditions are crucial for ensuring practical applicability. Collaboration with industry partners could facilitate widespread implementation and continuous system improvement.

Conclusion

Our research presents a highly accurate leak detection model, achieving an accuracy rate of 95.41%. By utilizing a machine learning algorithm in conjunction with thermal imaging, the model effectively identifies small breaches that are often missed by traditional methods. This approach integrates thermal data with flow sensor readings, providing a comprehensive solution that outperforms existing methods relying on isolated sensors or periodic checks.

This work also contributes a dataset, that was created by simulating leak and no-leak scenarios, capturing a total of 2071 images with a thermal camera. Despite the promising results, limitations include the infrared camera's frame rate and the flow sensors' effectiveness in detecting smaller, gradual leaks. The model was trained in a controlled environment, which may not fully capture real-world variability.

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