A Convolutional Neural Network Based Solution for Pipeline Leak Detection

Poster Abstract: A Convolutional Neural Network Based Solution for Pipeline Leak Detection

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***Abstract*— Using Artificial Intelligence (AI) in Internet of Things (IoT) environments has shown great potential to transform many industries. As oil and gas industries continue to push for digital transformation, safety critical applications such as pipeline leak detection could also benefit from the adoption of AI and IoT.**

In remote oil and gas installations such as oil production platforms and unmanned wellhead facilities, pipeline leaks are a common occurrence. The harsh operating environment, extreme temperature and weather conditions increases the potential for corrosion induced damages to the pipelines. The extreme conditions where the oil and gas pipelines are located also make it difficult to rely on human operators to physically monitor these pipelines and respond to observed leaks.

We propose a novel approach for pipeline leak detection in which video images from IoT cameras installed across various locations on the pipelines are continuously analyzed and a convolutional neural network model is implemented for detecting oil leaks from the pipeline. This approach is proposed to deliver greater benefits in terms of accuracy and efficiency.

Keywords: Artificial Intelligence, IoT, Computer Vision, Deep Learning, Pipeline Leak Detection, Oil and Gas

I. Introduction

Traditional pipeline leak detection methods which depend on pressure deviation measurement are usually ineffective for detecting small leakages that are less than 1% of the flow volume of the pipeline [1]. Considering that a pipeline carrying 500,000 barrels of crude oil will have 1% of its volume as 5,000 barrels, even such small leakages can have disastrous long term environmental consequences. Such small leakages can continue for days or weeks undetected using current leak detection practices.

An alternative to these traditional methods is to apply machine learning techniques. Researchers [2], [3] have demonstrated success of using machine learning for pipeline leak detection. In remote locations, A typical machine learning work-flow involves collecting the data on the IoT edge and sending the data to the cloud for the machine learning inference. However in recent times, the amount of data generated by IoT devices has significantly increased. Adopting a cloud computing deep learning approach for leak detection of pipelines in remote locations can be challenging for several reasons. Firstly, remote locations usually suffer from last mile connectivity issues. Secondly, insufficient and expensive bandwidth is usually a challenge. Thirdly, High latency is a problem. In safety critical situations such as pipeline leak detection where timing is off essence, the high latency of sending data to the cloud and back cannot be afforded. Fourthly, security and privacy challenges come with transmitting IoT data to the cloud especially for sensitive data. Lastly, for compliance reasons, some data cannot be transmitted to the cloud for processing. Given these reasons, the desire to push the machine learning tasks to the edge of the IoT network becomes of essence [4].

IoT cameras which are deployed around pipelines are usually monitored by human operators from a remote location - assuming there is sufficient last mile connectivity between the pipeline location and the location of the human operator. A more desirable solution will be to have a trained artificial intelligence model which is capable of distinguishing between a pipeline in its normal state and a leaking pipeline.

Several Artificial Intelligence (AI) models have achieved human like performance at various image classification tasks especially with the rise of deep learning algorithms such as Convolutional Neural Networks (CNN). An implementation of the CNN known as the Single Shot Detection (SSD) algorithm [5] leverages on the CNN through the use of various activation maps for its prediction classes.

In this poster, we propose a novel method for detecting crude oil leakages from surface oil and gas pipelines based on machine learning and computer vision techniques. In our proposed solution, a CNN model is trained with images of various pipelines in normal state and in leaking state. A Single-Shot Detection (SSD) algorithm is combined with the CNN model. Hence, our proposed solution incorporates both object classification as well as object localization techniques with relatively low computation. To overcome bandwidth constraints associated with remote pipeline locations, both the model training and inferencing will be carried out at the IoT edge gateway thereby eliminating the need for internet connectivity.

Our main contribution in this poster is a novel solution architecture for pipeline leak detection based on computer vision using Convolutional Neural Networks (CNN) and the Single Shot Detection (SSD) algorithm. This is to the best of our knowledge, the first publication on the use of a CNN model with SSD algorithm for leakage detection in crude oil pipelines.

II. Background and Related Work

Pipeline leak detection methods could be classified based on intervention means as manual, automated or semi-automated detection or based on inference as either direct or indirect inference [6]. Manual detection is conducted by humans, semi-automated involves solutions that are mostly carried out only with complementary input from humans while automated detection is achieved entirely without humans in the decision making process. Direct inference involves physical observation of the condition of the pipelines either by human operators or aircraft patrol. Indirect inference involves the deduction of a leak by inferring from a change in the characteristics of the pipe such as pressure or flow rate.

Pipeline leak detection could also be classified as hardware based or software based. Hardware based methods include acoustic detection [7] [8], optical methods [9] and ultrasonic flowmeters [1]. Software based methods include real-time transient modelling [10], mass/volume balance measurement [11] and negative pressure wave measurement [12] [13] [14]. Other methods include pressure measurement deviation method or use of infrared cameras.

Machine learning techniques have been proposed for pipeline leak detection systems such as SVM in [15]. Belsito et al. [16] proposed a leak detection system for detecting the leak size and location based on artificial neural networks. Carvalho et al. [17] proposed a method for detecting magnetic flux leakages from pipelines using artificial neural networks.

Araujo et al. [18] proposed a method for detecting hazardous leaks from pipelines based on neural networks and optical images. The deep learning models were trained in the cloud, the images were constantly sent to the cloud for inference and the results sent back to the pipeline location for decision making. The paper also utilized multiple sensors in addition to the optical imagery. Jiao et al. [19] proposed an object detection technique combining deep learning with unmanned aerial vehicles (UAV) for identifying oil spills from pipelines. The detection efficiency of this method was limited to line of sight coverage of the UAV.

