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Preventive and Predictive CNN Based Solution for Pipeline Leak, Blockage and Corrosion 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, corrosion and blockage detection could also benefit from the adoption of AI and IoT.

In our day-to-day life, we come across pipeline accidents and their after-effects. Structural deterioration of pipes in urban distribution network has presented great challenges to the utilities all over the world. When the deterioration exceeds its resiliency, the pipes leak or burst, leading to significant socio-economic overhead. The harsh operating environment, extreme temperature and weather conditions increases the potential for corrosion induced damages to the pipelines. The extreme conditions where the 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 preventive and predictive AI-based solution that can continuously monitor the health of a complex pipeline infrastructure. It is a complete solution where pipelines will be scrutinized for blockage, leakage, corrosion, and defects. We propose a novel approach 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 leaks from the pipeline. Flow sensors will be mounted on the hardware to measure the fluid flow rate. This approach is proposed to deliver greater benefits in terms of accuracy and efficiency.

Keywords : Artificial Intelligence, IoT, Deep Learning, Pipeline Leak Detection, Pipeline Corrosion Detection, Pipeline Blockage Detection

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 have demonstrated success of using machine learning for pipeline leak detection. In remote locations, A typical machine learning workflow 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 with various activation maps for its prediction classes.

In this poster, we propose a novel method for detecting crude oil leakages from surface 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 pipelines.

II. BACKGROUND AND RELATED WORK

Pipeline leak detection methods could be classified based on intervention means as manual, automated or semiautomated 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. PROPOSED SOLUTION

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].

Pipeline distribution systems contain different types of buried pipes (for example, cast iron, ductile iron, asbestos cement, polyethylene, steel, and polyvinyl chloride). As pipeline infrastructure becomes older, its structural condition, hydraulic capacity, and performance deteriorates.

Our proposed solution is a preventive and predictive AI-based solution that can continuously monitor the health of a complex pipeline infrastructure. It is a complete solution where pipelines will be scrutinized for blockage, leakage, corrosion, and defects. Flow sensors will be mounted on the hardware to measure the fluid flow rate. Local administrators can analyse complete pipeline conditions and take necessary corrective measures. End users can see the pipeline condition of their regions and file a complaint in case of any damage.

Solution can be described in 3 Sections as shown in figure 1:

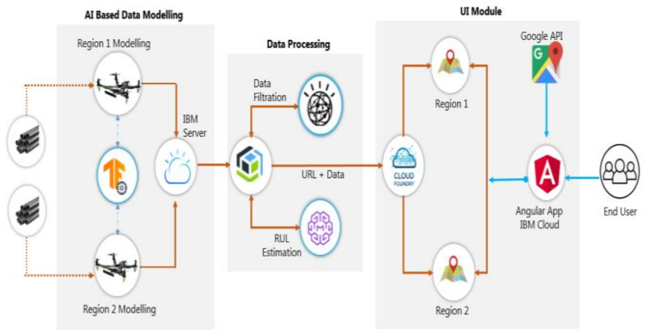

Fig 1: High Level Architecture

A. AI Based Data Modelling

IOT hardware with drone/camera feed will be an input to the model for detecting the pipe flow rate, diameter, area, blockage, corrosion, and breakage using TensorFlow neural networks. Flow sensors (hardware) mounted on the drone/camera will determine the fluid flow rate. These statistics will be used for estimating the remaining useful life of the pipe based on additional factors such as soil components, safety measures, geographical location, and fluid type.

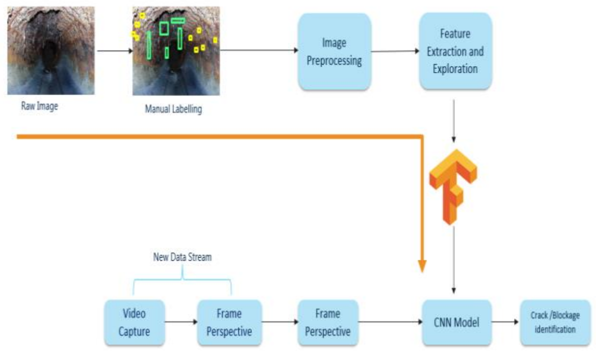

Fig 2: Crack and Blockage Identification process

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 pipelines at 720px and a bit rate of 2500kb/s.

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

B. Data Filtration

The processed data obtained from Section 1 is stored in a central server, database, or repository. When an end user requests to view the statistics using the UI, raw data for the requested location is fetched from the central server and cumulative data is prepared using Global APIs. This data provides information about the flow rate, prediction of pipe deterioration, and remaining useful life of the pipeline with recommendations.

C. User Interface

Authorized users/administrators can view the data on website. On successful log on to a specified zone, a Google API will request for the location and display the user's location data. Data of other regions can also be seen by selecting the location on the Google map. Based on the selected region, the data will be fetched from the central server with a live feed. Statistics of different regions can be compared. For alarming situations in any region, SMS/email messages can be sent to the designated person. The end users will have the read-only access to the UI and can file a complaint in case of any damage in their respective regions.

Detecting leaks in real time 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 3. shows our proposed solution architecture comprising of 3 different layers.

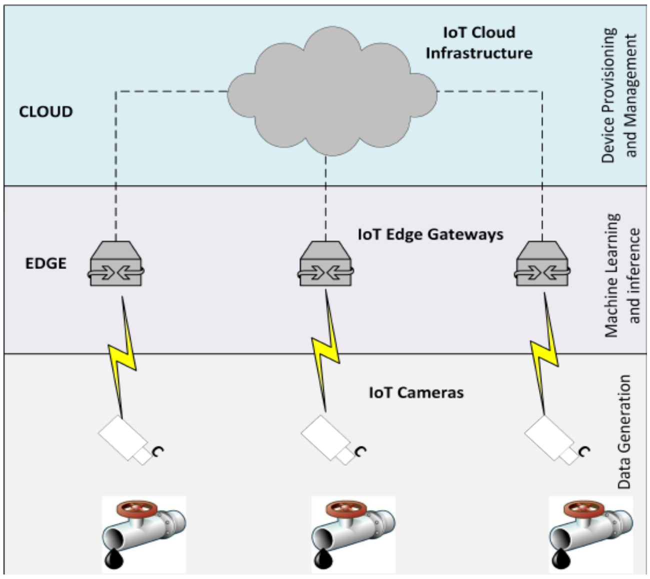

Fig 3: Detailed view of fetching data and storage on cloud

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.

In our proposed solution, the images will be transmitted to the IoT edge gateways for analytics and processing. A pre trained 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 connection.

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. We introduced a method for detecting pipeline leaks, blockages, corrosion in remote locations with limited last-mile connectivity using computer vision and Convolutional Neural Networks.

V. FUTURE SCOPE OF RESEARCH

Our solution architecture is proposed in the context of pipeline leak detection, corrosion, and blockage detection. Recommendation of alternate channel in case of pipeline blockage and water quality check are out of scope of our solution. Also, the subsea pipelines which require cameras designated for under water operations are out of scope. We consider these areas as opportunity for future research.

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