III. Solution Design

IoT devices usually generate massive amounts of data which are then transmitted to the cloud for processing. For pipeline leak detection, such data could include temperature, flow, vibration or image data. In our solution approach, we propose the use of images captured from several IoT cameras installed at various points on the pipeline.

Computer vision has been largely accelerated by the rise of deep learning techniques. In our proposed solution, we utilize a Convolution Neural Network (CNN) which is a subset of deep learning that involves the use of three layers - the convolutional layers, pooling layers and the fully connected layers. CNN combines these layers with convolving filters which are then applied to the features of the dataset [20].

Our proposed solution incorporates the Single Shot Detector (SSD) algorithm which improves on the CNN by performing both image classification and image localization tasks during a single forward pass of the CNN. The SSD algorithm applies a bounding box technique and an object detector which classifies the detected region as indicated on a label map [5].

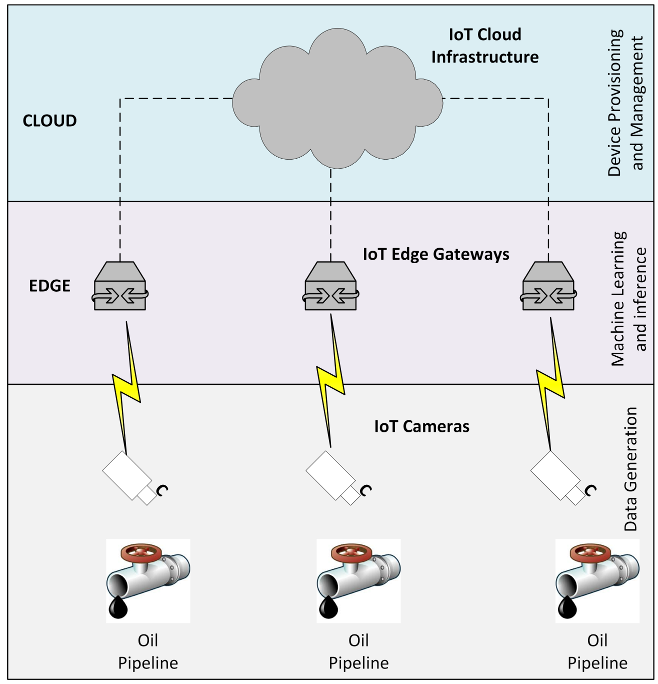

Fig. 1. Solution Architecture

Detecting leaks in realtime from a streaming video requires our model to perform both image classification and image localization tasks. The muti-scale sliding window detector in SSD is able to produce finer accuracy through the use of multiple layers. This finer accuracy is required for detecting smaller particles of leak that will be detected.

Fig 1. shows our proposed solution architecture comprising of 3 different layers. The first layer comprises of the IoT cameras which generate the data from the pipeline and its environment. In the second layer, we have the IoT Edge gateways which connect the IoT cameras to the cloud. In our solution architecture, the machine learning training and inference are performed on the IoT edge gateway. The third layer comprises of the IoT cloud infrastructure, where IoT device provisioning and management tasks are carried out asides other functions.

As shown in Fig. 1, several IoT video cameras are constantly monitoring the pipelines at various points and recognizing the environment around the pipeline. Each camera is configured to collect the video data from the oil pipelines at 720px and a bit rate of 2500kb/s.

A custom object detection model is built using the TensorFlow deep learning framework. In addition, we will configure a training pipeline in TensorFLow to automate our deep learning workflow, and then proceed to train our model.

In our proposed solution, the images will be transmitted to the IoT edge gateways for analytics and processing. A pretrained CNN model is deployed onto the IoT edge gateway. The CNN model is then further trained using localized images of the specific pipeline. Each layer of the CNN model processes the features of the images from the pipeline before the image is passed on to the output layer of the classifier. In the output layer, the classifier makes a prediction whether the image represents a leaking or a normal pipeline. The output layer produces a binary classification output indicating either a leak or no leak. The accuracy is measured by calculating the precision of the prediction known as mean average Prediction (mAP)

Since the IoT video cameras and IoT edge gateways are in remote offshore locations with limited bandwidth, transmitting video images to the cloud for processing requires more bandwidth. This increases the cost of inferencing. To solve this problem, the proposed deep learning model training and inferencing will be deployed on the IoT edge gateways. That eliminates dependency on internet connectivity for the prediction or inferencing by the CNN model.

A. Comparison with Existing Related Solutions

In terms of complexity, our proposed solution is less complex compared to the implementation approach in [18] which uses multiple measurement parameters. Also, since our implementation approach does not require online connectivity, this makes it feasible for implementation in remote oilfield areas where last-mile connectivity is a major barrier.

Also compared to satellite imaging solution approaches which require line of sight to the satellite and can only detect leaks from surface pipelines which are exposed to the sky, our proposed solution is more practicable since the IoT cameras can be deployed in sheltered locations such as oil platforms and drilling rigs.

Our proposed solution is also more effective in terms of response time than alternative solutions that use UAVs since the proposed IoT cameras will be fixed and stream continuously from the pipeline.

B. Next Steps

Our solution architecture is proposed in the context of surface oil and gas pipelines. Sub-sea pipelines which require cameras designated for underwater operations are out of scope of our solution. Also, pipelines which are buried underground were not covered within the scope of this poster since they would require some real sight visual capture of the pipeline section for the solution to work. We consider these areas as opportunities for future research.

IV. Conclusion

The proliferation of IoT devices has continued to create new value streams across multiple industries. By leveraging Artificial Intelligence (AI) techniques with IoT, the ability to attain human like performance in various activities without exposing humans to high risk environments is possible. In this poster, we introduced a method for detecting oil pipeline leaks in remote oil and gas locations with limited last-mile connectivity using computer vision and Convolutional Neural Networks.

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